Impact of Air Pollution on Birth Outcomes: Causal Evidence from India*

Shashank Misra† Shobhit Kulshreshtha‡

Abstract

India consistently ranks among the countries with the highest levels of ambient air pollution worldwide. At the same time, it faces significant challenges in neonatal health, with newborns having low birth weights which has been shown to have long-term impacts on health and labor market outcomes. Using data from the Indian Demographic and Health Survey (DHS), we examine the impact of in-utero exposure to particulate matter ($PM_{2.5}$) on birth outcomes. We exploit quasi-random variation in wind direction as an instrument for in-utero particulate matter exposure for each child. We find that reducing in-utero $PM_{2.5}$ exposure by one standard deviation would lead to a 1.1% increase in average birth weight and reduce the incidence of low birth weight (LBW) and very low birth weight (VLBW) births by 2.9 and 0.7 percentage points, respectively. We extend our analysis to examine potential nonlinear effects of pollution exposure on birth outcomes. While we find no evidence of heterogeneous effects across different pollution thresholds, our results indicate that pollution disproportionately affects individuals in the lower tail of the birth weight distribution, with no impact at the upper tail.

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†Department of Econometrics and Operations Research, Tilburg University

‡Centre for Health Economic Research, Uppsala University and GLO. Corresponding Author: shobhit.kulshreshtha@uu.se

1 Introduction

India has experienced rapid economic growth over the past few decades, accompanied by a significant increase in air pollution levels (Sicard et al., 2023). Air pollution, particularly particulate matter, has substantial adverse effects on the economy, contributing to the loss of healthy years of life and increasing the burden of disease. In 2019 alone, air pollution is estimated to have cost the Indian economy over $37 billion due to its negative impact on human capital as a result of premature deaths and morbidity (WHO, 2024). Research has shown that air pollution can have a negative effect on health and cognitive development of children (Balakrishnan & Tsaneva, 2021; Balietti et al., 2022), and a growing body of literature highlights the short- and long-term consequences of fetal exposure to particulate matter on child health (Ai et al., 2023; Palma et al., 2022). However, much of this literature focuses on developed countries, raising concerns that the effects of pollution on child health may differ between developed and developing countries contexts (Arceo et al., 2016). In this study, we examine the effect of in-utero exposure to particulate matter ($PM_{2.5}$) on neonatal health outcomes in India, using birth weight as the primary health outcome.

Studying the impact of air pollution on neonatal outcomes in low- and middle-income countries (LMICs) is essential for two main reasons (Currie et al., 2014). First, pollution levels in these countries are often much higher than in high-income nations. For instance, average $PM_{2.5}$ levels between 2010 and 2019 were approximately 40 μg/m^3 in India, compared to 10 μg/m^3 in the United States over the period 2010–2019.[1] This higher "dose" of pollution exposure may result in effect sizes that differ substantially from those observed in high-income countries, regardless of the specific outcome being measured. In support of this, Arceo et al. (2016) find that the negative impact of pollution on infant mortality is greater in a developing country such as Mexico than in the United States. Second, baseline maternal health and healthcare access in developing countries is typically poorer, which may cause the effects of air pollution on birth outcomes to be more heterogeneous. On one hand, poorer maternal health and limited healthcare access may amplify the adverse effects of pollution

[1] These figures are computed using pollution data from the Goddard Earth Sciences Data and Information Services Center (NASA) and the United States Environmental Protection Agency.

on neonatal outcomes. On the other hand, it may obscure pollution's effects, as other health complications during pregnancy could play a more dominant role. This highlights the need for context-specific research in developing countries, where vulnerabilities and exposure patterns differ. In the context of our study, India, despite its recent economic growth, continues to perform poorly in terms of neonatal health. The incidence of adverse birth outcomes in India is high not only relative to industrialized nations, but also compared to other low- and middle-income countries (Marete et al., 2020).

In this study, we use birth weight and derived measures as our primary indicators of child health. Birth weight and related measures are a well-established predictor of short- and medium-term health outcomes (Hummer et al., 2014; McGovern, 2019), also having implications for long-run health, including adult mortality (Bharadwaj et al., 2018; Risnes et al., 2011). Beyond health, birth weight is closely linked to cognitive development, educational attainment, and future earnings, making it a strong determinant of labor market outcomes (Behrman & Rosenzweig, 2004; Black et al., 2007; Cook & Fletcher, 2015; Royer, 2009). Higher birth weight has also been shown to have substantial economic benefits through reduced healthcare costs and increased productivity, as documented in both developed and developing countries (Alderman & Behrman, 2006; Almond et al., 2005). Thus, by estimating the effect of in-utero exposure to air pollution on birth weight and related indicators in India, our study offers valuable insights into how early-life environmental conditions can shape human capital development in LMICs.

We use two recent waves of the Indian Demographic and Health Survey (DHS), 2015–16 and 2019–21, to causally estimate the relationship between in-utero exposure to particulate matter ($PM_{2.5}$) and birth weight measures for children born between 2010 and 2019. A simple OLS regression of birth weight measures on in-utero pollution exposure may produce biased estimates due to omitted variable bias; such as time varying unobserved local characteristics that affect both pollution levels and birth outcomes, as well as attenuation bias from measurement error in our pollution variable. To address these concerns, we exploit quasi-random variation in pollution exposure during pregnancy, driven by heterogeneity in wind patterns (Bondy et al., 2020; Deryugina et al., 2019; Herrnstadt et al., 2021; Persico & Marcotte, 2022).

Using our instrumental variables (IV) strategy, we find that a one-standard-deviation increase in $PM_{2.5}$ exposure during pregnancy reduces birth weight by approximately 1.1% relative to the sample mean of 2.8 kilograms, equivalent to a decrease of about 32 grams. In addition, our estimates indicate that a one-standard-deviation increase in $PM_{2.5}$ exposure leads to a 2.9 percentage point increase in low birth weight (LBW) incidence and a 0.7 percentage point increase in very low birth weight (VLBW) incidence. Comparing our results with those of Palma et al. (2022), who find that a standard deviation increase in PM_{10} levels in Italy reduces birth weight by 0.5%, with corresponding increases of 1.1 and 0.3 percentage points for LBW and VLBW, respectively, our findings suggest a larger effect size in the Indian context.

We further investigate the possibility of nonlinear effects of pollution exposure on birth outcomes in three different ways. First, instead of focusing solely on average $PM_{2.5}$ exposure during the in-utero period, we examine variation in exposure over the entire pregnancy. We find that greater variation, as measured by the range and standard deviation of $PM_{2.5}$ over the in-utero period, increases the incidence of LBW and VLBW, while it reduces birth weight. Second, we test whether exposure to different "doses" of pollution, defined using different $PM_{2.5}$ cutoffs, generates non-linear effects (Chen et al., 2021). Our results indicate no meaningful non-linearity across these pollution dose categories. Third, we estimate the effect of pollution at different points of the conditional birth weight distribution. Comparing our findings with Pons (2022), who report no significant average effect of $PM_{2.5}$ exposure on birth weight in the United States but do find a reduction of 28 grams at the lower tail, our non-linear estimates similarly show the largest impacts at the bottom of the distribution. In our case, the effect at the lower tail is substantially larger, an estimated reduction of 118 grams.

The estimated impacts on the LBW and VLBW indicators remain highly robust across a wide set of alternative model specifications. In contrast, the continuous birth weight measure exhibits greater sensitivity to specification choices, with both the size and precision of the estimates varying more noticeably. This divergence suggests that the effects of exposure are most reliably detected for LBW and VLBW thresholds, whereas the continuous outcome is less stable across models.

We make a significant contribution to the growing literature on the health and economic consequences of air pollution. Numerous studies have provided causal evidence on the adverse effects of air pollution on short-, medium-, and long-run health outcomes (Almond et al., 2009; Chay & Greenstone, 2003; Fan et al., 2023; Neidell, 2004; von Hinke & Sørensen, 2023). Others have highlighted its impacts on cognitive development and labor market outcomes (Balakrishnan & Tsaneva, 2021; Isen et al., 2017; Sanders, 2012). Beyond health, labor, and cognition, research has also explored how pollution affects crime, real estate markets, and time use (Bondy et al., 2020; Chay & Greenstone, 2005; Herrnstadt et al., 2021; Jafarov et al., 2023). As noted by von Hinke and Sørensen (2023), much of the existing literature within economics focuses on immediate birth-related health outcomes. However, these studies have predominantly been conducted in industrialized countries due to better data availability, leaving a gap in causal evidence from LMICs (Li & Zhang, 2024; Tang et al., 2024).

Using nationally representative Indian data, our study fills this gap by providing causal evidence from a middle-income country characterized by high pollution levels and poor neonatal health outcomes. It also adds to the small but growing body of causal research on the fetal origins hypothesis in the Indian context, which posits that early life environmental conditions, including in-utero pollution exposure, have long-term consequences for health and human capital formation (Almond & Currie, 2011). Existing work in India remains limited; for example, Singh et al. (2019) examines postnatal anthropometric outcomes rather than neonatal birth outcomes. This study therefore complements and extends the literature by focusing on fetal exposure and immediate birth related indicators.

We also contribute to the emerging body of research analyzing the impacts of pollution on neonatal health in developing countries (Arceo et al., 2016; Bharadwaj & Eberhard, 2008; Jayachandran, 2009; Li & Zhang, 2024). As previously discussed, this line of inquiry is particularly important in low- and middle-income countries where higher pollution exposure and poorer maternal health conditions may lead to different effect sizes and mechanisms compared to high-income contexts. Our study enables meaningful comparisons with estimates from other settings while offering India-specific insights that are crucial for public health policy.

Our findings are especially timely and policy-relevant given the rising national and international attention on air quality in India (Murukutla et al., 2017). Our non-linear estimates highlight the importance of looking beyond average pollution exposure. Moreover, we find that the effects of air pollution are heterogeneous and disproportionately concentrated among fetuses already vulnerable and situated in the lower tail of the conditional birth weight distribution. Policies that stabilise exposure during high pollution episodes, such as temporary restrictions on major emission sources or targeted short-term mitigation measures, may not substantially reduce annual averages, but they can significantly reduce peak exposures and deliver meaningful health benefits for pregnant women and infants.

The rest of the paper is structured as follows, Section 2 outlines the background in India concerning pollution and health dynamics, Section 3 provides a brief description of the data sources used in this study, Section 4 illustrates the identification strategy and model specification, Section 5 reports the results and robustness of our estimates before providing concluding remarks in section 6.

2 Background

We consider the case of India in this study because it exhibits a striking profile in both dimensions of the relationship we are exploring, pollution levels and neonatal health outcomes. In terms of pollution, all Indian states have $PM_{2.5}$ levels exceeding the UN safe limit of 10 μg/m^3, an important measure of air pollution (Balakrishnan et al., 2019). $PM_{2.5}$ is considered the main pollutant to assess the impact of air pollution on various health indicators (Balietti et al., 2022). In addition, the Central Pollution Control Board of India considers the levels of particulate matter to be the most critical and general indicator of air quality to make policy decisions (Greenstone & Hanna, 2014).[2] Recently, it has been observed that nearly 80% of the Indian population live in regions with annual $PM_{2.5}$ concentration levels of more than 40 μg/m^3, which falls under the severe air pollution level category that can

[2]The Central Pollution Control Board (CPCB), established in 1974 under the Water (Prevention and Control of Pollution) Act and later empowered by the Air (Prevention and Control of Pollution) Act of 1981, serves as India's national authority for monitoring and controlling environmental pollution.

induce health complications according to the WHO (Balakrishnan et al., 2019).

India also performs abysmally when it comes to indicators measuring neo-natal health. Approximately 750 thousand neo-nates die in India every year, i.e., within the first month of birth (Sankar et al., 2016). In addition, 60% of all children deaths under the age of 5 occur within the neo-natal phase (El Arifeen et al., 2017). Birth weight is a critical indicator of neonatal health and India has one of the lowest average birth weight levels not only in the world, but also among LMICs (Marete et al., 2020). India continues to have a high prevalence of births that fall into the LBW category, estimated to be somewhere between 24 to 30 percent. The nation accounts for 40 percent of all LBW births globally (Bhilwar et al., 2016; Sankar et al., 2016). Given India's dual burden of high ambient pollution and suboptimal neonatal health, investigating the impact of in-utero exposure on birth weight is not only relevant, but vital to uncovering the mechanisms through which environmental stressors in-utero shape early-life health trajectories. The findings can also inform policy makers on how to improve public health and mitigate children's health problems due to air pollution in India.

Medical literature has reported various mechanisms through which exposure to pollutants, such as fine particulate matter, can impact in-utero fetal development and subsequently, birth weight. Particulate matter exposure can cause pulmonary inflammation among mothers, which can potentially disrupt oxygen supply and nutritional movement to the fetus, resulting in pregnancy related complications and lower birth weight of children born to these mothers (Sun et al., 2016). In addition, studies have argued that pregnant women can face high oxidative stress that is caused by the presence of metals in the particulate matter. An increase in oxidative stress is likely to hinder embryo growth, which can critically impact the development of the child in the early stages of pregnancy (Kannan et al., 2007). Moreover, increased oxidative stress can also cause the formation of DNA adducts within the placenta, impairing the ability of the uterus to support fetal growth (Topinka et al., 1997). As an additional mechanism, particulate matter exposure has also been linked to interference with maternal hormones, with evidence that it can lead to maternal thyroid imbalances, which in turn negatively impact birth-weight outcomes (Blazer et al., 2003; Janssen et al., 2017). These mechanisms highlight the plausible biological pathways through which ambient pollution, particularly $PM_{2.5}$, can adversely influence fetal development and hence cause lower birth weight. Together, these epidemiological patterns and biological mechanisms highlight the urgency of examining the causal impact of ambient $PM_{2.5}$ exposure on birth outcomes in the Indian context, where both environmental and neonatal health vulnerabilities converge.

3 Data and descriptive statistics

3.1 Birth and demographics data

3.1.1 Birth weight and size

We obtain data on birth outcomes from the Demographic Health Survey (DHS) of India which is a nationally representative repeated cross sectional survey covering key metrics related to maternal and child health and nutrition in India. We use the last two waves of the DHS, which were conducted during the years 2015-2016 and 2019-2021, respectively.[3] The women taking part in the survey who fall between the reproductive age of 15-49 are classified as 'eligible' for questions on the health of their offspring, and are asked detailed questions on births which took place in the last 5 years since the date of the survey. From the two waves of the survey we have information on the birth weight of children born in the period 2010 to 2021. We exclude children born in 2020 and 2021 from our analysis, as we believe that children born during the pandemic period might systematically vary from those born prior to this period. Moreover, there can be other unobservable factors during the pandemic period which may impact child health and the pollution levels in the region. Therefore, we restrict our analysis to births between the period 2010 and 2019. The final sample consists of 327,396 children born during this period.

We are able to determine the birth weight of the children using the women's questionnaire. The respondents report birth weight (in grams) of the most recent child, born within the last 5 years, either via a written medical card, which was recorded upon the birth of a child, or

[3] We are unable to use the previous three waves since they do not have information on the exact location of residence of respondents. A precise location of the respondent is crucial since we construct our measure of in-utero pollution exposure by matching district level particulate matter levels over this period.

via recall.[4] In our sample, approximately 60% report the birth weight via the medical card, while the remaining report the birth weight of their children via recall. The data enables us to construct three measures of birth weight, 1) a continuous measure of birth weight, 2) a binary measure of Low Birth Weight (LBW), which is 1 if the child was born with a weight of less than 2500 grams and 0 otherwise, and 3) a binary measure of Very Low Birth Weight (VLBW), which is 1 if the child was born with a weight of less than 1500 grams and 0 otherwise. As an additional outcome, we construct a binary variable that equals 1 if the child's size at birth is reported as average or above average, and 0 otherwise, using responses to a separate survey question on birth size.

3.1.2 Demographics and socio-economic background

DHS also provides information on various socio-economic and demographic characteristics of the households that are surveyed. We include a number of mother and child characteristics. Specifically, we include mother's anemic level, mother's BMI, age of the mother when child was born, gender of the child, and birth order of the child. As birth weight has been shown to be affected by the socioeconomic background of the mother and other characteristics of the household in the Indian context (Kader & Perera, 2014), we control for these variables in our baseline model. Specifically, we include wealth index to control for socio-economic background.[5] In addition, we include demographic characteristics such as religion and caste of the household. We also include a binary variable for whether the mother lives in an urban area or not. Moreover, the cooking fuel used by the family has been shown to influence the exposure of children to indoor air pollutants (Pope et al., 2010). As a result, we also control for a binary indicator taking the value 1 if the cooking fuel used by the household was dirty and 0 otherwise.[6]

[4]Since the birth weight is recorded only for the most recent birth within the last 5 years, we do not observe multiple birth weights (siblings) per mother.

[5]Wealth Index variable is provided on a 5 point scale ranging from 1 to 5 with 1 indicating the lowest wealth level and 5 indicating the highest wealth level.

[6]Dirty fuel sources include kerosene, coal, charcoal, wood, straw/shrubs/grass, agricultural crop waste, and animal dung.

3.2 Pollution data

Air pollution data are obtained from the Goddard Earth Sciences Data and Information Services Center (GES DISC) funded by NASA, which provides a total surface mass concentration of $PM_{2.5}$ with spatial resolution of $0.5° \times 0.625°$. The data is sourced from the MERRA-2 satellite. For our analysis, we obtained the monthly data for the Indian union for the period 2009 to 2019. For each year and month, we have calculated the average concentration of $PM_{2.5}$ at the district level. To construct in utero exposure to $PM_{2.5}$, we computed the 10-month average concentration including the month of birth and nine months preceding it. We make the assumption that the mother resided in the same district in which the child was born during her pregnancy. We will discuss the validity of this assumption in more detail in Section 5.2. Van Donkelaar et al. (2016) provide estimated concentration of pollution at a spatial resolution of $0.01° \times 0.01°$, which helps us reduce the measurement error in our pollution variable. To check the robustness of our results, we also make use of this dataset.

3.3 Weather data

3.3.1 Wind direction

To gather information on wind direction which influences the concentration of $PM_{2.5}$ in a district, we obtain wind data for India from the ERA5 hourly dataset on surface levels, available through the Copernicus Climate Data Store. We use 10 daily observations of wind direction at the surface level to construct district-wise monthly averages of both the share of time the wind blew from each of the four cardinal directions, and the average wind speed, based on the u- and v-components of wind data for the period 2009 to 2019.[7] The data are available at a resolution of $0.25° \times 0.25°$ (approximately 25 km $\times$ 25 km), enabling the construction of accurate aggregated wind patterns for each district and month.

