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

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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 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 1.4% increase in average birth weight. Combining our estimates with prior studies, we find that the observed improvements in both average birth weight and reductions in low birth weight incidence from meeting WHO air quality standards could yield substantial long-run economic benefits, potentially amounting to billions of dollars annually in addition to broader gains in child health.

JEL-codes: J13, I12, Q53

Keywords: birth weight, air pollution, in-utero exposure, India

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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 through 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 $36 billion due to its negative impact on human capital (WHO, 2024). Research has shown that air pollution can have a negative effect on health and cognitive development of children (Balakrishnan & Tsaneva, 2021; Balietti et al., 2022), and a growing body of literature highlights the short- and long-term consequences of fetal exposure to particulate matter on child health (Ai et al., 2023; Palma et al., 2022). However, much of this literature focuses on developed countries, raising concerns that the effects of pollution on child health may differ between developed and developing countries contexts (Arceo et al., 2016). In this study, we examine the effect of in-utero exposure to particulate matter ($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 $PM_{2.5}$ exposure between 2010 and 2019 was 38 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 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 may amplify the adverse effects of pollution on neonatal outcomes. On the other hand, it may

[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.

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 as the primary indicator of child health. Birth weight is a well-established predictor of short- and medium-term health outcomes (Hummer et al., 2014; McGovern, 2019), and it also has long-term implications, including adult mortality (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 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 for children born between 2010 and 2019. A simple OLS regression of birth weight 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 endogeneity concerns, we exploit quasi-random variation in pollution exposure during pregnancy, driven by heterogeneity in wind patterns.

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 1.4% relative to the sample mean of 2.8 kilograms—equivalent to a decrease of about 40 grams.

In comparison, Pons (2022) find no significant average effect of $PM_{2.5}$ on birth weight in the United States, though they do observe a reduction of 28 grams in the lower tail of the distribution. Using our non-linear estimates, we also find that the effect is higher (90 grams reduction) at the lower tail of the distribution. Moreover, Palma et al. (2022) find that an increase in PM_{10} levels by one standard deviation in Italy reduces birth weight by 0.5%. Our results indicate a larger effect size in the Indian context.

Furthermore, we estimate that reducing average in-utero $PM_{2.5}$ exposure for our sample to the World Health Organization (WHO)-recommended level of 10 μg/m^3 would lead to a 5.4 percentage point decline in the incidence of low birth weight (LBW), and a 1.2 percentage point reduction in the incidence of very low birth weight (VLBW). Back-of-the-envelope calculations suggest that compliance with WHO guidelines could generate economic gains exceeding $1 billion, solely from improvements in neonatal health outcomes. These findings are robust across a range of alternative model specifications and sensitivity tests addressing potential violations of the key assumptions underlying our IV strategy.

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. To our knowledge, this is the first paper to causally examine the relationship between in-utero exposure to air pollution and a range of birth outcomes in India—one of the most polluted countries globally. It is also only the second causal study in India to contribute to the literature on the fetal origins hypothesis, which posits that early-life environmental conditions, including in-utero exposure, have long-term effects on health and human capital formation (Almond & Currie, 2011). The only other Indian study we are aware of, Singh et al. (2019), examines postnatal anthropometric outcomes (e.g., height-for-age, weight-for-age) rather than neonatal birth outcomes.

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). By linking our causal estimates to prior literature on the economic costs associated with low birth weight, we also provide back-of-the-envelope calculations that quantify the potential economic benefits of improving in-utero air quality. These estimates offer a compelling case for stronger environmental regulation and public health interventions aimed at mitigating the adverse impacts of air pollution on early-life health.

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 we use our point estimates to derive the costs of pollution arising from sub-optimal birth outcomes in Section 6 and provide concluding remarks in Section 7.

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 pollutant (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[2] considers the levels of particulate matter to be the most critical and general indicator of air quality to make policy decisions (Greenstone & Hanna, 2014). 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 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 to improve public health and mitigate children health problems due to air pollution in India.

[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.

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.[4] 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 321,810 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 children born in the last 5 years, either via a written medical card, which was recorded upon the birth of a child, or via recall. 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]We are unable to use the previous three waves since they do not hvae 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

[4]Our data on in-utero variables weather variables (such as wind, pollution and other weather variables) spans from the years 2010-2019, hence, births in the first 9 months of 2010 are not included as in-utero data for these births stretches into 2009.

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]

3.2 Pollution Data

Air pollution data are taken 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 2010 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.

[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.

3.3 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.[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 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 (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.

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

[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.

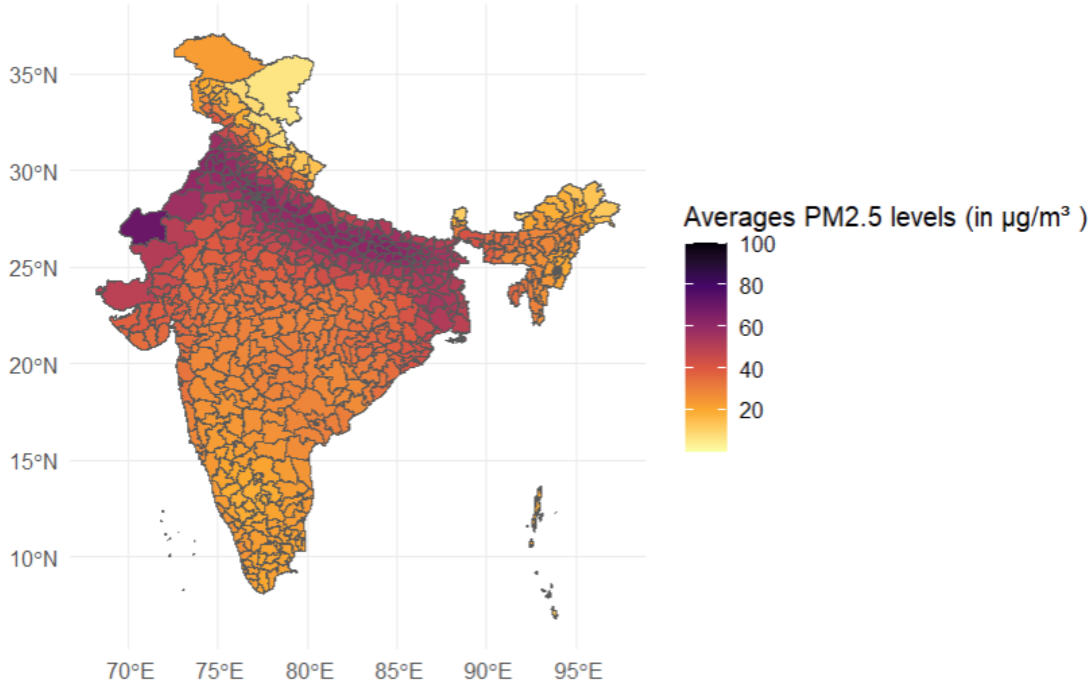
3.4 Descriptive Statistics

3.4.1 Regional and Temporal Variation: Pollution

Figure 1 illustrates regional patterns in particulate matter trends, 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.

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. Table 1 shows that approximately 15–19% of the variation in wind direction shares arises between districts within the same region. The presence of substantial cross-district variation within the same regions supports our identification strategy, which leverages wind direction as an instrument and includes region-by-month of birth fixed effects.

[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.

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

Direction	**Overall SD**	**Between SD**	**Within SD**	**Between (%)**	**Within (%)**
North	0.1327	0.0478	0.1197	18.72	81.28
East	0.1945	0.0603	0.1781	16.01	83.99
South	0.2527	0.0749	0.2347	15.02	84.98
West	0.1555	0.0511	0.1429	16.04	83.96

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 average temporal variation within districts. Percentages indicate the share of total standard deviation attributed to each source.

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 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 $PM2.5$ data with other weather variables such as wind speed and temperature at the month-district level, spanning from the years 2010-2019. We observe a clear pattern of extremely high average $PM_{2.5}$ levels, with a sizable share 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				
Birth Weight (grams)	2825.16	582.19	500	9,000
LBW	0.168	0.373	0	1
VLBW	0.010	0.100	0	1
Size is Average or Above	0.896	0.306	0	1
Mother is Anemic	0.824	0.826	0	3
Mother's BMI ($\times$100)	21.637	3.951	12.02	59.99
Mother's Age at Birth	25.02	4.789	11	49
Child's Birth Order	2.072	1.205	1	6
Female Birth	0.478	0.500	0	1
Religion				
Hindu	0.77	0.43	0	1
Muslim	0.11	0.32	0	1
Christian	0.08	0.27	0	1
Other Religion	0.04	0.20	0	1
Caste				
Scheduled Caste	0.21	0.40	0	1
Scheduled Tribe	0.20	0.40	0	1
OBC	0.41	0.49	0	1
Other Castes	0.18	0.39	0	1
Household				
Urban	0.240	0.427	0	1
Wealth Index	2.830	1.376	1	5
Dirty Cooking Fuel	0.589	0.492	0	1
Pollution Exposure				
$PM_{2.5}$ In-utero (μg/m^3)	39.864	14.676	4.739	94.203
Number of Observations		321,810		

Notes: Sample includes children born between 2010–2019 from waves 4 and 5 of DHS. BMI variable from DHS is scaled by 100 for readability. Household level cooking fuel has over 10 categories; we summarize it as a binary indicator for use of dirty fuel sources: kerosene, coal, charcoal, wood, straw/shrubs/-grass, agricultural crop waste, or animal dung.

Table 3: Summary Statistics: Weather and Pollution Variables

Variable	Mean	SD	Min	Max
Wind Shares				
East Share	0.228	0.219	0	1
North Share	0.135	0.180	0	1
South Share	0.417	0.278	0	1
West Share	0.220	0.205	0	1
Weather				
Temperature (K)	298.001	8.724	246.784	311.945
Wind Speed (m/s)	3.413	1.841	0.379	11.018
Pollution				
$PM_{2.5}$ (μg/m^3)	38.064	21.829	1.751	174.547
Number of Observations	71,160			
$PM_{2.5} >$ **35** (μ**g/m**^{3})	33,051 observations (45%)			

Notes: Summary based on merged monthly panel of 71,160 district-year-month observations (2010–2019). $PM_{2.5}$ values above 35 μg/m^3 are considered above 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 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.[10] 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 ($PM2.5$) 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

[10]The regions as defined in Section 3.4 are construed 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).

of 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 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 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.

