Ambient PM2.5 and Women's Health Outcomes in India

ECO-3500

Term Paper

Professor Bharat Ramaswami

Diza Sharma Riddhika Gulechha

December 8, 2025

1 Problem Statement

This paper examines the effect of ambient air pollution, measured through PM2.5 concentrations, on women's health outcomes in India, and how these effects vary across household wealth levels. We focus on BMI, anemia, and hemoglobin levels; and classify BMI into underweight and overweight; and anemia into severe and extreme, to see which outcome is most affected by PM2.5 exposure. We control for respiratory illnesses along with demographic and household factors that contribute to them. Possible mechanisms for this heterogeneity include differences in daily activities, healthcare access, nutrition, and exposure across wealth groups.

2 Motivation

Ambient air pollution is now recognised as one of the world's largest health burdens. Globally, 7.3 billion people are exposed to unsafe PM2.5 levels and pollution related illnesses and deaths have increased massively. In India, household air pollution has declined with cleaner cooking fuels, but ambient PM2.5 levels keep increasing, placing Indian cities as the most polluted in the world ("World's Most Polluted Cities 2024"). While these trends are well-recorded, far less is known about how PM2.5 exposure affects non-fatal health outcomes among women.

Given the hazardous pollution levels, understanding the implications for women's health is essential. In India, women face distinct exposure patterns because of their caregiving roles and large participation in the informal workforce. According to NFHS data, 57% of the women are anemic and unhealthy body weight is highly prevalent among women (Barman). Understanding whether ambient air pollution worsens these conditions is important as it affects women's energy levels, daily functioning and productivity.

Evidence from existing studies shows that exposure to air pollution is associated with a range of respiratory, metabolic and reproductive health risks. (O'Neill et al.). For this paper, we focus on 3 health outcomes: Anemia, BMI and Haemoglobin levels.

Emerging studies show that long-term exposure to PM2.5 is associated with reduced haemoglobin levels and risk of anaemia through inflammation, oxidative stress, and changes in iron metabolism (Haberzettl et al.). Dey et al. (2022) argue that exposure to PM2.5 can increase anemia prevalence among Indian women, particularly among poorer and less educated women. Similar findings have been reported in other Asian countries like South Korea, which confirms that air pollution is a cause of anemia. (Hwang and Kim)

Beyond anemia, pollution also affects body weight. Studies have found out that long-term exposure leads to a drop in metabolism. Sun, Qinghua et al. (2009) conducted an experiment on mice which provides the biological explanation for PM2.5 why pollution exposure leads to slower metabolism in humans. Several other papers confirm this, including Munir et al. (2024), report positive links between long-term PM2.5 exposure and obesity. This suggests that air pollution is related to women's BMI, and the need for it to be explored for women in India is increasing.

These associations are unlikely to be uniform across all women, making wealth an important source of heterogeneity. Poorer households are more likely to reside in highly polluted neighbourhoods, work in outdoor or informal jobs, and live in crowded or poorly ventilated homes, all of which increase exposure (Ji et al.). Limited access to mitigation measures and quality healthcare further their vulnerability to pollution-induced damage (Ji et al.). On the other hand, wealthier women may experience lower exposure and greater capacity to manage health risks. Understanding whether pollution affects health differently across wealth groups is important, as estimating an average effect on the entire population may obscure meaningful disparities. Currently, very few studies estimate this effect for women in India.

Current literature on air pollution and health in India remains limited, as much of the existing research stops around the 2019 Global Disease Burden report. Most papers focus on the 2010–2015 period (Chakraborty) (Pandey, Anamika et al.), or pair pollution data with the 2011 Census (Sachdeva, Ishaan, et al.), and don't make use of the more granular NFHS-5 data. Current studies rarely incorporate the AOD-based approach (deSouza et al. ; George et al.), and PM2.5 exposure is often constructed from regional or national pollution sources rather than satellite-based estimates.

To address these gaps, this paper combines SHRUG's globally consistent and high-resolution PM2.5 estimates with district-level NFHS-4 and NFHS-5 data to examine heterogeneity by wealth. While prior research documents the overall burden of air pollution, far fewer studies test whether the effect of pollution itself varies across the wealth distribution in India. Our empirical strategy therefore estimates interaction terms between pollution and wealth to capture differential health impacts across groups. Identifying and understanding these patterns is important as even small declines in haemoglobin or BMI can lead to large productivity and welfare losses. The findings of this paper strongly advocate for air quality management and nutrition interventions in low-income districts.

3 Analytical Framework

Women's exposure to air pollution is determined by where their family lives, the kind of jobs they hold, and their ability to access healthcare. As a result, pollution exposure can differ sharply by wealth, even when ambient PM2.5 levels are similar.

Building on this conceptual link between wealth and pollution exposure, we examine how PM2.5 relates to women's nutritional and anemic outcomes. The dependent variables are: three anemia indicators (severe, moderate, mild), one indicator for hemoglobin levels and one indicator BMI. We use BMI to derive two dummy variables for overweight and underweight.