Following the method used to calculate in-utero $PM_{2.5}$ exposure, we compute the 10-month average of the share of time the wind blew from each of the four cardinal directions during pregnancy and the month of birth of the child. This variable serves as an instrument

[7]Details on how to convert the u- and v-components of wind into wind speed and direction are provided in Appendix A.

for in-utero exposure to $PM_{2.5}$ concentration.

3.3.2 Temperature and wind speed

In-utero weather conditions are known to influence fetal growth and development (Deschênes et al., 2009; Hong, 2025). Accordingly, we include weather controls such as mean temperature and wind speed during the in-utero period.[8] Incorporating these controls allows us to account for the atmospheric conditions to which the fetus was exposed throughout preganancy. These data are obtained from the same source as the wind direction data; the ERA5 hourly surface-level dataset provided by the Copernicus Climate Data Store and are constructed at the district-month level using 10 daily observations. In-utero weather variables are calculated by averaging the monthly values over the ten-month period comprising the nine months preceding birth and the month of birth, consistent with the methodology used to construct the pollution and wind direction variables.

3.4 Descriptive statistics

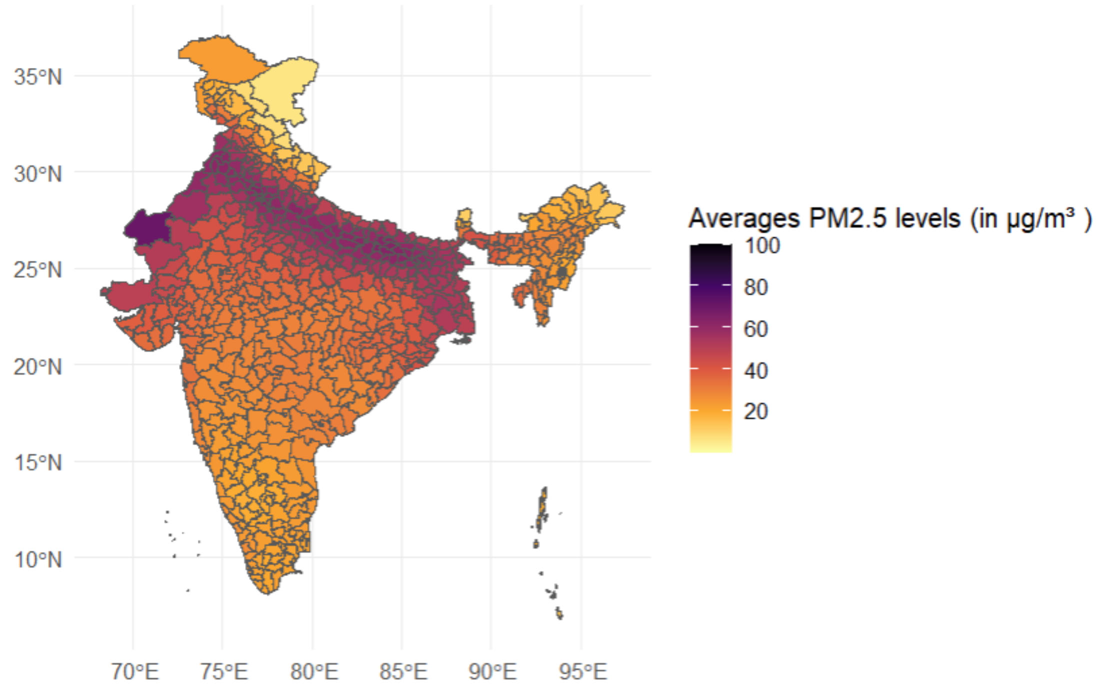
3.4.1 Regional and temporal variation: pollution

Figure 1 illustrates regional patterns in particulate matter, based on average $PM_{2.5}$ concentrations from 2010 to 2019. A clear north-south divide emerges, with significantly higher pollution levels in northern states compared to the south. One major source of pollution spikes is crop residue burning in the agricultural plains of North and Northwest India, typically occurring between mid-October and early November to prepare fields for the next harvest (Jain et al., 2014; Jethva et al., 2019). A second pollution wave affects the Indo-Gangetic Plain from November to January, driven by secondary aerosol formation due to increased biofuel use and waste burning, compounded by meteorological conditions that trap pollutants (Kanawade et al., 2020; Saharan et al., 2024; Sen et al., 2017). Additionally, dust storms in the Thar Desert during May to July elevate particulate levels in Northwestern state of Rajasthan and adjacent regions.

[8]As an additional robustness check, we also include in-utero exposure to precipitation, ozone and carbon monoxide using the data provided by GES DISC from NASA.

In contrast, southern India experiences relatively stable pollution levels year-round, with slight increases between November and April due to dry conditions. More generally, the monsoon period, for which the exact month(s) of incidence varies for each region results in improvements in particulate matter readings. The monsoon period is largely contained between the months of June and September for most regions in India. Figure B1 in the Appendix B presents the seasonal variation in average particulate matter concentration. We observe that temporal patterns are in line with aforementioned descriptions, with the Indo-Gangetic belt experiencing severe particulate matter pollution in the last quarter of the year and the North-Western desert regions encountering pollution spikes in the hot and dry summer months.

Figure 1: Average $PM_{2.5}$ concentrations across Indian districts



3.4.2 Regional and temporal variation: Wind direction

Table 1 presents the average within- and between-district variation in wind direction, measured by the standard deviation of the share of wind coming from each direction across districts within a region.[9] We observe considerable variation in wind patterns both across districts and over time within districts, indicating that there is substantial variation that can be used for our identification strategy. The regional and spatial variation in wind patterns implies that children born within the same region–month pair may be differentially exposed to pollution due to exogenous wind patterns, thereby generating plausibly random variation in in-utero $PM_{2.5}$ exposure.[10]

Table 1: Decomposition of Wind Direction Share Variation: District-Level Averages by Region

Direction	Overall SD	Between SD	Within SD	Between (%)	Within (%)
North	0.1392	0.0495	0.1254	17.5380	82.4620
East	0.1952	0.0618	0.1815	16.7280	86.4017
South	0.2490	0.0647	0.2350	12.0747	87.9253
West	0.1647	0.0629	0.1477	20.2078	84.5958

Notes: This table decomposes the standard deviation of district-level wind direction shares into between- and within-district components averaged *across* regions. Between SD reflects cross-sectional variation across districts within each region, while Within SD captures temporal variation within districts. Percentages indicate the share of total standard deviation attributed to each source. Table based on monthly district wise wind pattern data from 2009-2019

3.4.3 Summary statistics

Table 2 presents summary statistics for the sample of children used in our baseline analysis. The average birth weight in the sample is approximately 2,800 grams, with 17% of children classified as having low birth weight (LBW) and 1% as very low birth weight (VLBW). Nearly 90% of children were reported to be of average or above-average size at birth. The lower value of birth order (2.07) indicates that the majority of children were either first- or second-born. Approximately 48% of the children in the sample were female. Regarding

[9]Following the approach by Deryugina et al. (2019), we divide India into 30 regions using a K-means clustering algorithm based on district centroid coordinates, in order to create clusters of uniform size. Figure C1 displays the resulting clusters or regions. Average size of a region is ≈ 97,000 km^2.

[10]Table C1 in the Appendix, we report statistics on wind direction variation averaged across region-season pairs. The results show substantial variation in wind patterns both between districts and within districts among the same season–region pair. This indicates that, even after conditioning on region×season, wind directions are not fixed or fully predictable. Consequently, children born in the same region-season pair (or region×month) experience meaningful variation in in-utero wind patterns. This evidence suggests that seasonality and seasonal shifts do not perfectly predict wind patterns among districts contained within a region, neither across space or over time.

household characteristics, about 59% of households used dirty cooking fuel, highlighting the importance of controlling for this variable. On average, in-utero exposure to $PM_{2.5}$ was 40 μg/m^3, which substantially exceeds the levels recommended by the WHO. Other household and demographic characteristics used as covariates are also reported in the table.

Table 3 reports the summary statistics for our $PM_{2.5}$ data with other weather variables such as wind speed and temperature at the month-district level, spanning from the years 2009-2019. We observe a clear pattern of extremely high average $PM_{2.5}$ levels, with a sizable share (46%) of all of our district-month pairs having $PM_{2.5}$ levels which fall within the 'severe' category as defined by the WHO.

Table 2: Summary Statistics: DHS Sample

Variable	Mean	SD	Min	Max
Mother and Child Characteristics				
Mother's Age at Birth	25.002	4.790	11	49
Mother is Anemic	0.822	0.825	0	3
Mother's BMI	21.6	3.9	12.02	59.99
Child's Birth Order	2.072	1.206	1	6
Female Birth	0.478	0.500	0	1
Birth Weight (grams)	2825	583	500	9000
LBW	0.168	0.374	0	1
VLBW	0.010	0.099	0	1
Size: Average and Above	0.895	0.306	0	1
Religion				
Hindu	0.767	0.423	0	1
Muslim	0.112	0.316	0	1
Christian	0.078	0.268	0	1
Other Religion	0.043	0.203	0	1
Caste				
Scheduled Caste	0.205	0.404	0	1
Scheduled Tribe	0.201	0.401	0	1
OBC	0.409	0.492	0	1
Other Castes	0.184	0.388	0	1
Household				
Urban	0.241	0.428	0	1
Wealth Index	2.828	1.375	1	5
Dirty Cooking Fuel	0.590	0.492	0	1
Pollution Exposure				
$PM_{2.5}$ In-utero (μg/m^3)	39.817	14.696	4.739	94.203
Number of Observations		327,396		

Notes: Values computed from DHS microdata. LBW and VLBW indicate low birth weight (<2500g) and very low birth weight (<1500g). Dirty fuel includes kerosene, coal, charcoal, wood, straw, crop waste, or animal dung.

Table 3: Summary Statistics: Weather and Pollution Variables

Variable	Mean	SD	Min	Max
Wind Shares				
East Share	0.227	0.218	0	1
North Share	0.135	0.180	0	1
South Share	0.418	0.278	0	1
West Share	0.220	0.205	0	1
Weather				
Temperature (K)	297.894	7.205	242.995	311.732
Wind Speed (m/s)	3.413	1.842	0.379	11.193
Pollution				
$PM_{2.5}$ (μg/m^3)	38.037	21.755	1.504	186.617
Number of Observations	78,276			
$PM_{2.5}$ > **35** (μ**g/m**^{3})	36,347 observations (46%)			

Notes: Summary based on merged monthly panel of 78,276 district-month-year observations (2009–2019). $PM_{2.5}$ values above 35 μg/m^3 are considered "severe" by WHO standards. Wind shares represent the proportion of time wind blew from a particular 90-degree bin using 10 daily observations. Summary table reported based on all Indian districts except for Lakshwadeep for which data is missing.

4 Methodology

To estimate the relationship between in-utero pollution exposure and birth outcomes we use the following equation:

$$Y_{idrmt} = \beta\,\overline{PM2.5}_{i(d,m,t)} + \lambda X_i + \nu W_{i(d,m,t)} + \delta_{mr(d)} + \gamma_t + \epsilon_{idrmt} \tag{1}$$

where the dependent variable is the birth outcome of the child i, born in district d of region r, in month m of year t.[11] The key variable of interest is $\overline{PM2.5}_{i(d,m,t)}$, which measures in-utero exposure to air pollution and is constructed as the average concentration of particulate matter ($PM_{2.5}$) in the district (d) of the child during the month of birth (m) of year (t) and the nine preceding months of pregnancy. The parameter of interest, β, captures the effect of particulate matter exposure on the selected birth outcome. X and W are a vector of

[11] The regions as defined in Section 3.4 are constructed using the K-means clustering algorithm. We divide India into 30 region groups, which is similar to previous studies that have used this method in the Indian context (Balietti et al., 2022; Jafarov et al., 2023).

socio-demographic and in-utero weather controls respectively, as defined in Sections 3.1.2 and 3.3.2. Our specification includes region-by-month-of-birth fixed effects ($\delta_{mr(d)}$), which control for region-specific seasonal confounders that systematically influence birth outcomes as well as year-of-birth fixed effects (γ_t) to control for year-specific shocks that may affect all individuals born within the same cohort.

In a large country like India, seasonal trends vary substantially across regions. Consequently, factors such as cultural factors, labor market dynamics, income and consumption patterns differ not only across months but also across areas of the country. Incorporating region-by-month-of-birth fixed effects allows for greater flexibility in capturing seasonal unobservables that differ across regions, compared to a specification with only a month-of-birth fixed effects, which assume seasonal patterns are uniform nationwide. These fixed effects together imply that our identification comes from variation in pollution exposure among children born within the same region-month pair, while controlling for aggregate nation-wide year-specific confounders.

Despite the inclusion of a comprehensive set of controls and fixed effects, several potential confounders may still bias our estimate of the β parameter by simultaneously affecting both pollution exposure and birth outcomes. These include time-varying factors such as changes in industrialization, which can influence pollution levels while also improving birth outcomes through enhanced access to healthcare (Sanders, 2012). In such cases, our estimate of β may be biased downward. Moreover, prior health conditions and unobserved behavioral choices during pregnancy may influence relocation decisions. These decisions, in turn, affect pollution exposure while also directly impacting child health, thus introducing endogeneity. In the Indian context, however, internal migration and residential sorting are known to be relatively limited. Existing evidence shows that both the overall rate of internal migration and the extent of residential sorting are low in absolute terms and are also modest when compared with countries of similar size and stage of economic development (Jagnani, 2024). In rural areas, practices such as crop residue burning can simultaneously elevate local pollution levels and reduce soil fertility, which negatively affects farm income and potentially child health, thereby confounding the relationship of interest (Singh et al., 2019). In addition, as our analysis relies on satellite-derived pollution data, we are unable to measure individual-level exposure with high precision. While these data enable the construction of district-level estimates of ambient $PM_{2.5}$ concentrations linked to DHS respondents, they are available at a relatively coarse spatial resolution. This limitation introduces potential measurement error in estimating localized pollution exposure, which may result in attenuation bias, leading to estimates of β that are biased toward zero.[12]

To address the endogeneity concerns in our main specification, we employ an instrumental variables (IV) strategy following Balietti et al. (2022) and Deryugina et al. (2019). Specifically, we exploit quasi-random variation in in-utero exposure to $PM_{2.5}$ induced by prevailing wind directions during the gestation period. The first-stage equation is specified as follows:

$$\begin{aligned}\overline{PM2.5}_{i(d,m,t)} = &\sum_{r=1}^{30} \rho_1^r \text{Share}^S_{i(d,m,t)} + \sum_{r=1}^{30} \rho_2^r \text{Share}^N_{i(d,m,t)} + \sum_{r=1}^{30} \rho_3^r \text{Share}^E_{i(d,m,t)} \\ &+ \alpha X_i + \omega W_{i(d,m,t)} + \delta_{mr(d)} + \gamma_t + \varepsilon_{idrmt}\end{aligned} \tag{2}$$

We use wind patterns as instruments for particulate matter levels, specifically the direction of wind. In our first-stage equation, a child's in-utero exposure to particulate matter is instrumented by the share of time the wind blew from the North, East, and South ($Share^N_{i(d,m,t)}$, $Share^E_{i(d,m,t)}$, and $Share^S_{i(d,m,t)}$, respectively) during the in-utero period in the child's district of residence. Wind from the West serves as the reference category to avoid multicollinearity and to enable meaningful interpretation of the coefficients. We allow the effects of wind direction to vary by region. All other covariates and fixed effects remain as specified in Equation 1.

A potential threat to our identification strategy is the absence of within-region variation in wind direction. However, spatial and temporal variation in wind patterns within regions, as shown in Table 1, suggests that this concern is unlikely to affect our analysis. Our main specification includes region-by-month-of-birth fixed effects, meaning that the estimated impact of in-utero particulate matter exposure is identified from variation among births occurring in the same region-month pair. This means we require spatial and temporal

[12] To address this concern, we include data from Van Donkelaar et al. (2016) which provides particulate matter $PM_{2.5}$ at more granular level. We will discuss this in more detail in Section 5.2.

variation not only at an aggregate level within regions, but also among region-month-of-birth pairs. Table C1 showcases that we have sufficient variation in wind patterns across districts and within districts contained within a region even for the same season. The observed variation in wind patterns reinforces the validity of our identification strategy by demonstrating that wind-driven differences in pollution exposure are likely to persist even after accounting for the fixed effects embedded in our model.

Another potential threat to our identification strategy arises if the regions are too small, causing the wind instruments to reflect primarily local pollution sources. In such cases, wind patterns may capture emissions from nearby sources that are likely correlated with unobserved, time-varying determinants of birth outcomes, thereby reintroducing endogeneity. To mitigate this concern, we define regions that are sufficiently large so that wind instruments capture variation in pollution driven by non-local sources, i.e., emissions originating outside the immediate area. Our first-stage specification allows the effects of wind direction to vary only at the regional level, imposing a uniform impact across all districts within a region. This restriction helps ensure that the variation in pollution captured by our instruments reflects broader, regional air flows rather than localized sources. However, defining regions that are too large may violate the monotonicity assumption, as wind from a given direction could have heterogeneous effects across distant districts within the same region. To assess the robustness of our identification, we repeat the analysis using alternative region definitions based on different numbers of clusters. We will discuss this in more detail in Section 5.2.

To causally capture the relationship between $PM_{2.5}$ pollution and birth outcomes based on our instrument, it must hold that wind direction impacts birth outcomes only through its influence on pollution levels. This assumption is plausible, as wind direction itself is a natural and quasi-random meteorological phenomenon that is unlikely to directly affect fetal development or correlate with other determinants of birth outcomes. Based on our first stage fitted values, the second stage specification is the following:

$$Y_{idrmt} = \beta \widehat{PM2.5}_{i(d,m,t)} + \lambda X_i + \nu W_{i(d,m,t)} + \delta_{mr(d)} + \gamma_t + \epsilon_{idrmt} \tag{3}$$

Equation (3) follows the same structural form as Equation 1, with the key distinction that the main explanatory variable, $\widehat{PM2.5}$, represents predicted in-utero $PM_{2.5}$ exposure values obtained from the first-stage regression in Equation 2. We use a Linear Probability Model (LPM) to estimate the relationship between binary outcomes, including LBW and VLBW, and pollution exposure. We choose LPM because it is able to accommodate multiple fixed effects and produces marginal effects that are straightforward to interpret. In addition, LPM with fixed effects tends to provide more accurate probability estimates in cases of rare outcomes, as in our study, compared to alternative binary outcome models with fixed effects, such as fixed effects logit (Timoneda, 2021). In the results section that follows, we present both OLS estimates based on Equation 1 and IV estimates based on Equation 3.

