Air Pollution and Women's Reproductive Health and Healthcare in India

Abstract

Air pollution has been shown to have wide-ranging negative effects on health, including effects on fertility. Less is known about the way people respond to high levels of air pollution and the indirect effects air pollution may have on access to reproductive healthcare. This paper merges data from India's Demographic and Health Surveys (2015/2016) to satellite-derived PM2.5 data to estimate the effect of air pollution in India on fertility outcomes and the use of reproductive healthcare. To address endogeneity concerns, we use local wind direction as an instrumental variable for air pollution. We find no significant short-term effect of air pollution on the probability of giving birth, but for every 10 $\mu g/m^3$ increase in PM2.5 levels in the 12 months preceding the survey, the probability of having had a miscarriage during this time period increases by 0.17 percentage points (pp), or 15.5% over the sample mean. Air pollution also reduces the likelihood of using modern family planning methods by 4.06pp (12.3%) and of having any antenatal healthcare visits by 3.2pp (19.5%). Among women who used antenatal healthcare, we find a delay in the first antenatal healthcare visit, as well as a lower probability of having blood pressure taken or being told about possible complications (among other significant measures of quality). We also find that women in rural areas exposed to higher levels of pollution over the last 12 months are less likely to have visited a doctor or a nurse and more likely to have visited a community health worker instead.

JEL: J13, I12, Q53

Keywords: air pollution, fertility, reproductive healthcare, India

1. Introduction

It is well known that outdoor air pollution causes inflammation in the lungs and has negative impacts on respiratory and cardiovascular health (Dominski et al., 2021; Hoek et al., 2013). More recently, studies have shown that air pollution is also associated with neuroinflammation and impaired brain functioning (Aguilar-Gomez et al., 2022; Power et al., 2015). Recent research has also shown that air pollution has important negative effects on women's reproductive health outcomes with reduced fertility, longer time to conception, reduced in-vitro fertility treatment success (Aguilera et al., 2023) as well as higher miscarriage and stillbirth rate (Ha et al., 2022). Oxidative stress and placental inflammation have been hypothesized as some of the key mechanisms underlying the relationship between air pollution and reproductive outcomes (Aguilera et al., 2023; Silvestro et al., 2020).

In addition to direct health impacts, air pollution may also have indirect impacts on reproduction if people change their behavior to respond to any (anticipated) air pollution effects on their or their children's health or non-health outcomes. For example, Gao et al. (2024) find that higher pollution negatively affects the fertility outcomes of ethnic Han people in China. Importantly, they find evidence for a behavioral response to air pollution because the fertility decisions of ethnic minorities not bound by the one-child rule are not affected. In addition, they find that the fertility choices of people who tend to have higher demand for child quality are more sensitive to air pollution. Chaijaroen and Panda (2025) similarly find a negative effect of air pollution on births in Thailand which is accompanied by an increase in short term contraceptive use by women and is present especially in areas with higher access to information.

In this paper, we examine the relationship between air pollution and reproductive outcomes in India with a special focus on the use of reproductive healthcare. Our study is thus related to the literature on air pollution and fertility as well as, more broadly, to the recent literature on environmental stressors and reproductive healthcare. For example, Nguyen (2025) studies climate-induced weather shocks and shows that women exposed to drought in the past 12 months are less likely to use (modern) contraception. Similarly, in a review of the literature, Pappas et al. (2024) show that extreme weather events (floods, windstorms, and droughts) disrupt maternal health services. Little is known about how access to reproductive healthcare may be affected by air pollution.

Air pollution may affect reproductive healthcare if women are less likely to travel outside the home to get contraception and antenatal care in periods of high air pollution. This may be due to health concerns as well as a lower willingness to engage in a healthcare system that may be overwhelmed by patients with pollution-induced respiratory illnesses. Anecdotal evidence from India shows drastic increases in outpatient visits related to respiratory illnesses in periods of high air pollution.[1] Liu et al. (2022) provide evidence consistent with this particular demand-side mechanism in their study on health-seeking behavior in China. Specifically, they find that higher monthly air pollution is associated with lower likelihood of visiting a health facility when ill or injured. In addition, high air pollution has been associated with lower labor productivity both for indoor (Adhvaryu et al., 2022; Batheja et al., 2025; Chang et al., 2016) and outdoor workers (Hill et al., 2024; Graff Zivin & Neidell, 2012). A decrease in income due to air pollution may thus also be associated with lower demand for preventive healthcare and contraception.

In our study, we use information on geographic location to match household survey data from the fourth round of India's Demographic and Health Surveys (2015/2016) to data for satellite-derived surface PM2.5 levels. We then examine the effect of air pollution in the last 12 months on fertility outcomes and the use of reproductive healthcare during this time period. Our identification strategy relies on using local wind direction as an instrumental variable for air pollution. We show that, in India, there is no significant short-term effect of air pollution on the probability of giving birth, but air pollution does increase the incidence of miscarriage. Specifically, for every 10 $\mu g/m^3$ increase in PM2.5 levels in the 12 months preceding the survey, the probability of having had a miscarriage during this time period increases by 0.17 percentage points (pp), or 15.5% over the sample mean. Interestingly, the effect on women living in rural areas is almost twice as large as the effect on women in urban areas (0.23pp vs 0.12pp). This suggests that air pollution may also affect miscarriage rates through indirect, non-biological pathways.

We further test whether air pollution affects access to (quality) reproductive healthcare with a special focus on differences between rural and urban areas. We find that air pollution lowers the probability of using modern family planning methods by 4.06pp, or 12.3%. It also reduces both

[1] https://www.business-standard.com/industry/news/hospitals-report-40-50-rise-in-opd-visits-admissions-amid-pollution-surge-124111901141_1.html

the access and quality of antenatal healthcare, especially for rural women. On average, air pollution is associated with a lower likelihood of having any antenatal healthcare visits (effect size of 3.2pp, or 19.5%), and among the women who used antenatal healthcare, we find a delay in the first antenatal healthcare visit, as well as a lower probability of having blood pressure taken or being told about possible complications (among other significant measures of quality). We also find that women in rural areas exposed to higher levels of pollution over the last 12 months are less likely to have visited a doctor or a nurse and more likely to have visited a community health worker instead. We further confirm the robustness of our findings using district-level data from India's Annual Health Survey (AHS) from 2012/2013.

India is one of the countries with the highest levels of air pollution in the world. Some regions in the Indo-Gangetic plains (which also have the highest population density in India) were exposed to as high as 16 times the levels set by the WHO standard of PM2.5 levels below $10\mu g/m^3$ (Ravishankara et al., 2020). While vehicular and industrial emissions are major sources of pollution in urban areas, crop burning is a common source of pollution in rural areas, and rural and urban areas are equally exposed to air pollution (Bikkina et al., 2019). It is estimated that, in 2019, 10.4% of all deaths in India were attributed to ambient particulate matter pollution and the economic loss due to lost output from related premature deaths and morbidity was 0.84% of India's GDP, with significant variation across states (Pandey et al., 2021). Understanding the total effects of air pollution, including those on reproductive health outcomes, is vital in quantifying the full costs of air pollution in India. In addition, this study sheds light on the little studied effects on healthcare services and brings attention to the need to prepare healthcare services for shocks related to air pollution and other environmental stressors in a developing country context.

2. Conceptual Framework

Gao et al (2024) incorporate air pollution in a standard quantity-quality fertility model to show that when the negative effect of air pollution on children's health and educational outcomes is considered, increased pollution is expected to increase parental investment per child to mitigate those negative effects. This would make fertility more expensive and thus lower fertility for households with higher preferences for child quality, especially when their fertility is constrained as it is in China by the One Child Policy. In this paper, we test the predictions of their model in the context of India where no fertility restrictions are present. In addition, we extend the evidence on the effect of air pollution to the study of the use of contraceptives and antenatal care. Below we present a simple conceptual framework that illustrates the ways in which air pollution may affect demand for reproductive healthcare.

