Title: Air Pollution and Maternal Healthcare-Seeking Behavior in India

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Abstract

Air pollution has well-documented adverse health effects and generates substantial demand for healthcare services. This paper examines how pollution-driven pressures on the healthcare system may change the type of other services sought and provided. We combine satellite-derived PM2.5 data with household survey data from India to study the effect of ambient air pollution on delivery location choices and the quality of postnatal care. Using local wind direction as an instrument for air pollution in the month prior to delivery, we find that a 10 $\mu g/m^3$ increase in PM2.5 is associated with a 0.98% decrease in the probability of delivery in a public institution, conditional on institutional delivery. This decline is not explained by women with riskier pregnancies choosing private care. We find that air pollution decreases time spent in public but not private facilities, possibly reflecting overcrowding in the public sector. We also find that higher PM2.5 levels reduce the likelihood that the polio and hepatitis B vaccines are administered at birth, with the largest declines occurring in public facilities. Our results bring attention to the burden air pollution has on the healthcare system in India and underscore the importance of fully accounting for the indirect institutional costs.

JEL: J13, I12, Q53

Keywords: air pollution, reproductive healthcare, institutional delivery, India

1. Introduction

Air pollution has been shown to have both short-run and long-run adverse effects on a variety of health outcomes, including respiratory and cardiovascular health, which in turn leads to higher healthcare utilization (Manan et al., 2018; Brunekreef & Holgate, 2002; Bu et al., 2021; Dominski et al., 2021). For example, Deryugina et al. (2019) show that increases in PM2.5 lead to more emergency room visits, more hospitalizations, higher inpatient spending and mortality among the elderly population in the US. In China, Liao et al. (2021) find that higher PM2.5 concentrations increase healthcare spending and the probability of hospitalization, especially among the young. Such transitory health shocks due to air pollution have recently been shown to disrupt healthcare services in Brazil with capacity-constrained hospitals turning away patients with elective procedures to accommodate sicker patients (Guidetti et al., 2024). Air pollution may thus affect healthcare utilization as well as the supply of healthcare services. In addition, it may influence both the type of care people seek and the care they ultimately receive. For example, research in India has shown that other environmental stressors, such as extreme heat, reduce antenatal healthcare utilization by pregnant women (Dey et al., 2025b) and increase the likelihood of home births (Dey et al., 2025a).

Our study complements prior research by studying the effect of air pollution on type of delivery as well as the quality of post-delivery care. Specifically, we merge 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 use local wind direction as an instrument for PM2.5 levels and examine the effect of PM2.5 levels in the month prior to the month of birth on place of delivery (home, public institution, other institution) as well as several important measures of

healthcare quality (polio and hepatitis vaccines given at birth, time spent in the delivery institution, mother checked up before discharge, child checked up within 7 days of delivery).

We find that PM2.5 has a small and statistically insignificant effect on the probability of a home delivery but a 10 $\mu g/m^3$ increase in PM2.5 is associated with 0.71 percentage point (or, 0.98%) decrease in the probability of delivery in a public institution, conditional on institutional delivery. We do not find evidence that women are choosing private facilities due to riskier pregnancies. Rather, we show that the effects of air pollution on type of delivery are muted in areas with high public healthcare capacity (measured by number of beds or number of healthcare workers per capita) and strong in areas with low public healthcare capacity. This is consistent with air pollution causing overcrowding in public facilities which may lead to people choosing other options either because of capacity constraints or because of women's preferences for a less crowded environment to deliver a child. We are unable to directly test for this mechanism, however, due to lack of dynamic hospital capacity data.

We also find that PM2.5 is associated with lower likelihood of the polio and hepatitis B vaccines given at birth, as well as shorter duration of institutional stay with the effects largely concentrated in public institutions. The fact that private institutions appear to provide more consistent time within the facility offers one potential reason why women may choose to shift away from public facilities and seek care in private settings. Private institutions, however, are not insured against the impact of air pollution as they experience reductions in vaccination rates as well. In addition, prior research has shown that private providers may often lack training and resources and deliveries in public facilities are, on average, safer (Coffey et al., 2025; Franz, 2025; Verma & Cleland, 2022). Thus, we show that environmental shocks like air pollution can lead people to receive suboptimal care as well as choose suboptimal treatment options.

India is one of the countries with the highest levels of air pollution in the world. The Global Burden of Disease Study from 2019 found that the annual average population-weighted mean PM2.5 concentration in India was 91.7 $\mu g/m^3$, with significant variation across states - from 15.8 $\mu g/m^3$ in Kerala to 217.6 $\mu g/m^3$ in Delhi (Pandey et al., 2021) - when the World Health Organization's recommended annual limit at the time was only 10 $\mu g/m^3$. As a result, the Global Burden of Disease Study found that air pollution accounted for 17.8% of all deaths in the country. Our paper illustrates the importance of understanding not only the direct but also the indirect effects of air pollution in order to quantify its full costs and address all the sources of this high disease burden more effectively.

2. Data

2.1 Demographic and Health Survey

This paper uses nationally representative data from the fourth round of the Demographic and Health Survey (DHS-4) for India. The data was collected from January 2015 to December 2016, and it includes information on demographics as well as women's full birth history and healthcare utilization, among other variables. Relevant to this study, the survey collects information on place of delivery (at home, at a public institution, at other institutions) for all children born in the 5 years prior to the interview date. Our main analysis on place of delivery thus includes information on 242,810 births of 178,823 women who gave birth between 2010 and 2016.

The data also contain information on immunizations for all children in the study period and specifically whether the polio and hepatitis vaccines were given at birth. For the last child born during the 5-year period prior to the interview date, we also have information on time spent in an institution for delivery as well as whether the child and mother were checked up before discharge.

We merge DHS data to satellite-derived air pollution data using information on the GPS coordinates of each DHS 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).

2.2 Air pollution data

The main measure of air pollution used in this study is the PM2.5 – the concentration of particles smaller than 2.5 micrometers in diameter in the air. Air pollution data - from NASA's MERRA-2 satellite reanalysis project - are reported as 1-hour temporal data with a horizontal resolution of 0.5 x 0.625 degrees grid (Global Modeling and Assimilation Office (GMAO), 2015a). 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 month during the study period (2010 to 2016) for each grid cell. It should be noted that each grid cell corresponds to approximately 55.5 km (north-to-south) by 35-50 km (east-to-west) and it may contain more than one DHS cluster.

