Aspirations in the Air: Effect of Development Schemes on AQI

Evidence from a Spatial RD in India

Aayushi Agarwal Bhaskar Agarwal Gaurav Banerjee Nandish Patel

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1 Introduction

Development is a double-edged sword. On one hand, it promises better infrastructure, improved livelihoods, and economic growth. On the other, it often comes with environmental costs that aren't immediately visible but deeply consequential. In India, where massive development schemes touch millions of lives, understanding this trade-off isn't just an academic exercise: it's a matter of public health. This paper asks a straightforward question: when the government invests heavily in developing certain districts, what happens to the air people breathe? We focus on India's Aspirational Districts Scheme, launched in 2018 to rapidly transform 117 underdeveloped districts, and use spatial regression discontinuity to measure its impact on PM2.5 pollution levels. What we find challenges simple narratives about development and environment, revealing that the answer depends critically on what kind of development happens and where.

2 Background

2.1 Motivation

When we first started thinking about this research question, we were struck by a simple but profound dilemma. We all want development—better roads, more industries, improved living standards. But what if development comes at a cost we don't often talk about? What if the very policies designed to lift people out of poverty are also making the air they breathe more toxic? India is home to some of the most polluted cities in the world. If you've ever visited Delhi in winter or walked through an industrial town in the evening, you know what we're talking about. The air feels heavy, sometimes you can even see it—a grey-brown haze hanging over everything. This isn't just uncomfortable; it's deadly. According to various health studies, air pollution contributes to millions of premature deaths in India every year. But here's what made us curious: development policies are being rolled out across hundreds of districts in India. Some districts get these programs, others don't. What happens to air quality in the places that receive development interventions? Does it get better because people switch from burning wood to using clean cooking gas? Or does it get worse because suddenly there are more construction sites, more factories, more vehicles on newly built roads? This isn't just an academic question. If we're going to design policies that genuinely improve people's lives, we need to understand their full impact—not just on income or education, but also on the environment that people live in every single day. The problem is, it's really hard to figure out what causes what. Do districts with worse air quality get selected for development programs? Or do development programs themselves change air quality? We spent a lot of time thinking about how to untangle this mess, and that's what led us to the approach we'll describe in this paper.

2.2 Two Ways Development Could Affect Air Quality

As we dug deeper into this question, we realized that development could affect air quality in completely opposite ways. Let us explain both possibilities, because understanding these competing mechanisms is crucial to making sense of our results.

Mechanism I: Development Could Make Air Quality Better

Think about a typical household in rural India. Many families still cook using traditional stoves that burn wood, dung cakes, or crop residue. These stoves produce a lot of smoke—not just inside the house (which is terrible for women and children who spend time cooking), but also outside, contributing to the overall pollution in the area. Now, imagine a development program comes in and helps families switch to LPG gas cylinders or cleaner cooking technologies. Suddenly, you have hundreds or thousands of households that are no longer burning biomass every day. That should improve air quality, right? There are other ways development might help too. Better waste management systems mean less garbage being burned in open pits. We've seen this ourselves—in many towns, people simply burn their trash because there's no other option. Development programs that set up proper waste collection and disposal can eliminate this source of pollution. Similarly, programs that teach farmers alternatives to burning crop residue after harvest could reduce those massive seasonal spikes in air pollution that we see in states like Punjab and Haryana. So through this lens, development looks like it should improve air quality. More resources mean cleaner technologies, better systems, less pollution. This is what we call the "optimistic mechanism."