5 Results

5.1 Baseline results

Panel A of Table 4 presents OLS results based on Equation 1, while Panel B reports IV estimates from Equation 3 for three outcomes: birth weight (in grams), an indicator for low birth weight (LBW), and an indicator for very low birth weight (VLBW). Using our causal IV estimates, we find that a one standard deviation decrease in $PM_{2.5}$ exposure during the gestational period (14.7 μg/m^3) increases birth weight by 1.1% relative to the mean, and there implies a 2.9 and 0.7 percentage point reduction in the incidence of LBW and VLBW, respectively, holding other factors constant.[13] A one standard deviation change in ambient $PM_{2.5}$ exposure also explains 5.5%, 8%, and 7.3% of the standard deviation in birth weight, LBW, and VLBW, respectively. Table C4 in the Appendix presents the estimates using average or above-average birth size as the outcome. The results suggest that greater in-utero exposure to $PM_{2.5}$ is associated with a reduced likelihood of the child being born with average or above-average size.

Our OLS estimates are consistently smaller in magnitude than the corresponding IV estimates across all birth outcomes. However, for the continuous birth weight measure we

[13] Table C2 in the Appendix presents the first stage estimates for the instruments - regions interacted with share of wind from North, East and South directions. Table C3 in the Appendix presents the coefficients for the control variables used in the second stage Equation 3.

find that the effect is statistically insignifcant. This suggests that the OLS estimates may be biased downward due to unobserved confounders or due to attenuation bias arising from measurement error, as discussed in the previous section. A simple Hausman test confirms that the difference between OLS and IV estimates is statistically significant for the LBW and VLBW outcomes, but not for the continuous birth weight measure. This indicates that endogeneity and measurement error may be more pronounced in the case of binary birth weight indicators. Our first stage F-statistic calculated based on a Wald test for the joint significance of our excluded instruments also indicates that our IV estimates do not suffer from weak instrument bias.[14] In the table, we also report Shea's partial R-squared, which measures the proportion of variation in pollution that is explained by the instrumental variable, in our case wind direction, after accounting for other covariates in the model. We find that changes in wind direction explain nearly 23% of the overall variation in pollution over time, indicating that wind patterns are a strong and relevant source of identifying variation in our instrumental variables strategy.[15]

Comparing our estimates with the existing literature, we find that a one standard deviation increase in in-utero exposure to $PM_{2.5}$ reduces birth weight by approximately 32 grams in India. This effect is substantially larger than the statistically insignificant average impact found for the United States (Pons, 2022) and is higher than the 0.5% reduction in birth weight associated with a one-standard-deviation increase in PM_{10} exposure in Italy (Palma et al., 2022). Moreover, studies have documented that the adverse effects of air pollution on child health outcomes may vary by the timing of exposure during pregnancy (Kumar, 2016; Stieb et al., 2012). To examine potential heterogeneity across the three trimesters, we estimate Equation 3 separately for each trimester to assess the trimester-specific effects of in-utero exposure to $PM_{2.5}$ on birth weight. The results, presented in Table C6 in the Appendix, indicate that exposure to $PM_{2.5}$ during any trimester is negatively and significantly

[14]The joint significance test for our first stage estimates is performed after we have used robust standard errors clustered at district level.

[15]We also compute Shea's partial R-squared separately for each district and summarize the distribution of these values in Table C5 in the Appendix, with the corresponding density plot shown in Figure C2 in the Appendix. From the table we observe that the average district-level Shea's partial R-squared is approximately 0.25. This finding further supports the relevance of wind direction as an instrument, demonstrating that it remains strong even when identification relies on within-district variation over time.

associated with lower birth weight.

Table 4: Effect of $PM_{2.5}$ Exposure on Birth Outcomes: OLS and IV Estimates

	Panel A: OLS Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
$PM_{2.5}$ Exposure	-0.669	0.0006^{**}	0.00008^{*}
	(0.425)	(0.0003)	(0.00005)
Adjusted R^2	0.053	0.016	0.002
	Panel B: IV Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
Instrumented $PM_{2.5}$ Exposure	-2.195^{**}	0.002^{***}	0.0005^{***}
	(1.026)	(0.0006)	(0.0001)
First Stage F-statistic	129	129	129
Shea Partial R-squared	0.23	0.23	0.23
Mean of Dependent Variable	2825	0.17	0.01
Observations	327,396	327,396	327,396

Notes: All controls mentioned in Equation 3 are included in the model. Clustered robust standard errors at the district level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. F-statistics reported are heteroskedasticity-robust F-statistics, based on a joint significance test of excluded instruments, with standard errors clustered at the district level from the first stage.

5.2 Robustness checks

To test the reliability of our findings and demonstrate the robustness of our identification strategy, we conduct a comprehensive set of robustness and sensitivity checks. This section addresses potential methodological concerns and outlines the steps we take to ensure that our results are not driven by alternative explanations or violation of model assumptions.

5.2.1 Concerns related to instrumental variable assumptions

Monotonicity: As discussed in Section 4, there is a trade-off in selecting the optimal size of regions over which the wind instruments are allowed to vary. By restricting the impact of wind direction coefficients to be uniform across all districts within a region, we aim to ensure that our instruments primarily capture variation in pollution from non-local sources, that is, pollution originating from outside the region. However, increasing the size of these regions may risk violating the monotonicity assumption, as the same wind direction could have heterogeneous effects on different districts within a region. Such heterogeneity could compromise the validity of our IV strategy, making it essential to test this assumption.

To address this concern, we reduce the size of the regions by increasing the number of regions and re-estimate the first-stage fitted values of in-utero pollution exposure. This approach, adopted in several prior studies using similar IV strategies, rests on the logic that with smaller regions, it becomes less likely that a given wind direction affects districts in systematically different ways, thereby reducing the likelihood of monotonicity violations. Figures C3, C4, and C5 in the Appendix present the IV coefficient estimates for our three birth outcomes, using alternative specifications with 40, 50, and 60 regions. Except for the continuous measure of birth weight, the results remain robust across these specifications, indicating that our IV estimates are not biased as a result of a violation in monotonicity assumption and hence can be intepreted as local average treatment effects (LATE) for the LBW and VLBW measures respectively.

Hierarchical Clustering: To test the robustness of our results to the method of region construction, we employ an alternative deterministic clustering algorithm of hierarchical clustering to construct our 30 regions. We then re-estimate our main results using this alternative regional specification. As shown in Panel a of Table 5, the coefficients obtained from this approach are similar to those from our baseline model for LBW and VLBW, suggesting that our findings are not sensitive to the specific clustering method used.

First Stage using District-Month-Year Pairs: In our baseline IV specification, we use the average wind direction shares over the 10-month in-utero period as instruments for the corresponding average in-utero pollution exposure. However, aggregating wind patterns over such a long duration may smooth out important month-to-month variation, potentially weakening the first-stage relationship. To address this concern, we adopt a more granular approach by predicting monthly pollution levels at the district level using district-month-year-specific wind patterns. These predicted monthly pollution levels are then aggregated over the gestational period for each child, based on their district of residence. The first-stage regression used to estimate monthly pollution is specified as follows:

$$PM2.5_{drmt} = \sum_{r=1}^{30} \rho_1^r \text{Share}_{dmt}^{S} + \sum_{r=1}^{30} \rho_2^r \text{Share}_{dmt}^{N} + \sum_{r=1}^{30} \rho_3^r \text{Share}_{dmt}^{E} \\ + \omega W_{dmt} + \delta_{mr(d)} + \gamma_t + \varepsilon_{drmt} \tag{4}$$

where $PM2.5_{drmt}$ denotes the average concentration of $PM_{2.5}$ in district d, belonging to region r, in month m of year t. Share of wind blowing from North, South and East are also defined at the district (d), month (m) and year of birth (t) level. All other remaining variables are defined as in Equation 2. This specification allows us to flexibly estimate monthly pollution levels at the district level, which can then be aggregated into individual-level in-utero exposure measures with better temporal precision. Using these first-stage estimates, we present the corresponding second-stage results in Panel b of Table 5. The results remain robust to this alternative method of constructing the exposure estimates.

Instrumental Reduction: In our baseline model, we use three wind directions as instruments to predict in-utero $PM_{2.5}$ exposure. These wind directions are interacted with 30 regions, yielding a total of 90 instruments. As an alternative specification, we reduce the number of instruments by focusing on the wind direction most likely to carry polluted air. Specifically, we estimate the first stage using only the wind direction that exhibits the strongest predictive power (largest absolute coefficient based on Equation 2) for in-utero $PM_{2.5}$ exposure. The results using the most predictive wind direction are presented in Panel c of Table 5. The results from this alternative method continue to support baseline findings.

Placebo Test: To ensure that our instruments capture meaningful variation in pollution driven by differential wind directions rather than spurious correlations, we conduct a placebo exercise. Specifically, we randomize wind direction variables across individuals in the sample and re-estimate our baseline model over multiple iterations. Across these placebo regressions, we consistently find null results with coefficients symmetric around 0, indicating that the original estimates are unlikely to be driven by random chance and that the instrumented variation reflects genuine quasi-experimental exposure to pollution. The point estimates for the placebo tests are presented in Figures C6, C7, and C8 in the Appendix.

Agricultural fires as source of pollution: Up to this point, our analysis has relied exclusively on wind direction as an instrument for ambient air pollution, without explicitly incorporating information on pollution sources. A growing literature has identified agricultural fires as a major contributor to seasonal increases in $PM_{2.5}$ concentration, and studies have used crop burning interacted with wind direction as an instrument for local air pollution in the Indian context (Garg et al., 2024; Jagnani & Mahadevan, 2025; Pullabhotla & Souza, 2022; Singh et al., 2019). Following this approach allows us to focus on pollution originating from non-local sources and to more credibly identify the effect of transported ambient air pollution on birth outcomes.

We construct fire-based instruments using the methodology outlined in Pullabhotla and Souza (2022), and describe this in detail in Appendix D. Table D2 reports the IV estimates using agricultural fires located within a distance $f \in \{200, 250, 300, 350, 400\}$ kilometers (kms) from the district of birth, interacted with local wind direction.[16] The results indicate that the estimated effects on LBW are robust across all distance bands, except at the 200-kilometer radius. For the continuous measure of birth weight and for VLBW, the coefficients are similar in magnitude and direction to the baseline results; however, they are not statistically significant, likely due to limited precision. Overall, these findings provide further support for the credibility of our identification strategy, demonstrating that our main results are robust to the use of alternative instruments based on agricultural fires interacted with wind direction.

[16]We present the first-stage results in Table D1 in Appendix D. These results show that when the number of agricultural fires increases in a given direction and the share of wind blowing from that direction is high in a particular month, the concentration of $PM_{2.5}$ in the district also rises.

Table 5: Alternate First Stages

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Hierarchical Clustering			
$PM_{2.5}$ Exposure	-1.081	0.001^{***}	0.0003^{***}
	(1.015)	(0.0006)	(0.0001)
First Stage F-statistic	159	159	159
Panel b: First Stage: District-Month-Year Pairs			
$PM_{2.5}$ Exposure	-2.540^{**}	0.002^{***}	0.001^{***}
	(1.222)	(0.001)	(0.0001)
First Stage F-statistic	44	44	44
Panel c: Instrumental Reduction			
$PM_{2.5}$ Exposure	-4.158^{***}	0.002^{***}	0.0002^{***}
	(0.540)	(0.0002)	(0.00005)
First Stage F-statistic	92	92	92
Observations	327,396	327,396	327,396

Notes: IV estimates. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.2.2 Alternative specifications

Maternal health, pregnancy complications, and behavioral or educational characteristics of the mother can also influence a child's birth weight. To demonstrate that these variables are not causing endogeneity in our model, we control for a set of maternal and birth-specific characteristics in an extended model. These include binary indicators for whether the mother has any chronic health condition, smokes, or consumes alcohol; a categorical variable for maternal education attainment; the number of antenatal checkups attended; a categorical variable for place of delivery; indicators for multiple births (twins), and whether the child was delivered via surgery. We present the results in Panel a of Table 6. While the point estimate is lower than in the baseline specification, the results remain robust to the inclusion of these additional maternal and birth-related controls. For the continuous measure of birth weight the estimate is statistically significant only at 10% level of significance.

Prior studies have shown that other air pollutants, such as ozone and carbon monoxide (CO), as well as weather variables like precipitation, can be correlated to particulate matter levels and at the same time, directly impact neo-natal outcomes (Balietti et al., 2022; Peet, 2021). To account for potential confounding effects from these factors, we include in-utero ozone, CO, and precipitation as additional controls in our baseline model as a robustness check. The results, presented in Panel b of Table 6, indicate that our main findings remain robust for LBW and VLBW.[17] In addition, we noted that approximately 60% of our sample reports birth weights of their offspring via a medical card, whereas 40% report birth weights via recall. In order to avoid potential measurement error in our outcomes, we retain only the sample which reported birth weight via a medical card and re-estimate our results. In Panel c of Table 6, we observe that our key results remain similar in terms of magnitude and statistical significance.

Table 6: Alternative Model Specifications

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Additional Mother and Birth Controls			
$PM_{2.5}$ Exposure	-1.242*	0.001***	0.0002***
	(0.633)	(0.0004)	(0.0001)
Observations	327,396	327,396	327,396
Panel b: Precipitation, CO, and Ozone			
$PM_{2.5}$ Exposure	-1.962	0.002***	0.0006***
	(1.211)	(0.0007)	(0.0001)
Observations	321,346	321,346	321,346
Panel c: Card only Sample			
$PM_{2.5}$ Exposure	-2.220**	0.001**	0.0003***
	(1.125)	(0.0007)	(0.0001)
Observations	185,814	185,814	185,814

Notes: Number of observations in Panel b are lower because precipitation data is not available for some small districts. Clustered robust standard errors at district level are reported in parentheses. All regressions include full set of controls and fixed effects as the baseline equation. *** p<0.01, ** p<0.05, * p<0.1

5.2.3 Sensitivity checks

As a sensitivity check, we replicate our analysis after filtering out outliers in birth weight. Specifically, we include children who 1) were born with a birth weight between the 1st and 99th percentiles, and 2) were born with a birth weight between 1,600 and 4,000 grams. The

[17]In Table C7 in the Appendix we provide the estimated coefficients for carbon monoxide and ozone. We observe that higher exposure to ozone has a negative effect on a child's birth weight but does not statistically significantly impact LBW and VLBW. Moreover, the estimate for carbon monoxide on VLBW is significantly different from 0 although the magnitude is very close to 0. Suggesting that $PM_{2.5}$ concentration is the main pollutant affecting children's birth outcomes.

results, presented in Tables C8 and C9 in the Appendix, are consistent with our baseline findings for LBW. Figures C9 and C10 show that our estimates remain significant at the 5% level when using alternative geographical clusters for standard error computation, specifically, at the region and state levels. However, our estimates are not statistically significant for the continuous measure of birth weight as can be seen in Figure C11. In addition, Figures C12, C13, and C14 in the Appendix present estimates obtained by iteratively excluding births from one State or Union Territory (UT) at a time. Given the overlapping confidence intervals, the iterative exclusion analysis confirms that our results are not disproportionately influenced by any single region.

As discussed in Section 3.2, one of our key assumptions is that the mother resided in the same district throughout the entire duration of her pregnancy, including at the time of the child's birth. While this assumption cannot be directly tested, we assess the sensitivity of our results by excluding the months closest to birth when calculating in-utero exposure to $PM_{2.5}$. This approach accounts for the possibility that women often relocate to their parental home around the time of delivery (Diamond-Smith et al., 2024). Table C10 in the Appendix presents estimates using in-utero $PM_{2.5}$ exposure calculated over the first 7, 8, or 9 months prior to birth. Across all specifications, the results remain robust, suggesting that our findings are not sensitive to the specific exposure window used.

The DHS also provides information on how long the mother has been residing at her current place of residence. However, it does not indicate whether the previous residence was within the same district or in a different district. As a result, we cannot determine whether the individual moved within the district or between districts. Using the mother's reported duration of residence and the child's year of birth, we find that 4.64% of mothers (15,183 observations) gave birth before moving to their current place of residence. To test the robustness of our results, we re-run the analysis on a sub-sample that excludes these observations. Table C11 presents the results for this specification. Our findings remain robust.

Till now we have used the $PM_{2.5}$ data with spatial resolution of $0.5° \times 0.625°$. However, Van Donkelaar et al. (2016) provides estimated concentration of $PM_{2.5}$ concentration at the spatial resolution of $0.01° \times 0.01°$. Using this data allows us to address concerns about measurement error in district-level $PM_{2.5}$ concentrations, as it is more granular than the data used in our baseline analysis. We first check whether the aggregated values of $PM_{2.5}$ concentration at the district-month-year level are similar across the two datasets. Figure C15 in the Appendix shows that concentration of $PM_{2.5}$ from the two datasets at district-month-year pairs are highly correlated, with a correlation coefficient of 0.80. We then run the whole analysis using data at higher spatial resolution. Table C12 in the Appendix presents the OLS and IV estimates using this data. Our results remain robust for LBW and VLBW. However, the estimate for birth weight is negative but not statistically different from 0 at 5% level of significance.

5.2.4 Summary of robustness checks

In summary, our estimates for LBW and VLBW remain robust after addressing concerns related to the instrumental variables strategy and alternative model specifications. In addition, the findings are largely unchanged when we exclude outliers, restrict the analysis to mothers' duration of residence in their current location, or vary the spatial resolution of the pollution data. By contrast, the estimates for the continuous measure of birth weight are less robust. In several specifications the coefficient is not statistically different from zero, although the point estimates generally remain negative. This suggests that in-utero pollution exposure may not affect continuous birth weight on average, but it does not rule out the possibility of heterogeneous or non-linear impacts, which we examine in the next section.