As a robustness check, we also use an alternative measure of air pollution – the composite air quality index AQI. We calculate AQI, capturing the concentration of multiple pollutants (PM2.5, PM10, and nitrogen dioxide), using the formula obtained from the technical assistance document of the US Environmental Protection Agency (EPA) for reporting of daily AQI.[1]

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

2.3 Weather data

Weather data including daily mean temperature, total precipitation, and wind speed and direction 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). For wind direction, we construct the number of days in each month 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 month. We use these share variables as our instrumental variables in the instrumental regression analysis (more details below).

3. Empirical specification

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

$$y_{i,c,g,y,m} = \beta_0 + \beta_1 PM2.5_{c,g,y,m-1} + X_{hh}\lambda + W_{c,g,y,m-1}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + v_{i,c,g,y,m} \quad (1)$$

where the dependent variable, y_{icgmy} is the outcome of interest for child i born in month m in year y and living in grid-cell c of the geographical region g. The variable of interest is fine particulate matter represented as $PM2.5$ which is the monthly average level of PM2.5 concentration in the grid-cell before the child's month of birth. Since we don't have exact information on the day of birth, we use a conservative measure of pollution in the month prior to the month of birth. As a robustness check, we also provide results for the effect of pollution in the month of birth.

The term Xi includes a set of household-level characteristics that are plausibly unaffected by recent outdoor pollution levels: the mother's age (and age square), the mother's education (an indicator for having no education, primary education, incomplete secondary education, and

complete secondary education), indicators for rural area of residence, an indicator of Hindu religion, and an indicator of caste (scheduled castes, scheduled tribes, and other disadvantaged castes), as well as a five-category wealth index from poorest to richest. The standard errors are clustered at the district level.

We include fixed effects for month of birth, $\eta_{i,(m)}$, and year of birth, $\eta_{i,(y)}$, to remove any time trends and seasonality effects. In addition, we include a host of weather controls for the month before the child's birth, $W_{c,g,y,m-1}$, to account for the fact that pollution and weather may be correlated. Specifically, we include total precipitation, and the averages of temperature and wind speed (all 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. Figure A1 provides a bin scatterplot showing the correlation between the averages of PM2.5 and weather variables. It appears that higher mean temperatures are associated with relatively higher pollution levels, while total precipitation levels and average wind speed are associated with relatively lower pollution levels.

We follow Balietti et al. (2022) and Deryugina et al. (2019) and group grid cells into geographical regions using a k-means clustering algorithm. Using fixed effects for the geographical region of residence, α_g , allows us to account for any geographical unobserved factors that may affect the outcome of interest.

The identifying assumption in this specification is that after controlling for observable household-level characteristics, seasonality and flexible weather controls, exposure to air pollution is uncorrelated with the error term, $v_{i,c,g,y,m}$. One threat to identification is that air 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 air

pollution on human health and may be able to relocate away from highly polluted areas. If these women are also more likely to use private healthcare services, this may artificially create a negative effect of air pollution on demand for public 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 public health infrastructure, then higher air pollution may be artificially associated with higher use of public healthcare, once again biasing the coefficient of interest. To understand the degree and source of potential omitted variable bias, we examine the sensitivity of our results to adding different regression controls.

In addition, consistent with other studies that measure the causal impacts of air pollution (Balietti et al., 2022; Bondy et al., 2020; Deryugina et al., 2019; Herrnstadt et al., 2021), we also use an instrumental variables approach, with wind days as an instrument. 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 directions (north, east, south, and west) as our main explanatory variable. We allow the impact of local wind direction on local air pollution to vary by geographical region and thus account for the fact that wind coming from the same direction may have different effects on air pollution in different areas depending on the source of air pollution or other geographic characteristics. 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).[2]

The estimating equations are:

[2] We also provide results from robustness analyses with 40 and 50 clusters in Appendix Table A6.

$$PM2.5_{c,g,y,m-1} = \gamma_0 + \sum_g^G \gamma_1^g Share_{ic}^N + \sum_g^G \gamma_2^g Share_{ic}^E + \sum_g^G \gamma_3^g Share_{ic}^S + X_{hh}\lambda + W_{c,g,y,m-1}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + u_{i,c,g,y,m-1} \quad (2)$$

$$y_{i,c,g,y,m} = \beta_0 + \beta_1 \widehat{PM}2.5_{c,g,y,m-1} + X_{hh}\lambda + W_{c,g,y,m-1}\psi + \alpha_g + \eta_{i(m)} + \eta_{i(y)} + v_{i,c,g,y,m} \quad (3)$$

where $Share_{i,c}^{\omega}$ with $\omega \in \{N, E, S\}$ represents the respective shares of days in the month before the child's month of birth 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.

Figures A2 and A3 present first-stage evidence to motivate our identification strategy. First, Figure A2 shows the time trend of PM2.5 and wind days. It appears that air pollution is closely linked to northeast winds throughout the year, while it only follows southeast winds from August to December later in the year. Southwest winds and northwest winds appear to be clean winds, particularly during June through November, since they are associated with relatively lower air pollution. Next, Figure A3 further shows that the wind directions that statistically explain variations in pollution levels differ across the thirty regions. Online Appendix Table 1 reports the regression results from the first stage regression model. Local wind direction is a strong predictor of air pollution with an F-statistic of 46.5 for the full sample of births and 44.2 for the sample of institutional births.

4. Results

4.1 Descriptive statistics

Table 1 presents the descriptive statistics for our sample of 178,823 women who had 242,810 births in the five years prior to the interview date. The mean age of mothers at the time of

interview was 27.4 years and 35.8% of them had no education. About 75% of the women lived in rural areas. Of all deliveries, 24.8% were at home, 54.4% took place in a public institution, and 20.1% were in a private institution. Only 0.7% of deliveries were reported to be in a different type of institution (NGO or trust hospital or other). Given the small proportion of births in other institutions, in this paper, we combine births in private and other institutions and refer to them as non-public sector, or "private", births. Conditional on institutional delivery, 72.4% of all deliveries were at a public institution. For institutional births, 80% of infants received the polio vaccine at birth and 67% received the hepatitis B vaccine at birth. For women's latest birth in the 5-year period prior to the survey, the average length of stay at a delivery facility was 3.63 days, 76% of mothers were checked before discharge, while only 32.5% of infants were checked within the first week after birth.

Panel C of Table 1 also presents summary statistics for our key explanatory variable – PM2.5 air pollution – which is unique at the level of the grid cell, year of birth and month of birth. The average PM2.5 level is 42.7 $\mu g/m^3$ with a standard deviation of 24.5 $\mu g/m^3$. The distribution of average PM2.5 in the past one month before the month of birth, as shown in Figure A4, suggests that there is sufficient variation in PM2.5 to study the relationship between air pollution and delivery care at different levels of PM2.5.