In our regression equations, PM2.5 concentration is the explanatory variable. We include controls for smoking behavior, cigarette consumption, age, sex of household head, caste, religion, partner's education, and the woman's education. To account for unobserved factors, all regressions include district and year fixed effects, with standard errors clustered at the district level. Year fixed effects absorb shocks, policy changes, and seasonal migration that might affect all districts in a given year. District fixed effects absorb time-invariant characteristics of each district, such as long-standing policies, health infrastructure, or persistent pollution patterns, that might bias the estimated relationship between pollution and women's health.

Clustering of standard errors prevents downward bias in standard errors and avoids overstated statistical significance. Finally, to test for differences in wealth levels, we interact PM2.5 with household wealth quintiles, which examines whether the health effects of pollution vary across the wealth distribution.

3.1 Regression Specifications

We run the following basline regressions using NFHS-4 data (2015-16) NFHS-5 data (2019-21) matched to SHRUG PM2.5 at the cluster level across Indian districts.

All regression specifications include district fixed effects δ_d and year fixed effects γ_t. Standard errors are clustered at the district level for all models. We also control for a common set of demographic and household characteristics, including smoking behaviour (Smokes_tabacco and Smokes_Cigs), age, caste, religion, education, the sex of the household head, and partner's education.

R1: Baseline Regressions

$$\begin{aligned} Haemoglobin = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Smokes\_tabacco + \beta_3 Age + \beta_4 Caste \\ & + \beta_5 Religion + \beta_6 Educ + \beta_7 hh\_sex + \beta_8 Partner\_educ \\ & + \beta_9 Smokes\_Cigs + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} Anemia_i = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Smokes\_tabacco + \beta_3 Age + \beta_4 Caste \\ & + \beta_5 Religion + \beta_6 Educ + \beta_7 hh\_sex + \beta_8 Partner\_educ \\ & + \beta_9 Smokes\_Cigs + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{2}$$

where i indexes anemia categories (mild, moderate, and severe) as defined by NFHS biomarker cutoffs.

$$\begin{aligned} BMI = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Smokes\_tabacco + \beta_3 Age + \beta_4 Caste \\ & + \beta_5 Religion + \beta_6 Educ + \beta_7 hh\_sex + \beta_8 Partner\_educ \\ & + \beta_9 Smokes\_Cigs + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{3}$$

where i indexes anemia categories (mild, moderate, severe) as defined by NFHS biomarker cutoffs. δ_d and γ_t denote district and year fixed effects, respectively.

R2: Baseline Wealth Regressions

$$\begin{aligned} Haemoglobin = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\ & + \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\ & + \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\ & + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{4}$$

$$\begin{aligned} Anemia_i = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\ & + \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\ & + \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\ & + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{5}$$

where i indexes anemia categories (mild, moderate, severe) as defined by NFHS biomarker cutoffs.

$$\begin{aligned} BMI = \beta_0 &+ \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\ &+ \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\ &+ \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\ &+ \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{6}$$

R3: Overweight BMI

$$\begin{aligned} OverweightBMI = \beta_0 &+ \beta_1 PM2.5 + \beta_2 Smokes\_tabacco + \beta_3 Age + \beta_4 Caste \\ &+ \beta_5 Religion + \beta_6 Educ + \beta_7 hh\_sex + \beta_8 Partner\_educ \\ &+ \beta_9 Smokes\_Cigs + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{7}$$

$$\begin{aligned} OverweightBMI = \beta_0 &+ \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\ &+ \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\ &+ \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\ &+ \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{8}$$

R4: Underweight BMI

$$\begin{aligned} UnderweightBMI = \beta_0 &+ \beta_1 PM2.5 + \beta_2 Smokes\_tabacco + \beta_3 Age + \beta_4 Caste \\ &+ \beta_5 Religion + \beta_6 Educ + \beta_7 hh\_sex + \beta_8 Partner\_educ \\ &+ \beta_9 Smokes\_Cigs + \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{9}$$

$$\begin{aligned} UnderweightBMI = \beta_0 &+ \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\ &+ \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\ &+ \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\ &+ \delta_d + \gamma_t + \epsilon_i \end{aligned} \tag{10}$$

R5: Poor Regressions

We restrict the regression sample to women belonging to poor households ($poor = 1$ in the NFHS wealth indicator).

$$
\begin{aligned}
UnderweightBMI^{poor} = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\
& + \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\
& + \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\
& + \delta_d + \gamma_t + \epsilon_i
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
OverweightBMI^{poor} = {} & \beta_0 + \beta_1 PM2.5 + \beta_2 Wealth + \beta_3 (Wealth \times PM2.5) \\
& + \beta_4 Smokes\_tabacco + \beta_5 Age + \beta_6 Caste + \beta_7 Religion \\
& + \beta_8 Educ + \beta_9 hh\_sex + \beta_{10} Partner\_educ + \beta_{11} Smokes\_Cigs \\
& + \delta_d + \gamma_t + \epsilon_i
\end{aligned} \tag{12}
$$