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:

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

We use wind patterns as instruments for particulate matter levels, driven by the direction of wind flows. 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 across districts. However, the regional and spatial variation in wind patterns, 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 and month. If temporal and spatial wind patterns were uniform across all districts within a region, our instrument would fail to capture sufficient exogenous variation in pollution levels attributable to wind trajectories. 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:

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

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 (15 μg/m^3) is associated with a 1.4% increase in birth weight relative to the mean, and a 3 and 0.6 percentage point reduction in the incidence of LBW and VLBW, respectively, holding other factors constant.[11] A one standard deviation change in ambient $PM_{2.5}$ exposure also explains 6.8%, 7.2%, and 6% of the standard deviation in birth weight, LBW, and VLBW, respectively. Table C3 in the Appendix presents the estimates using 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. Compared to existing estimates, we find that a one standard deviation increase in in-utero exposure to $PM_{2.5}$ reduces birth weight by approximately 40 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).

Our OLS estimates are consistently smaller in magnitude than the corresponding IV estimates across all birth outcome indicators. This suggests that the OLS estimates may be biased downward due to unobserved confounders and/or attenuation bias arising from measurement error, as discussed in the previous section. A simple Hausman test confirms that

[11] Table C1 in the Appendix presents the first stage estimates for the instruments - regions interacted with share of wind from North, East and South directions. Table C2 in the Appendix presents the coefficients for the control variables used in the second stage Equation 3.

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. Nevertheless, both the OLS and IV estimates are statistically significant across all birth outcomes. These findings underscore the economically and statistically significant impact of ambient air pollution on birth outcomes and highlight the importance of addressing in-utero environmental exposures as a means of improving fetal development.

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 C4 in the Appendix, indicate that exposure to $PM_{2.5}$ during any trimester is negatively and significantly associated with lower birth weight.

Table 4: Effect of $\mathrm{PM}_{2.5}$ Exposure on Birth Outcomes: OLS and IV Estimates

	Panel A: OLS Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
$PM_{2.5}$ Exposure	-1.763***	0.0008***	0.0001**
	(0.388)	(0.0002)	(0.00004)
Adjusted R^2	0.053	0.016	0.002
	Panel B: IV Estimates		
Dependent variable:	Birth Weight	LBW	VLBW
Instrumented $\mathrm{PM}_{2.5}$ Exposure	-2.660***	0.0018***	0.0004***
	(0.723)	(0.0004)	(0.0001)
First Stage F-statistic	110	110	110
Mean of Dependent Variable	2825	0.17	0.01
Observations	321,810	321,810	321,810

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 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 them 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 C2, C3, and C4 in the Appendix present the IV coefficient estimates for our three birth outcomes, using alternative specifications with 40, 50, and 60 regions. The results remain robust across these specifications, lending support to the validity of the monotonicity assumption in our setting.

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, 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:

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

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) 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 C5, C6, and C7 in the Appendix.

Table 5: Alternate First Stages

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Hierarchical Clustering			
$PM_{2.5}$ Exposure	-1.710^{**}	0.001^{***}	0.0003^{***}
	(0.736)	(0.0004)	(0.0001)
First Stage F-statistic	130	130	130
Panel b: First Stage: District-Month-Year Pairs			
$PM_{2.5}$ Exposure	-3.420^{**}	0.003^{***}	0.001^{***}
	(1.064)	(0.001)	(0.0001)
First Stage F-statistic	215	215	215
Panel c: Instrumental Reduction			
$PM_{2.5}$ Exposure	-3.269^{***}	0.002^{***}	0.0003^{***}
	(0.890)	(0.0005)	(0.0001)
First Stage F-statistic	83	83	83
Observations	321,810	321,810	321,810

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.

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. 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, with the exception of the very low birth weight outcome.

Table 6: Alternative Model Specifications

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Additional Mother and Birth Controls			
$PM_{2.5}$ Exposure	-1.507^{***}	0.001^{***}	0.0003^{***}
	(0.504)	(0.0003)	(0.0001)
Observations	321,810	321,810	321,810
Panel b: Precipitation and Other Pollution Controls			
$PM_{2.5}$ Exposure	-1.814^{**}	0.002^{***}	0.0005^{***}
	(0.920)	(0.0006)	(0.0001)
Observations	318,743	318,743	318,743
Panel c: Card only Sample			
$PM_{2.5}$ Exposure	-2.507^{***}	0.001^{**}	0.0001
	(0.801)	(0.0005)	(0.0001)
Observations	182,697	182,697	182,697

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 results, presented in Tables C5 and C6 in the Appendix, are consistent with our baseline findings. Figures C8, 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. In addition, Figures C11, C12, and C13 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 C7 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 4.48% of mothers (14,431 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 C8 presents the results for this specification. Our findings remain robust.

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 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.

5.3.1 Using Dispersion Variables

Until now, 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 level—affects 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 C9 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, the overall findings are consistent with our earlier results based on average exposure levels, while also highlighting the importance of exposure variability as a measure to estimate the effect of ambient air pollution exposure on child's birth weight.

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:

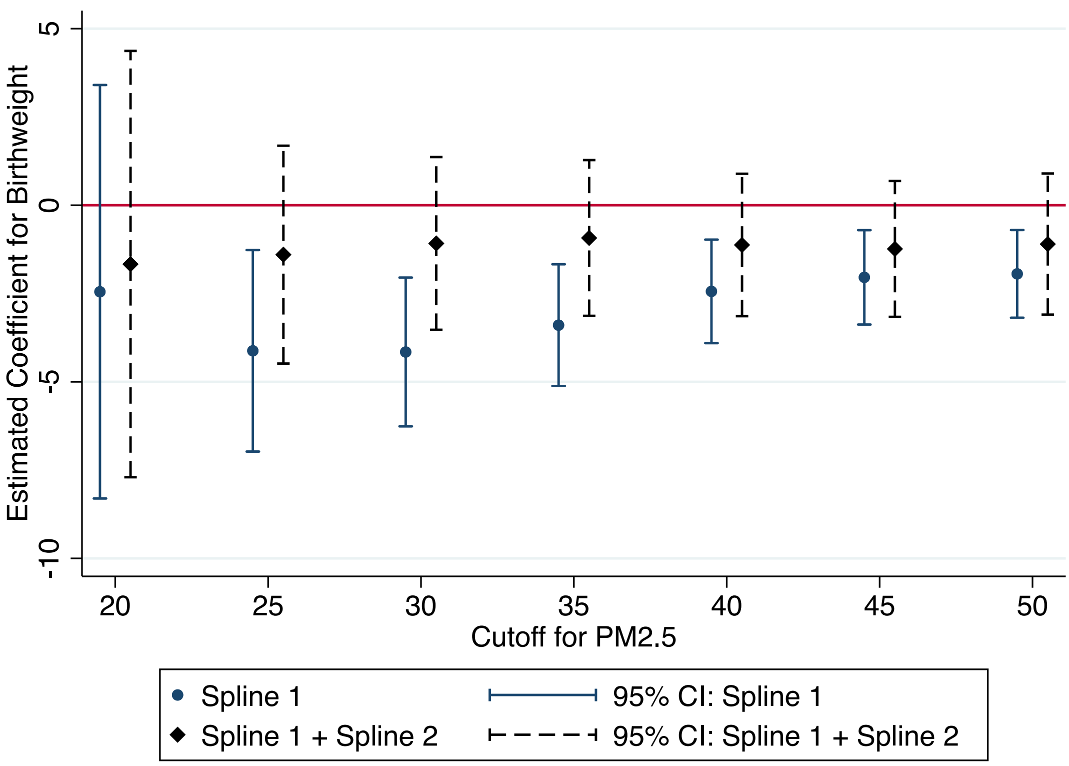
$$\begin{aligned} Y_{idrmt} &= \beta_1 \widehat{\overline{PM2.5}}_{i(d,m,t)} + \beta_2 [\widehat{\overline{PM2.5}}_{i(d,m,t)} - k].I(\widehat{\overline{PM2.5}}_{i(d,m,t)} \geq k) \\ &+ \lambda X_{idrmt} + \nu W_{i(d,m,t)} + \delta_{mr} + \gamma_t + \epsilon_{idrmt} \end{aligned} \tag{5}$$

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 β_1 is statistically insignificant at the lowest cutoff ($k = 20$), but becomes significant for cutoff values of 25 and above. However, $\beta_1 + \beta_2$ is not statistically different from zero across all cutoff levels. Although the estimated values of β_1 are statistically significant at certain levels, they approach zero as k increases, and the confidence intervals begin to overlap for higher values of k. This suggests that at lower cutoff values, higher in-utero exposure to $PM_{2.5}$ significantly reduces birth weight, indicating some evidence of non-linearity. However, at higher values of k, there is little evidence of such non-linearity.

We conduct a similar analysis for the binary indicators of low birth weight and very low birth weight, with the results displayed in Figures C14 and C15, 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 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 level of birth to estimate their effect on child 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, one estimates quantile regressions of the outcome variable (birth weight) on individual-level covariates within each group. However, in our context, the number of observations per group is too small to reliably estimate these first-stage quantile regressions.