4.2 The effect of air pollution on type of delivery

Next, in Table 2, we discuss the main results of the analysis. The OLS specification in columns 1 and 2 shows a statistically significantly negative association between PM2.5 and both home and public deliveries. Specifically, a 10-unit increase in PM2.5 (about 40% of the standard deviation of PM2.5) is associated with a 0.17 percentage point (pp) decrease in the probability of home deliveries (significant at the 10% level) and a 0.66pp decrease in the probability of

delivery in a public institution, conditional on institutional delivery. The overall conditional probability of delivery in a public institution is 72.4%. Thus, a decrease of 0.66pp corresponds to a 0.91% decrease in the probability of delivery in a public institution.[3]

In Appendix Table A1, we examine the sensitivity of our results to the addition of various controls. First, in Panel A, we show a simple regression model for the effect of air pollution on home delivery and delivery in a public institution (conditional on institutional delivery). Higher air pollution is statistically significantly correlated with higher probability of home deliveries and lower probability of conditional public deliveries. The results are largely robust to accounting for temporal trends with month and year fixed effects in Panel B, controlling for individual and household characteristics in Panel C as well as weather controls in Panel D. Once we control for geographical region fixed effects, however, the effect of air pollution on home deliveries is greatly reduced, changes sign and loses some statistical significance (effect changes from 0.00071 in Panel D to -0.00017 in Panel E). On the other hand, the effect on public deliveries remains similar (a change from -0.00056 in Panel D to -0.00066 in Panel E). In panel F, we further control for nightlights – a variable commonly used as a measure of economic activity. The monthly nightlights data can capture short-run changes in economic activity that may not be

[3] For reference, we examine the effect of the Janani Suraksha Yojana (JSY) program, which provides financial assistance for institutional deliveries in public facilities, on the probability of a public delivery. We find that a one percentage point increase in district-level JSY usage is associated with a 0.46pp increase in the probability of a delivery in a public facility, conditional on institutional deliveries, and 0.70pp increase in the non-conditional public sector delivery. While our effects might be small, given the large population in India, they are meaningful.

captured by the more permanent individual and household controls. It is, however, only available after 2012 and, as a result, this control is not used in our main regression analysis. Nevertheless, we show that the results for public delivery continue to remain largely the same (a coefficient of -0.00063 in Panel F). Overall, the results of these analyses show that while the effect of air pollution on home delivery seems to be greatly affected by omitted variable bias, the effect of air pollution on the type of institutional delivery is robust to the inclusion of different controls.

Next, in Table 2, we present the instrumental variable results. We find that a 10-unit increase in PM2.5 is associated with a 0.71pp (or, 100*0.71/72.4=0.98%) decrease in the probability of delivery in a public institution. The results for type of delivery, conditional on institutional delivery, are consistent in both magnitude and sign across the fully controlled OLS and instrumental variable specifications (0.71pp vs 0.66pp). On the other hand, while the OLS specification finds a negative association between air pollution and home deliveries, the instrumental variable analysis shows that PM2.5 has a small (positive) and statistically insignificant effect on the probability of a home delivery. Thus, we focus our discussion on the instrumental variable results for the rest of the analysis.

4.3 Mechanisms

One reason why we may see a decrease in public deliveries could be that pollution affects pregnancy outcomes and women are more likely to seek private care if they have riskier or problem pregnancies. We examine this hypothesis by studying the effect of PM2.5 in the month prior to the month of birth on (a) the probability of a woman delivering by c-section, (b) the probability of having a low birthweight baby (weight <=2,500gr), and (c) pregnancy complications (measured by having one of the following: convulsions during pregnancy, not from fever, and swelling of the legs, body or face). The results for the sample with non-missing

information on these outcomes are presented in Appendix Table 2. They show small and statistically insignificant effects of air pollution on cesarean delivery and having a low-birthweight baby but significantly positive effect on pregnancy complications. While these results may suggest that women choose private facilities because they have riskier pregnancies, we examine the effect of air pollution on delivery in a public institution by pregnancy complications and find that air pollution has a consistently negative effect for all pregnancies. Specifically, for pregnancies with complications, a 10-unit increase in PM2.5 is associated with 0.79pp lower probability of delivery in a public institution, conditional on institutional delivery; while for pregnancies without complications, the effect is 0.83pp. Thus, pregnancy risk does not seem to be the main factor explaining the relationship between air pollution and type of delivery.

An alternative hypothesis for why air pollution affects type of institutional delivery is that episodes of high air pollution overwhelm public facilities with patients with acute respiratory illnesses and this crowding of health facilities may drive some pregnant women away from the public sector – either because of capacity constraints or because of women's preferences for a less crowded environment for delivery. Transitory health shocks due to air pollution have recently been shown to disrupt healthcare services in Brazil with capacity-constrained hospitals turning away patients with elective procedures to accommodate sicker patients (Guidetti et al., 2024). Similarly, in Mexico, Aguilar-Gomez et al. (2025) show that another environmental stressor - extreme heat - results in higher hospitalization and emergency room visit rates which leads to congestion in healthcare utilization and results in more and sicker emergency room patients bring discharged early. We explore the crowding hypothesis by using facility data from the District Level Household Survey (DLHS) from 2012-2013 which includes information on public health facilities for 553 of our 640 districts. We create indicators for healthcare capacity

using two different measures. First, we calculate the total number of beds per 10,000 people in each district combining data from primary health centres, community health centres, and district hospitals which perform deliveries. Second, we calculate the district-level number of doctors, medical officers, and nurses and midwives per 10,000 people who work in the primary health centres, community health centres, and district hospitals which perform deliveries. We then re-examine the probability of home deliveries and public deliveries, splitting the sample by districts below and above the median number of beds per capita and the median number of health professionals per capita.

The results are presented in Table 3. In panel A, we show that air pollution has no statistically significant effect on type of delivery in districts with above or below median healthcare capacity when capacity is measured by number of healthcare professionals per capita. When capacity is measured by number of beds in Panel B, air pollution in districts with above median capacity has a significantly negative effect on home births: a 10-unit increase in PM2.5 is associated with a 1.29pp lower probability of a home delivery. When we combine health professionals and bed per capita in a joint capacity measure in Panel C, we find that in districts with above median health professionals per capita or above median beds per capita air pollution has a negative effect on home deliveries, albeit half the size of that in panel B (coefficient of -0.00056, significant at the 10% level), and a small, non-significant effect on public deliveries. On the other hand, in districts with below median health professionals per capita and below median beds per capita, air pollution has no effect on home deliveries (coefficient of 0.00006) but is associated with a lower probability of a delivery in a public institution (significant at the 10% level). The effect of air pollution on public deliveries in this subsample is about 45% higher than the effect in the sample with high capacity (-0.00051 vs -0.00035). This analysis presents some

suggestive evidence that our results may be consistent with crowding being a key mechanism underlying the relationship between air pollution and type of delivery in the Indian setting. However, the absence of dynamic hospital-capacity measures limits our ability to test this channel directly.