3.2 Causality

While we include a set of covariates, district and year fixed effects, our estimates should be interpreted as associations, rather than causal effects. There are three reasons behind this. First, district and time fixed effects remove all cross district differences in long run air quality, making the PM 2.5 coefficients reflect only within district variation. While this improves comparability, India's PM 2.5 levels are concentrated geographically, with little yearly variation that is mostly driven by weather. This leaves very little variation left to measure, making it harder to isolate the impacts of air pollution. This effect is reflected in our coefficients becoming smaller and insignificant after adding fixed effects. Secondly, although we have an extensive list of control variables, omitted variable bias may still exist because of factors that differ with time within districts such as changes in nutritional programs, district health interventions, seasonal disease patterns, and migration. Thirdly, reverse causality can affect our wealth estimates because wealthier households may sort themselves into less polluted neighbourhoods, and these patterns are not captured by district fixed effects.

4 Data Sources

We use the women's individual re-codes within the NFHS 4 and 5 surveys, measuring indicators of population, health and nutrition. The data includes women from 25-30 households, sampled randomly from each of 28,526 clusters (villages in rural areas and census enumeration blocks in urban areas), which were in turn randomly sampled from each district in India.

SHRUG PM2.5 dataset is the estimated annual ground-level fine particulate matter (PM2.5) for 1998-2020 by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments. To relate it with NFHS 4,5 we focus on the years 2015 and 2019.

The descriptive statistics of the variables used in the analysis are displayed in Table A. Average ambient air pollution levels are moderate according to the WHO specifications. Mean PM2.5 is $53.3\,\mu\text{g/m}^3$[3], with large variation across the sample (SD = 24). The minimum levels are around $8\,\mu\text{g/m}^3$, while the maximum exceeds $100\,\mu\text{g/m}^3$, which is in the unhealthy category.

Health indicators highlight the prevalence of malnutrition and anemia in women. 22% of women in the sample are underweight, while 18% are overweight. Mild anemia affects 38.6% of women, moderate anemia affects 12% and severe anemia 1%. The dataset contains women with ages from 15 to 49, with the average age being 29.4. Mean education level is 1.42, highlighting low levels of schooling. Partner education shows a similar pattern (mean = 1.61). This justifies adding low education levels as a control, because they could affect awareness and timely access and awareness of medication.

The average wealth index score is 2.95 (on a scale of 1 to 5), suggesting the average person surveyed falls close to the middle category. Household heads are predominantly male. Smoking of either tobacco or cigarettes is extremely rare among women in the sample.

Here, PM2.5 represents annual ambient particulate matter exposure at the district level. Body mass index, anemia categories, and haemoglobin levels are used as the primary health outcomes. Age, education, partner's education, caste, religion, and the sex of the household head capture demographic and socioeconomic characteristics that may influence both exposure and health. Smoking variables (tobacco, cigarettes, and pipes) help account for behavioural factors related to respiratory or metabolic health. The wealth index is used to measure household economic status and to construct interaction terms in the heterogeneity regressions. Overweight and underweight indicators are used in the BMI subgroup analyses.

Table 1: Summary Statistics

	Mean	SD	Min	Max
Exposure				
Mean PM2.5 detected in polygon	53.28047	24.17680	7.91016	109.01160
Anthropometrics and anemia				
Body mass index	2166.10000	409.94760	1201	4999
Severe anemia	0.0098959	0.0989846	0	1
Moderate anemia	0.1197596	0.3246805	0	1
Mild anemia	0.3858619	0.4867986	0	1
Hemoglobin (g/dL)	1.174158	0.1648605	0.2	2.54
Household and demographic characteristics				
Religion	2.466087	10.04411	1	96
Highest educational level	1.416823	1.016886	0	3
Sex of household head	1.133445	0.3400558	1	2
Respondent's current age	29.83217	9.764066	15	49
Caste or tribe	991.247	0.6401354	991	998
Husband/partner's education level	1.607700	1.009015	0	8
Wealth index	2.946114	1.387255	1	5
Nutrition and smoking outcomes				
Underweight	0.2225442	0.415955	0	1
Overweight	0.1808561	0.3848992	0	1
Smokes pipe	0.0003490	0.018677	0	1
Smokes cigarettes	0.0030827	0.0554363	0	1