Suppose women choose consumption and investment in health to maximize their utility subject to a budget constraint and a health production function:

$$\max_{C,I} U(C,H) \ s.t. \ p_c C + p_h I = Y \ and \ H = h(I; \epsilon, s, \mu)$$

where p_c and p_h represent the marginal cost of the consumption good, C, and the health investment good, I, respectively. Health (H) is a function of investments in health which build on a health endowment, ϵ, health shocks, s, as well as community characteristics that determine access to and quality of healthcare services, μ. The reduced-form demand function for the health investment good can be presented as a function of prices and income, as well as endowments and shocks: $I = f(p_h, p_c, Y; \epsilon, \mu, s)$. This simple model shows that air pollution could affect a woman's demand for healthcare in a number of ways.

First, air pollution may reduce demand for healthcare if the cost of the investment good, p_h, increases. Health investments can include both monetary and time investments. While there is no reason to expect the fees for antenatal care or contraceptives to increase due to pollution, the cost of the time investment is likely to go up. That is because the price of the time investment is the opportunity cost of time which increases if women have to wait longer for service when health providers are overwhelmed with patients with respiratory illnesses due to pollution. In addition, air pollution may increase the psychological cost of the time investment as women may prefer to stay home and reduce their exposure to air pollution.

Second, air pollution may reduce demand for healthcare if the price of the consumption good increases or household income decreases. High air pollution can lead to people spending less time outdoors and, thus, less time working in order to reduce their exposure to air pollution. It can also lower labor productivity for those who do keep working. This may result in lower household income and as a result, lower demand for antenatal care or contraceptives.

Third, air pollution may increase demand for healthcare if there is a negative health shock, s. Air pollution can serve as a negative health shock both to the mother's health and her unborn child. Since we are focusing on demand for contraceptives and antenatal health services, however, this effect may not be present if women are not aware of air pollution affecting the health of their baby or if they are less sensitive to the quantity-quality tradeoff because of few restrictions on their fertility.

Finally, air pollution may affect demand for healthcare if it affects the quality and availability of healthcare services, μ. If air pollution causes disruption in the provision of services because of hospitals being overwhelmed with patients with respiratory illnesses and only lower-quality care is available, then women may choose to delay seeking antenatal care as it might now have lower perceived benefit. Similarly, if supply of contraceptives is disrupted, we would see lower use of modern methods of contraception.

3. Data

3.1 Demographic and Health Survey

For the main analysis, we use nationally representative cross-sectional data from the fourth round of the Demographic and Health Survey (DHS-4) for India collected from January 2015 to December 2016. DHS-4 interviewed 699,686 women aged 15-49. DHS data include women's full birth history, as well as information on births, miscarriages, and use of contraception and antenatal healthcare in the 12 months prior to the survey. DHS data also contain information on various individual and household characteristics including woman's age, education, area of residence, religion, caste, and household wealth index. Importantly, DHS also provides the GPS locations of each survey cluster (equivalent to census villages), randomly displaced by up to 2 km in urban areas and up to 5 km in rural areas (with 1% of rural areas displaced by up to 10 km). We use information on geographic location and month and year of interview to link DHS data to other geo-coded data (like air pollution, wind and weather controls) for the 12 months prior to the household survey.

3.2 Air pollution data

Air pollution data on fine particulate matter, PM2.5, are from NASA's Modern-Era Retrospective analysis for Research and Applications (MERRA-2) satellite reanalysis project (Global Modeling and Assimilation Office (GMAO), 2015a). Air pollution data are reported as a 1-hour temporal data with a horizontal resolution of 0.5 x 0.625 degrees grid. 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 for each DHS cluster. In our sample, the average PM2.5 concentration in the last twelve months prior to the month of interview is $44.83\mu g/m^3$ with a standard deviation of $16.33\mu g/m^3$. Figures A1 and A2 display the area study map and the distribution of PM2.5 averages over 12 months across all DHS clusters.

3.3 Weather data

Weather data including mean temperature, total precipitation, and wind speed and directions are downloaded 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 (GMAO), 2015b). We construct the number of days during the study period (the past 12 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 by the total number of days in the twelve months to calculate a share.

3.4 Annual Health Survey

As a robustness check, we also use district-level data from the India Annual Health Survey from 2012-2013 - the closest year to our study period with publicly available data.[2] The Annual Health Surveys collect information on maternal and child health, including the use of antenatal care, in nine states with high neonatal deaths: Assam, Bihar, Chhattisgarh, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttarakhand, and Uttar Pradesh.

4. Empirical specification

The main relationship we would like to estimate could be presented in this simple equation:

$$y_{icgmy} = \beta_0 + \beta_1 PM2.5_{cgmy} + X_i\lambda + W_{cgmy}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + v_{icgmy} \quad (1)$$

where the dependent variable, y_{icgmy} is the outcome of interest for woman i interviewed in month m in year y and living in grid-cell c of the geographical region g. The size of the grid-cell is approximately 53 Km. The variable of interest is fine particulate matter represented as $PM2.5$

[2] Data available here: https://www.data.gov.in/resource/key-indicators-annual-health-survey-ahs-2012-13.

which is the 12-month average level of PM2.5 concentration in the grid-cell before the month of interview in survey year y. The term Xi includes a set of individual- and household-level characteristics that are plausibly unaffected by recent outdoor pollution levels. In particular, the individual-level characteristics include woman's age (and age square) and woman's education (an indicator for having no education, primary education, incomplete secondary education, and complete secondary education). The household-level characteristics include indicators for rural area of residence, Hindu religion, and scheduled castes or scheduled tribes and other backward castes. The standard errors are clustered at the district level.

We include month of interview, $\eta_{i,(m)}$, and survey year, $\eta_{i,(y)}$, fixed effects to remove any time trends and seasonality effects. In addition, we include a host of weather controls to account for the fact that pollution and weather may be correlated.[3] Specifically, we include the averages of precipitation, temperature, and wind speed measured at the grid-cell level as well as the square of these variables to capture non-linearities in the relationship between weather and pollution. 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). The identifying assumption in this specification 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}.

One threat to identification is that pollution may be correlated with unobserved individual or household characteristics. For example, richer and more educated women may have better information about the effects of pollution on health and may be able relocate away from highly polluted areas. If these women are also more likely to use antenatal healthcare, for example, this may artificially create a negative effect of pollution on antenatal healthcare even if there were no relationship between the two variables. On the other hand, if areas with higher pollution are also richer areas with more economic activity and better (health) infrastructure, then higher pollution

[3] Figure A3 shows the relationship between PM2.5 concentration levels and the mean temperature, total precipitation, and average wind speed over the 12 months prior to the survey across the study region. PM2.5 levels are positively associated with mean temperature, while negatively associated with total precipitation. PM2.5 and wind speed exhibit a non-linear relationship with an inverse U-shape. Low and high wind speeds are associated with low levels of PM2.5, while moderate wind speeds increase PM2.5 levels.

may be artificially associated with higher use of antenatal healthcare, once again biasing the coefficient of interest. In addition, classical measurement error in the pollution variable could bias the coefficient as well.

Consistent with other studies that measure the impacts of air pollution (Balietti et al., 2022; Bondy et al., 2020; Deryugina et al., 2019; Herrnstadt et al., 2021), we use wind direction as an instrumental variable to address the endogeneity concerns. Specifically, we explain the variation in PM2.5 with the share of days in each DHS cluster when wind originated from one of the four quadrant wind directions (north, east, south, and west). The impact of local wind direction on local pollution may vary depending on the location of the source of pollution or other geographic characteristics. That is why, we interact our instrument, local wind direction, with geographical region and allow the effects of the instrument to vary by region. The estimating equations are:

$$PM_{cgmy} = \gamma_0 + \sum_g^G \gamma_1^g Share_{ic}^N + \sum_g^G \gamma_2^g Share_{ic}^E + \sum_g^G \gamma_3^g Share_{ic}^S + X_i\lambda + W_{cgmy}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + u_{icg} \tag{2}$$

$$y_{icgmy} = \beta_0 + \beta_1 \widehat{PM}2.5_{cgmy} + X_i\lambda + W_{cgmy}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + v_{icgmy} \tag{3}$$

where $Share_{i,c}^{\omega}$ with $\omega \in \{N, E, S\}$ represents the respective shares of days in the past 12 months when the wind was blowing from North, East, and South where woman i was living in grid-cell c of the geographical region g. $Share_{ic}^{West}$ is the omitted category. The γ^g parameters are estimated based on the variation across all cells within 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 regions (which results in 90 excluded instruments in the first stage with 30 regions for each of the three wind directions: north, east, and south). Figure A4 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. Table A1 reports the regression results from the first stage. Wind direction is a strong predictor of air pollution with an F-statistic of 19.194.