4.4 Heterogeneity analyses

Next, in Table 4, we examine heterogeneity in the treatment effect by area of residence and poverty status. Splitting the sample by area of residence, we find that air pollution has a consistently negative effect on public deliveries but the effect in urban areas – which may have better access to different healthcare options - is 1.9 times higher than the effect in rural areas (1.14pp vs 0.59pp associated with a 10-unit increase in PM2.5).

We also show that for the poorest households (those in the bottom two categories of the five-point wealth index), air pollution has no significant effect on the probability of a public delivery. On the other hand, for households in the remaining 3 wealth categories, air pollution has a strong negative effect on public deliveries – a 10-unit increase in PM2.5 is associated with 1.13pp decrease in the conditional probability of delivery in a public institution – an effect which is more than four times higher than the effect for the poorest households (0.26pp). This shows that air pollution largely affects the delivery choices of people who may be better able to afford private healthcare.

In Appendix Table 3, we also examine whether the Janani Suraksha Yojana (JSY) program, which provides financial assistance for institutional deliveries in public facilities, has an effect on the relationship between air pollution and type of delivery. We define JSY treatment intensity at the district-year of birth level and examine heterogeneity in the treatment effect splitting the sample by district-years where more than 25% vs fewer than 25% of the women

used JSY services.[4] We find that while air pollution has a statistically significant negative effect on public deliveries across both samples, the effect is 1.7 times higher in districts with lower usage of the JSY program: a 10-unit increase in PM2.5 is associated with 0.73pp decrease in the probability of public delivery, conditional on institutional deliveries, compared to 0.42pp in districts with higher usage of the program. One explanation for this finding is that the cash incentives provided by the JSY program may encourage people to remain in public health facilities rather than shift to private healthcare. This suggests that the JSY program, which has already been shown to cause overcrowding and harm healthcare outcomes in low-capacity areas (Andrew and Vera-Hernandez, 2024), might exacerbate crowding effects if air pollution does contribute to congestion in public facilities.

4.5 The effect of air pollution on quality of care

So far, we have demonstrated that air pollution is associated with a lower probability of deliveries in public health facilities. In this section, we examine whether air pollution is associated with sub-optimal delivery care and specifically, whether there is any difference in the quality indicators between private and public healthcare institutions. We focus on institutional deliveries only and we test whether air pollution has an impact on vaccination rates at birth, as well as time spent in the institution during delivery, and post-natal checkup on mother and baby. In Table 5, we present the results for all institutional deliveries as well as disaggregated by type of institution. Overall, we find that higher levels of PM2.5 pollution are associated with lower probability of the polio and hepatitis B vaccines being given at birth. While vaccination rates are

[4] Only districts with more than 25 observations at the district-year of birth are included in this analysis. The median percentage for women using JSY services is 20.4%.

available for all births in the last 5 years before the survey, the information on time spent at the institution is only available for the last birth. With that caveat in mind, we see statistically significant reductions in time spent at a delivery institution. We find small and statistically insignificant effects on the probability of a mother getting checked out before discharge and the baby getting checked out within the first 1 week of delivery.

Next, splitting the sample by public and private deliveries, we see that the vaccination effects are present at both types of institutions, although most pronounced in public institutions where a 10-unit increase in PM2.5 is associated with 0.49pp lower probability of polio vaccination and 0.91pp lower probability of hepatitis vaccination at birth. In private institutions, air pollution is associated with somewhat smaller effects: 0.38pp for polio and 0.75pp for hepatitis, and the effect for polio is not statistically significant. While the vaccination effects are mostly similar across types of institutions, we find large differences in the effect of time spent in the delivery institution. Specifically, a 10-unit increase in PM2.5 is associated with 0.0883 fewer days spent in an institution for public institution, which corresponds to a 2.4% decrease given a baseline of 3.63 days). For private institutions the effect is almost three times smaller (0.0308 days for every 10-unit increase in PM2.5) and is not statistically significant.[5]

[5] This analysis includes all non-missing information for time spent in the delivery institutions. If we exclude approximately 3% of observations that are outliers (greater than 7 days), the mean number of days spent at the hospital is 2.5, and the regression results are similar: a 10-unit increase in PM2.5 corresponds to a 0.0571 days decrease in time spent at a public institution, and a 0.0107 days decrease in time spent at a private institution.

In summary, we find evidence that air pollution is indeed associated with sub-optimal post-delivery care. Public institutions experience a reduction in the time spent at the institution, while private institutions appear to be able to maintain consistency in this outcome. Less time spent in the delivery institution may signal lower likelihood of catching any health problems for mothers or infants. This may help explain, at least in part, why there appears to be a shift from deliveries in public institutions toward deliveries in private facilities. Private facilities, however, are not fully insured from the effects of air pollution on the healthcare system overall, as vaccination rates are affected there as well. We are unable to directly test whether this finding is due to crowding and human capital constraints that reduce access to qualified personnel who can administer vaccines or it's other logistics constraints that reduce availability of vaccines.

While the long-run implications of the reduction in the quality of healthcare are not the focus of this paper, there is ample evidence that the polio and the hepatitis B vaccinations at birth reduce the risk of early contagion by the mother or in the household and prevent long-term chronic health problems.[6] More broadly, it is worth noting that prior research has shown that deliveries in public institutions tend to be safer and to have lower neonatal mortality than deliveries in private facilities (Coffey et al., 2025; Franz, 2025; Verma & Cleland, 2022). This has been attributed to the often lower quality of care in private facilities where providers may lack training and resources or use unnecessary (and harmful) procedures on the infants. The overall shift away from public facilities may thus have other negative consequences for the health of the infant that we are not able to capture here.

[6] See, for example, https://www.aap.org/en/news-room/fact-checked/fact-checked-hepatitis-b-vaccine-given-to-newborns-reduces-risk-of-chronic infection/

4.6 Robustness Analyses

In Appendix Table 4, we present sensitivity analysis to the measure of air pollution. We use a composite index of overall air quality (AQI), and the direction of the results remains the same with negative effects on public deliveries and hepatitis B vaccination rates, as well as time spent in a delivery institution. Further, in Appendix Table 5, we present sensitivity analysis using air pollution in the month of birth instead of air pollution in the month prior to the birth month. Once again, we find small and statistically insignificant effects on home births but statistically significant effect on public births (effect size of 0.84pp for every 10-unit increase in PM2.5 compared to 0.71pp when using air pollution in the month prior to the birth month). We also find consistently negative effects on the probability of being given the polio and hepatitis B vaccines at birth as well as on the time spent in a delivery institution. Finally, in Appendix Table 6, we present sensitivity analysis for number of clusters used in the instrumental variables analysis. The results remain qualitatively similar.