5.3 Non-linear effects

While our findings suggest that average in-utero exposure to $PM_{2.5}$ has a significant and negative impact on birth weight, prior research has highlighted that the relationship between air pollution and health outcomes may not be strictly linear (Aragón et al., 2017; Chen et al., 2021; Pons, 2022). This non-linearity could arise due to heterogeneity in pollution exposure levels or thresholds beyond which health effects intensify. Moreover, the impact of air pollution may differ across the distribution of birth weight, indicating that certain segments of the population, such as those already at risk of being low birth weight may be more vulnerable (Pons, 2022). In this section, we examine the non-linear effects of in-utero $PM_{2.5}$ exposure on birth weight outcomes.

5.3.1 Using dispersion variables

In our baseline analysis, we have relied on the average in-utero exposure to $PM_{2.5}$ concentrations to estimate its effect on a child's birth weight. However, this approach may obscure important temporal variation in exposure. For instance, two fetuses may experience the same average $PM_{2.5}$ concentration over the course of pregnancy, yet one may be exposed to extremely high levels during certain months and very low levels during others, while the other may be exposed to a relatively constant concentration throughout. Such differences in the timing and intensity of exposure may have distinct implications for fetal development.

To address this concern, we examine whether variability in in-utero $PM_{2.5}$ exposure, rather than just the average levels, affect birth weight. Specifically, we estimate the effects using three measures of dispersion in monthly exposure: (i) the range, defined as the difference between the maximum and minimum monthly $PM_{2.5}$ exposure during the pregnancy; (ii) the inter-quartile range (IQR), defined as the difference between the third and first quartile of monthly $PM_{2.5}$ exposure during the pregnancy; and (iii) the standard deviation of $PM_{2.5}$ concentrations during pregnancy. These measures are constructed using predicted monthly district-level $PM_{2.5}$ concentrations obtained from the first-stage regression described in Equation 4.

Table C13 in the Appendix presents the results. We find that both the range and the standard deviation of in-utero $PM_{2.5}$ exposure have statistically significant and negative effects on birth weight, and are positively associated with the likelihood of low or very low birth weight. Although the effect of the inter-quartile range is not statistically significant at 5% level of significance, the overall findings are consistent with our earlier results based on average exposure levels. These findings highlight the importance to look beyond the average in-utero air pollution exposure in making policy decision to improve birth outcomes.

5.3.2 Spline regression

It is plausible that the effect of in-utero exposure to $PM_{2.5}$ on birth weight is non-linear, with marginal reductions in birth weight being larger at higher levels of $PM_{2.5}$ compared to lower levels. To explore this potential non-linearity, we follow the approach of Chen et al. (2021) and introduce a spline term into our baseline IV model, as specified in Equation 3. This allows us to estimate the heterogeneous effect of $PM_{2.5}$ exposure across different concentration thresholds (k). The equation with spline term is as follows:

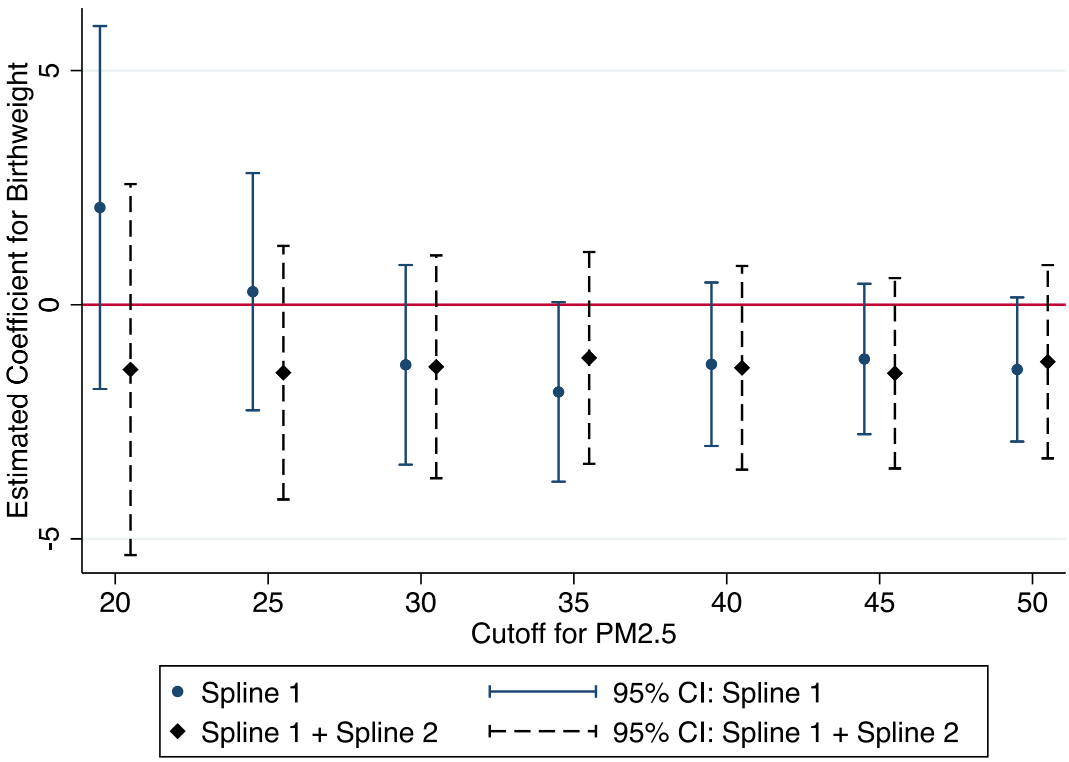
$$\begin{aligned} Y_{idrmt} = \beta_1 \widehat{PM2.5}_{i(d,m,t)} + \beta_2 [\widehat{PM2.5}_{i(d,m,t)} - k].I(\widehat{PM2.5}_{i(d,m,t)} \geq k) \\ + \lambda X_{idrmt} + \nu W_{i(d,m,t)} + \delta_{mr} + \gamma_t + \epsilon_{idrmt} \end{aligned} \tag{5}$$

Here, k denotes the cutoff level of $PM_{2.5}$ concentration. For values of $PM_{2.5}$ below k, the coefficient β_1 captures the marginal effect of a one-unit increase in $PM_{2.5}$ on outcome variables, namely birth weight or indicators of low and very low birth weight. For values of $PM_{2.5}$ equal to or above the cutoff, the marginal effect is given by $\beta_1 + \beta_2$. We estimate the model using various cutoff values of k, ranging from 20 to 50 in increments of 5. All other variables are defined as in Equation 3.

Figure 2 presents the estimated values of β_1 and $\beta_1+\beta_2$ using birth weight as the outcome. We find that both β_1 and $\beta_1 + \beta_2$ are not statistically different from zero across all cutoff levels. However, the estimated values of β_1 are weakly statistically significant for certain cut-off levels at 10% level of significance. We also find that the confidence intervals overlap for all values of k, with the two point estimates being almost the same for different cut-off levels. This suggests that there is no evidence of non-linearity in terms of different exposure to $PM_{2.5}$ concentration on birth weight.

We conduct a similar analysis for the binary indicators of low birth weight and very low birth weight, with the results displayed in Figures C16 and C17 in the Appendix, respectively. We observe some divergence between β_1 and $\beta_1+\beta_2$ at higher cutoff values for both outcomes. However, the confidence intervals overlap, and thus we cannot say with certainty that the two values are statistically different. Overall, we find only weak or no evidence of non-linearity in the relationship between in-utero $PM_{2.5}$ exposure and birth outcomes.

Figure 2: Non-linear effects using spline regression for birth weight



5.3.3 Grouped quantile regression

Given that we calculate $PM_{2.5}$ concentrations at the district-month-of-birth level to estimate their effect on child's birth weight, it is plausible that children across different points in the birth weight distribution are affected differently by such exposure (Pons, 2022). In this context, a more appropriate empirical strategy is the grouped quantile regression (GQR) estimator developed by Chetverikov et al. (2016), which allows for heterogeneity in treatment effects across the distribution of the outcome variable.

To implement this approach, we divide our covariates into two categories: group-level variables, where the groups (g) are defined as district-month-of-birth pairs; and individual-level variables, including maternal and child characteristics. Ideally, GQR involves a two-stage procedure. In the first stage, quantile regressions of the outcome variable (birth weight) are estimated on individual-level covariates within each group. In the second stage, the effect of $PM_{2.5}$ concentration is estimated using the group-level aggregated outcomes. However, in our setting, the number of observations within each group is too small to reliably estimate the first-stage quantile regressions.

To address this concern we employ an alternative approach. In this approach, we first regress birth weight of children on individual level maternal and child characteristics. The equation is as follows:

$$Y_i = \lambda X_i + \varepsilon_i \tag{6}$$

Here, Y_i is the birth outcome of child i and X_i include all maternal, child and household characteristics as explained in Equation 1. We then take the estimated residuals ($\hat{\varepsilon}_i$), interpreted as birth weights adjusted for individual characteristics, as the new dependent variable. Following the simplified method suggested by Chetverikov et al. (2016) and implemented by Pons (2022), we compute the quantiles $u \in \{5, 15, 25, ..., 95\}$ of the adjusted birth weights at the group level. These group-level quantiles ($\bar{\hat{\varepsilon}}_g(u)$) serve as the dependent variables in our second-stage analysis. In this stage, we regress the group-level conditional birth weight quantiles on the predicted in-utero $PM_{2.5}$ exposure ($\widehat{PM2.5}_{dm}$), instrumented using wind direction as in our first-stage specification (Equation 2), and averaged across years for each district-month group, denoted as $PM2.5_g$. We also control for group-level covariates such as average temperature, wind speed, and month-of-birth-by-region fixed effects, consistent with the specification of our baseline second stage model in Equation 3. The group-quantile regression equation is as follows:

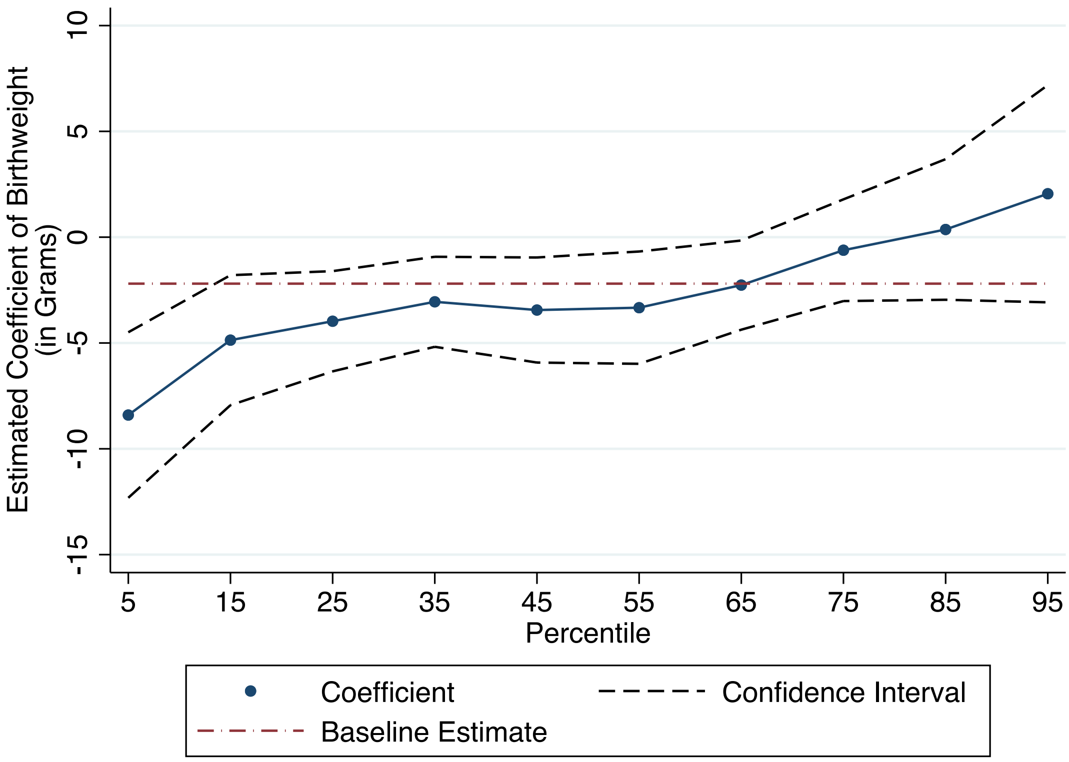
$$\bar{\hat{\varepsilon}}_g(u) = \beta(u)\widehat{PM2.5}_g + \omega(u)W_g + \delta_{mr} + \epsilon_g \tag{7}$$

Where, $\hat{\varepsilon}$, is the predicted residual from Equation 6. We then compute the quantiles $\hat{\varepsilon}$ for every group g across ($u \in 5, 15, 25, \ldots, 95$) of the conditional birth weight distribution . Our key variable of interest is $\widehat{PM2.5}_g$, which is the average of predicted exposure to $PM_{2.5}$ concentration for all the children in the district-month-of-birth pairs. W_g is the vector of weather controls, including temperature and wind speed averaged across all the children belonging in the group g. ϵ_g is the random error term. The standard errors are calculated using bootstrapping, clustered at district level.

Figure 3 presents the results from estimating Equation 7. Consistent with the findings of Pons (2022), who observed only a 28 gram reduction at the lower tail of the distribution, we find that the effect of in-utero $PM_{2.5}$ exposure is stronger at the lower end of the birth weight distribution, with a reduction of 118 grams for a one standard deviation increase in in-utero $PM_{2.5}$ concentration. The estimated coefficients are statistically significant up to the 65th percentile, beyond which they become insignificant. This pattern suggests that the adverse impact of air pollution is concentrated among children born with lower birth weights.

Alternatively, we repeat the grouped quantile regression analysis using the directly computed empirical quantiles (u) of birth weight for each group without adjusting for individual characteristics. The corresponding results are shown in Figure C18 in the Appendix. The pattern remains consistent: the effect size is largest in the lower tail of the distribution and becomes positive at the upper tail. However, the effect is statistically insignificant at almost every quantile. The findings presented in this section reinforces the conclusion that the impact of in-utero exposure to air pollution is disproportionately borne by children at the lower end of the birth weight distribution after adjusting for observable individual characteristics.

Figure 3: Non-linear effects using grouped quantile regression for birth weight, adjusted for individual characteristics



6 Conclusion

This paper provides novel causal evidence on the impact of in-utero exposure to air pollution on birth outcomes in India, a country characterized by both high ambient air pollution and poor neonatal health indicators. Leveraging exogenous variation in wind direction to instrument for ambient $PM_{2.5}$ exposure during pregnancy, we document that even modest reductions in particulate matter can yield significant improvements in neonatal health. Specifically, we find that a one standard deviation decrease in $PM_{2.5}$ exposure over the in-utero period would lead to a 1.1% increase in average birth weight, a 2.9 percentage point reduction in LBW births and a 0.7 percentage point decrease in VLBW births respectively. Our findings are highly robust for the LBW and VLBW measures, highlighting the role of $PM_{2.5}$ as a significant contributor to India's poor neo-natal health record.

Moving beyond average in-utero pollution exposure, our analysis shows that the variability of pollution during pregnancy has consequences for neonatal health as well. Greater dispersion in $PM_{2.5}$ exposure over the in-utero period is associated with worse birth outcomes. Additionally, we find that air pollution does not affect all fetuses uniformly. Those in the lower tail of the conditional birthweight distribution are disproportionately harmed, indicating that the most vulnerable fetuses bear the greatest burden of pollution exposure.

Our research also comes with several limitations. First, we are unable to precisely account for time spent outdoors, pollution avoidance or defensive behaviors, and migration patterns, all of which influence actual ambient exposure during pregnancy. Second, since our data come from a repeated cross-section rather than a longitudinal panel, we are unable to examine the long-term effects of in-utero pollution exposure, or direct mediation effects through birth-weight on these longer run relationships, which remains an important area for future research. Third, and finally, we focus only on birth weight and related measures as indicators of neonatal health. Other important neonatal health outcomes such as gestational age, Apgar scores, congenital anomalies, and early-life morbidity are not examined in this paper, even though air pollution may also affect these outcomes.

Overall, our findings highlight the importance of prenatal environmental conditions in shaping early-life health outcomes and suggest that reducing air pollution exposure during pregnancy may have long term benefits that will improve public health in LMICs.

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Appendix

A. Calculation of Wind Direction and Wind Speed based on U-V wind components

The wind speed (WS) and wind direction (θ) can be calculated from the zonal (u) and meridional (v) wind components using the following formulas:

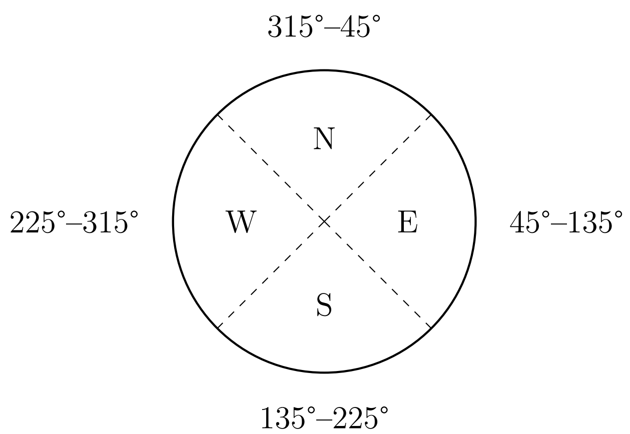
$$WS = \sqrt{u^2 + v^2} \tag{8}$$

$$\theta = \left(\arctan 2(v, u) \cdot \frac{180}{\pi}\right) + 180 \tag{9}$$

- u is the zonal (east-west) component (positive toward the east), v is the meridional (north-south) component (positive toward the north),

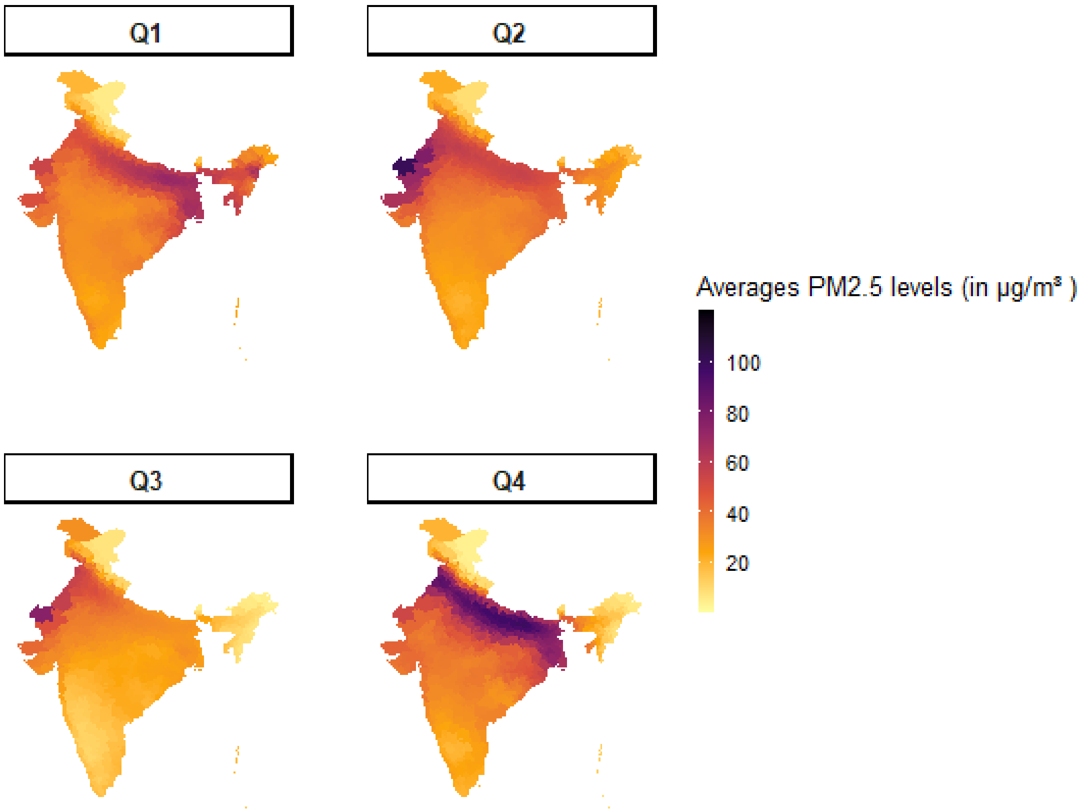
As described in Section 3.3.1, we observe 10 wind direction measurements per day, yielding 10 district-wise daily wind direction observations. After assigning each of these 10 daily observations to one of the four cardinal direction bins shown in Figure A1, we aggregate the data to the district–month level by calculating, for each district–month, the share of all wind direction observations in that month that were in each of the 4 cardinal bins. Similarly, for each of the 10 district level daily wind observations, we record the corresponding wind speed, and then compute the district–month average wind speed by taking the mean of all wind-speed observations within each district–month.