5. Results

5.1 Descriptive statistics

Table 1 shows the descriptive statistics for our sample of 699,497 women with non-missing pollution data. The average age is 29.83 and 34% of women have no formal education. Seventy-one percent of women live in rural areas. About 8% of women gave birth in the last 12 months prior to the month of interview and 1.1% had a miscarriage. Only 37% used family planning with 33% using modern contraception. Among women who gave birth, 16% did not use any antenatal care. Of those who used antenatal care, 53% saw a doctor at some point during their pregnancy and 47% saw an Auxiliary Nurse Midwife (ANM).

5.2 Effect of pollution on fertility outcomes

In Table 2, we present the results for the effect of air pollution on fertility outcomes measured over the last 12 months preceding the survey. In column 1, the OLS analysis, controlling for individual and household characteristics, weather controls and time and region fixed effects, shows that for every 10 $\mu g/m^3$ increase in PM2.5 levels in the 12 months preceding the survey (an increase equivalent to close to ½ of the standard deviation of PM2.5), the probability of giving birth increases by 0.16 percentage points (pp). Given a sample mean of 7.7% of women giving birth in the 12 months prior to the survey, the effect of a 10 $\mu g/m^3$ increase in PM2.5 levels can be translated to an increase of 2.08% (100*0.16/7.7) in the probability of giving birth. Accounting for the potential endogeneity in the pollution variable using an instrumental variable regression model, however, reduces the coefficient by half and the effect is not statistically significant anymore.

While Gao et al (2024) find a large decrease in the probability of giving birth associated with air pollution for Han Chinese, it may be the case that Indian households are less responsive to air pollution compared to Han Chinese because of lack of awareness of the health impacts of air pollution or inability to control fertility due to worse health infrastructure. To test these mechanisms, we perform heterogeneity analysis by mother's education level, area of residence, and wealth. Columns 2 through 7 of Table 2 summarize these results. We find uniformly statistically insignificant effects of air pollution on fertility in all of these samples, which suggests that lack of information or inability to control fertility are likely not the key reason why we don't find significant effects in India, although the magnitude of the effects for the less educated and rural sample is relatively large compared to the effects for the other samples.

Instead, our results are consistent with Indian households not responding to short-term changes in pollution levels similar to Gao et al (2024)'s finding on ethnic minorities in China who are not bound by the one child policy.[4]

While Indian households may not have a binding constraint on the number of (quality) children they may have, they may be affected by traditional norms of preference for sons. The male skewed gender ratio in India has been shown to be due to infanticide and neglect of girls and elderly women, as well as sex-selective abortions (Calvi, 2020; Nandi & Deolalikar, 2013; Sahni et al., 2008). Given this context of sex selection that may occur even before birth, it is possible that women may choose to give birth to a son but not a daughter when exposed to high levels of pollution. With strong preference for sons, the benefit of having a son may outweigh any potential health costs associated with having a child affected by air pollution. Next, we test this hypothesis in column 8 and column 9 of Table 2. While the OLS results are consistent with our intuition, the IV estimates yield statistically insignificant effects (although they have the expected signs).[5]

Overall, considering the main analysis as well as the additional heterogeneity analyses, we can say we don't find any strong evidence for short-term effects of air pollution on fertility in the Indian context. Next, in column 10, we examine the effect of air pollution on the probability of miscarriage. Both the OLS and IV results show a positive and statistically significant relationship between higher PM2.5 levels and higher probability of having had a miscarriage in the last 12 months, with the IV results being almost three times larger than the OLS results.[6] Specifically, for every 10 $\mu g/m^3$ increase in PM2.5 levels in the 12 months preceding the survey, the probability of having a miscarriage increases by 0.17pp, or 15.5%, given a baseline of 1.1% of women having a miscarriage in that time period. The effect is economically and statistically

[4] We also test the medium-term effect of air pollution where we average air pollution levels over the last three years prior to the survey year. We see that rural households in particular respond to higher air pollution levels over the medium term by increasing their fertility by 0.61 pp (7.9%). The effect for urban households is smaller (0.16pp) and statistically insignificant.
[5] We further perform heterogeneity analysis by district sex ratio. We find small and statistically insignificant effects on birth, birth of a son and birth of a daughter both for districts with below median sex ratio and districts with above median sex ratio.
[6] This suggests a downward bias possibly due to positive correlation between pollution and district/household income and a negative correlation between district/household income and probability of a miscarriage.

significant and is present for the samples of women with and without secondary education, rural and urban areas and poor and non-poor households (Table A2).

This is consistent with a strong biological effect of pollution on miscarriage rates, as already well-established in the literature. Interestigly, however, the effect on miscarriage rates is almost twice as large in rural areas (0.23 pp) as it is in urban areas (0.13pp) – also consistent with the large, although not statistically significant, effect of pollution on the probability of giving birth in rural areas. One reason for the difference in miscarriage rates between rural and urban areas could be that air pollution levels in rural areas are higher than air pollution levels in urban areas. In our sample, however, this doesn't appear to be the case. The average air pollution level for rural areas is 45.0 $\mu g/m^3$ with a standard deviation of 16.2 $\mu g/m^3$ compared to average air pollution level of 44.4 $\mu g/m^3$ with a standard deviation of 16.7 $\mu g/m^3$ for urban areas. Another reason could be that women in urban areas are better able to avoid pollution if they have access to air filters or have others means of avoiding high levels of pollution exposure, including spending less time working outdoors. Yet, Jafarov et al. (2023) report that air filtration is not widespread and there isn't a strong impact of air pollution on time use among urban households. Another explanation could be better access to (quality) reproductive healthcare services in urban areas compared to rural areas. Next, we test the effect of air pollution on reproductive healthcare with a special focus on differences between urban and rural areas.

5.3 Effect of pollution on reproductive healthcare

5.3.1 Effect on use of contraception

First, in order to test the hypothesis of changes in access to (quality) reproductive healthcare, we examine the effect of air pollution on the use of family planning methods. Table 3 shows that, overall, higher air pollution is associated with a lower probability of using any family planning method, with large decreases in the probability of using modern contraception, which are not entirely offset by the higher probability of using traditional methods. Specifically, the instrumental variables analysis shows that an increase of 10 $\mu g/m^3$ in PM2.5 levels in the 12 months preceding the survey decreases the probability of using modern contraception by 4.06pp and increases the probability of using traditional methods by 1.29pp. Splitting the sample by area of residence (rural versus urban), we see that while both rural and urban households have a significant reduction in the use of modern contraception, the decrease for urban households is less than half the size of the decrease for rural households (1.93pp vs 5.07pp) and is mostly offset by an increase in the use of traditional family planning methods. As a result, the effect of air pollution on the overall probability of using any family planning methods is small in magnitude and not statistically significant for urban households (0.43pp) but large and statistically significant for rural households (3.35pp). Our results are similar to the findings in Nguyen (2025) who shows that drought exposure in the 12 months prior to the survey is associated with a 4.4pp reduction in the probability of using modern contraception in Vietnam.

This result is consistent with air pollution causing a larger disruption in the access to modern family planning methods in rural areas compared to urban areas and could explain why we see a relatively large (although not statistically significant) positive effect of air pollution on the probability of having a recent birth in rural areas. Another explanation for this finding could be that air pollution causes a greater shock to labor productivity and income in rural areas than urban areas because labor supply in rural areas and among self-employed or casual workers is more flexible.[7] Thus, women in rural areas may be less able to afford modern contraception. Lack of access to modern contraception, whether due to supply-side or demand-side considerations, could be contribute to the higher (even if not statistically significant) birth rates in rural areas. If rural women are more likely to conceive, they may also be more likely to have a miscarriage compared to urban women.

Next, we study the effect of air pollution on access to (quality) antenatal care.