5. Conclusion

This paper shows that higher air pollution in India is associated with a lower likelihood of delivering in a public healthcare facility, conditional on institutional delivery. Air pollution also affects the quality of post-delivery institutional care as infants are less likely to get critical vaccinations. We also find that air pollution decreases time spent in public but not private facilities, possibly reflecting overcrowding in the public sector, which may help explain why some women shift toward private providers. Heterogeneity analyses by district-level measures of healthcare capacity are consistent with air pollution causing overcrowding, although we are unable to directly test this channel because of lack of dynamic data on hospital capacity. Overall,

our findings draw attention to the needs of the healthcare system to better adapt to air pollution as well as climate or other environmental shocks.

Data Availability

All datasets were derived from sources in the public domain:

India Demographic and Health Survey, 2015-2016, available at https://dhsprogram.com/methodology/survey/survey-display-355.cfm .

NASA's MERRA-2 satellite reanalysis project, available at https://gmao.gsfc.nasa.gov/reanalysis/ .

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Figures and Tables

Table 1. Summary statistics

	Mean	SD	Observations
Panel A. Mother Characteristics			
Individual-level characteristics			
Woman's age	27.455	5.38	178,823
Woman's education			
No education	0.358	0.48	178,823
Primary education only	0.077	0.27	178,823
Incomplete secondary education	0.376	0.48	178,823
Secondary education or more		0.28	178,823
Household-level characteristics			
Rural	0.748	0.43	178,823
Religion (Hindu=1)	0.721	0.45	178,823
Social class (SC/ST=1)	0.387	0.49	178,823
Social class (OBC=1)	0.384	0.49	178,823
Household wealth index:			
Wealth Index 1 (Poorest)	0.247	0.43	178,823
Wealth index 2	0.229	0.42	178,823
Wealth index 3	0.201	0.4	178,823
Wealth index 4	0.173	0.38	178,823
Wealth index 5 (Richest)	0.150	0.36	178,823
Panel B: Birth Characteristics			
Place of delivery			
Home	0.248	0.43	242,810
Public facility	0.544	0.5	242,810
Private facility	0.201	0.4	242,810
Other facility	0.007	0.08	242,810
Public facility conditional on institutional delivery	0.724	0.45	182,585
Child vaccination status conditional on institutional delivery			
Polio	0.798	0.4	174,829
Hepatitis B	0.667	0.47	172,825
Delivery outcomes conditional on institutional delivery for last birth only			
Time spent at health facility (days)	3.628	6.98	137,211
Mother checked before discharge	0.759	0.43	137,644
Child checked within 1 week of delivery	0.325	0.47	137,737
Panel C: Air pollution and weather in the last month prior to birth			
PM2.5	42.72	24.52	49,148
Temperature	24.62	6.54	49,148

Precipitation	36.73	60.29	49,148
Wind speed	4.75	1.38	49,148
AQI	152.02	94.83	49,141

Note: The data source is the fourth round of the India Demographic and Health Survey.

Table 2. Effects of Air Pollution on Delivery Outcomes

	OLS estimates		IV estimates	
	Deliver at Home	Deliver at Public Institution (conditional on not home)	Deliver at Home	Deliver at Public Institution (conditional on not home)
	(1)	(2)	(3)	(4)
Pollution in the month before the birth month	-0.00017*	-0.00066**	0.00006	-0.00071**
	(0.00010)	(0.00012)	(0.00019)	(0.00022)
F-test			46.52	44.21
Observations	242,810	182,585	242,810	182,585
Number of clusters	640	640	640	640

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table 3. Effects of Air Pollution on Delivery Outcomes: Facility Capacity

	Above median capacity		Below median capacity	
	Deliver at Home	Deliver at Public Institution (conditional on not home)	Deliver at Home	Deliver at Public Institution (conditional on not home)
Panel A: Capacity measured by healthcare professionals per capita				
Pollution in the month before the birth month	-0.00072	-0.00046	0.00022	-0.0005
	(0.00046)	(0.00042)	(0.00022)	(0.00031)
Observations	104,207	81,552	110,015	78,432
Number of clusters	320	320	233	233
Panel B: Capacity measured by beds per capita				
Pollution in the month before the birth month	-0.00129**	-0.00014	0.00023	-0.00018
	(0.00050)	(0.00052)	(0.00019)	(0.00024)
Observations	104,561	81,545	109,661	78,439
Number of clusters	320	320	233	233
Panel C: Capacity measured by healthcare professionals or beds per capita				
Pollution in the month before the birth month	-0.00056*	-0.00035	0.00006	-0.00051*
	(0.00031)	(0.00033)	(0.00022)	(0.00030)
Observations	124,045	96,287	90,177	63,697
Number of clusters	371	371	182	182

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table 4. Heterogeneity Analysis

	Rural		Urban	
	Deliver at Home	Deliver at Public Institution (conditional on not home)	Deliver at Home	Deliver at Public Institution (conditional on not home)
Pollution in the month before the birth month	0.00014	-0.00059**	0.00032	-0.00114**
	(0.00020)	(0.00022)	(0.00025)	(0.00042)
Observations	185,109	132,663	57,701	49,922
Number of clusters	627	627	637	637

	Poorest		Less Poor	
	Deliver at Home	Deliver at Public Institution (conditional on not home)	Deliver at Home	Deliver at Public Institution (conditional on not home)
Pollution in the month before the birth month	0.00027	-0.00026	0.00017	-0.00113**
	(0.00024)	(0.00022)	(0.00020)	(0.00032)
Observations	122,038	77,479	120,772	105,106
Number of clusters	637	637	640	640

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table 5. Effects of Air Pollution on Vaccination Status at Birth and Other Delivery Outcomes