Figure A1: Classification of wind direction based on 90° bins



B. Spatial and Temporal Variation of $PM_{2.5}$

Figure B1: Quarter of Year Wise PM2.5



C: Additional Tables and Figures

Figure C1: 30 clusters based on K-means clustering algorithm

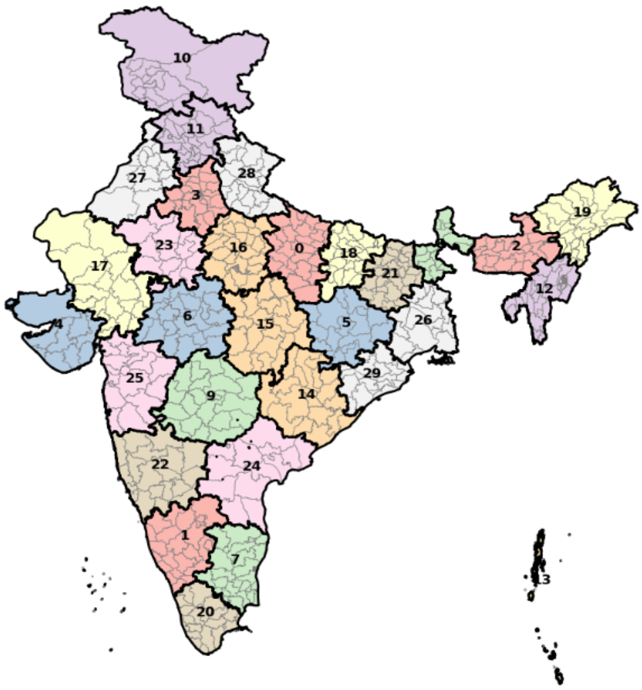


Figure C2: Density Plot of Shea's Partial R-squared

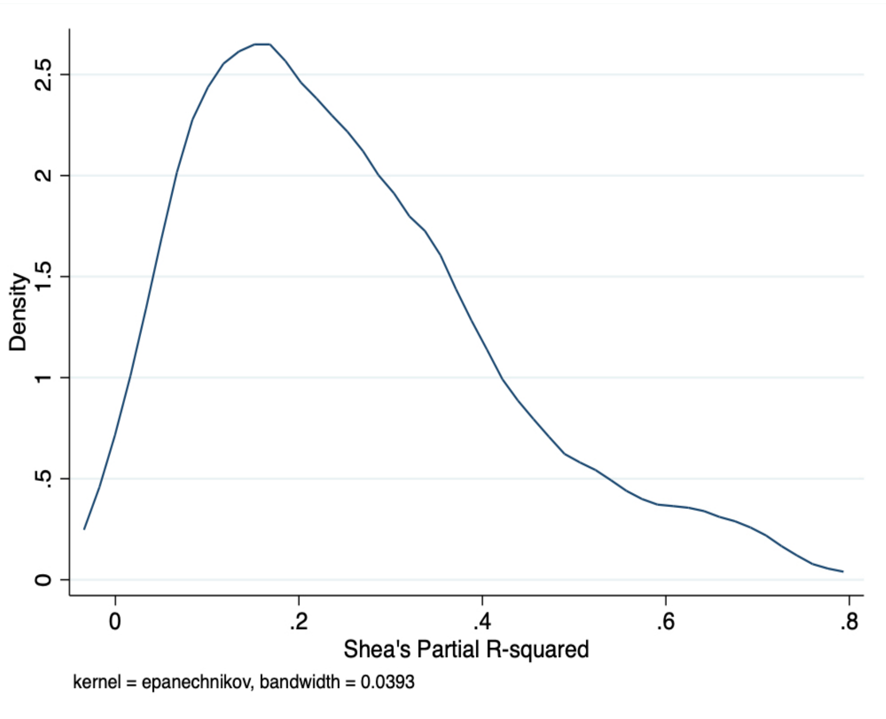


Figure C3: Monotonicity (Continuous Measure of Birth Weight): Alternative Number of Regions for Instrument

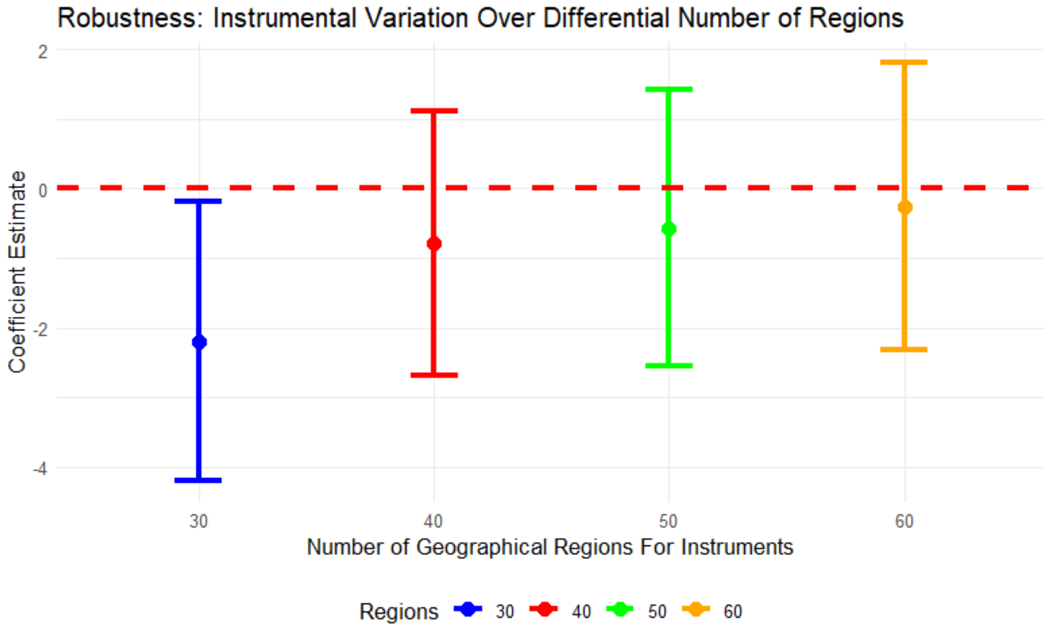


Figure C4: Monotonicity (LBW Binary Measure): Alternative Number of Regions for Instrument

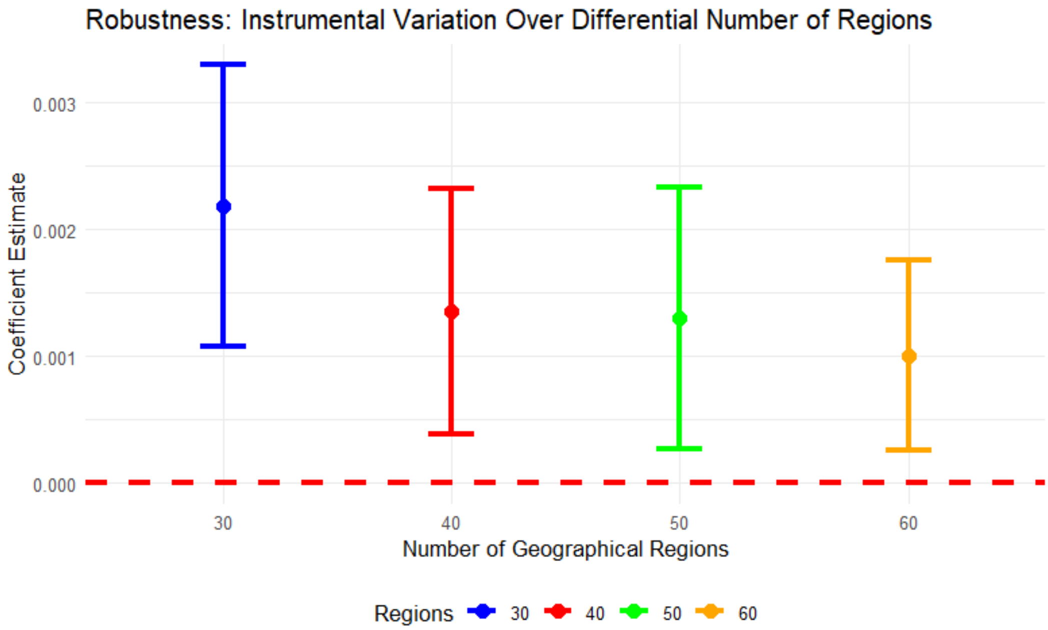


Figure C5: Monotonicity (VLBW Binary Measure): Alternative Number of Regions for Instrument

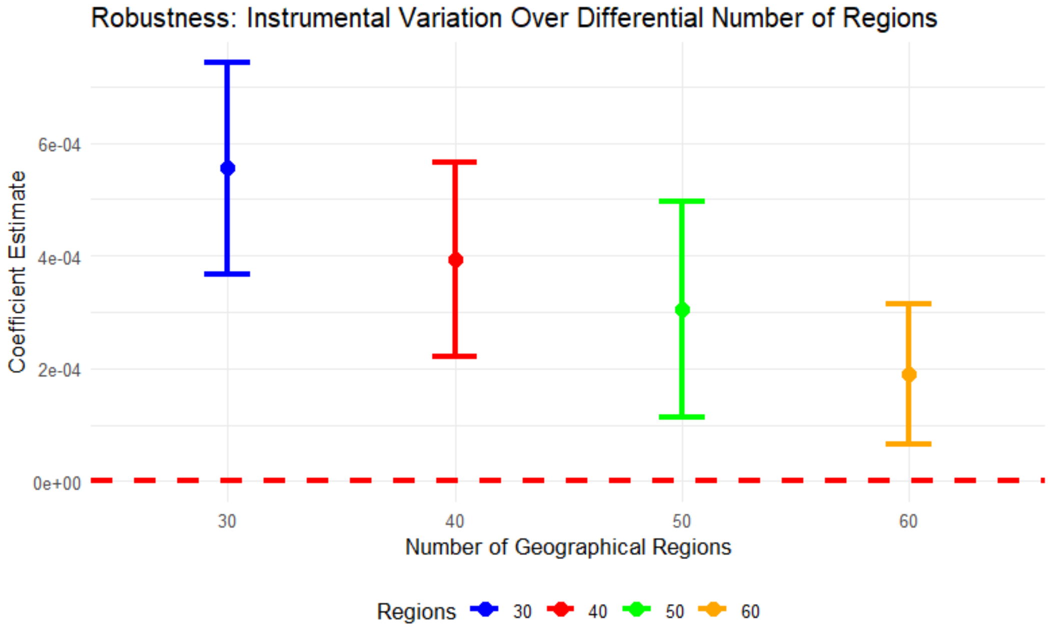


Figure C6: Placebo Exercise Results (Continuous birthweight measure): 250 iterations