5 Results

5.1 Baseline Regressions

Table 2: Effects of PM2.5 on Women's Health Outcomes

Outcome	**Baseline**	**+ Controls**	**+ (Controls + FE)**
Severe anemia	0.000012	-0.000050^{**}	0.00023
	(0.0000)	(0.0000245)	(0.00027)
Moderate anemia	0.00032^{*}	0.0001666^{***}	0.000320
	(0.000084)	(0.000097)	(0.00067)
Mild anemia	0.00093^{*}	0.0008727^{*}	0.0020
	(0.00014)	(0.000139)	(0.0015)
Hemoglobin	-0.00063^{*}	$-.0005219^{*}$	-0.001209
	(0.000085)	(0.0000785)	(0.00081)
BMI	-1.229^{*}	0.305^{*}	-4.846^{*}
	(0.179)	(0.212)	(0.890)

Table 2 presents the baseline, baseline with controls and fixed effects associations between PM2.5 and health outcomes. The single asterisk (*) highlights significant at 1% (**) significant at 5% and (***) significant at 10% level. The second column adds individual and household controls. The third column includes district and year fixed effects. Across specifications, higher PM2.5 levels are negatively associated with severe anemia, hemoglobin and BMI, and positively associated with moderate and mild anemia, with a small magnitude. Full regression tables are provided in Appendix Table 5.

In the baseline, districts with higher air pollution tend to have women with lower hemoglobin and severe anemia levels and the magnitude is small. After adding controls in column 2, this effect becomes significant at the 5% level for severe anemia, but remains insignificant for hemoglobin. Once district and time effects are included in column 3, the coefficients for severe anemia and hemoglobin become insignificant, suggesting the previous results could be due to cross district variation. This loss of significance could have two reasons. Firstly, districts with higher PM 2.5 already have poor health systems and nutrition. Second, as suggested in the causality section, due to district and time fixed effects, there is little variation left to estimate. Our results suggest the lack of a causal effect of high air pollution on severe anemia and hemoglobin levels.

In the baseline (1) and control (2) columns, districts with higher levels of air pollution have higher levels of moderate (0.00032) and mild anemia (0.00093) although the effect is small. Once district and year fixed effects are included in column 3, the coefficient becomes statistically insignificant, explanations of which can be similar to the severe anemia case.

BMI remains statistically significant across all specifications with a large magnitude (-4.84) in column 3, highlighting a robust negative relationship between BMI and air pollution. This motivates further analysis using overweight and underweight as separate outcomes.

5.2 Heterogeneity by Wealth:PM2.5 x Wealth Interactions

Table 3 represents the interactions between PM2.5 and household wealth quintiles. Here, the categorical variable wealth compares the wealth levels "poorer" "middle" "rich" and "richest" to the "poorest" category. Our results suggest that richer households are more affected by higher PM 2.5 levels. Full regression tables are provided in Appendix Table 6.

The relationship between air pollution and hemoglobin levels, bmi, severe anemia, moderate anemia and mild anemia is not statistically significant for the poorest women across all three specifications. In contrast, we find that poorer, middle, rich and richer category women have higher hemoglobin and lower severe, moderate and mild anemia levels compared to poorest women after controlling for pollution in columns 1 and 2. These wealth groups face smaller falls in hemoglobin levels and larger increases in severe and mild anemia cases caused by air pollution compared to the poorest category. The size of this effect is small across columns 3 with coefficients being significant and rising from 0.000036 to 0.00016 for severe anemia and being insignificant and rising from 0.000028 to 0.0025 for moderate anemia.

We pose two possible explanations for this. First, because wealthier women may spend more time indoors or in controlled environments, they could be sensitive to rising air pollution. Secondly, poorer women may already have low hemoglobin, making it harder to isolate the effect of rising air pollution. Once district and time fixed effects are included, we see that the larger effect of severe anemia on the "poorer" and moderate anemia on all wealth levels becomes insignificant, suggesting the above link could be driven by cross district variations.

Our results find a large and significant effect on wealth on BMI. With increasing wealth levels, the relationship between PM2.5 and BMI is negative, large and highly significant across all specifications. However, upon adding time and district fixed effects, magnitudes decrease.