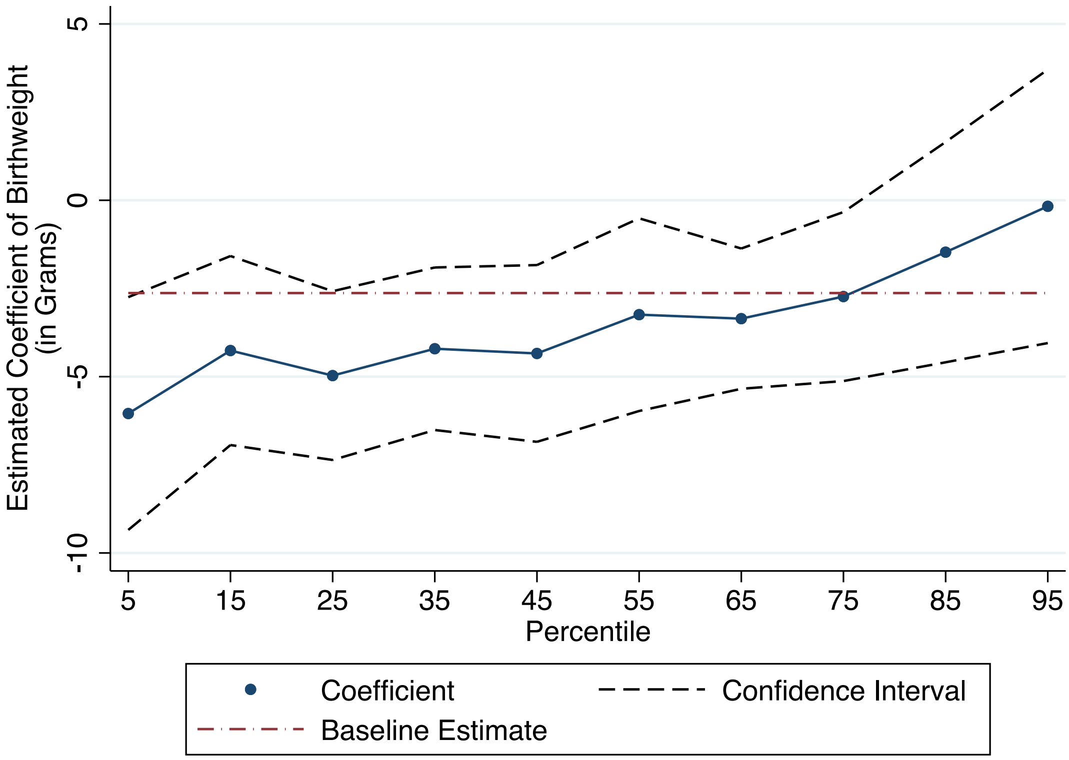
Therefore, following the simplified method suggested by Chetverikov et al. (2016) and implemented by Pons (2022), we instead directly compute empirical quantiles (u), ranging from 5th to 95th with a step of 10, of birth weight for each group without conditioning on individual characteristics. These group-level quantiles serve as the dependent variables in our second-stage analysis. In this stage, we regress the group-level 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. 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:

$$\bar{y}_g(u) = \beta(u)\widehat{PM2.5}_g + \omega(u)W_g + \delta_{mr} + \varepsilon_g \tag{6}$$

Figure 3 presents the results from estimating Equation 6 across various quantiles of the birth weight distribution ($u \in 5, 15, 25, \ldots, 95$). 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 90 grams for a one standard deviation increase in in-utero $PM_{2.5}$ concentration. The estimated coefficients are statistically significant up to the 75th 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.

As mentioned earlier, we are unable to estimate quantile regressions within each group using individual-level controls due to small sample size. To address this issue we employ an alternative approach. In this approach we first estimate a linear regression of birth weight on individual-level maternal and child characteristics and use the residuals—interpreted as adjusted birth weights—as the new dependent variable. We then repeat the grouped quantile regression analysis using these adjusted values. The corresponding results are shown in Figure C16 in the Appendix. The pattern remains consistent: the effect size is largest in the lower tail of the distribution and becomes statistically insignificant at higher quantiles. This finding 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, even after adjusting for observable individual characteristics.

Figure 3: Non-linear effects using grouped quantile regression for birth weight



6 Economic Costs of Pollution

A substantial body of literature highlights the critical role of birth weight in shaping a wide range of long-term child outcomes. In this section, we link our estimates to the findings of some of the studies in this literature. Table C10 in the Appendix provides a brief overview of some of these studies. We focus on reporting estimates from studies which are performed using data from developing countries, preferably in the Indian setting, since their setting and estimates would be the ones which most closely resemble the backdrop of our analysis. This is due to the fact that health shocks at birth in the context of developing countries may be more poignant, as they occur in environments with limited access to medical care, inadequate nutrition, and fewer resources to mitigate their long-term effects, ultimately amplifying their impact on later outcomes (Currie & Vogl, 2013). Hence, similar topical studies from developed countries may not be directly comparable, given the stark differences in baseline health conditions, institutional capacity, and the ability to buffer early-life shocks.

The average in-utero exposure for $PM2.5$ within our sample was 40 μg/m^3. The 2005 WHO Air Quality Guidelines recommend that average annual concentrations of $PM2.5$ should not exceed 10 μg/m^3. Reducing average in-utero $PM2.5$ exposure to this threshold, equivalent to a 30-unit reduction would imply based on our estimates, approximately speaking, an 80-gram increase in birth weight on average, and a 5.4 percentage point decline in the incidence of LBW. To interpret these effects in light of the broader literature on the longer-term consequences of birth weight on child health and cognition, we draw comparisons from the studies summarized in Table C10. Assuming linear transformation of effects reported, an 80g gain translates into approximately 0.34 and 0.2 percentile increases in weight-for-age and height-for-age, respectively (Keshav, 2021). Similarly, based on estimates from Baguet and Dumas (2019), an 80g increase would correspond to a 0.015 standard deviation increase in educational attainment, and according to Kumar et al. (2022), a 0.03 standard deviation improvement in cognitive test scores. On the LBW margin, Alderman and Behrman (2006) estimate that shifting one child from LBW to normal weight yields a lifetime productivity gain of \$510 (Based on 2006 USD, equivalent to \$810 in 2025). In the Indian context, where approximately 25 million births occur annually, a 5.4 percentage point reduction in LBW prevalence implies 1.35 million fewer LBW births per year. Applying the estimate from Alderman and Behrman (2006), this corresponds to a potential $1.1 Billion (2025 USD) in aggregate lifetime gains as a result of decline in LBW incidence simply by complying with WHO air quality standards. While figures in this section are useful for contextualizing the potential scale of benefits, they rely on simplifying assumptions and should therefore be interpreted as illustrative rather than precise estimates.

7 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 $PM2.5$ leads to a 1.4% increase in average birth weight and a 3 percentage point reduction in LBW births respectively. These findings are robust across a range of robustness and sensitivity checks.

Linking our results to previous literature on the consequences of birth weight on a number of child cognition and health outcomes, our back-of-the-envelope calculations suggest that aligning in-utero $PM_{2.5}$ levels with WHO air quality standards could yield substantial economic benefits, including over one billion dollars annually from reductions in lifetime productivity losses stemming from LBW infants each year, along with broader long-run gains in child cognition and health. While these estimates rely on simplifying assumptions, they highlight the potentially large returns to improving air quality for maternal and child health.

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:

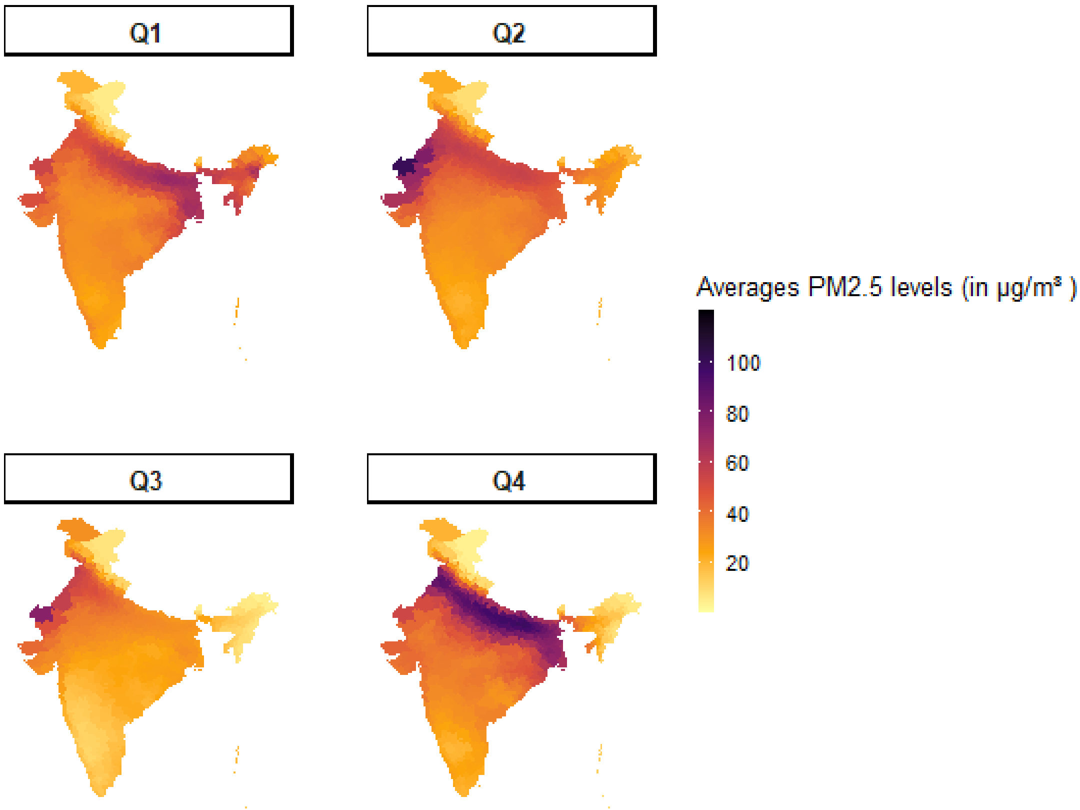
$$WS = \sqrt{u^2 + v^2} \tag{7}$$

$$\theta = \left(\arctan 2(v, u) \cdot \frac{180}{\pi}\right) + 180 \tag{8}$$

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

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

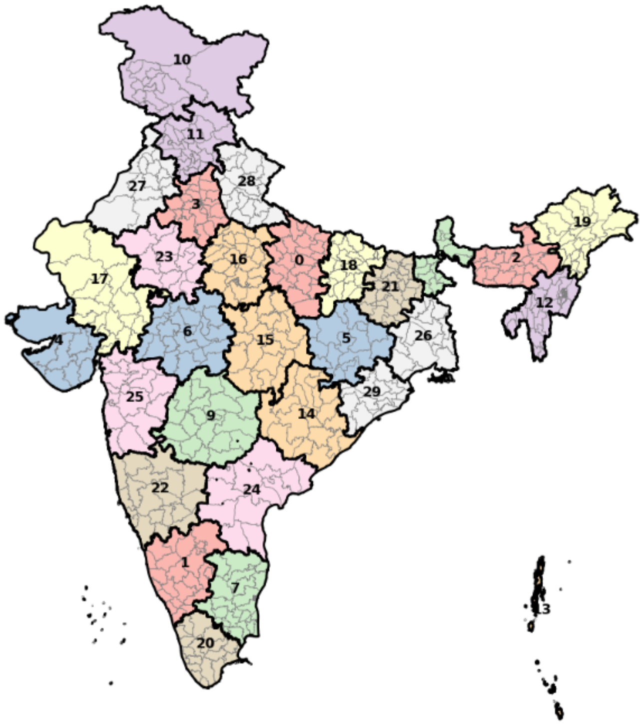


Figure C2: Monotonicity (Continuous Measure of Birth Weight): Alternative Number of Regions for Instrument