	Polio given at birth	Hep given at birth	Time in institution	Mother checked before discharged	Child checked within 1 week
	(1)	(2)	(3)	(4)	(5)
Panel A: Overall					
Pollution in the month	-0.00044**	-0.00087**	-0.00639**	0.00027	0.00017
before the birth month	(0.00022)	(0.00024)	(0.00271)	(0.00024)	(0.00025)
Observations	174,829	172,825	137,211	137,644	137,737
Number of clusters	640	640	640	640	640
Panel B: Public Institutions					
Pollution in the month	-0.00049**	-0.00091**	-0.00883**	0.00026	0.00019
before the birth month	(0.00024)	(0.00027)	(0.00246)	(0.00027)	(0.00027)
Observations	126,486	124,936	98,317	98,670	98,392
Number of clusters	640	640	640	640	640
Panel C: Private Institutions					
Pollution in the month	-0.00038	-0.00075**	-0.00308	0.00002	0.00011
before the birth month	(0.00024)	(0.00029)	(0.00594)	(0.00025)	(0.00031)
Observations	48,343	47,889	38,894	38,974	39,345
Number of clusters	638	638	638	638	638

Notes:

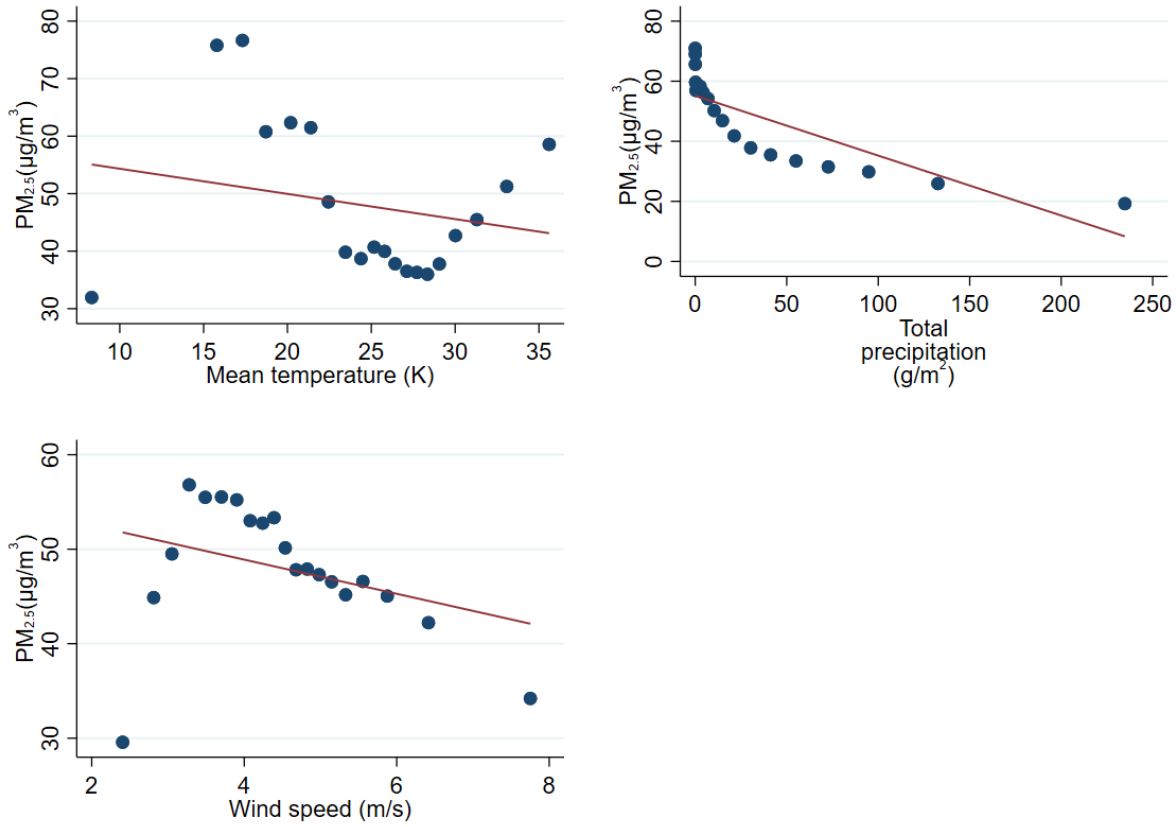
[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Appendix Figures and Tables

Figure A1. PM2.5 and weather bin scatterplot



Note: Each triangle groups observations into a bin for that weather, and the lines are fitted values.