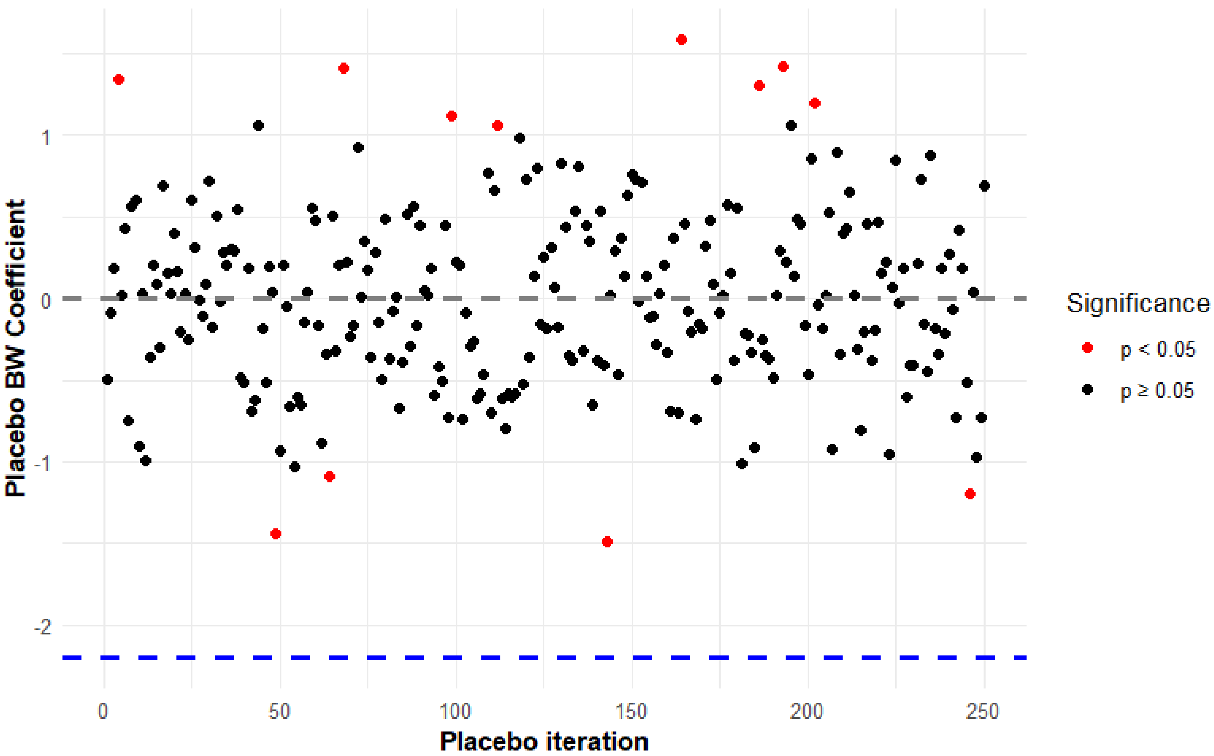


Figure C7: Placebo Exercise Results (LBW indicator): 250 iterations

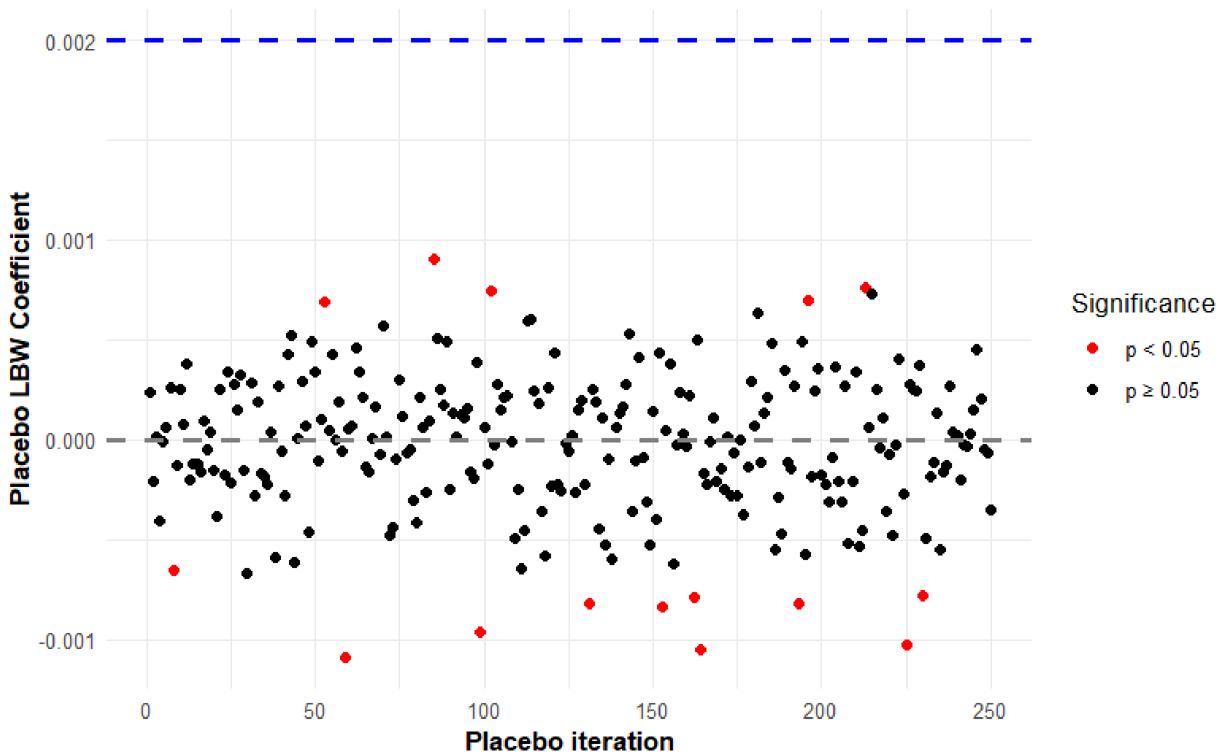


Figure C8: Placebo Exercise Results (VLBW indicator): 250 iterations

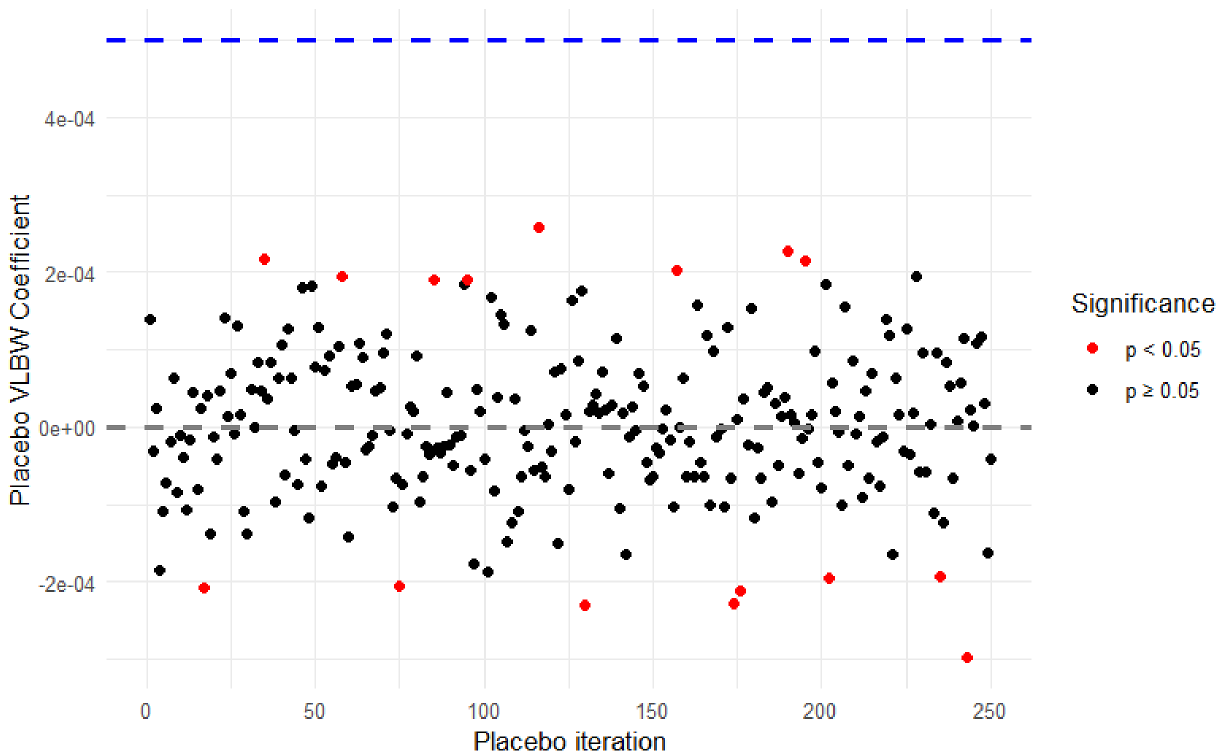


Figure C9: Baseline Results LBW: Alternative Clustering of Standard Errors

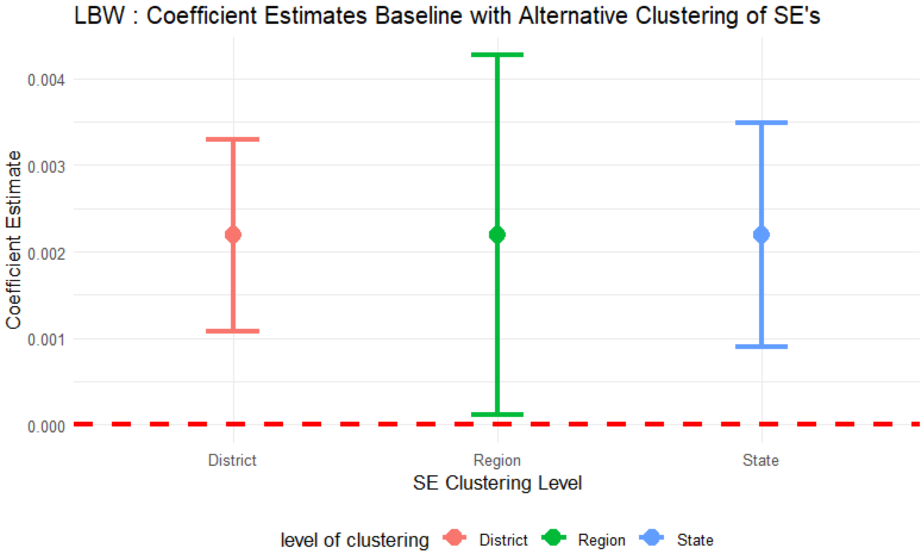


Figure C10: Baseline Results VLBW: Alternative Clustering of Standard Errors

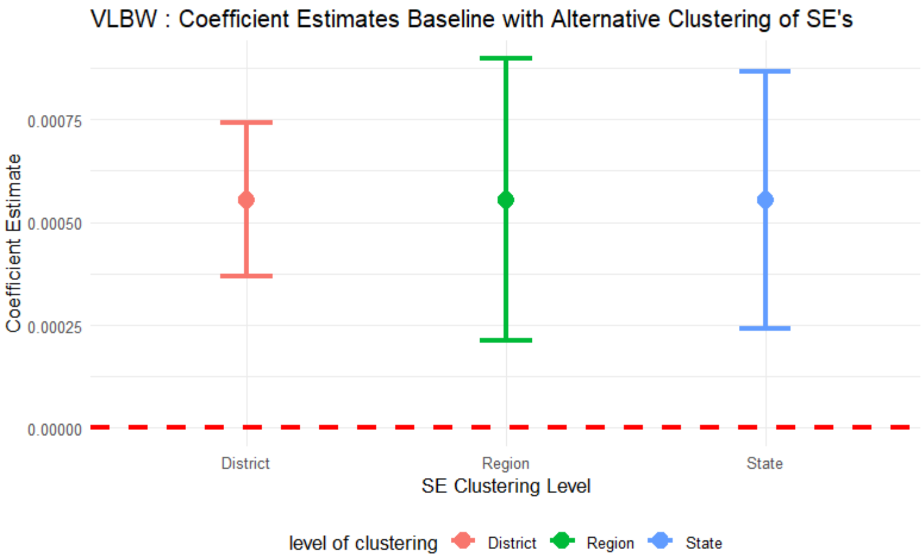


Figure C11: Baseline Results Birth Weight: Alternative Clustering of Standard Errors

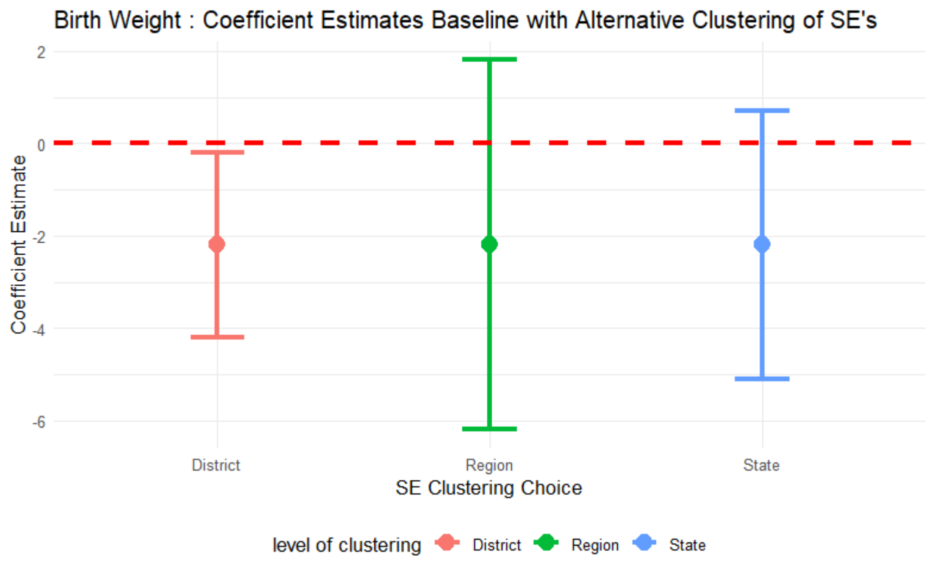


Figure C12: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for birth weight

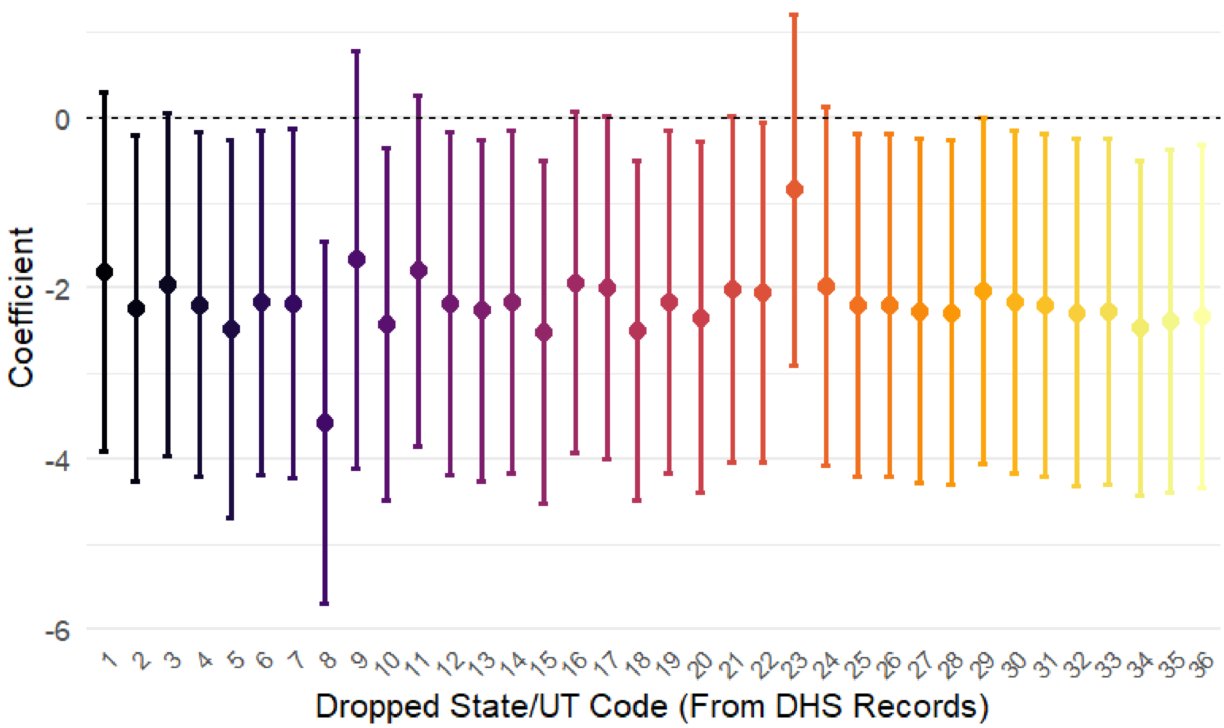


Figure C13: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for LBW indicator

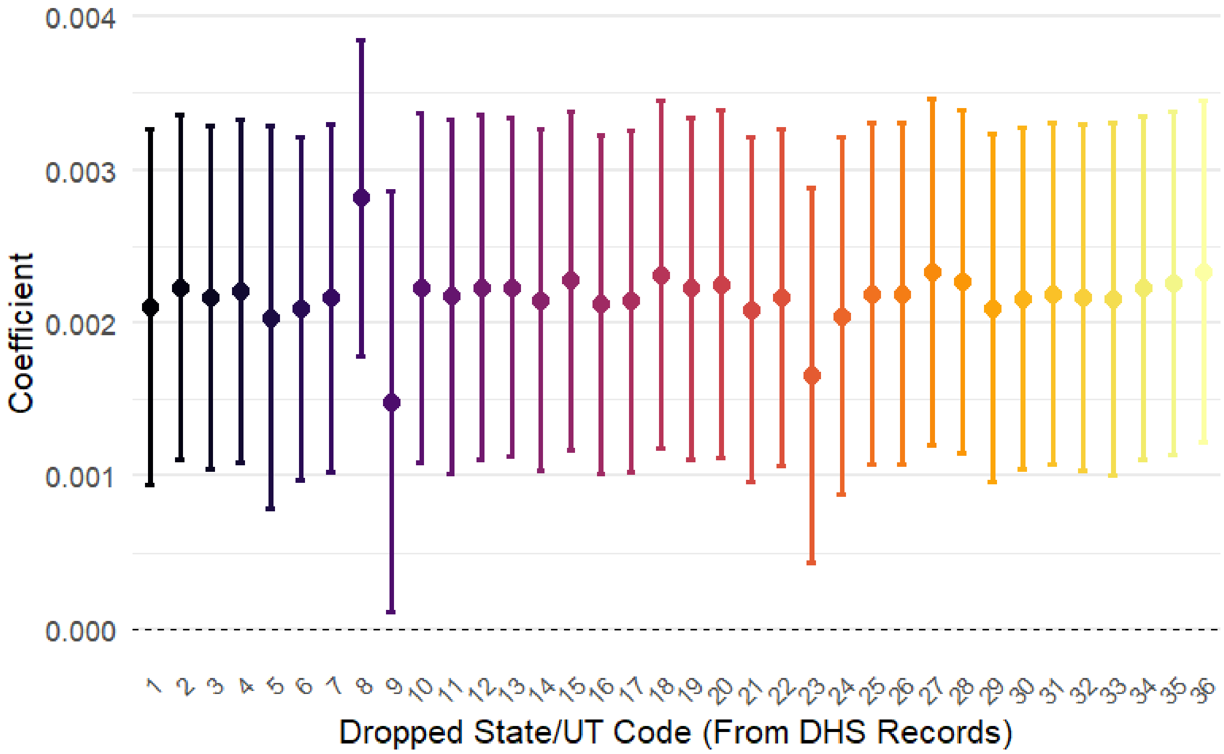


Figure C14: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for VLBW indicator

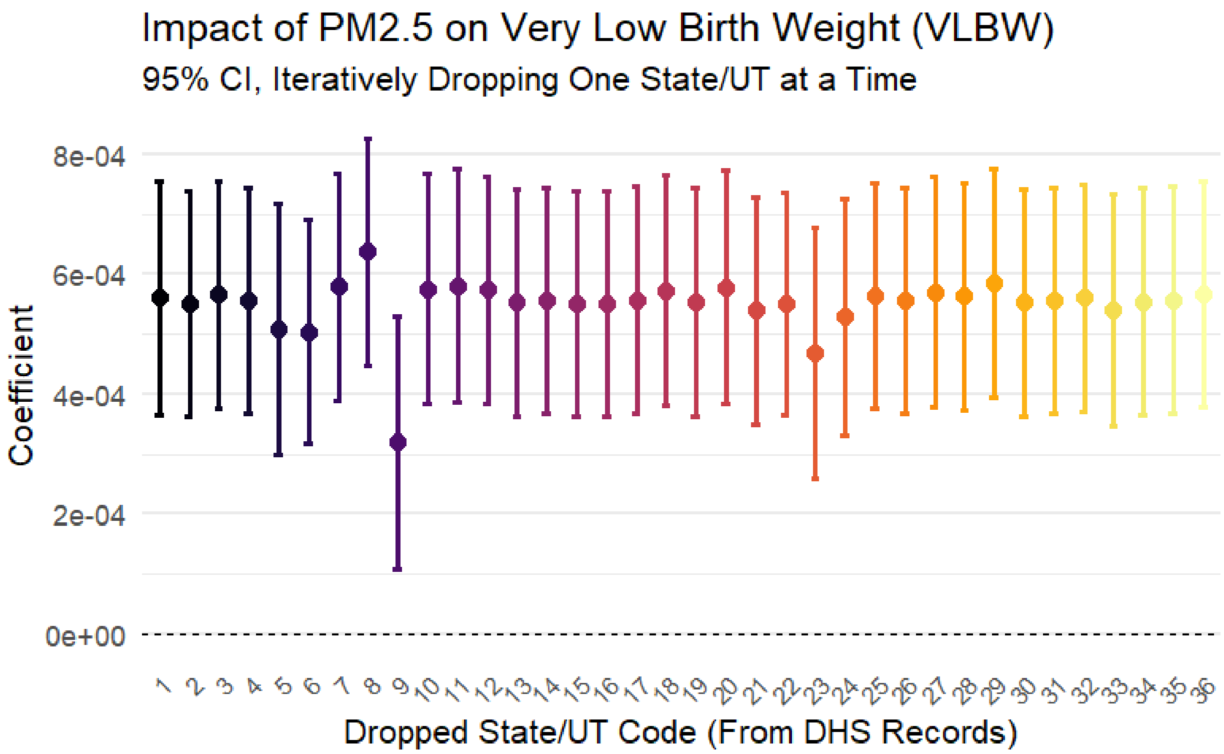


Figure C15: Comparing $PM_{2.5}$ concentration from Van Donkelaar et al. (2016) and NASA MERRA-2