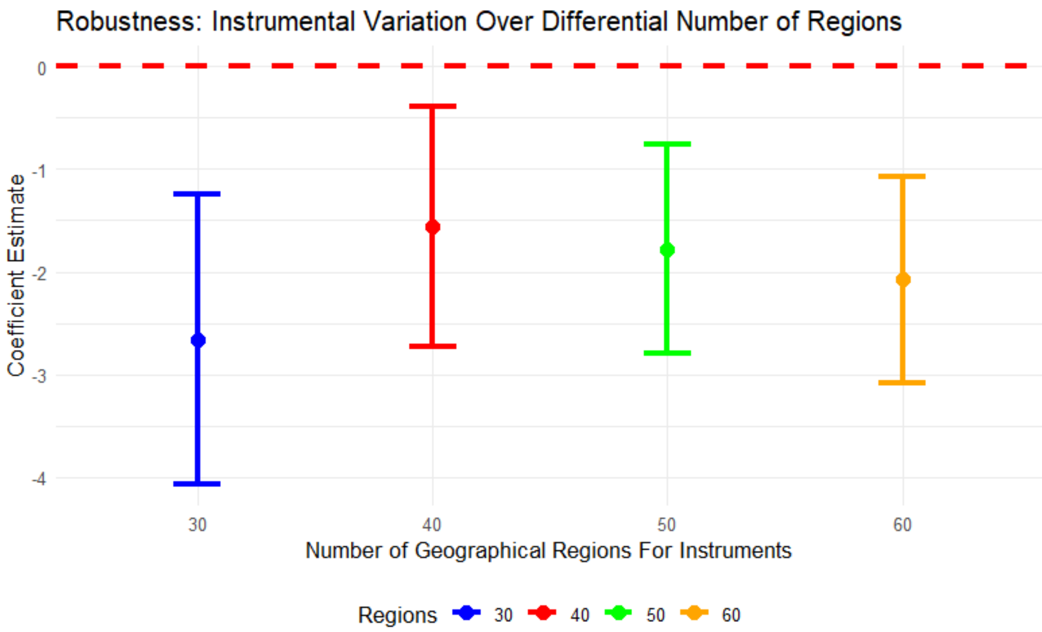


Figure C3: Monotonicity (LBW Binary Measure): Alternative Number of Regions for Instrument

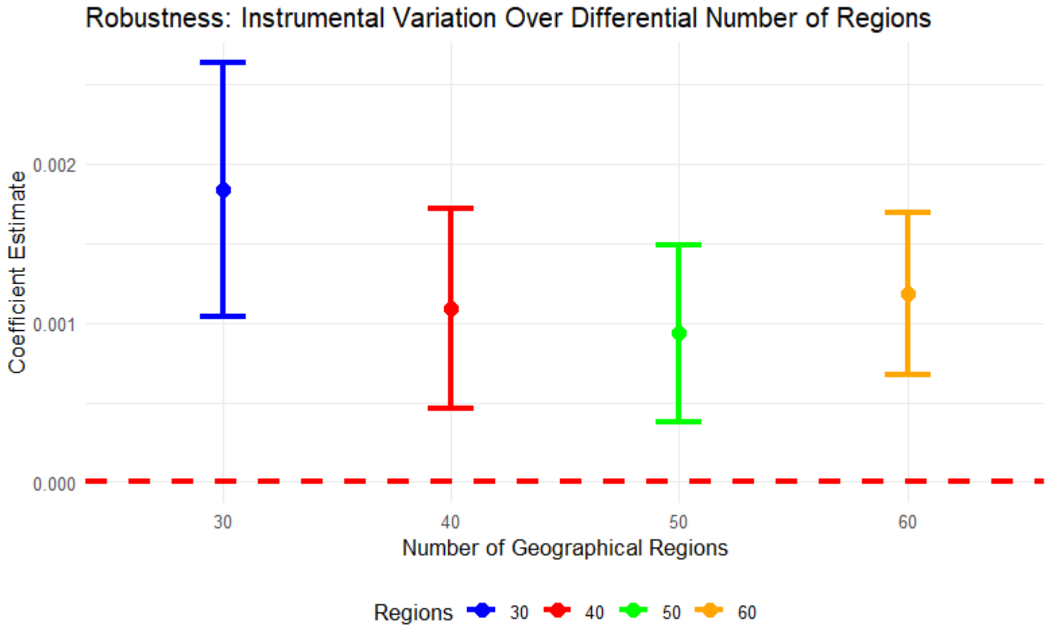


Figure C4: Monotonicity (VLBW Binary Measure): Alternative Number of Regions for Instrument

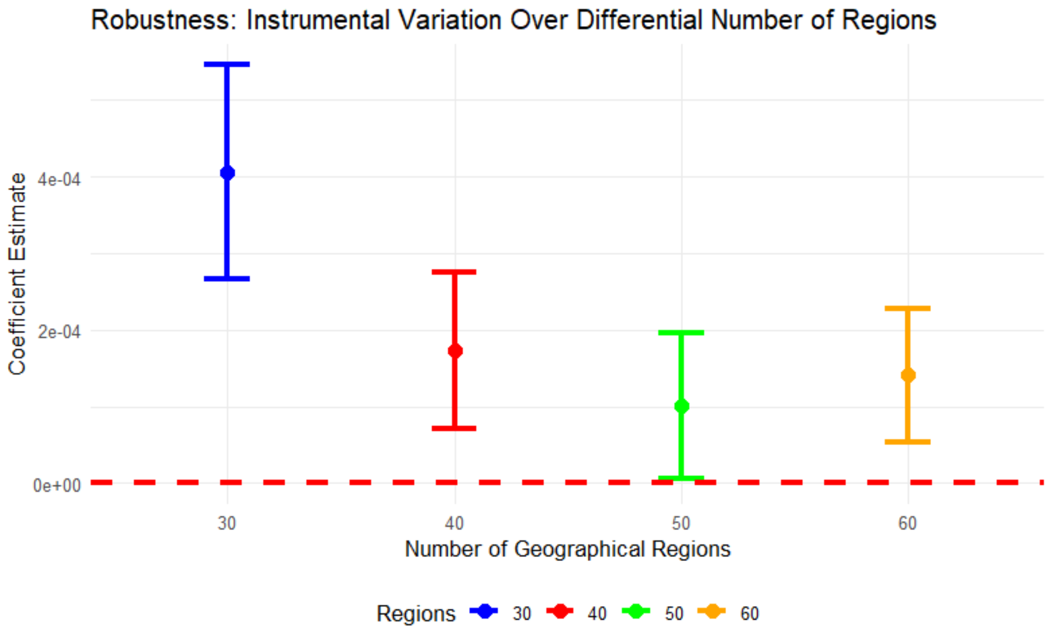


Figure C5: Placebo Exercise Results (Continuous birthweight measure): 250 iterations