Figure A2. Time trend of PM2.5 and wind days

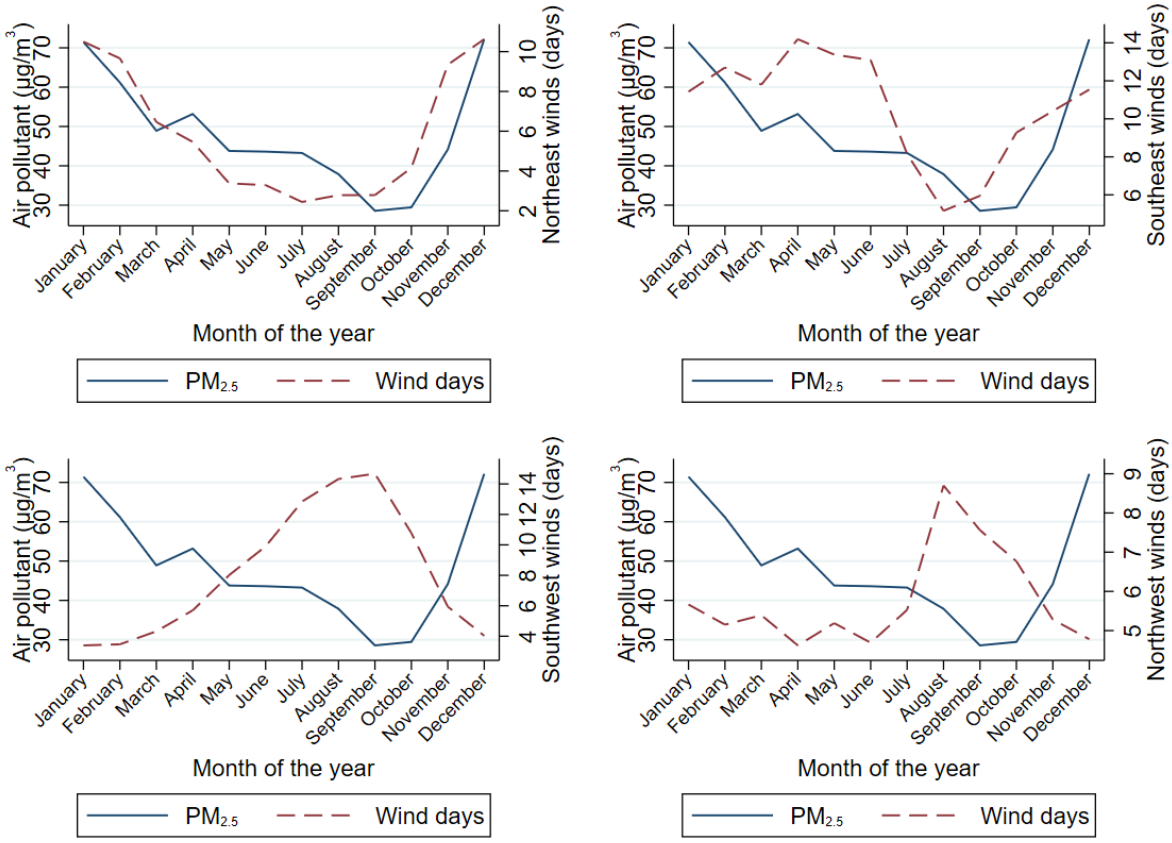
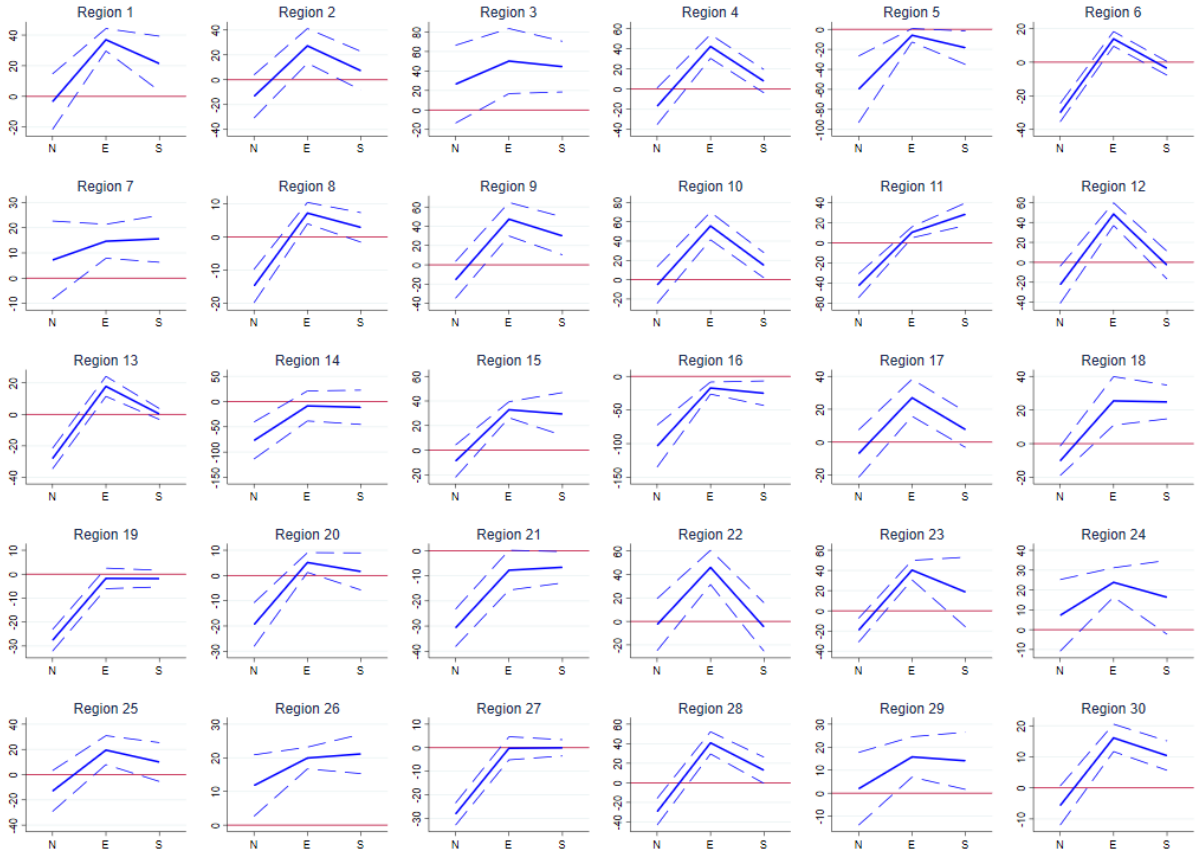


Figure A3. Monthly wind direction and PM2.5: first-stage estimates by geographical regions



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, the month of birth, and birth year 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 A4. PM2.5 exposure distribution