Table 3: Effect of PM2.5 and Wealth Interactions on Health Outcomes

VARIABLES	**(1) Baseline**	**(2) + Controls**	**(3) + Controls + FE**
Hemoglobin			
PM2.5	−0.0001601	0.0000198	−0.00075
PM2.5 × Wealth_Q1	−0.0004415*	−0.0005286*	−0.000222**
PM2.5 × Wealth_Q2	−0.0005368*	−0.0006522*	−0.000325*
PM2.5 × Wealth_Q3	−0.000648*	−0.0007249*	−0.000351*
PM2.5 × Wealth_Q4	−0.00048*	−0.00056*	−0.000144
Severe Anemia			
PM2.5	−0.0000656*	−0.0001036***	0.000665
PM2.5 × Wealth_Q1	0.0000354	−0.0000109	0.0000367
PM2.5 × Wealth_Q2	0.000046***	0.0000858	0.0001634**
PM2.5 × Wealth_Q3	0.0000966*	0.0000679	0.000125***
PM2.5 × Wealth_Q4	0.000759*	0.0001154***	0.0001302***
Moderate Anemia			
PM2.5	0.0000109	−0.0002111	−0.000109
PM2.5 × Wealth_Q1	0.0002433**	0.0003718***	0.0002523
PM2.5 × Wealth_Q2	0.0002614**	0.0004239***	0.000289
PM2.5 × Wealth_Q3	0.00045*	0.0005278**	0.000254
PM2.5 × Wealth_Q4	0.00047*	0.0005392*	0.0000282
Mild Anemia			
PM2.5	0.0000382	−0.000244	0.001239
PM2.5 × Wealth_Q1	0.000729*	0.0011*	0.000549**
PM2.5 × Wealth_Q2	0.00102*	0.00117*	0.0004458***
PM2.5 × Wealth_Q3	0.00120*	0.00146*	0.000649**
PM2.5 × Wealth_Q4	0.000957*	0.00128*	0.0004212
BMI			
PM2.5	−0.15311	0.305	−2.16***
PM2.5 × Wealth_Q1	−0.689*	−0.645*	0.161
PM2.5 × Wealth_Q2	−1.167*	−1.37*	−0.129
PM2.5 × Wealth_Q3	−1.486*	−1.5*	−0.186
PM2.5 × Wealth_Q4	−0.782*	−1.07*	0.0206

5.3 BMI: Expanding Nutritional Outcomes

Table 4: Effects of PM2.5 on Nutritional Outcomes with Wealth Interactions

VARIABLES	**(1) Baseline**	**(2) + Controls**	**(3) + Controls + FE**
Panel A: Overweight			
PM2.5	0.0001394^{***}	-0.0006447^{*}	0.0003834^{*}
PM2.5 × Wealth Q1	-0.0004169^{*}	-0.0004104^{**}	0.0001495
PM2.5 × Wealth Q2	-0.000969^{*}	-0.0012872^{*}	0.0002525
PM2.5 × Wealth Q3	-0.00149^{*}	-0.0014549^{*}	−0.0002759
PM2.5 × Wealth Q4	-0.0011^{*}	-0.0013711^{*}	−0.0001934
Panel B: Underweight			
PM2.5	0.0004259^{**}	0.0009711^{*}	−0.0001502
PM2.5 × Wealth Q1	0.00064^{*}	0.000755^{*}	0.0001202
PM2.5 × Wealth Q2	0.00072^{*}	0.0008942^{*}	0.0001462
PM2.5 × Wealth Q3	0.00050^{**}	0.0005685^{**}	−0.0001427
PM2.5 × Wealth Q4	−0.00012	0.0000522	−0.0003622
Panel C: Subsample (Poor Women Only)			
PM2.5 (Overweight)	–	–	-0.0073145^{**}
PM2.5 (Underweight)	–	–	0.0041849^{*}

Table 4 shows that higher air pollution exposure is related to lower probability of women being overweight and this result is significant in columns 1 and 2. Once district and year fixed effects are added in column 3, this relationship becomes insignificant.

Higher air pollution exposure is related to higher probability of women being underweight (0.000383) and is significant across all three columns, suggesting a robust relationship between undernutrition and air pollution. Our results suggest that the probability of being overweight increases and being underweight decreases with higher wealth levels and this is significant across all three specifications.

The wealth groups poorer, middle, rich, richest face larger probabilities of being overweight and smaller probabilities of underweight compared to poorest women across columns 1 and 2. Once district and time fixed effects are added in column 3, these results become insignificant.

Panel C restricts the analysis to poor households. The probability of being underweight marginally increases (0.0041849) and being overweight marginally reduces (-0.0073145) with higher air pollution exposure among poor women, and this result is significant with a small magnitude in the controls and fixed effects specification, suggesting a small but robust relationship between nutritional outcomes and air pollution.

5.4 Limitations

While the analysis provides evidence of an association between ambient PM2.5 exposure and women's anemia and nutritional outcomes, several limitations must be acknowledged. Key control variables such as smoking, education, and wealth are based on broad categorical or binary measures that cannot capture continuous values, reflect detailed differences, and capture the mechanisms underlying heterogeneity. Differences across wealth quintiles may reflect underlying structural differences such as diet, occupation, or indoor air quality effects among the poorest rather than differential pollution vulnerability. Hemoglobin values also reflect NFHS's measurement protocol and may include non-classical measurement error. PM2.5 exposure is averaged annually, while anemia and BMI are measured at the time of survey (2015 and 2019). These limitations may affect the precision and interpretability of the results. The external validity of these results may be low as they may not generalize to microenvironments such as urban slums, industrial clusters, or high-exposure occupations, although they give a broad overview.

6 Conclusion

In this paper, we examined the relationship between ambient air pollution (PM 2.5) and women's health outcomes such as anemia, hemoglobin levels and BMI. We find that the links between air pollution and hemoglobin, severe, moderate, and mild anemia are small in magnitude and are explained by cross district differences, providing us with limited evidence of a causal relationship. Higher air pollution leads to falling BMI, and this evidence is robust across all specifications.