5.3.2 Effect on antenatal care

In Table 4, we present the results of the instrumental variables analysis for usage of antenatal healthcare for all women who have given birth in the last 12 months. We show that in the full sample, for every 10 $\mu g/m^3$ increase in PM2.5 levels in the 12 months preceding the survey, there is a 3.2pp increase in the probability of not using antenatal healthcare, which corresponds to a 19.5% increase relative to the sample mean probability. The effect is even larger in rural areas (4.22pp) but also present in urban areas (1.74pp). Even if we consider the difference in

[7] For example, Jafarov et al. (2023) show that higher air pollution in India is associated with reductions in time spent on outdoor labor activities for those who are self-employed and casual-laborers and they also show no effect on urban residents. At the same time, Gupta et al. (2017) and Merfeld (2023) find a negative effect on agricultural production in rural India.

baseline probability of no antenatal healthcare between rural and urban areas, the differences in effect sizes remain (effect of 22.8% for rural areas given a sample mean of 18.5% of women not receiving antenatal care in rural areas, and effect of 18.5% for urban areas given a sample mean of 9.4%). We also find that women in both rural and urban areas who do get antenatal care are significantly more likely to delay their first antenatal healthcare appointment. And women in both rural and urban areas are significantly less likely to have taken iron pills (for anemia) in the last 12 months preceding the survey.

Next, we attempt to examine the quality of antenatal healthcare received using information on whether women were weighed, had their blood pressure taken, gave a urine sample, gave blood, and were told about possible complications. The results are summarized in Columns 4 through 9 of Table 4. Across all measures and across all samples, we find large and statistically significantly negative effects of air pollution on the quality of healthcare and once again, larger effect sizes in rural areas than urban areas.

In Table 5, we further examine whether changes in air pollution are associated with changes in the provider of antenatal healthcare. In rural areas, we see that higher air pollution has a statistically significantly negative effect on the probability of receiving antenatal care from the more qualified doctors (3.57pp) and Auxiliary Nurse Midwives, ANM (4.26pp), and an increase in the probability of receiving care from the less qualified community health workers (including accredited social health activists (ASHA)). We see smaller and statistically insignificant effects on the use of these providers for urban areas. Urban women are more likely to report seeing other providers, although the effect is small (0.14pp), and less likely to see Anganwadi workers (1.55pp), who are usually responsible for health and nutrition services.

Overall, there are two key implications of these results. First, the results suggest that air pollution changes access to (quality) healthcare whether because of supply-side constraints when health centers get overwhelmed with patients with respiratory illnesses due to pollution or because of demand-side constraints if women are less willing or able to travel to a health center because of health concerns, long waiting times, or cost considerations. This is consistent with the study by Liu et al (2022) which shows that higher monthly air pollution in China is associated with lower likelihood of visiting a health facility when ill or injured. The effect sizes in Liu et al (2022) are remarkably similar to our results – a 10μg/m3 increase in monthly average PM2.5

was associated with an 18% increase in the probability of refraining from visiting health facilities. The second implication of our results is that the worsening of access to (quality) antenatal healthcare could have contributed to the higher miscarriage rates if it resulted in a failure to detect pollution-induced risk factors associated with miscarriage such as infections, anemia and hypertension although this type of mediator analysis is beyond the scope of the paper.[8]

5.3.3 Analysis using the Annual Health Survey

To further test the robustness of our novel findings, we use district-level data from India's Annual Health Survey. We regress district-level reproductive healthcare indicators for the study period (2012-2013) on district average PM2.5 level in 2012 and include weather controls and region fixed effects, similar to our main household-level specification. The results are presented in Table A3. We find large and statistically significant positive effects of PM2.5 pollution levels on the proportion of women having an abortion (which may include spontaneous abortions, i.e., miscarriages, or may be an indicator of the increase in undesired pregnancies due to the reduced use of contraceptives). Similar to our main results, we also see negative effects on the use of contraceptives (especially modern contraceptives) and on access to (quality) reproductive healthcare: a smaller proportion of women received any ANC, received the full schedule of ANC, as well as had ANC before the abortion or an abortion by a skilled professional. Overall, the analysis using data from the AHS supports the robustness of our results.

6. Conclusion

Air pollution has been shown to have wide-ranging negative effects on health, including effects on fertility. Less is known about the way people respond to high levels of air pollution and the indirect effects of air pollution on fertility. This paper examines the effect of PM2.5 levels on reproductive health in India – one of the countries with the highest levels of air pollution in the world. We show no short-term changes in the probability of giving birth but significant increases in miscarriage probability. We also find that a higher level of air pollution in the past twelve

[8] One caveat of this analysis is that the survey data contains information on antenatal healthcare for all women who have given birth in the last 12 months but does not include women who have had a miscarriage (unless they already have had a successful pregnancy during that time period – which only 7% of them do). We assume the findings are broadly applicable to all women.

months is associated with a significant reduction in access to reproductive healthcare during that time period. Specifically, we find that women exposed to higher PM2.5 levels were less likely to use modern methods of contraception and less likely to use antenatal healthcare if they got pregnant. Further, air pollution affected the types of providers women were likely to see for antenatal care, reducing the probability of them seeing a more qualified doctor or nurse and increasing the probability of seeing a less qualified community health worker. Further work is needed to establish to what extent women's lower access to (quality) reproductive healthcare is due to supply-side and demand-side factors and whether better access to reproductive healthcare can mitigate some of the negative impacts of air pollution on miscarriage rates.

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Figures and Tables

Table 1. Individual- and Household-level Summary Statistics

Variable	Mean	SD
Birth outcome:		
Birth in the last 12 months	0.077	0.27
Miscarriage in the last 12 months	0.011	0.10
Contraceptive use in the last 12 months:		
Family planning method	0.374	0.48
Modern family planning method	0.329	0.47
Traditional family planning method	0.045	0.21
If given birth in the last 12 months:		
Saw a doctor for ANC	0.543	0.50
Saw ANM for ANC	0.467	0.50
Saw traditional healer for ANC	0.008	0.09
Saw CHW for ANC	0.005	0.07
Saw Anganwadi worker for ANC	0.106	0.31
Saw Asha worker for ANC	0.065	0.25
Saw other worker for ANC	0.002	0.04
Did not have any ANC	0.164	0.37
Month of 1st ANC visit	3.325	1.58
Number of ANC visits (conditional on any)	5.056	4.21
Weighed at ANC visit	0.897	0.30
Blood Pressure taken at ANC visit	0.894	0.31
Urine sample taken at ANC visit	0.86	0.35
Blood sample taken at ANC visit	0.87	0.34
Told about possible complications during ANC visits	0.621	0.49
Took iron pills	0.793	0.55
Individual-level characteristics:		
Age	29.829	9.76
No education	0.339	0.47
Primary education only	0.068	0.25
Incomplete secondary education	0.391	0.49
Secondary education or more	0.087	0.28
Household-level characteristics:		
Rural	0.706	0.46
Hindu	0.743	0.44
Scheduled Castes/Scheduled Tribes	0.359	0.48
Other Backward Castes	0.392	0.49

Notes: The overall sample size is 696,497. Modern methods include sterilization of women and men, using IUDs/copper-t/loop, oral pills, male and female condoms, and other modern methods. Traditional methods include using rhythm, periodically abstaining, withdrawing, and other methods. ANC and ANM refer to Antenatal Care and Auxiliary Nurse Midwife, respectively.