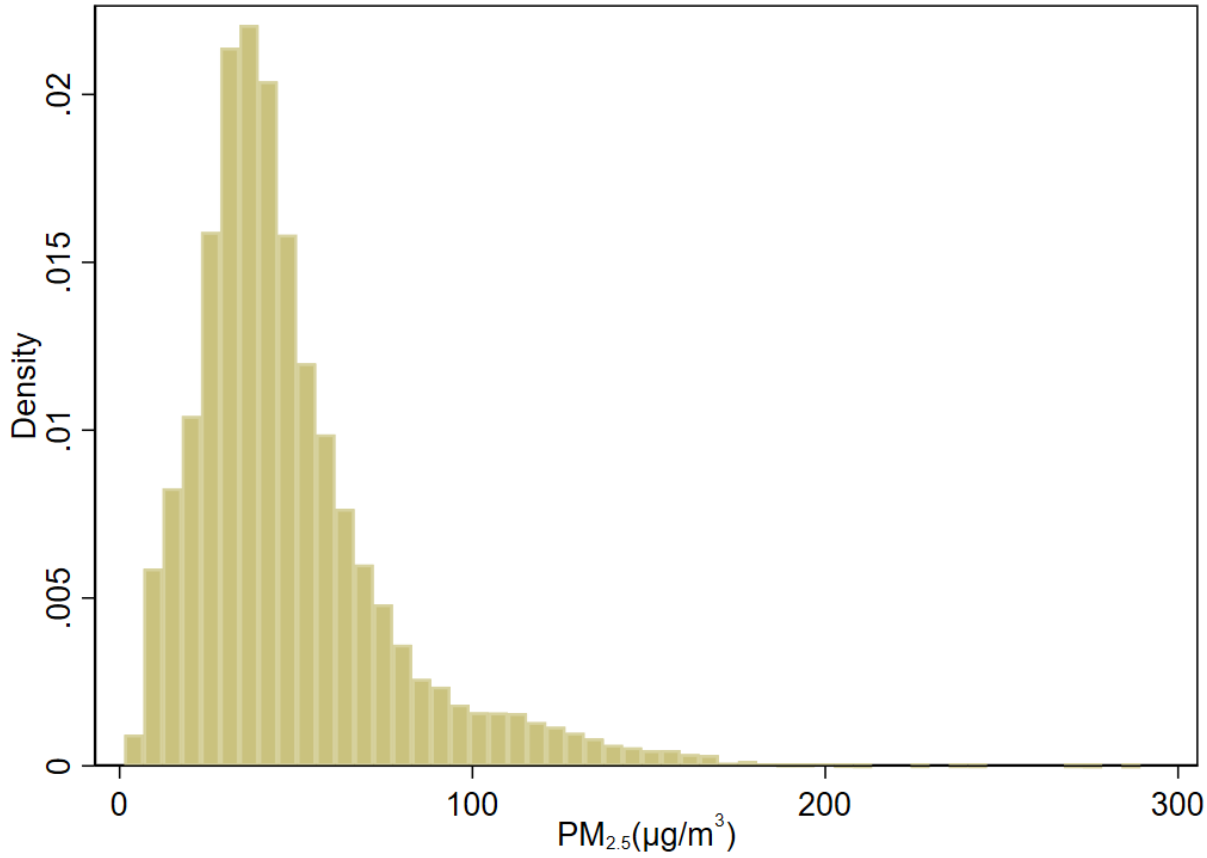


Table A1. Sensitivity of the OLS results to the addition of various controls

	Deliver at Home	Deliver at Public Institution (conditional on not home)
Panel A: Simple regression model, no controls		
Pollution in the month before the birth month	0.00072**	-0.00032**
	(0.00014)	(0.00015)
Panel B: Adding month and year FE		
Pollution in the month before the birth month	0.00091**	-0.00051**
	(0.00020)	(0.00019)
Panel C: Adding individual and household controls to Panel B specification		
Pollution in the month before the birth month	0.00058**	-0.00077**
	(0.00014)	(0.00015)
Panel D: Adding weather controls to Panel C specification		
Pollution in the month before the birth month	0.00073**	-0.00056**
	(0.00012)	(0.00013)
Panel E: Adding geographic region fixed effects to Panel D specification		
Pollution in the month before the birth month	-0.00017*	-0.00066**
	(0.00010)	(0.00012)
Panel F: Adding nightlights controls to Panel E specification		
Pollution in the month before the birth month	-0.00012	-0.00063**
	(0.00011)	(0.00013)

Notes:

[1] The number of observations for Panels A through E is 242,810 for the outcome "Deliver at home" and 182,585 for the outcome "Deliver in Public Institution". For Panel F, due to missing information for time periods, the number of observations is lower: 166,150 for the outcome "Deliver at home" and 128,030 for the outcome "Deliver in public institution".

Table A2. Effects of air pollution on the probability of having a c-section delivery, a low-birth-weight baby, and pregnancy complications

	Deliver by c-section	Have a low-birthweight baby	Pregnancy complications
Pollution in the month before the birth month	-0.00014 (0.00013)	-0.00009 (0.00018)	0.00072** (0.00020)
Observations	182,585	165,404	137,980
Number of clusters	640	640	640

	Deliver Public if not home (pregnancy with complications)	Deliver Public if not home (pregnancy without complications)
Pollution in the month before the birth month	-0.00079** (0.00026)	-0.00083** (0.00025)
Observations	55,135	82,845
Number of clusters	640	640

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table A3. Effects of Air Pollution on Delivery Outcomes: Janani Suraksha Yojana (JSY)

	Districts with fewer than 25% of women using JSY		Districts with more than 25% of women using JSY	
	Deliver Home	Deliver Public	Deliver Home	Deliver Public
Pollution in the month before the birth month	-0.00026	-0.00073**	0.00045**	-0.00042**
	(0.00021)	(0.00027)	(0.00020)	(0.00021)
Observations	135,149	95,913	101,714	81,610
Number of clusters	543	543	411	411

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table A4. Alternative Measure of Air Pollution: Air Quality Index (AQI)

	Deliver at Home	Deliver at Public Institution (conditional on not home)	Polio given at birth	Hep given at birth	Time in institution	Mother checked before discharged	Child checked within 1 week
AQI in the month before the birth month	0.00011	-0.00049**	-0.0001	-0.00027**	-0.00331**	0.00012	0.00005
	(0.00011)	(0.00013)	(0.00011)	(0.00013)	(0.00119)	(0.00013)	(0.00013)
Observations	242,802	182,582	174,827	172,823	137,210	137,642	177,447
Number of clusters	640	640	640	640	640	640	640

Notes:
[1] Standard errors reported in parentheses are clustered at the district level.
[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.
[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table A5. Effects of Contemporaneous Pollution Exposure on Delivery and Other Outcomes

	Deliver Home	Deliver Public (conditional on not home)	Polio given at birth	Hep given at birth	Time in institution	Mother checked before discharged	Child checked within 1 week
Pollution in the month of birth	0.00007	-0.00084**	-0.00048**	-0.00079**	-0.00823**	0.00019	0.00013
	(0.00019)	(0.00023)	(0.00022)	(0.00025)	(0.00265)	(0.00024)	(0.00025)
Observations	242,811	182,586	174,830	172,826	137,212	137,644	137,737
Number of clusters	640	640	640	640	640	640	640

Notes:

[1] Standard errors reported in parentheses are clustered at the district level.

[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.

[3] **denotes significance at the 5% level; * denotes significance at the 10% level.

Table A6. Robustness Checks for the Geographical Regions of 40 and 50

	Deliver at Home	Deliver at Public Institution (conditional on not home)	Polio given at birth	Hep given at birth	Time in institution	Mother checked before discharged	Child checked within 1 week
Panel A: IV with 40 clusters							
Pollution in the month before the birth month	0.00016	-0.00076**	-0.00048**	-0.00095**	-0.00549**	0.00024	0.00024
	(0.00019)	(0.00022)	(0.00022)	(0.00024)	(0.00266)	(0.00025)	(0.00025)
Observations	242,810	182,585	174,829	172,825	137,211	137,737	137,737
Number of clusters	640	640	640	640	640	640	640
Panel B: IV with 50 clusters							
Pollution in the month before the birth month	0.00003	-0.00082**	-0.00040**	-0.00079**	-0.00289	0.00027	0.00027
	(0.00017)	(0.00020)	(0.00017)	(0.00022)	(0.00259)	(0.00021)	(0.00021)
Observations	242,810	182,585	174,829	172,825	137,211	137,737	137,737
Number of clusters	640	640	640	640	640	640	640

Notes:
[1] Standard errors reported in parentheses are clustered at the district level.
[2] IV estimates using local wind direction as an instrument. All regressions include individual and household-level characteristics, as well as fixed effects for geographic regions, the month of birth, and birth year.
[3] **denotes significance at the 5% level; * denotes significance at the 10% level.