We find a robust and positive association between underweight and air pollution, while there is not significant evidence for overweight and air pollution. Our findings suggest that pollution does not disproportionately worsen anemia outcomes for wealthier women.

For the most disadvantaged group in our categories (poor women) higher pollution exposure is associated with an increase in underweight risk even after adding controls and fixed effects.

Our findings highlight the urgent need for air quality improvements by monitoring industrial emissions, and district level programs to tackle undernutrition. In the short run, districts with high pollution should improve access to nutritional supplements. In the longer run, we suggest implementation of emission controls for industries and improved air pollution monitoring in areas across districts with a history of higher exposure.

Given these patterns, we present a strong case for expanding pollution mitigation and nutrition support efforts in low-income districts. Future work can explore the relationship between pollution and labor migration, women's mobility, and cross examine the validity of these outcomes at the household, male and child level. We suggest longitudinal health and air pollution studies to strengthen causal relationships.

7 Appendix

Table 5: Regression Results on PM2.5 and Women's Health

	(1)	(2)	(3)	(4)	(5)
Mean PM2.5 detected in polygon	0.000237	0.000321	0.00205	-0.00121	-4.846***
	(0.000270)	(0.000679)	(0.00154)	(0.000812)	(0.890)
smokes pipe	-0.0194***	-0.0241	-0.0554	0.0552	-60.84
	(0.00471)	(0.0541)	(0.0935)	(0.0342)	(55.06)
smokes cigarettes	0.00188	-0.00614	-0.0428	0.0117	3.713
	(0.00606)	(0.0190)	(0.0325)	(0.0128)	(23.56)
respondent's current age	0.00000204	-0.00148***	-0.000731***	0.00132***	13.28***
	(0.0000493)	(0.000148)	(0.000208)	(0.0000778)	(0.227)
caste or tribe	-0.000617	0.00781***	0.00722*	-0.00469***	-8.037**
	(0.000993)	(0.00250)	(0.00380)	(0.00151)	(3.476)
religion	-0.0000177	0.000171	0.000111	-0.0000794	-0.395*
	(0.0000450)	(0.000146)	(0.000223)	(0.0000857)	(0.205)
highest educational level	-0.00234***	-0.0131***	-0.00443**	0.00743***	69.45***
	(0.000477)	(0.00163)	(0.00222)	(0.000862)	(2.125)
sex of household head	0.000981	-0.000770	0.00587	-0.00202	-11.23***
	(0.00111)	(0.00316)	(0.00495)	(0.00163)	(3.883)
husband/partner's education level	-0.00174***	-0.00211	-0.00445**	0.00358***	37.51***
	(0.000421)	(0.00143)	(0.00200)	(0.000697)	(1.849)
Year=2015	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Constant	0.599	-7.578***	-6.928*	5.884***	10132.4***
	(0.984)	(2.472)	(3.752)	(1.499)	(3442.3)
Observations	83746	83746	83746	83746	83746

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression Results on Heterogeneity effects of PM2.5 and Women's Health