Table 2. Effect of Air Pollution on Fertility Outcomes

Dependent variable: Binary (0/1)	Overall (1)	Mother with no education or primary education only (2)	Mother with some secondary education (3)	Rural (4)	Urban (5)
Panel A: OLS estimates					
PM2.5 ($\mu g/m^3$)	0.00016**	0.00026**	-0.00001	0.00022**	-0.00002
	(0.00008)	(0.00010)	(0.00009)	(0.00010)	(0.00009)
Panel B: IV estimates using wind directions					
PM2.5 ($\mu g/m^3$)	0.00006	0.00018	-0.00009	0.00025	-0.00005
	(0.00012)	(0.00014)	(0.00019)	(0.00020)	(0.00012)
Mean of dependent variable	0.077	0.077	0.077	0.084	0.060
First-stage (F-test)	19.194	18.593	20.514	21.500	18.822
Observations	696,497	363,140	333,357	491,920	204,104

	Poor households (6)	Non-poor households (7)	Give birth to a girl in the last 12 months (8)	Give birth to a boy in the last 12 months (9)	Incidence of miscarriage (10)
Panel A: OLS estimates					
PM2.5 ($\mu g/m^3$)	0.00018	-0.00001	0.00003	0.00013**	0.00006***
	(0.00012)	(0.00008)	(0.00004)	(0.00005)	(0.00002)
Panel B: IV estimates using wind directions					
PM2.5 ($\mu g/m^3$)	-0.00006	-0.00004	-0.00003	0.00009	0.00017***
	(0.00017)	(0.00011)	(0.00028)	(0.00007)	(0.00003)
Mean of dependent variable	0.095	0.065	0.037	0.041	0.011
First-stage (F-test)	22.341	16.766	19.194	19.194	19.194
Observations	281,104	415,393	696,497	696,497	696,497

Notes: Standard errors reported in parentheses are clustered at the district level. The number of clusters is 640. The dependent variable in columns 1 through 7 is whether a woman has given birth in the past 12 months before the survey. All regressions include individual and household-level characteristics, weather controls, as well as fixed effects for geographic regions, the month of interview, and survey year. **denotes significance at the 5% level and ***denotes significance at the 1% level.

Table 3. Effect of Air Pollution on the Use of Contraception

Dependent variable: Binary (0/1)	Any method (1)	Modern method (2)	Traditional method (3)
Panel A1: OLS estimates (overall sample)			
PM2.5 ($\mu g/m^3$)	-0.00230***	-0.00309***	0.00079***
	(0.00052)	(0.00048)	(0.00020)
Panel B1: IV estimates using wind directions (overall sample)			
PM2.5 ($\mu g/m^3$)	-0.00277***	-0.00406***	0.00129***
	(0.00065)	(0.00055)	(0.00030)
Mean of dependent variable	0.373	0.328	0.045
First-stage (F-test)	19.194	19.194	19.194
Observations	696,497	696,497	696,497
Panel A2: OLS estimates (rural sample)			
PM2.5 ($\mu g/m^3$)	-0.00282***	-0.00366***	0.00085***
	(0.00055)	(0.00050)	(0.00020)
Panel B2: IV estimates using wind directions (rural sample)			
PM2.5 ($\mu g/m^3$)	-0.00335***	-0.00507***	0.00172***
	(0.00099)	(0.00084)	(0.00042)
Mean of dependent variable	0.370	0.325	0.045
First-stage (F-test)	21.500	21.500	21.500
Observations	491,920	491,920	491,920
Panel A3: OLS estimates (urban sample)			
PM2.5 ($\mu g/m^3$)	-0.00059	-0.00142***	0.00083***
	(0.00053)	(0.00054)	(0.00029)
Panel B3: IV estimates using wind directions (urban sample)			
PM2.5 ($\mu g/m^3$)	-0.00043	-0.00193***	0.00151***
	(0.00067)	(0.00061)	(0.00040)
Mean of dependent variable	0.381	0.336	0.045
First-stage (F-test)	18.822	18.822	18.822
Observations	204,577	204,577	204,577

Notes: Standard errors reported in parentheses are clustered at the district level. The number of clusters is 640 for the overall sample, 627 for the rural sample, and 637 for the urban sample. Any method refers to the combination of modern and traditional methods of contraception. Modern methods include sterilization of women and men, using IUDs/copper-t/loop, oral pills, male and female condoms, and other modern methods. Traditional methods include using rhythm, periodically abstaining, withdrawing, and other methods. All regressions include individual and household-level characteristics, weather controls, as well as fixed effects for geographic regions, the month of interview, and survey year.
***denotes significance at the 1% level.

Table 4. Effects of Air Pollution on Access and Quality of Antenatal Health Care

	Woman's Access to Antenatal Care			
	No antenatal care	Month of first antenatal care	Number of antenatal visits (conditional on any)	Took iron pills
	(1)	(2)	(3)	(4)
Panel A: All residences				
PM2.5 ($\mu g/m^3$)	0.00320***	0.01044***	-0.00702	-0.00511***
	(0.00091)	(0.00242)	(0.00824)	(0.00085)
Mean of dep. var.	0.164	3.325	5.056	0.793
Observations	53,883	44,940	44,612	53,883
F-stat	19.412	20.158	20.158	19.412
Panel B: Only rural residence				
PM2.5 ($\mu g/m^3$)	0.00422***	0.01097***	-0.01317	-0.00457***
	(0.00136)	(0.00348)	(0.01091)	(0.00125)
Mean of dep. var.	0.185	3.401	4.720	0.774
Observations	41,592	33,818	33,593	41,592
F-stat	21.811	22.202	22.326	21.811
Panel C: Only urban residence				
PM2.5 ($\mu g/m^3$)	0.00174*	0.01524***	-0.01563	-0.00406***
	(0.00102)	(0.00424)	(0.01357)	(0.00124)
Mean of dep. var.	0.094	3.094	6.081	0.857
Observations	12,291	11,122	11,019	12,291
F-stat	19.382	19.054	19.230	19.382

	Quality of Antenatal Care				
	Weighed	BP taken	Urine sample given	Blood taken	Told about possible complications
	(5)	(6)	(7)	(8)	(9)
Panel A1: All residences					
PM2.5 ($\mu g/m^3$)	-0.00643***	-0.00649***	-0.00621***	-0.00689***	-0.00646***
	(0.00069)	(0.00064)	(0.00068)	(0.00069)	(0.00094)
Mean of dep. var.	0.897	0.894	0.860	0.870	0.621
Observations	45,048	45,048	45,048	45,048	45,048
F-stat	20.125	20.125	20.125	20.125	20.125
Panel B1: Only rural residence					
PM2.5 ($\mu g/m^3$)	-0.00734***	-0.00801***	-0.00689***	-0.00823***	-0.00697***
	(0.00103)	(0.00102)	(0.00103)	(0.00111)	(0.00138)
Mean of dep. var.	0.886	0.876	0.841	0.848	0.611
Observations	33,913	33,913	33,913	33,913	33,913
F-stat	22.191	22.191	22.191	22.191	22.191
Panel C1: Only urban residence					
PM2.5 ($\mu g/m^3$)	-0.00463***	-0.00398***	-0.00528***	-0.00455***	-0.00551***
	(0.00077)	(0.00062)	(0.00083)	(0.00066)	(0.00121)
Mean of dep. var.	0.932	0.947	0.919	0.938	0.652
Observations	11,135	11,135	11,135	11,135	11,135
F-stat	18.962	18.962	18.962	18.962	18.962

Notes: Standard errors reported in parentheses are clustered at the district level. All regressions include individual and household-level characteristics, weather controls, as well as fixed effects for geographic regions, the month of interview, and survey year.

* denotes significance at the 10% level, **denotes significance at the 5% level, and ***denotes significance at the 1% level.

Table 5. Effect of Air Pollution on Providers of Antenatal Health Care

	Visit doctor	ANM nurse	CHW health worker	ASHA health worker	Anganwadi	Traditional	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All residences							
PM2.5	-0.00118	-0.00504***	0.00011*	0.00104**	-0.00122**	-0.00002	0.00011*
($\mu g/m^3$)	(0.00117)	(0.00125)	(0.00006)	(0.00043)	(0.00053)	(0.00008)	(0.00006)
Mean of dep. var.	0.543	0.467	0.005	0.065	0.105	0.008	0.002
Observations	53,883	53,883	53,883	53,883	53,883	53,883	53,883
F-stat	19.412	19.412	19.412	19.412	19.412	19.412	19.412
Panel B: Only rural residence							
PM2.5	-0.00357**	-0.00426**	0.00026***	0.00126*	-0.00188**	-0.00014	0.00010
($\mu g/m^3$)	(0.00180)	(0.00182)	(0.00010)	(0.00069)	(0.00085)	(0.00014)	(0.00009)
Mean of dep. var.	0.494	0.473	0.005	0.076	0.116	0.009	0.002
Observations	41,592	41,592	41,592	41,592	41,592	41,592	41,592
F-stat	21.811	21.811	21.811	21.811	21.811	21.811	21.811
Panel C: Only urban residence							
PM2.5	-0.00228	-0.00117	0.00001	0.00039	-0.00155**	0.00005	0.00014***
($\mu g/m^3$)	(0.00145)	(0.00143)	(0.00010)	(0.00044)	(0.00063)	(0.00011)	(0.00005)
Mean of dep. var.	0.711	0.445	0.005	0.029	0.069	0.007	0.001
Observations	12,291	12,291	12,291	12,291	12,291	12,291	12,291
F-stat	19.382	19.382	19.382	19.382	19.382	19.382	19.382

Notes: Standard errors reported in parentheses are clustered at the district level. All regressions include individual and household-level characteristics, weather controls, as well as fixed effects for geographic regions, the month of interview, and survey year.
* denotes significance at the 10% level, **denotes significance at the 5% level, and ***denotes significance at the 1% level.