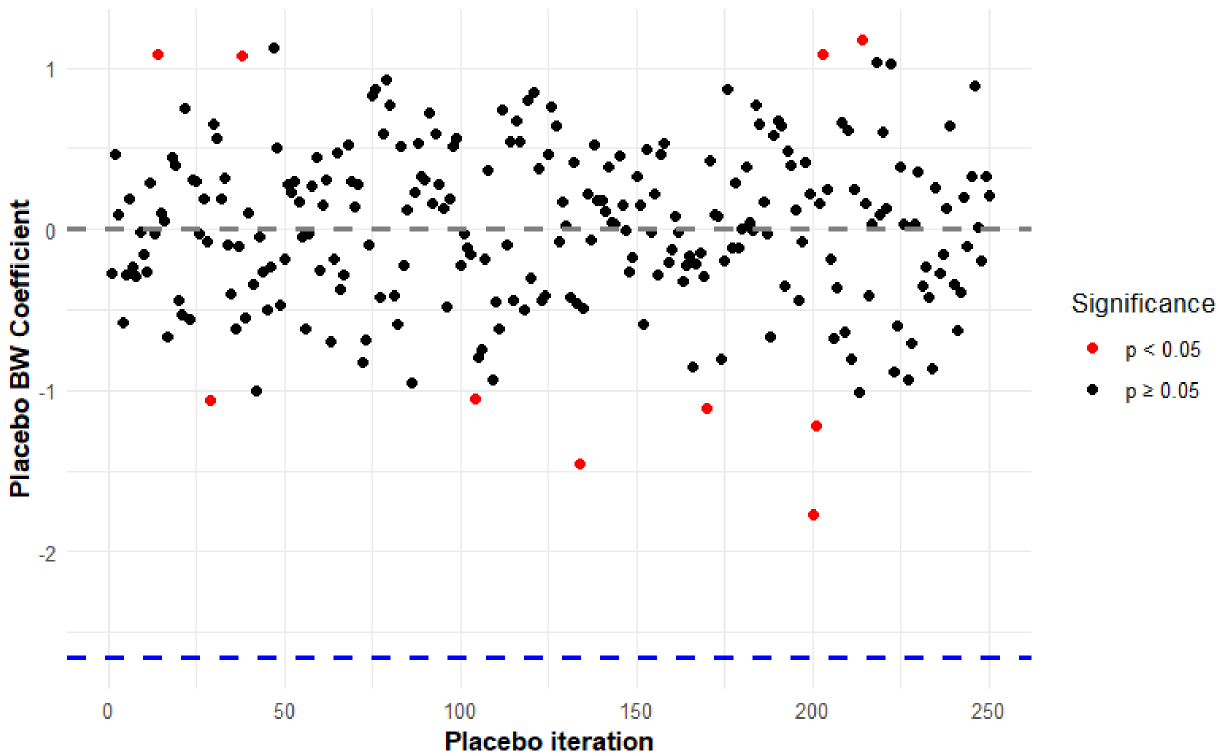


Figure C6: Placebo Exercise Results (LBW indicator): 250 iterations

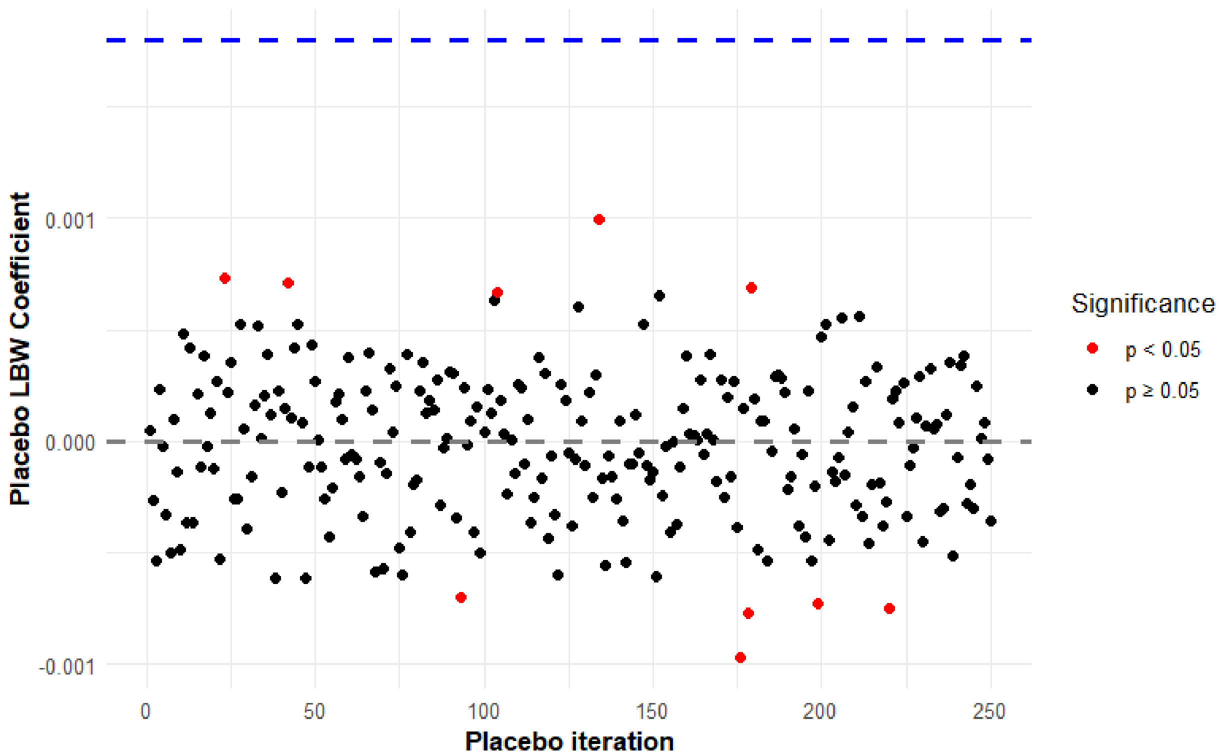


Figure C7: Placebo Exercise Results (VLBW indicator): 250 iterations

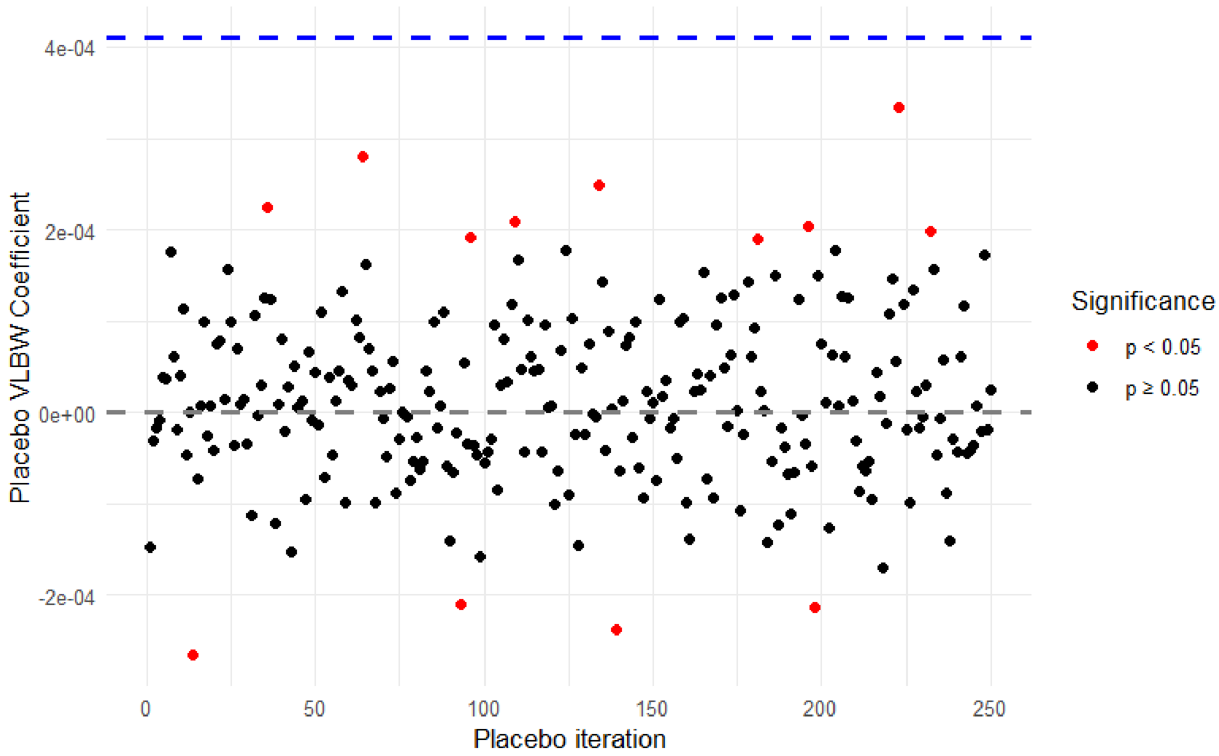


Figure C8: Baseline Results Birth Weight: Alternative Clustering of Standard Errors