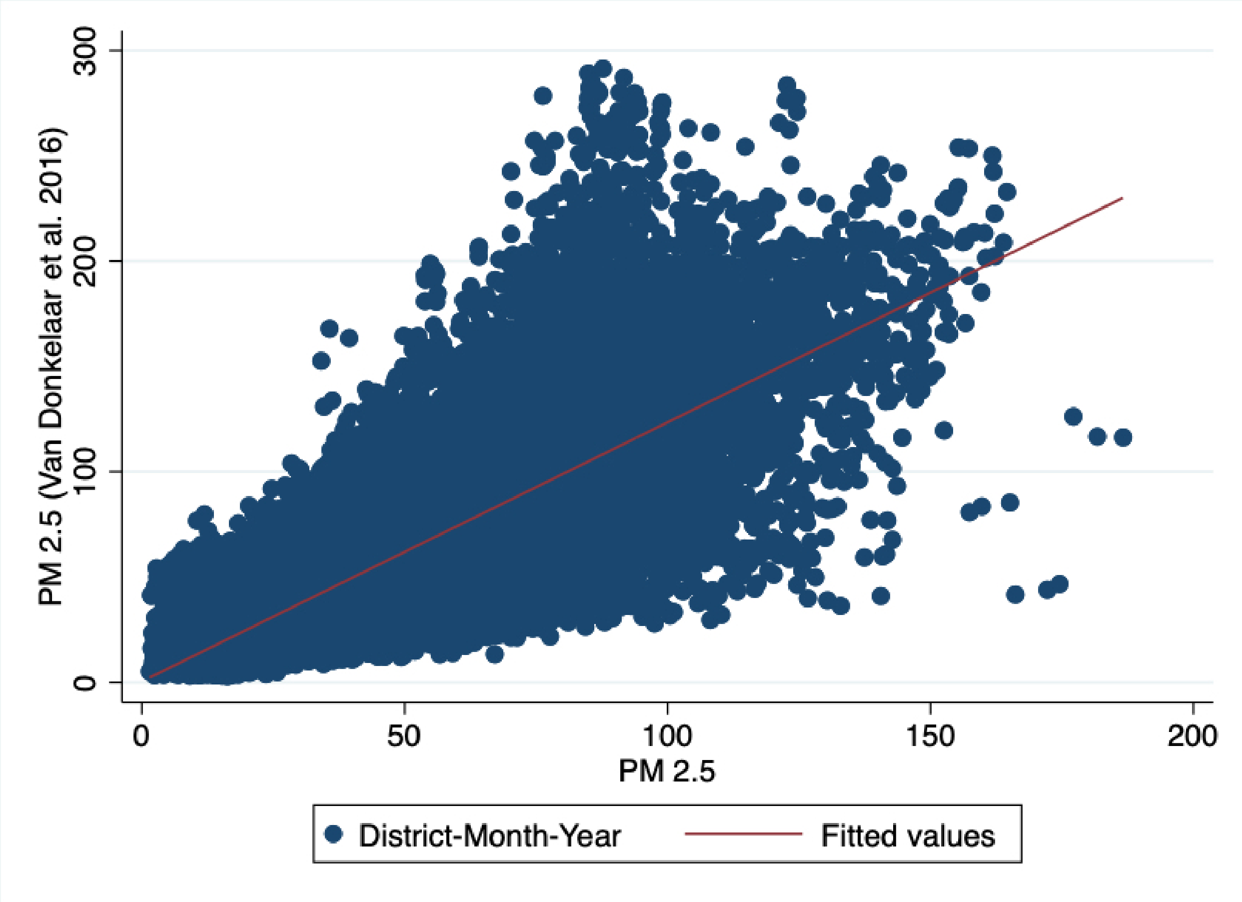


Figure C16: Non-linear effects using Spline Regression for Low Birth Weight

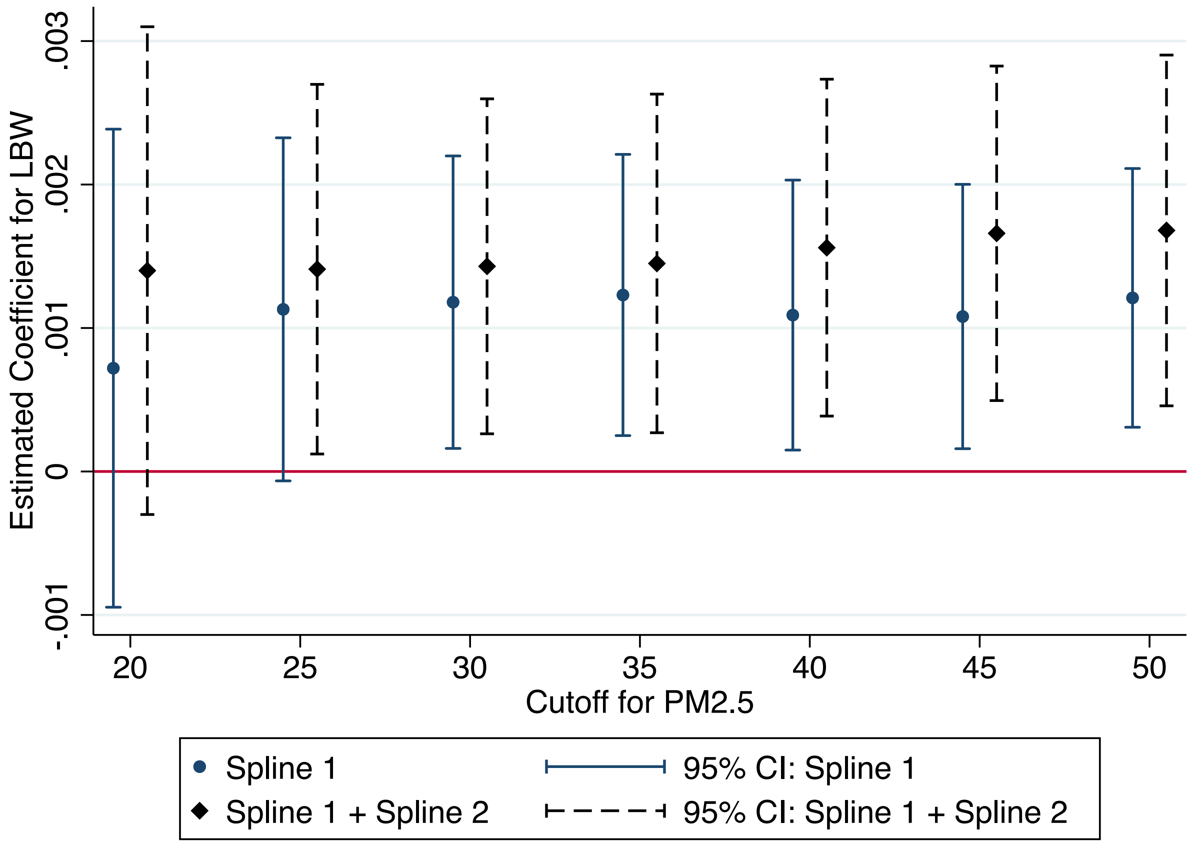


Figure C17: Non-linear effects using Spline Regression for Very Low Birth Weight

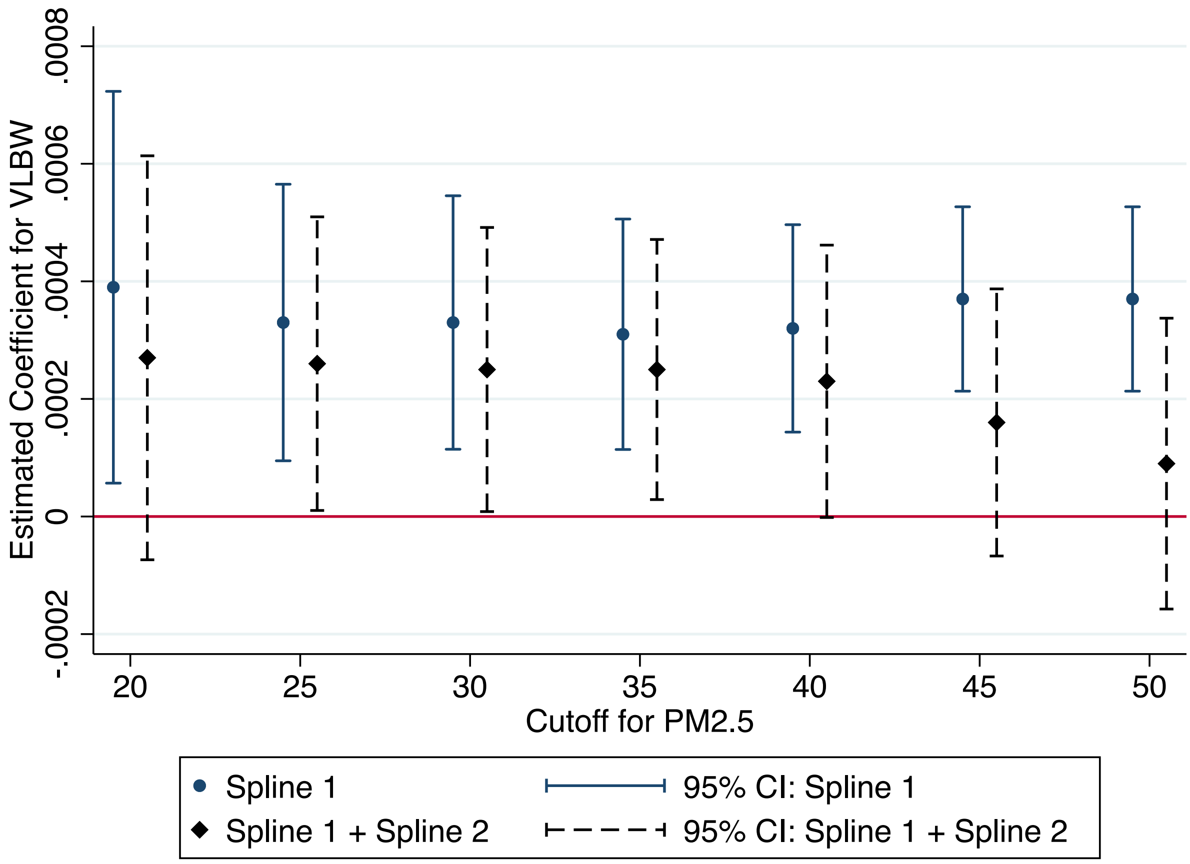


Figure C18: Non-linear effects using grouped quantile regression using birth weight

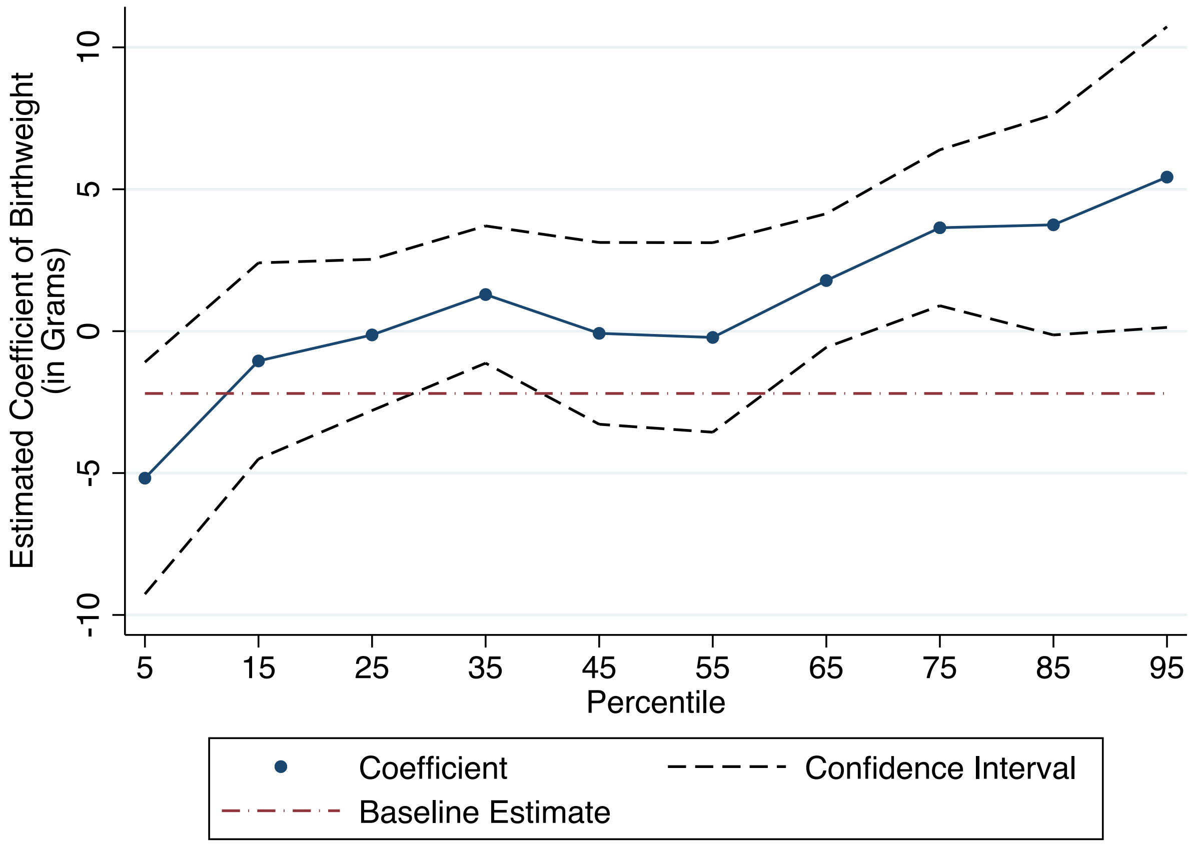


Table C1: Decomposition of Wind Direction Share Variation: District-Level Averages by Season

Season	**Direction**	**Overall SD**	**Between SD**	**Within SD**	**Between (%)**	**Within (%)**
Jan–Mar	North	0.1117	0.0769	0.0746	46.85	55.06
Jan–Mar	East	0.1521	0.1012	0.1046	48.98	53.33
Jan–Mar	South	0.1470	0.0982	0.0995	48.61	53.42
Jan–Mar	West	0.1255	0.0837	0.0850	47.02	56.63
Apr–Jun	North	0.0561	0.0299	0.0426	25.43	74.57
Apr–Jun	East	0.1060	0.0592	0.0843	29.98	75.12
Apr–Jun	South	0.1875	0.0844	0.1611	25.29	74.71
Apr–Jun	West	0.1543	0.0894	0.1204	37.24	67.57
Jul–Sep	North	0.0471	0.0259	0.0356	25.30	77.31
Jul–Sep	East	0.0781	0.0416	0.0617	25.23	80.10
Jul–Sep	South	0.1386	0.0759	0.1105	32.82	67.18
Jul–Sep	West	0.1100	0.0716	0.0792	37.68	67.40
Oct–Dec	North	0.1305	0.0836	0.0926	43.05	56.95
Oct–Dec	East	0.1489	0.0867	0.1157	39.51	62.60
Oct–Dec	South	0.1358	0.0730	0.1070	33.37	66.63
Oct–Dec	West	0.1033	0.0539	0.0819	30.74	73.21

Notes: This table decomposes the standard deviation of district-level wind direction shares into between- and within-district components by season averaged across regions similar to Table 1.

Table C2: First Stage Results

	North Share	East Share	South Share
Region 0	28.032**	-0.821	24.349***
	(10.590)	(13.863)	(5.175)
Region 1	-1.917	-15.800***	-32.862***
	(3.265)	(3.345)	(3.156)
Region 2	2.769	-35.814***	-6.405
	(10.663)	(5.894)	(4.770)
Region 3	58.174***	47.978***	1.279
	(6.330)	(14.940)	(5.220)
Region 4	-10.686	15.779	-17.178*
	(40.431)	(17.803)	(9.496)
Region 5	-5.938	-2.589	-9.690*
	(14.358)	(11.259)	(5.225)
Region 6	29.738***	-5.260	-17.816***
	(7.148)	(4.112)	(2.459)
Region 7	-10.619*	-12.244***	-20.436***
	(5.414)	(4.296)	(3.929)
Region 8	-79.590***	-53.021***	76.869***
	(15.195)	(11.489)	(8.685)
Region 9	-30.975***	-9.025**	-14.524***
	(3.950)	(3.319)	(2.157)
Region 10	-75.197***	15.267	3.359
	(20.029)	(13.571)	(5.709)
Region 11	8.336	35.455**	5.994
	(10.253)	(12.731)	(6.204)
Region 12	-40.770**	-18.551***	-27.622***
	(19.768)	(6.591)	(5.018)
Region 13	-219.071***	26.476***	-55.836***
	(54.458)	(7.566)	(6.256)
Region 14	-26.656	-10.838**	-6.183*
	(18.701)	(4.111)	(3.309)
Region 15	-50.319**	-25.845***	5.823
	(19.110)	(5.218)	(6.733)
Region 16	43.809***	-34.906**	18.790***
	(8.203)	(13.297)	(6.626)
Region 17	31.239	37.513**	-23.430**
	(29.908)	(15.601)	(8.914)
Region 18	38.402***	31.183**	10.259
	(11.515)	(12.421)	(11.401)
Region 19	-43.109***	-5.555	-33.294***
	(13.119)	(6.654)	(5.299)
Region 20	-6.960**	-10.053**	-21.718***
	(3.189)	(4.399)	(3.665)

Table C2: First Stage Results (Contd.)

	North Share	East Share	South Share
Region 21	41.139***	27.435***	7.591
	(8.997)	(8.612)	(7.570)
Region 22	-20.027***	-35.925***	-12.604***
	(5.314)	(3.876)	(2.773)
Region 23	9.339	-34.579***	8.644**
	(9.307)	(7.465)	(3.579)
Region 24	-3.941	-13.879	-22.418***
	(8.961)	(8.762)	(5.516)
Region 25	2.366	-13.517***	-13.785***
	(5.578)	(4.428)	(2.009)
Region 26	32.477***	19.436***	3.109
	(7.717)	(5.058)	(3.932)
Region 27	73.913***	17.098	16.774**
	(25.624)	(12.574)	(8.040)
Region 28	1.660	-93.076***	43.244***
	(26.672)	(19.586)	(11.749)
Region 29	5.424	3.451	-12.473**
	(9.873)	(8.325)	(6.171)

Notes: First stage results for all the instruments using Equation 2. All other controls and fixed effects are included as mentioned in Equation 2. Robust standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Second Stage Results: Covariates

	Birth Weight	LBW	VLBW
Temperature	-2.577	-0.001	-0.0007***
	(1.659)	(0.001)	(0.0001)
Wind Speed	4.660	-0.006**	-0.0013***
	(4.525)	(0.002)	(0.0004)
Caste (Base: SC)			
ST	23.200***	-0.010**	-0.0028***
	(6.969)	(0.004)	(0.0007)
OBC	15.211***	-0.008***	-0.0004
	(3.597)	(0.002)	(0.0005)
General	11.998**	-0.002	0.0001
	(4.682)	(0.003)	(0.0007)
Religion (Base: Hindu)			
Muslim	18.110***	-0.003	-0.00003
	(5.706)	(0.003)	(0.0008)
Christian	127.037***	-0.032***	-0.0015*
	(14.578)	(0.005)	(0.0009)
Others	18.425	0.001	0.0005
	(11.566)	(0.006)	(0.0012)
Dirty Cooking Fuel	2.305	-0.003	-0.0003
	(3.341)	(0.002)	(0.0005)
Girl Child	-66.955***	0.025***	0.0009***
	(2.177)	(0.001)	(0.0003)
Urban	-19.310***	0.011***	0.0020***
	(3.793)	(0.002)	(0.0006)
BMI	13.168***	-0.004***	-0.0001**
	(0.348)	(0.0002)	(0.0001)
Wealth Index (Base: Poorest)			
Poorer	33.962***	-0.017***	-0.0012*
	(4.016)	(0.002)	(0.0006)
Middle	69.501***	-0.033***	-0.0031***
	(4.853)	(0.003)	(0.0007)
Richer	93.026***	-0.042***	-0.0039***
	(5.578)	(0.003)	(0.0008)
Richest	134.656***	-0.066***	-0.0068***
	(6.706)	(0.004)	(0.0010)

Table C3: Second Stage Results: Covariates (Contd.)