Appendix Figures and Tables

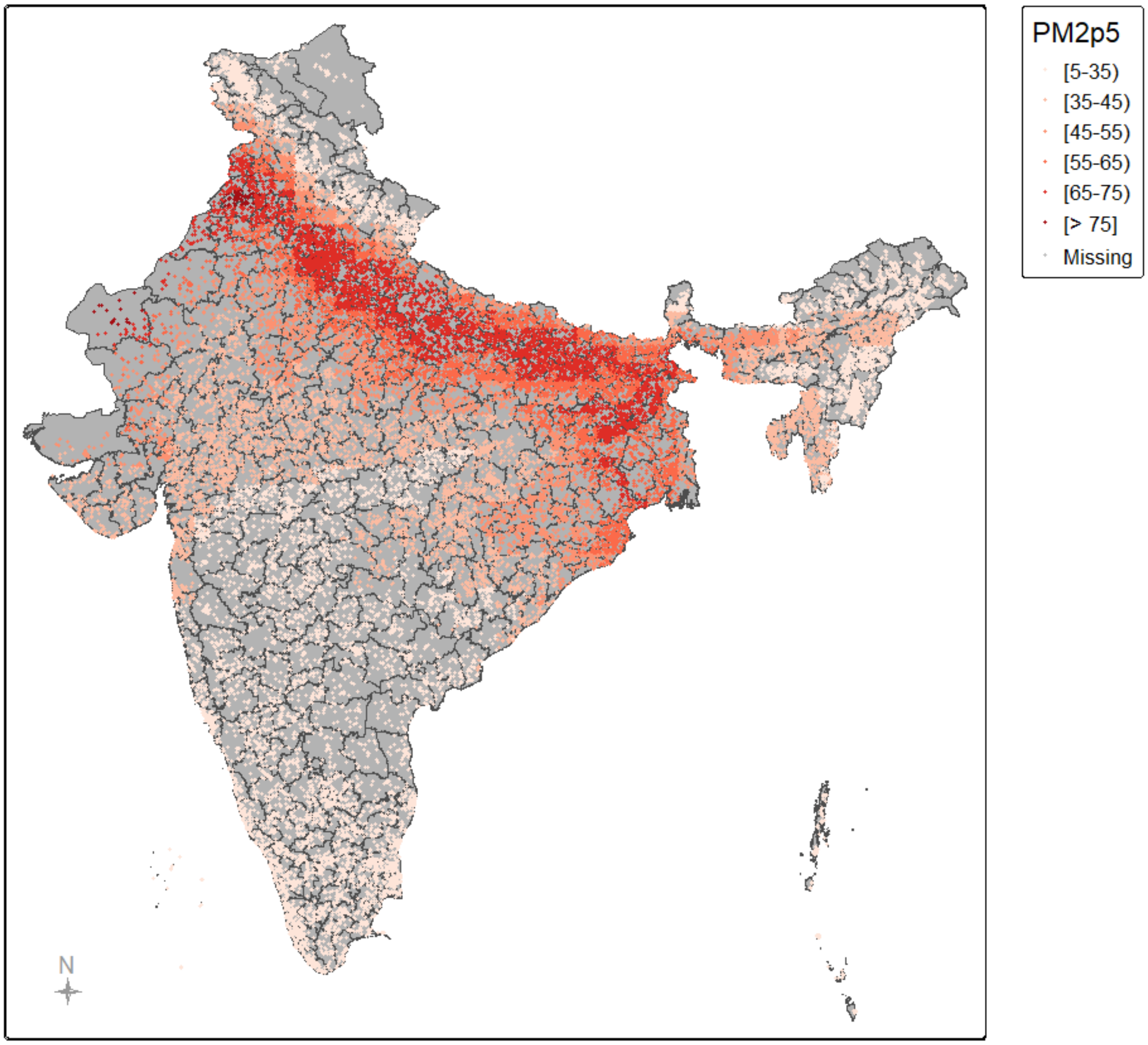

Figure A1. Map of the Study Area

Note: The dots represent the average 12-month PM2.5 levels (in $\mu g/m^3$) for DHS clusters in the survey period. The number of DHS clusters is 28,330. The district boundaries are shown in gray.