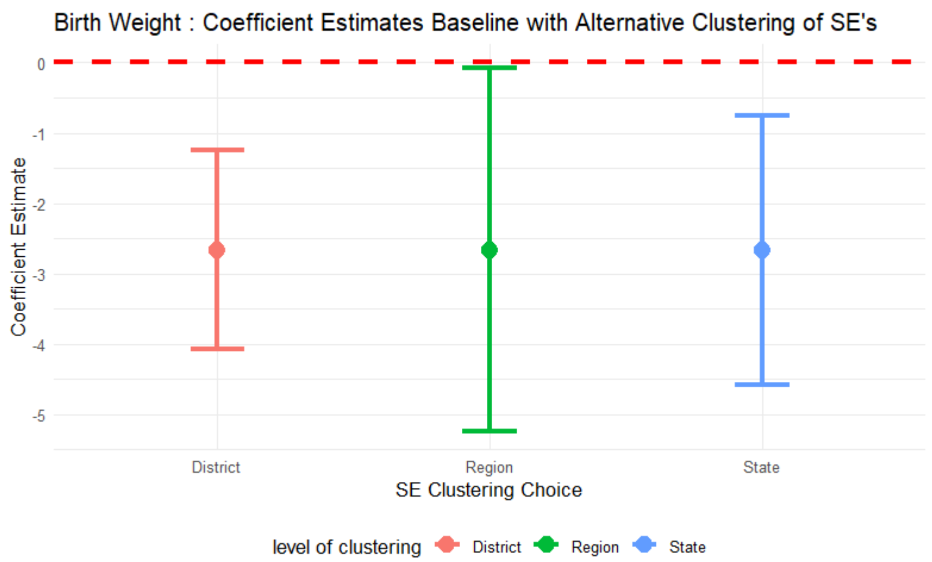


Figure C9: Baseline Results LBW: Alternative Clustering of Standard Errors

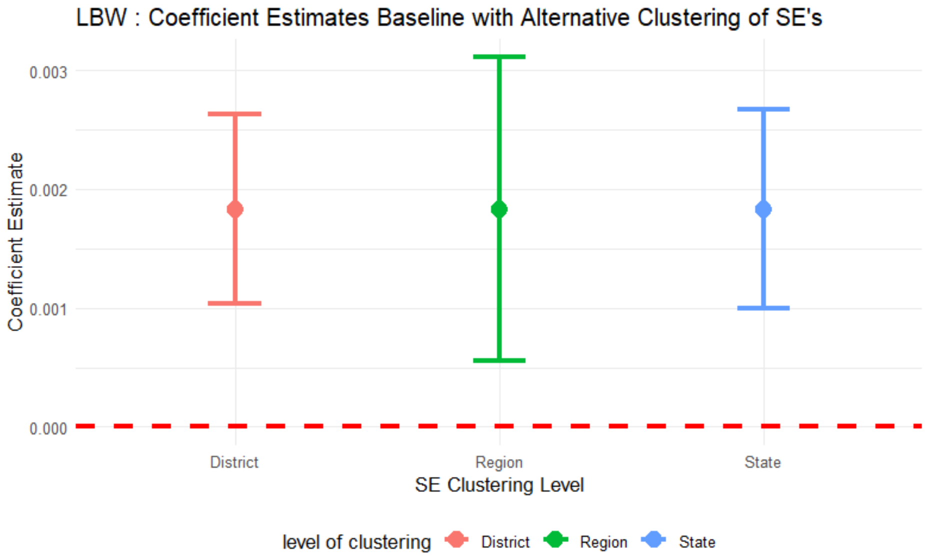


Figure C10: Baseline Results VLBW: Alternative Clustering of Standard Errors

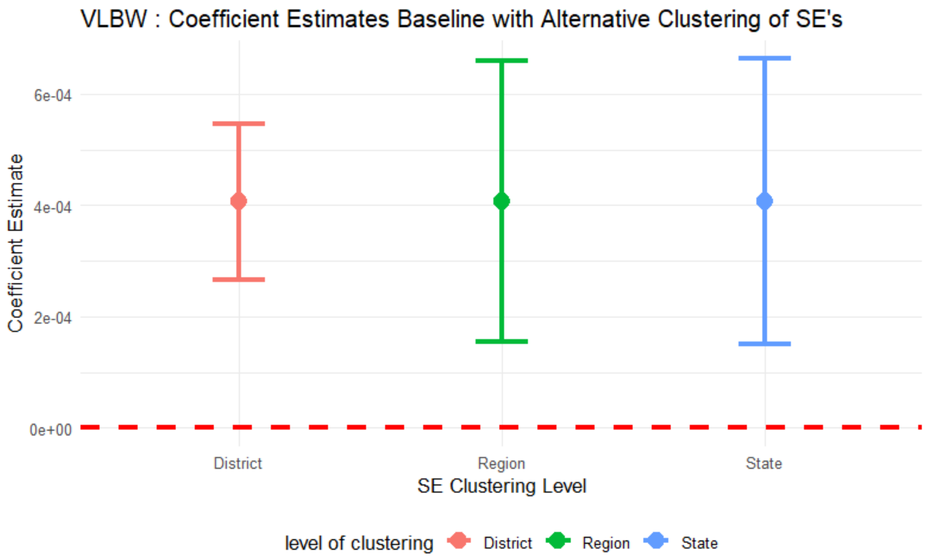


Figure C11: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for birth weight

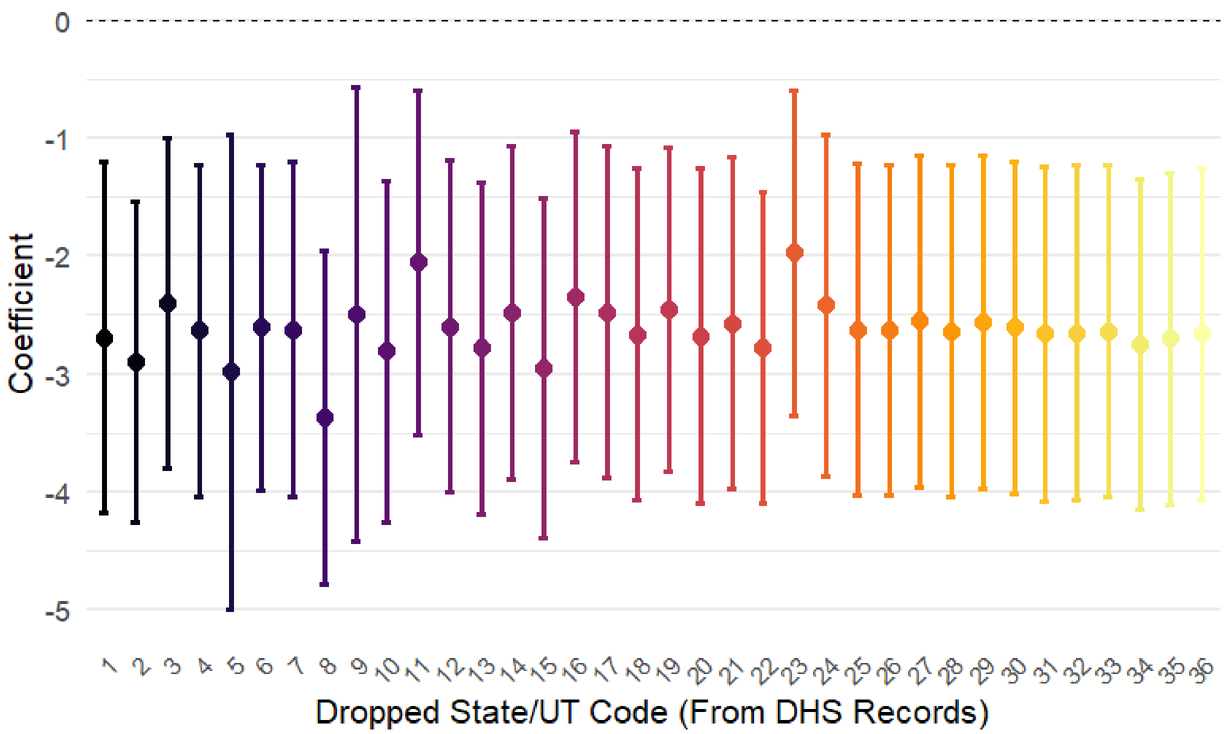


Figure C12: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for LBW indicator

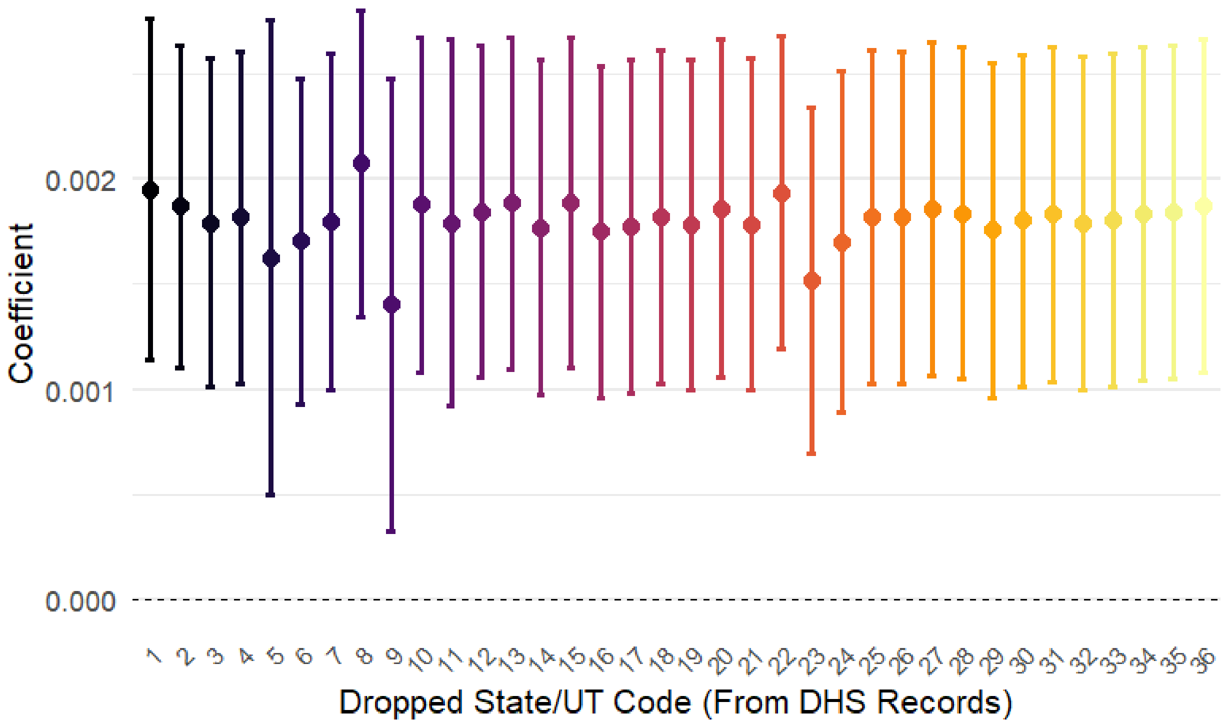


Figure C13: Iteratively dropping States/UTs from the Indian Union one at a time and rerunning baseline first and second stage models for VLBW indicator