	Birth Weight	LBW	VLBW
Anemia (Base: No Anemia)			
Mild	-8.532***	0.004**	0.0004
	(2.514)	(0.002)	(0.0004)
Moderate	-13.061***	0.009***	0.0014***
	(3.172)	(0.002)	(0.0005)
Severe	-42.966***	0.034***	0.0070***
	(9.351)	(0.006)	(0.0019)
Birth Order	15.842***	-0.005***	-0.0008***
	(1.760)	(0.001)	(0.0002)
Age at Birth	0.548	-0.0003	0.00003
	(0.356)	(0.0002)	(0.0001)

Notes: Second stage results for covariates using Equation 3. Other controls include region-month and year fixed effects. Robust standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: Effect of Pollution Exposure on Birth Size: IV Estimates

Dependent variable:	Above-Average Size
$PM_{2.5}$ Exposure	-0.002^{***}
	(0.0005)
First Stage F-statistic	129
Mean of Dependent Variable	0.90
Observations	327,029

Notes: IV estimates. Clustered robust standard errors reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table C5: Summary Statistics for Shea's Partial R-squared

Statistics	Value
Mean	0.251
Minimum	0.005
25 Percentile	0.127
50 Percentile	0.222
75 Percentile	0.341
Maximum	0.754
Standard Deviation	0.161
Number of Observations	639

Notes: Shea's partial R-squared calculated for every district using the first stage IV regression as specified in Equation 2.

Table C6: Effect of $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates (Trimester Wise)

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: First Trimester			
$PM_{2.5}$ Exposure	-2.396***	0.002***	0.0004***
	(0.776)	(0.0004)	(0.0001)
Panel b: Second Trimester			
$PM_{2.5}$ Exposure	-1.668**	0.001***	0.0003***
	(0.827)	(0.0005)	(0.0001)
Panel c: Third Trimester			
$PM_{2.5}$ Exposure	-1.425**	0.001***	0.0004***
	(0.705)	(0.0004)	(0.0001)
Observations	327,396	327,396	327,396

Notes: Instrumental variable (IV) using wind direction as the instrument for in-utero exposure during the first, second and third trimester. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table C7: Results from the estimates of Ozone and Carbon Monoxide

Dependent variable:	Birth Weight	LBW	VLBW
$PM_{2.5}$ Exposure	-1.962	0.0022^{***}	0.0006^{***}
	(1.213)	(0.0007)	(0.0001)
Carbon Monoxide	-0.102	0.00001	-0.00003^{***}
	(0.102)	(0.0001)	(0.00001)
Ozone	-1.259^{**}	-0.00002	-0.0001
	(0.636)	(0.0004)	(0.0001)
First Stage F-statistic	45	45	45
Observations	321,436	321,436	321,436
Mean of Dependent Variable	2825	0.17	0.01

Notes: IV estimates. Clustered robust standard errors at the district level are in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table C8: Effect of $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates (weight above the 1st and below the 99th sample percentile)

Dependent variable:	Birth Weight	LBW
$PM_{2.5}$ Exposure	-1.109	0.002^{***}
	(0.842)	(0.0005)
First Stage F-statistic	132	132
Observations	315,871	315,871
Mean of Dependent Variable	2838	0.15

Notes: IV estimates. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table C9: Effect of $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates (Birth Weight 1600g–4000g Sample)

Dependent variable:	Birth Weight	LBW
$PM_{2.5}$ Exposure	-1.189	0.002^{***}
	(0.7420)	(0.0005)
First Stage F-statistic	131	131
Observations	307,838	307,838
Mean of Dependent Variable	2810	0.15

Notes: IV estimates. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table C10: Effect of 7 to 9 months in-utero $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: First 7 months			
$PM_{2.5}$ Exposure	-2.415^{***}	0.002^{***}	0.0004^{***}
	(0.920)	(0.0005)	(0.0001)
Panel b: First 8 months			
$PM_{2.5}$ Exposure	-2.458^{**}	0.002^{***}	0.0005^{***}
	(0.973)	(0.0005)	(0.0001)
Panel c: First 9 months			
$PM_{2.5}$ Exposure	-2.358^{**}	0.002^{***}	0.0005^{***}
	(1.000)	(0.0005)	(0.0001)
Observations	327,396	327,396	327,396

Notes: Instrumental variable (IV) using wind direction as the instrument for in-utero exposure during the first 7, 8 or 9 months excluding the month of birth. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table C11: Effect of $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates (Excluding mothers who have moved)

Dependent variable:	Birth Weight	LBW	VLBW
$PM_{2.5}$ Exposure	-1.716^{***}	0.001^{***}	0.0003^{***}
	(0.561)	(0.0004)	(0.0001)
Observations	312,213	312,213	312,213

Notes: IV estimates. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table C12: OLS and IV Estimates using data from Van Donkelaar et al. (2016)

	Panel A: OLS Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
$PM_{2.5}$ Exposure	-0.731***	0.001***	0.0001***
	(0.282)	(0.0002)	(0.00003)
Adjusted R^2	0.053	0.017	0.002
	Panel B: IV Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
Instrumented $PM_{2.5}$ Exposure	-0.644	0.001***	0.0002***
	(0.499)	(0.0003)	(0.0005)
First Stage F-statistic	67	67	67
Mean of Dependent Variable	2825	0.17	0.01
Observations	327,396	327,396	327,396

Notes: All controls mentioned in Equation 3 are included in the model. Clustered robust standard errors at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. F-statistics reported are heteroskedasticity-robust F-statistics, based on a joint significance test of excluded instruments, with standard errors clustered at the district level from the first stage.

Table C13: Effect of Variation in $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Range			
$PM_{2.5}$ Exposure	-1.593***	0.001**	0.0002**
	(0.539)	(0.0003)	(0.00006)
Panel b: Inter-quartile Range			
$PM_{2.5}$ Exposure	-0.956*	0.0002	0.0001
	(0.563)	(0.0003)	(0.0001)
Panel c: Standard Deviation			
$PM_{2.5}$ Exposure	-4.426***	0.002***	0.0005***
	(1.747)	(0.0009)	(0.0002)
Observations	327,396	327,396	327,396

Notes: Instrumental variable (IV) for monthly $PM_{2.5}$ exposure using monthly wind direction as the instruments using Equation 4 and then calculating the variation in every child's in-utero exposure. Clustered robust standard errors at the district level are reported in parentheses. All regressions include full controls and fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

D: Agricultural fires as the source of pollution

Several studies have shown that agricultural fires in India can raise air pollution levels not only within the district where they occur but also in nearby and distant areas (Garg et al., 2024; Jagnani & Mahadevan, 2025; Pullabhotla & Souza, 2022; Singh et al., 2019). To use agricultural fires as a source of pollution, we follow the approach of Pullabhotla and Souza (2022).

Following Pullabhotla and Souza (2022), we classify all agricultural fires into four directions relative to the child's district of birth: North (N), South (S), East (E), and West (W). Figure D1 shows a simple illustration of how the fires are classified. The district of interest is placed at the center, and we draw a circle with radius $f \in \{200, 250, 300, 350, 400\}$ kilometers. All fires that fall within this radius are included (shown as blue dots), while those outside the circle are excluded (shown as orange dots). In the example in the figure, there are three fires in the south, two fires in the north and west, and none in the east that are used to construct the instruments. We present the prevalence of agricultural fires across India in Figure D2.

Using this classification, we construct our instruments at the district-month-year pairs, by taking the share of days the wind blew from each direction and interacting these wind shares with the logarithm of the number of fires in the corresponding direction for that district-month-year pair. This allows us to capture variation in pollution that originates from agricultural fires from all the directions of the district in a given month and year.

In our baseline specification, we use the cumulative wind direction over the 10-month period, including the month of birth, as an instrument for in-utero pollution exposure. However, when working with agricultural fires, we do not aggregate fire events over the same 10-month window. Instead, we keep the fire data at the monthly level so that we can capture variation in agricultural fire activity across different months during pregnancy. Therefore, we use a modified version of Equation 4:

$$\begin{aligned} PM2.5_{drmt} = &\sum_{j \in \{N,S,E\}} \rho_j \text{Share}^j_{dmt} + \sum_{j \in \{N,S,W,E\}} \nu_j (\text{Share}^j_{dmt} \times \log(\text{Fires}^j_{dmt})) \\ &+ \sum_{j \in \{N,S,W,E\}} \mu_j \log(\text{Fires}^j_{dmt}) + \omega W_{dmt} + \delta_{mr(d)} + \gamma_t + \varepsilon_{drmt} \end{aligned} \tag{10}$$

Here, $PM2.5_{drmt}$ denotes the average concentration of $PM_{2.5}$ in district d, belonging to region r, in month m of year t. The wind-share variables and the logarithm of the number of fires in each direction are also defined at the district–month–year level. In this specification, we include the share of wind blowing from the North, South, and East (with West serving as the omitted category), the logarithm of the number of fires within distances $f \in \{200, 250, 300, 350, 400\}$ kilometers in all four directions, and the interactions between wind shares and fire counts. All other covariates are defined as in Equation 2. This setup allows us to estimate monthly pollution levels that reflect variation in fire activity around each district, which can then be aggregated to construct individual-specific measures of in-utero exposure with finer temporal precision. The first-stage estimates for different values of distance, are reported in Table D1.

Table D2 presents the corresponding second-stage results for the different values of f. The estimates for LBW remain robust across all distance bands, except for 200 kilometers. For birth weight and VLBW, the coefficients have similar magnitudes and signs, as compared to the baseline results, across specifications but are imprecisely estimated and therefore statistically insignificant.

Figure D1: Classification of agricultural fires based on 90° bins

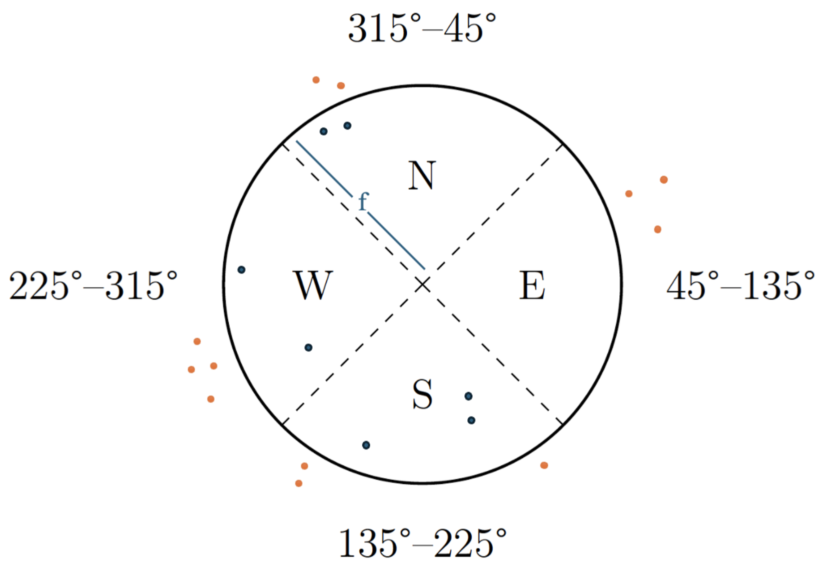


Figure D2: Map showing frequency of agricultural fires across different parts of India

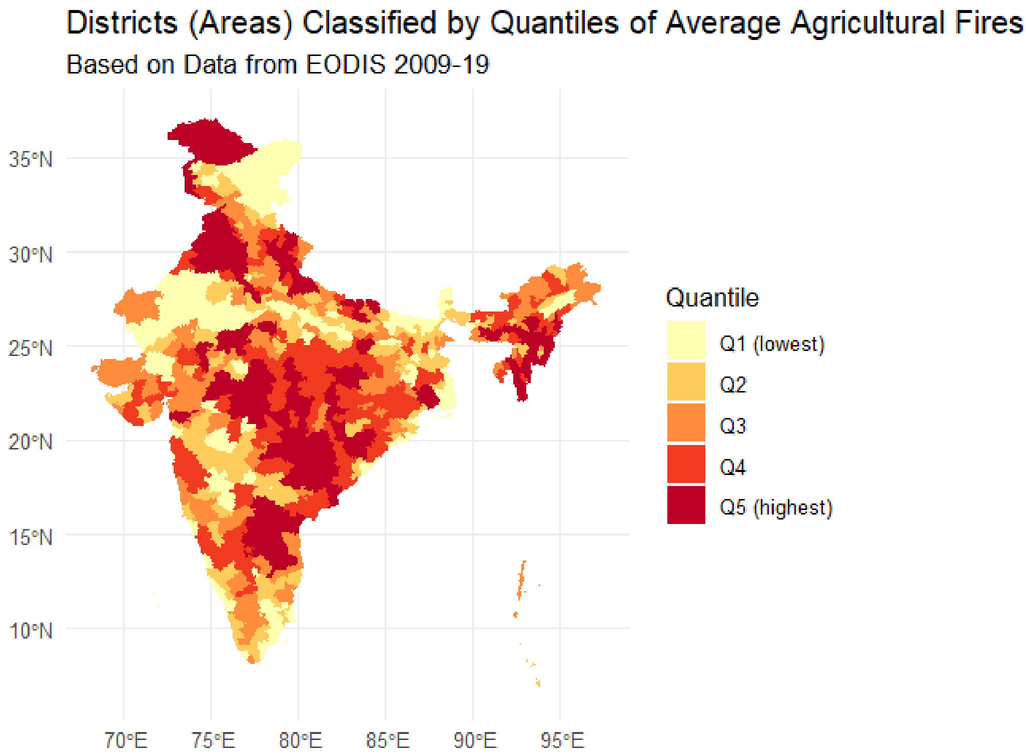


Table D1: First stage estimates: regressing $PM_{2.5}$ concentration on agricultural fires and wind direction

Variables	$PM_{2.5}$ concentration				
	$f = 200$	$f = 250$	$f = 300$	$f = 350$	$f = 400$
North Direction					
Wind Share	-1.188	-1.026	-1.077	-1.475	-1.718
	(1.988)	(2.000)	(1.992)	(2.023)	(1.981)
Log(Fires)	-0.188**	-0.186**	-0.207**	-0.201**	-0.126
	(0.092)	(0.087)	(0.088)	(0.083)	(0.081)
Wind Share × Log(Fires)	1.985***	1.939***	1.805***	1.962***	1.953***
	(0.415)	(0.374)	(0.368)	(0.359)	(0.344)
South Direction					
Wind Share	0.559	0.824	0.716	0.645	0.780
	(0.955)	(0.940)	(0.945)	(0.956)	(0.953)
Log(Fires)	0.102	0.022	-0.047	-0.110	-0.100
	(0.132)	(0.119)	(0.114)	(0.120)	(0.132)
Wind Share × Log(Fires)	0.028	0.170	0.275	0.404*	0.383*
	(0.240)	(0.216)	(0.207)	(0.211)	(0.222)
East Direction					
Wind Share	4.009***	4.468***	4.751***	4.567***	4.518***
	(1.445)	(1.480)	(1.517)	(1.549)	(1.570)
Log(Fires)	0.680***	0.675***	0.653***	0.570***	0.512***
	(0.092)	(0.090)	(0.092)	(0.097)	(0.098)
Wind Share × Log(Fires)	-0.385	-0.266	-0.268	-0.0250	0.047
	(0.242)	(0.222)	(0.227)	(0.227)	(0.218)
West Direction					
Wind Share	-	-	-	-	-
	-	-	-	-	-
Log(Fires)	0.043	-0.114	-0.164	-0.203*	-0.235**
	(0.114)	(0.112)	(0.110)	(0.105)	(0.101)
Wind Share × Log(Fires)	0.015	0.261	0.362*	0.455**	0.485**
	(0.206)	(0.208)	(0.211)	(0.210)	(0.209)
Average Wind Speed	0.833***	0.855***	0.867***	0.889***	0.899***
	(0.220)	(0.217)	(0.216)	(0.217)	(0.217)
Average Temperature	1.128***	1.131***	1.135***	1.131***	1.126***
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Observations	78,276	78,276	78,276	78,276	78,276
R-squared	0.791	0.791	0.791	0.791	0.791

Notes: Other controls include region-month and year fixed effects. Clustered robust standard errors at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D2: Using agricultural fires interacted with wind direction as instruments

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Agricultural fires within 200 Kms			
$PM_{2.5}$ Exposure	-0.339	0.001	0.0001
	(1.347)	(0.001)	(0.0002)
First Stage F-statistic	11.83	11.83	11.83
Panel b: Agricultural fires within 250 Kms			
$PM_{2.5}$ Exposure	-1.098	0.002**	0.0003
	(1.369)	(0.001)	(0.0002)
First Stage F-statistic	11.56	11.56	11.56
Panel c: Agricultural fires within 300 Kms			
$PM_{2.5}$ Exposure	-1.967	0.002**	0.0002
	(1.393)	(0.001)	(0.0002)
First Stage F-statistic	9.93	9.93	9.93
Panel d: Agricultural fires within 350 Kms			
$PM_{2.5}$ Exposure	-1.594	0.002**	0.0002
	(1.408)	(0.001)	(0.0002)
First Stage F-statistic	9.28	9.28	9.28
Panel e: Agricultural fires within 400 Kms			
$PM_{2.5}$ Exposure	-1.894	0.002**	0.0002
	(1.369)	(0.001)	(0.0002)
First Stage F-statistic	9.17	9.17	9.17
Observations	327,396	327,396	327,396

Notes: All controls mentioned in Equation 3 are included in the model. Clustered robust standard errors at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. F-statistics reported are heteroskedasticity-robust F-statistics, based on a joint significance test of excluded instruments, with standard errors clustered at the district level from the first stage.

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