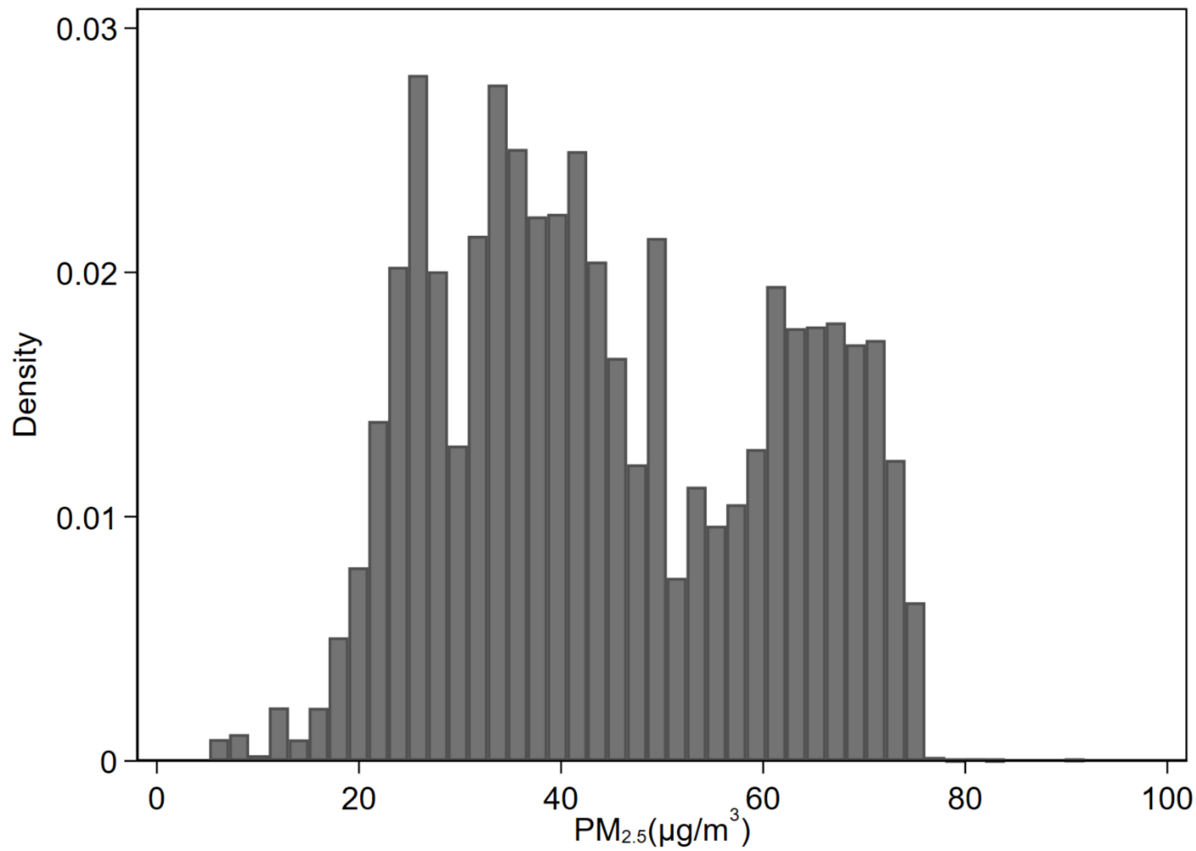

Figure A2. Distribution of PM2.5 concentration levels

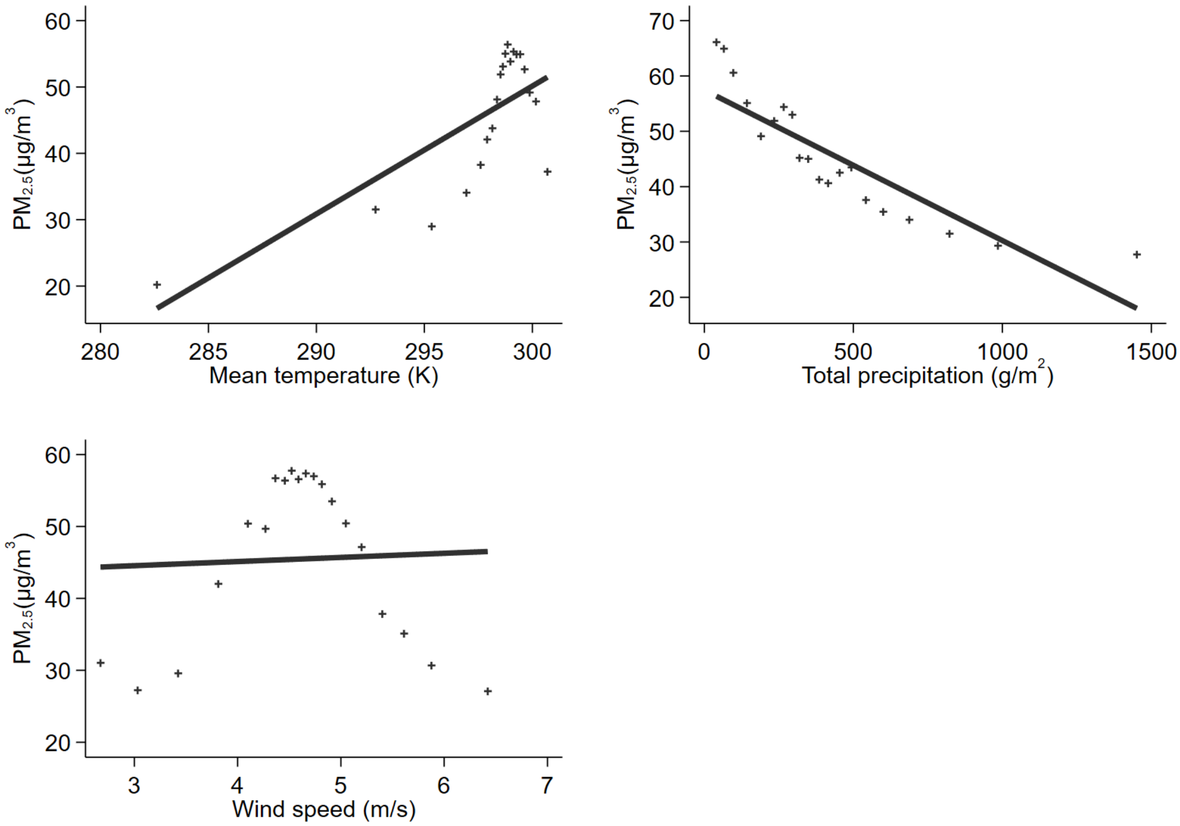

Figure A3. PM2.5 concentration levels and the Weather Bin Scatterplot

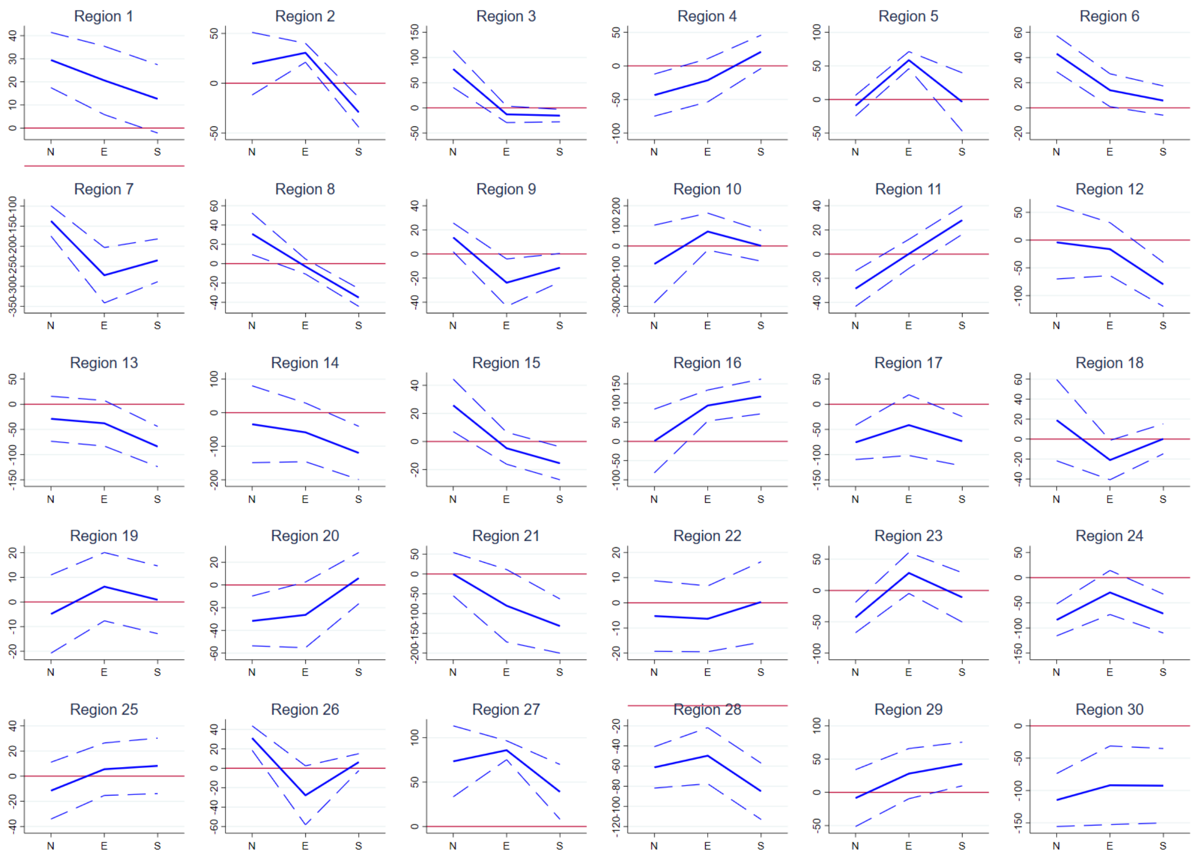

Figure A4. Annual wind direction and PM2.5: first stage estimates by regions.

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.