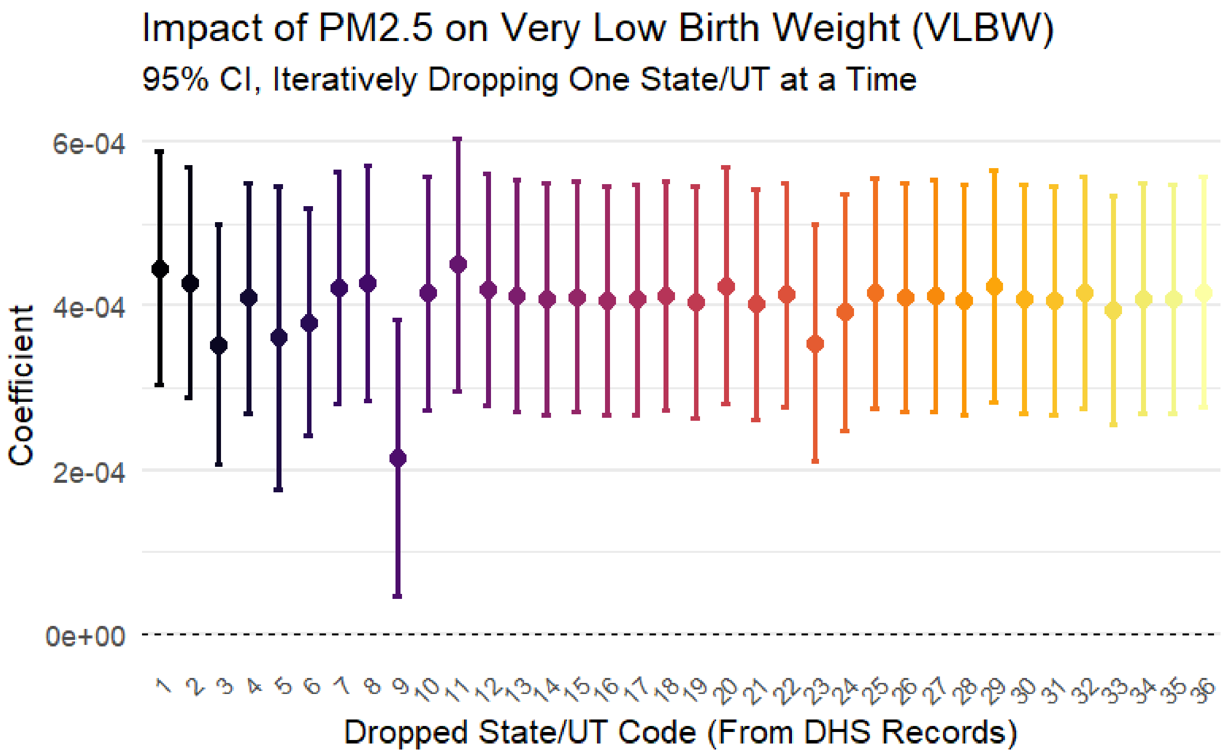


Figure C14: Non-linear effects using Spline Regression for Low Birth Weight

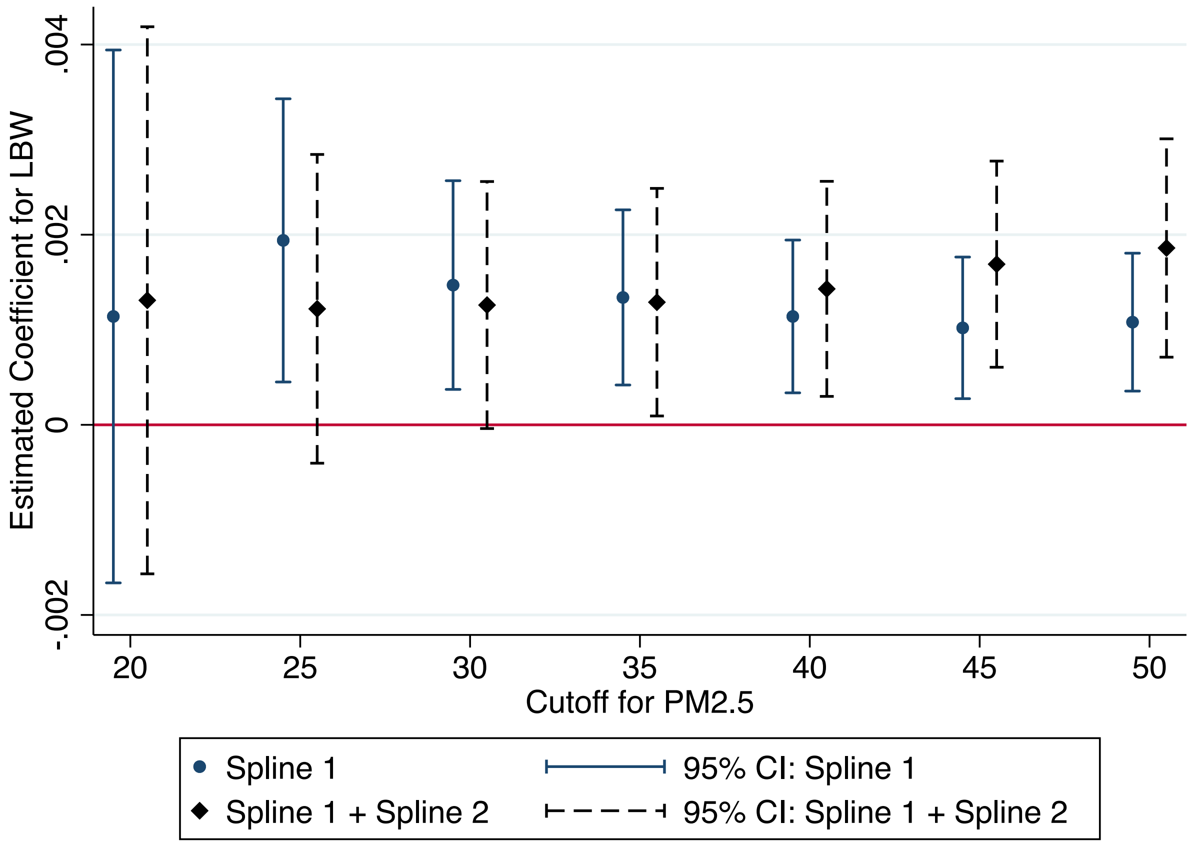


Figure C15: Non-linear effects using Spline Regression for Very Low Birth Weight

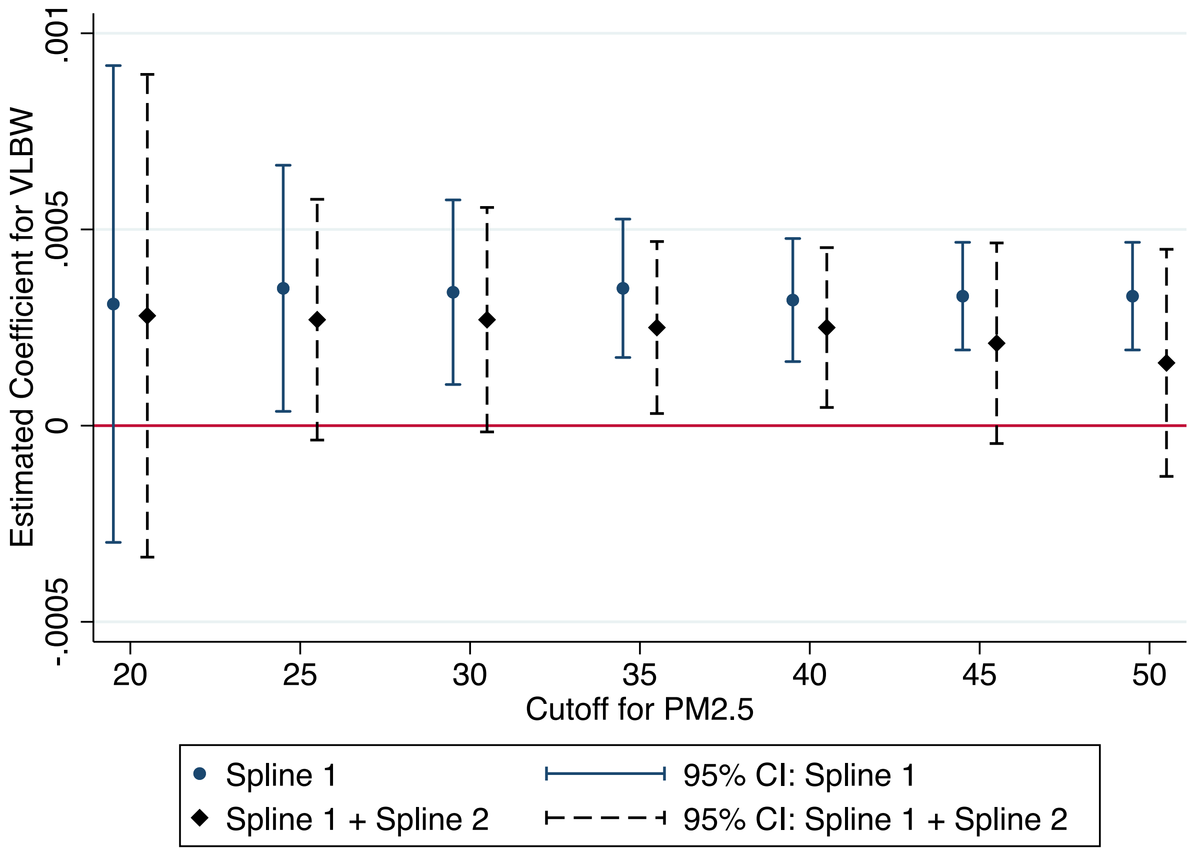


Figure C16: Non-linear effects using grouped quantile regression using birth weight, adjusted for individual characteristics