Mechanism II: Development Could Make Air Quality Worse

But wait—there's another story we could tell, and it's quite different. Development often means construction. Roads being built, buildings going up, infrastructure projects everywhere. Anyone who's lived near a construction site knows what this means: dust everywhere, trucks rumbling by all day, diesel generators running constantly. All of this produces pollution. Then there's industrialization. Development programs often try to boost industrial output—more factories, more manufacturing. These activities produce emissions. Even if individual factories follow pollution control norms (which, let's be honest, doesn't always happen), having more industrial activity in an area generally means more pollution overall. And here's something we found particularly interesting: better roads might actually increase pollution in the short to medium term. How? Better roads mean more vehicles. Development increases incomes, and people buy motorcycles, cars, trucks. More vehicles mean more emissions, especially in India where emission standards aren't always strictly enforced and many vehicles are quite old. There's also a concentration effect. As development happens, economic activity tends to cluster in certain areas. Urbanization increases. Instead of pollution being spread out over a large rural area, it gets concentrated in smaller spaces where more people are affected by it. So through this lens, development looks like it should worsen air quality. More construction, more industry, more vehicles, more concentrated activity. This is what we call the "pessimistic mechanism."

So Which Is It?

The honest answer? We don't know—and that's exactly why this research is important! Both mechanisms make sense theoretically. Both are probably happening simultaneously. The real question is: which effect is stronger? Does the positive impact of cleaner cooking and better waste management outweigh the negative impact of construction and industrialization? Or is it the other way around? Moreover, the answer might be different in different places. A state that emphasizes clean cooking programs might see air quality improvements. A state that focuses heavily on infrastructure and industrial development might see air quality deteriorate. This is fundamentally an empirical question—something we need to measure and test, not just theorize about.

2.3 The Aspirational Districts Scheme: Our Natural Experiment

To answer this, we needed a situation where development happened in some places but not others, where that difference wasn't driven by factors independently affecting air quality. Enter "exogenous variation." In January 2018, the Indian government launched the Aspirational Districts Scheme (ADS)—identifying 117 of India's most underdeveloped districts for extra attention, resources, and support. NITI Aayog managed this program, focusing on basic infrastructure, health and nutrition, education, and agriculture with financial inclusion. Districts were selected based on a composite deprivation index. Crucially, these boundaries were drawn long ago, often during British colonial times. Nobody created these boundaries anticipating the 2018 scheme. This creates a "natural experiment." Imagine two similar villages just kilometers apart. One falls just inside an ADS district and gets extra development attention; the other falls just outside and doesn't. Otherwise, they're quite similar. By comparing areas just inside ADS boundaries to areas just outside, we can isolate the program's effect on air quality. Villages on either side should be similar except for the intervention. This approach gives us a credible way to answer: How does development actually affect air quality based on what happened in these 117 districts?

3 Methodology

3.1 Subdistricts Data

A geographic RDD study by definition requires spatial data for the units of interest. The granularity of said units for this study will be the subdistrict level - we compare subdistricts just along a treatment border to isolate the causal effect of the treatment (ADS). From among the several available formats of spatial data, we have used subdistrict shapefiles (.shp) which is compatible with most packages in the statistical software of our choice, R. To access authentic and updated subdistrict polygons, we downloaded all India level shapefiles from the Onlinemaps portal of SoI. It contains 4723 features, 5 fields (tehsil, district, state, shape length and shape area) and projected CRS (Coordinate Reference System) of "LCC WGS84".

3.2 ADS Treatment Status

As discussed earlier, we use the 2018 updated list of 'Aspirational Districts' to identify treatment status. A detailed list containing names of all 117 districts under ADS is presented in Table 4.4. To arrive at an indicator for treatment status, we have to generate a binary variable in the subdistricts shape file using the list of the 'Aspirational Districts'. However, the list of districts provided by NITI Aayog does not have any geo-spatial attributes. Hence, we use a fuzzy matching algorithm known as 'Jaro Distance' to merge data using string values (i.e., the names of the districts). This algorithm assigns a similarity score to each string in the master common id with all the strings in the secondary common id using the following formula and then, the string in the secondary dataframe with the highest similarity can be assigned to the respective string in the master dataframe.

$$\text{Similarity} = \begin{cases} 0, & \text{if } m = 0, \\ \frac{1}{3}\left(\frac{w_1 m}{|a|} + \frac{w_2 m}{|b|} + \frac{w_3(m-t)}{m}\right), & \text{otherwise.} \end{cases}$$

Here, m is the number of character matches, t is the number of transpositions, $|a|$ is the number of characters in string a and w_i are weights summing to 3 Vanderloo (2023).