Table A1. First-stage regression results

	PM2.5
Share of the wind from the North, region 1	-26.18***
	(-3.31)
Share of the wind from the North, region 2	-32.35***
	(-5.60)
Share of the wind from the North, region 3	-53.34*
	(-2.15)
Share of the wind from the North, region 4	7.638
	(0.48)
Share of the wind from the North, region 5	-18.06**
	(-2.59)
Share of the wind from the North, region 6	-68.06***
	(-4.70)
Share of the wind from the North, region 7	-102.3***
	(-9.55)
Share of the wind from the North, region 8	-69.85**
	(-3.29)
Share of the wind from the North, region 9	4.782
	(1.34)
Share of the wind from the North, region 10	1.063
	(0.03)
Share of the wind from the North, region 11	3.738
	(0.33)
Share of the wind from the North, region 12	-57.58***
	(-3.84)
Share of the wind from the North, region 13	-76.31***
	(-5.89)
Share of the wind from the North, region 14	16.79
	(0.56)
Share of the wind from the North, region 15	-63.89**
	(-2.98)
Share of the wind from the North, region 16	-46.92*
	(-2.36)
Share of the wind from the North, region 17	-63.59***
	(-3.68)
Share of the wind from the North, region 18	-10.23
	(-0.37)
Share of the wind from the North, region 19	-37.41*
	(-2.29)
Share of the wind from the North, region 20	-4.604
	(-0.38)
Share of the wind from the North, region 21	-52.59***
	(-3.39)
Share of the wind from the North, region 22	21.34
	(0.67)
Share of the wind from the North, region 23	-52.63***
	(-6.81)
Share of the wind from the North, region 24	-72.35***

	(-4.98)
Share of the wind from the North, region 25	32.36
	(0.97)
Share of the wind from the North, region 26	18.44**
	(3.19)
Share of the wind from the North, region 27	17.96
	(1.33)
Share of the wind from the North, region 28	-75.64***
	(-10.66)
Share of the wind from the North, region 29	-23.63
	(-1.35)
Share of the wind from the North, region 30	-99.94***
	(-6.97)
Share of the wind from the East, region 1	6.694
	(0.60)
Share of the wind from the East, region 2	-34.64***
	(-5.41)
Share of the wind from the East, region 3	22.67**
	(2.91)
Share of the wind from the East, region 4	51.03*
	(2.34)
Share of the wind from the East, region 5	20.61**
	(3.00)
Share of the wind from the East, region 6	-29.09**
	(-2.66)
Share of the wind from the East, region 7	-134.3***
	(-6.87)
Share of the wind from the East, region 8	-1.916
	(-0.30)
Share of the wind from the East, region 9	-2.695
	(-0.31)
Share of the wind from the East, region 10	4.052
	(0.25)
Share of the wind from the East, region 11	13.69
	(1.07)
Share of the wind from the East, region 12	-36.44
	(-1.77)
Share of the wind from the East, region 13	-68.45***
	(-6.34)
Share of the wind from the East, region 14	18.59
	(0.78)
Share of the wind from the East, region 15	-3.624
	(-0.39)
Share of the wind from the East, region 16	55.44***
	(3.57)
Share of the wind from the East, region 17	1.184
	(0.04)
Share of the wind from the East, region 18	9.206
	(0.89)
Share of the wind from the East, region 19	-3.066

	(-0.22)
Share of the wind from the East, region 20	45.81***
	(3.57)
Share of the wind from the East, region 21	-45.03
	(-1.29)
Share of the wind from the East, region 22	24.52
	(0.88)
Share of the wind from the East, region 23	6.773
	(1.11)
Share of the wind from the East, region 24	21.73
	(1.15)
Share of the wind from the East, region 25	40.86
	(1.90)
Share of the wind from the East, region 26	-91.30***
	(-6.00)
Share of the wind from the East, region 27	44.49***
	(5.57)
Share of the wind from the East, region 28	-42.95***
	(-5.18)
Share of the wind from the East, region 29	32.34*
	(2.25)
Share of the wind from the East, region 30	-18.58
	(-1.23)
Share of the wind from the South, region 1	-11.41
	(-1.02)
Share of the wind from the South, region 2	14.76
	(1.54)
Share of the wind from the South, region 3	43.58***
	(4.14)
Share of the wind from the South, region 4	73.87***
	(4.78)
Share of the wind from the South, region 5	3.528
	(0.34)
Share of the wind from the South, region 6	-53.17***
	(-4.51)
Share of the wind from the South, region 7	-129.3***
	(-8.48)
Share of the wind from the South, region 8	16.47*
	(2.27)
Share of the wind from the South, region 9	16.47***
	(3.44)
Share of the wind from the South, region 10	31.37*
	(2.13)
Share of the wind from the South, region 11	39.59***
	(3.75)
Share of the wind from the South, region 12	-56.18***
	(-3.34)
Share of the wind from the South, region 13	-92.55***
	(-9.46)
Share of the wind from the South, region 14	20.64

	(0.98)
Share of the wind from the South, region 15	-3.417
	(-0.28)
Share of the wind from the South, region 16	83.83***
	(3.66)
Share of the wind from the South, region 17	-25.54
	(-1.16)
Share of the wind from the South, region 18	13.38
	(1.26)
Share of the wind from the South, region 19	22.21*
	(2.04)
Share of the wind from the South, region 20	43.43***
	(4.08)
Share of the wind from the South, region 21	-68.22*
	(-2.49)
Share of the wind from the South, region 22	26.29
	(0.86)
Share of the wind from the South, region 23	6.812
	(0.91)
Share of the wind from the South, region 24	-8.026
	(-0.52)
Share of the wind from the South, region 25	49.43**
	(2.87)
Share of the wind from the South, region 26	50.47***
	(9.53)
Share of the wind from the South, region 27	23.11*
	(2.18)
Share of the wind from the South, region 28	-51.19***
	(-5.31)
Share of the wind from the South, region 29	57.64***
	(4.09)
Share of the wind from the South, region 30	-38.81**
	(-2.61)
Individual-level characteristics	
Woman's current age	0.00578
	(0.70)
Woman's age square	-0.000249*
	(-2.15)
Woman's education:	
No education	0.507***
	(3.79)
Primary education	0.0859
	(0.79)
Incomplete secondary education	0.192**
	(2.73)
Secondary education	0.296***
	(4.71)
Household-level characteristics	
Rural	0.349*
	(1.97)
Religion (Hindu = 1)	-0.368

	(-1.64)
Social class (SC/ST = 1)	-0.257
	(-1.59)
Social class (OBC = 1)	0.0769
	(0.61)
Weather controls	
Mean temperature	-22.18***
	(-3.98)
Mean temperature square	0.0429***
	(4.40)
Total precipitation	-0.0128***
	(-4.02)
Total precipitation square	0.00000639***
	(5.02)
Wind speed	19.71***
	(7.03)
Wind speed square	-2.272***
	(-7.86)
Geographical regions FEs	Yes
Month of interview FEs	Yes
Survey year FEs	Yes
Observations	696,497
F-stat	19.194

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

Table A2. Effect of Air Pollution on the Incidence of Miscarriage, Disaggregated by Education, Type of Residence, and Household Wealth

	Full sample	Mother with no education or primary education only	Mother with some secondary education	Rural	Urban	Poor	Non-Poor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PM2.5	0.00017***	0.00018***	0.00019***	0.00023***	0.00012**	0.00018***	0.00015***
($\mu g/m^3$)	(0.00003)	(0.00004)	(0.00006)	(0.00005)	(0.00005)	(0.00004)	(0.00004)
Mean of dep. var.	0.011	0.010	0.012	0.011	0.011	0.011	0.011
Observations	696,497	363,140	333,357	491,920	204,577	281,104	415,393
F-stat	19.194	18.593	19.927	21.500	18.822	22.341	16.766

Notes: Standard errors reported in parentheses are clustered at the district level. All regressions include individual and household-level characteristics, weather controls, as well as fixed effects for geographic regions, the month of interview, and survey year.
**denotes significance at the 5% level and ***denotes significance at the 1% level.

Table A3. Effect of Air Pollution on Reproductive Health Care Using India's Annual Health Survey

	Abortion (1)	ANC before abortion (2)	Abortion by skilled provider (3)	Use of any contraceptive (4)
PM2.5 ($\mu g/m^3$)	0.07061*** (0.02731)	-0.38046*** (0.10832)	-0.40050*** (0.15137)	-0.60722*** (0.08902)
Mean of dep. var.	4.947	47.544	55.262	59.695
Number of districts	281	281	281	281
F-stat	43.036	43.036	43.036	43.036
	Use modern contraceptive method (5)	Use traditional contraceptive method (6)	Any ANC (7)	Schedule of ANC (8)
PM2.5 ($\mu g/m^3$)	-0.93444*** (0.07841)	0.32649*** (0.06891)	-0.09823* (0.05675)	-0.10633*** (0.04925)
Mean of dep. var.	46.986	12.711	90.020	70.140
Observations	281	281	281	281
F-stat	43.036	43.036	43.036	43.036

Notes: Standard errors reported in parentheses are clustered at the district level. All regression includes weather controls and region fixed effects.
* denotes significance at the 10% level and ***denotes significance at the 1% level.