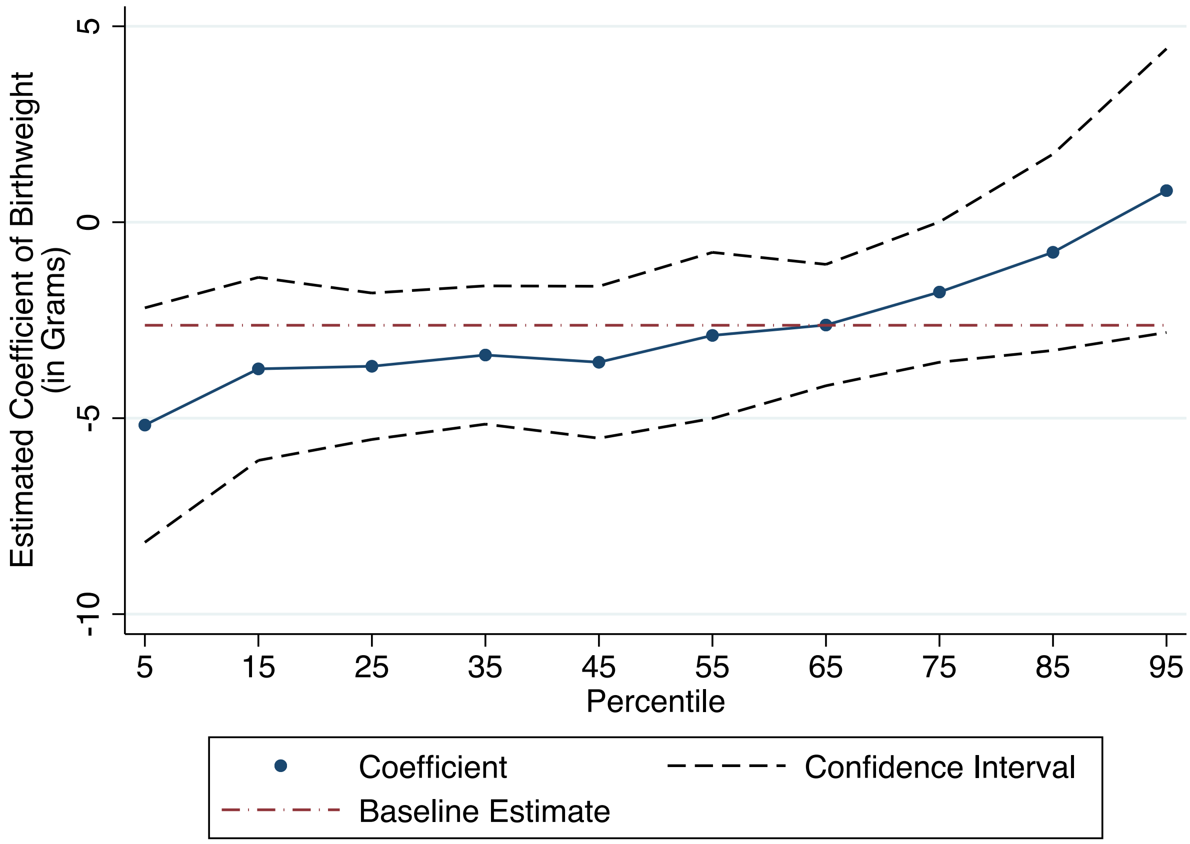


Table C1: First Stage Results

	North Share	East Share	South Share
Region 0	19.241	-3.163	25.160***
	(12.314)	(18.313)	(5.560)
Region 1	-11.903***	-15.996***	-35.861***
	(3.273)	(3.873)	(3.393)
Region 2	-7.538	-47.010***	-9.930
	(18.691)	(7.677)	(7.188)
Region 3	54.669***	43.693***	0.288
	(6.546)	(14.794)	(5.019)
Region 4	-19.474	19.694	-18.561**
	(34.884)	(17.945)	(8.994)
Region 5	-5.636	-2.328	-9.864*
	(12.175)	(9.376)	(5.478)
Region 6	14.728**	-9.207**	-14.201***
	(7.225)	(3.845)	(2.782)
Region 7	-23.897**	-13.729***	-14.717***
	(10.998)	(3.812)	(3.562)
Region 8	-170.222***	-100.721***	130.142***
	(28.737)	(17.879)	(14.962)
Region 9	-37.638***	-6.723*	-13.314***
	(5.061)	(3.458)	(2.527)
Region 10	128.319**	-49.314**	-21.335***
	(51.142)	(22.299)	(7.495)
Region 11	28.985*	58.660**	-17.400
	(17.214)	(23.870)	(11.154)
Region 12	-25.400	-14.648	-49.849***
	(21.076)	(10.134)	(7.496)
Region 13	-174.837***	24.912***	-40.454***
	(58.617)	(7.747)	(7.339)
Region 14	-32.109	-11.838**	-5.389
	(22.229)	(4.794)	(3.630)
Region 15	-51.772***	-18.234***	0.904
	(13.971)	(4.318)	(4.627)
Region 16	40.717***	-34.324**	17.131**
	(8.151)	(13.924)	(7.355)
Region 17	31.714	35.944**	-22.324**
	(30.096)	(16.278)	(9.135)
Region 18	30.542**	25.943**	11.518
	(12.874)	(12.999)	(11.992)
Region 19	-75.646***	-25.617***	-34.923***
	(22.668)	(8.485)	(9.440)
Region 20	-6.994***	-9.952***	-12.845***
	(2.372)	(2.881)	(2.887)

Table C1: First Stage Results (Contd.)

	North Share	East Share	South Share
Region 21	39.126***	12.715	8.800
	(11.097)	(11.190)	(8.736)
Region 22	-27.030***	-25.448***	-17.140***
	(8.293)	(5.564)	(3.272)
Region 23	6.981	-26.656***	5.423
	(9.386)	(7.404)	(3.428)
Region 24	-1.646	-19.003**	-16.905***
	(10.457)	(7.963)	(4.535)
Region 25	-2.962	-11.497*	-13.953***
	(8.590)	(6.515)	(2.469)
Region 26	24.441**	16.574***	1.894
	(9.792)	(5.951)	(4.361)
Region 27	72.951***	16.213	16.653**
	(26.486)	(11.491)	(7.750)
Region 28	18.408	-222.566***	55.899***
	(37.739)	(28.755)	(18.628)
Region 29	10.215	3.662	-13.914**
	(10.090)	(7.958)	(5.953)

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 C2: Second Stage Results: Covariates

	Birth Weight	LBW	VLBW
Temperature	0.954	-0.0010**	0.0001
	(0.833)	(0.0004)	(0.0001)
Wind Speed	4.626	-0.0047*	-0.0012***
	(4.498)	(0.0025)	(0.0004)
Caste (Base: SC)			
ST	26.089***	-0.0088**	-0.0021***
	(7.619)	(0.0040)	(0.0007)
OBC	15.527***	-0.0082***	-0.0005
	(3.587)	(0.0023)	(0.0005)
General	12.952***	-0.0020	0.0003
	(4.727)	(0.0028)	(0.0007)
Religion (Base: Hindu)			
Muslim	18.361***	-0.0023	0.0002
	(5.554)	(0.0030)	(0.0008)
Christian	130.260***	-0.0306***	-0.0006
	(15.679)	(0.0056)	(0.0008)
Others	23.745*	0.0033	0.0020*
	(12.774)	(0.0061)	(0.0012)
Dirty Cooking Fuel	1.015	-0.0029	-0.0004
	(3.439)	(0.0021)	(0.0005)
Girl Child	-66.737***	0.0245***	0.0010***
	(2.239)	(0.0014)	(0.0003)
Urban	-19.315***	0.0108***	0.0021***
	(3.827)	(0.0023)	(0.0006)
BMI	13.231***	-0.0037***	-0.0001**
	(0.359)	(0.0002)	(0.0001)
Wealth Index (Base: Poorest)			
Poorer	34.647***	-0.0167***	-0.0011
	(4.033)	(0.0024)	(0.0007)
Middle	70.170***	-0.0326***	-0.0029***
	(4.849)	(0.0029)	(0.0007)
Richer	94.600***	-0.0430***	-0.0039***
	(5.488)	(0.0032)	(0.0008)
Richest	133.784***	-0.0667***	-0.0072***
	(6.755)	(0.0039)	(0.0010)

Table C2: Second Stage Results: Covariates (Contd.)

	Birth Weight	LBW	VLBW
Anemia (Base: No Anemia)			
Mild	-8.546***	0.0040**	0.0003
	(2.574)	(0.0017)	(0.0004)
Moderate	-13.448***	0.0094***	0.0014***
	(3.192)	(0.0019)	(0.0005)
Severe	-42.397***	0.0347***	0.0073***
	(9.447)	(0.0061)	(0.0019)
Birth Order	15.654***	-0.0055***	-0.0009***
	(1.811)	(0.0009)	(0.0002)
Age at Birth	0.653*	-0.0004*	0.0001
	(0.366)	(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 C3: Effect of Pollution Exposure on Birth Size: IV Estimates

Dependent variable:	Below-Average Size
$PM_{2.5}$ Exposure	0.002^{***}
	(0.0003)
First Stage F-statistic	110
Mean of Dependent Variable	0.10
Observations	321,452

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 C4: 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	-2.568***	0.002***	0.0004***
	(0.609)	(0.0004)	(0.0001)
Panel b: Second Trimester			
$PM_{2.5}$ Exposure	-1.837***	0.001***	0.0002***
	(0.649)	(0.0004)	(0.0001)
Panel c: Third Trimester			
$PM_{2.5}$ Exposure	-1.289***	0.001***	0.0003***
	(0.458)	(0.0003)	(0.0001)
Observations	321,810	321,810	321,810

Notes: Instrumental variable (IV) using wind direction as the instrument for in-utero exposure during the first, second and third trimester. Third trimester also includes 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 C5: 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	-2.060***	0.0014***
	(0.614)	(0.0004)
First Stage F-statistic	109	109
Observations	310,573	310,573
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 C6: 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	-2.014***	0.0014***
	(0.561)	(0.0004)
First Stage F-statistic	107	107
Observations	302,730	302,730
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 C7: 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	-2.638***	0.002***	0.0004***
	(0.656)	(0.0004)	(0.0001)
Panel b: First 8 months			
$PM_{2.5}$ Exposure	-2.655***	0.002***	0.0004***
	(0.685)	(0.0004)	(0.0001)
Panel c: First 9 months			
$PM_{2.5}$ Exposure	-2.659***	0.002***	0.0004***
	(0.704)	(0.0004)	(0.0001)
Observations	321,810	321,810	321,810

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 C8: 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***	0.0013***	0.0003***
	(0.561)	(0.0004)	(0.0001)
Observations	307,379	307,379	307,379

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 Variation in $PM_{2.5}$ Exposure on Birth Outcomes: IV Estimates

Dependent variable:	Birth Weight	LBW	VLBW
Panel a: Range			
$PM_{2.5}$ Exposure	-1.368^{***}	0.001^{***}	0.0002^{***}
	(0.508)	(0.0003)	(0.00006)
Panel b: Inter-quartile Range			
$PM_{2.5}$ Exposure	-0.556	0.0005	0.0001
	(0.589)	(0.0003)	(0.0001)
Panel c: Standard Deviation			
$PM_{2.5}$ Exposure	-4.698^{***}	0.003^{***}	0.0007^{***}
	(1.630)	(0.0009)	(0.0002)
Observations	321,810	321,810	321,810

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.

Table C10: Birth Weight and Its Long-Run Consequences in Developing Countries

Study	**Country / Data**	**Key Result**
Alderman and Behrman (2006)	Literature based synthesized evidence from studies in multiple developing countries	Estimated $510 lifetime economic benefit per child moved from LBW to normal weight, primarily via higher productivity
Keshav (2021)	39 longitudinal datasets from developing countries	Birth weight strongly associated with height and weight outcomes; 100g increase linked to 0.43 and 0.25 unit increase in Weight for Age and Height for Age percentiles
Baguet and Dumas (2019)	Phillipines, CLHNS Dataset tracking a 1983-84 birth cohort from infancy until age 22	100 g increase in birth weight associated with a 0.019 SD increase in years of schooling at age 8 and an increase 0.02 SD increase in IQ at age 8
Kumar et al. (2022)	India, use the Indian Young Lives Surveys (YLS), a survey dataset designed to analyze the impact of early life inequality and poverty on life outcomes	A 10% increase in birth weight and being born within the LBW threshold leads to a 0.11 SD positive impact and 0.09 SD negative impact on cognitive test scores among children aged 5-8 respectively
Sicuri et al. (2011)	Mozambique, rural sample covering over 3000 births	Average cost per LBW infant in the first year following birth for the health system amounts is 4.5 times that of a normal birth weight infant