	(1)	(2)	(3)	(4)	(5)
Mean PM2.5 detected in polygon	0.0000665	-0.000110	0.00124	-0.000752	-2.169*
	(0.000292)	(0.000728)	(0.00160)	(0.000852)	(1.222)
poorest	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
poorer	-0.00499	-0.0275***	-0.0418***	0.0240***	58.38***
	(0.00429)	(0.0104)	(0.0148)	(0.00531)	(11.48)
middle	-0.0124***	-0.0331***	-0.0513***	0.0349***	152.7***
	(0.00419)	(0.0111)	(0.0151)	(0.00617)	(13.59)
richer	-0.0141***	-0.0367***	-0.0689***	0.0417***	268.2***
	(0.00419)	(0.0116)	(0.0159)	(0.00621)	(15.66)
richest	-0.0148***	-0.0507***	-0.0683***	0.0428***	358.6***
	(0.00440)	(0.0114)	(0.0173)	(0.00691)	(17.41)
poorest × Mean PM2.5 detected in polygon	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
poorer × Mean PM2.5 detected in polygon	0.0000367	0.000252	0.000549**	-0.000223**	0.162
	(0.0000676)	(0.000165)	(0.000240)	(0.0000898)	(0.200)
middle × Mean PM2.5 detected in polygon	0.000163**	0.000290	0.000446*	-0.000326***	-0.129
	(0.0000656)	(0.000183)	(0.000252)	(0.000102)	(0.222)
richer × Mean PM2.5 detected in polygon	0.000125*	0.000254	0.000649**	-0.000351***	-0.187
	(0.0000660)	(0.000188)	(0.000264)	(0.000103)	(0.261)
richest × Mean PM2.5 detected in polygon	0.000130*	0.0000282	0.000421	-0.000145	0.0207
	(0.0000681)	(0.000184)	(0.000274)	(0.000114)	(0.290)
smokes pipe	-0.0200***	-0.0250	-0.0563	0.0561*	-44.76
	(0.00478)	(0.0537)	(0.0935)	(0.0340)	(51.67)
respondent's current age	0.0000623	-0.00113***	-0.000396*	0.00107***	10.42***
	(0.0000517)	(0.000152)	(0.000213)	(0.0000790)	(0.223)
caste or tribe	-0.000790	0.00716***	0.00625*	-0.00406***	-2.767
	(0.000996)	(0.00246)	(0.00377)	(0.00148)	(2.992)
religion	-0.0000225	0.000153	0.0000861	-0.0000620	-0.232
	(0.0000454)	(0.000145)	(0.000222)	(0.0000843)	(0.191)
highest educational level	-0.00139***	-0.00751***	0.00101	0.00342***	23.14***
	(0.000524)	(0.00173)	(0.00238)	(0.000882)	(1.968)
sex of household head	0.000903	-0.00137	0.00529	-0.00159	-6.273
	(0.00111)	(0.00316)	(0.00495)	(0.00162)	(3.886)
husband/partner's education level	-0.00117***	0.000787	-0.00137	0.00136*	12.72***
	(0.000435)	(0.00148)	(0.00204)	(0.000718)	(1.705)
smokes cigarettes	0.00168	-0.00672	-0.0436	0.0122	9.374
	(0.00605)	(0.0191)	(0.0326)	(0.0128)	(23.35)
Year=2015	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)
Constant	0.785	-6.904***	-5.905	5.219***	4633.7
	(0.988)	(2.436)	(3.733)	(1.470)	(2965.7)
Observations	83746	83746	83746	83746	83746

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression Results on Nutrional effects of PM2.5 and Women's Health

	(1)	(2)
Mean PM2.5 detected in polygon	-0.00547***	0.00245*
	(0.000203)	(0.00128)
smokes pipe	-0.0270	0.0115
	(0.0551)	(0.0662)
smokes cigarettes	0.00577	-0.00305
	(0.0232)	(0.0150)
respondent's current age	0.0111***	-0.00629***
	(0.000378)	(0.000199)
caste or tribe	-0.00522	0.00303
	(0.00541)	(0.00318)
religion	-0.000369**	0.0000760
	(0.000155)	(0.000217)
highest educational level	0.0563***	-0.0381***
	(0.00270)	(0.00185)
sex of household head	-0.0107***	0.0102**
	(0.00371)	(0.00398)
husband/partner's education level	0.0288***	-0.0205***
	(0.00258)	(0.00174)
Year=2015	0	0
	(.)	(.)
Constant	5.501	-2.830
	(5.356)	(3.155)
Observations	83746	83746

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regression Results on Nutritional + Heterogeneity effects of PM2.5 and Women's Health

	(1)	(2)
Mean PM2.5 detected in polygon	-0.00314***	0.00109
	(0.000499)	(0.00149)
poorest	0	0
	(.)	(.)
poorer	0.0360***	-0.0652***
	(0.0100)	(0.0144)
middle	0.119***	-0.114***
	(0.0121)	(0.0153)
richer	0.223***	-0.152***
	(0.0142)	(0.0160)
richest	0.300***	-0.176***
	(0.0157)	(0.0166)
poorest × Mean PM2.5 detected in polygon	0	0
	(.)	(.)
poorer × Mean PM2.5 detected in polygon	0.000150	0.000120
	(0.000169)	(0.000238)
middle × Mean PM2.5 detected in polygon	-0.000252	0.000146
	(0.000205)	(0.000237)
richer × Mean PM2.5 detected in polygon	-0.000276	-0.000143
	(0.000244)	(0.000253)
richest × Mean PM2.5 detected in polygon	-0.000193	-0.000362
	(0.000265)	(0.000264)
smokes pipe	-0.0127	0.00555
	(0.0556)	(0.0643)
respondent's current age	0.00875***	-0.00483***
	(0.000221)	(0.000196)
caste or tribe	-0.00118	-0.000551
	(0.00265)	(0.00293)
religion	-0.000241	-0.0000334
	(0.000174)	(0.000221)
highest educational level	0.0183***	-0.0139***
	(0.00203)	(0.00183)
sex of household head	-0.00685*	0.00724*
	(0.00409)	(0.00392)
husband/partner's education level	0.00863***	-0.00713***
	(0.00164)	(0.00171)
smokes cigarettes	0.0108	-0.00493
	(0.0230)	(0.0145)
Year=2015	0	0
	(.)	(.)
Constant	1.270	0.888
	(2.632)	(2.904)
Observations	83746	83746

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regression Results for Poor Women: Effects of PM2.5 on Nutritional Outcomes

	(1) Underweight BMI	(2) Overweight BMI
PM2.5 detected (polygon)	0.00245*	-0.00547***
	(0.00128)	(0.00040)
Smokes pipe	0.0115	-0.0270
	(0.0662)	(0.0573)
Respondent age	-0.00629***	0.0111***
	(0.00020)	(0.00022)
Caste/tribe	0.00303	-0.00522*
	(0.00318)	(0.00292)
Religion	0.00008	-0.00037*
	(0.00022)	(0.00020)
Highest education	-0.0381***	0.0563***
	(0.00185)	(0.00202)
Sex of HH head	0.0102**	-0.0107***
	(0.00398)	(0.00407)
Partner education	-0.0205***	0.0288***
	(0.00174)	(0.00171)
Smokes cigarettes	-0.00305	0.00577
	(0.0150)	(0.0233)
Year 2015 (ref.)	0	0
Constant	-2.830	5.501*
	(3.155)	(2.896)
Observations	83746	83746

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

8 References

References

[1] Barman, Manabindra. "Anaemia prevalence and socio-demographic factors among women of reproductive age (WRA): A geospatial analysis of empowered action group (EAG) states in India." *Science Direct*, 2024. https://www.sciencedirect.com/science/article/abs/pii/S187758452400011X. Accessed 06 Dec 2025.

[2] Chakraborty, Jayajit. "Air Quality and Environmental Injustice in India: Connecting Particulate Pollution to Social Disadvantages." *MDPI*, 4 Jan 2021. https://www.mdpi.com/1660-4601/18/1/304. Accessed 19 Nov 2025.

[3] Dey, Sagnik, et al. "Reducing the burden of anaemia in Indian women of reproductive age with clean-air targets." *Nature Sustainability*, 2022. https://www.nature.com/articles/s41893-022-00944-2. Accessed 06 Dec 2025.

[4] deSouza, Priyanka N. "An environmental justice analysis of air pollution in India." *Nature*, 2023. https://www.nature.com/articles/s41598-023-43628-3. Accessed 19 Nov 2025.

[5] George, Paul E., et al. "Impact of ambient air pollution and socio-environmental factors on the health of children younger than 5 years in India: a population-based analysis." *The Lancet Regional Health: South Asia*, 2024. https://www.thelancet.com/journals/lansea/article/PIIS2772-3682(23)00188-9/fulltext. Accessed 19 Nov 2025.

[6] Haberzettl, Petra, et al. "Exposure to Fine Particulate Air Pollution Causes Vascular Insulin Resistance by Inducing Pulmonary Oxidative Stress." *National Library of Medicine*, 2016. https://pmc.ncbi.nlm.nih.gov/articles/PMC5132639/. Accessed 06 Dec 2025.

[7] Hwang, Juyeon, and Hyun-Jin Kim. "Association of ambient air pollution with hemoglobin levels and anemia in the general population of Korean adults." *PubMed*, 9 Apr 2024. https://pubmed.ncbi.nlm.nih.gov/38594672/. Accessed 7 Dec 2025.

[8] Ji, Weibiao, et al. "Trends and regional disparities in the global burden of disease attributable to household air pollution in 204 countries and territories, 1990–2021: an analysis of the global burden of disease study." *National Library of Medicine*, 2025. https://pmc.ncbi.nlm.nih.gov/articles/PMC12182166/. Accessed 19 Nov 2025.

[9] Munir, Mehnaz, et al. “Effects of ambient air pollution on obesity and ectopic fat deposition: a protocol for a systematic review and meta-analysis.” *National Library of Medicine*, 2024. `https://bmjopen.bmj.com/content/14/2/e080026.full`. Accessed 06 Oct 2025.

[10] O’Neill, Marie S. “Health, Wealth, and Air Pollution: Advancing Theory and Methods.” *Environmental Health Perspectives*, 2003. `https://ehp.niehs.nih.gov/doi/epdf/10.1289/ehp.6334`. Accessed 19 Nov 2025.

[11] Pandey, Anamika, et al. “Health and economic impact of air pollution in the states of India: the Global Burden of Disease Study 2019.” *The Lancet Planetary Health*, 2021, vol. 5, issue 1, e25–e38.

[12] Sachdeva, Ishaan, et al. “Air quality and respiratory health in children.” *ERS Publications*, 2023. `https://publications.ersnet.org/content/breathe/19/2/230040.abstract`. Accessed 19 Nov 2025.

[13] Sun, Qinghua, et al. “Ambient Air Pollution Exaggerates Adipose Inflammation and Insulin Resistance in a Mouse Model of Diet-Induced Obesity.” *AHAIASA Journals*, 2009. `https://www.ahajournals.org/doi/10.1161/CIRCULATIONAHA.108.799015`. Accessed 06 Dec 2025.

[14] “World’s Most Polluted Cities 2024.” *AQI.in*. `https://www.aqi.in/in/world-most-polluted-cities`. Accessed 19 Nov 2025.