After applying the algorithm, some corrections had to be made manually. Figure 1 plots the filtered subdistricts for the 27 states with treatment status.

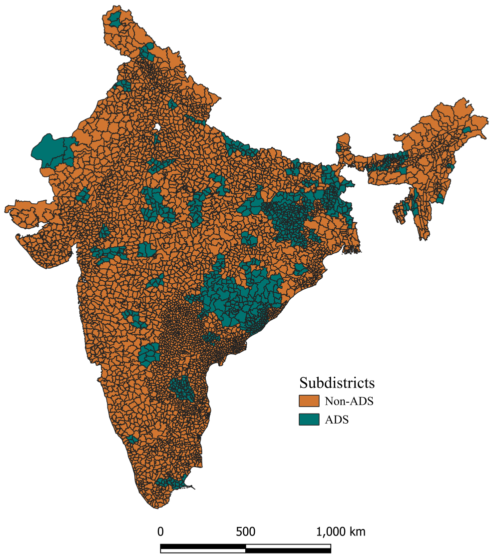


Figure 1: ADS (treated) vs Non-ADS (non-treated) subdistricts

3.3 Distance to Cutoff

A distinctive feature of a regression discontinuity design is the running variable. While a dummy can indicate whether a unit is treated or not, it is the running variable which determines how close the unit was to the treatment cutoff. We employ the more traditionally used Euclidean distance from the cutoff boundary for each unit as the running variable. The geographic cutoff was created using the boundary of the treated polygons. This was primarily done using R and QGIS. The cleaned cutoff boundary is plotted in Figure 2.

Now, we can use the cutoff boundary to calculate distance to cutoff for each unit. If the units are points, then the calculation is intuitive. However, for us the units under study are subdistrict polygons. As a result, we calculate distance to the cutoff from the centroid of each polygon. We ensured that the distances to cutoff are positive for the treated units and negative for the control units.

3.4 Controls Data

Ideally, the assumption that treatment is randomly assigned just around the cutoff implies that there is no requirement for controls in a regression discontinuity design Huntington-Klein (2021). However, in the context of geographic cutoffs these assumptions may not hold good and potential confounders have to be addressed. The justification for including controls is not the scope of this section. It will be discussed later. Here, we shall focus on the data collection aspect of the controls.

To get subdistrict level controls, we used the SHRUG dataset Asher et al. (2021). From the SHRUG dataset, we used the Indian population census data for 2001 (PC01) and 2011 (PC11) to interpolate pre-treatment controls for the year 2018 Census of India (2011). For each census year, SHRUG provides a PCA (Population Census Abstract) directory, a town directory and a village directory. The SHRUG dataset is designed for the very purpose of spatial analysis. However, the two shapefiles provided by SHRUG come with their own problems of either deprecated and incomplete shapefiles.

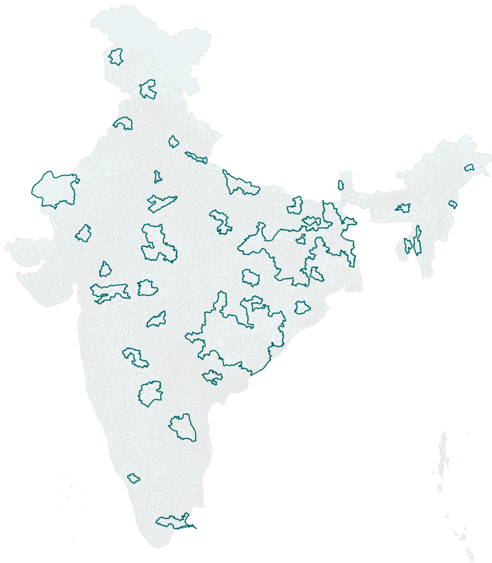


Figure 2: Treatment Cutoff Boundaries

Thus, our master shapefile will remain the one provided by SoI and we will use SHRUG only for the control variables.

Table 1: Description of SHRUG variables

S. No	Controls	Description	Directory
1.	pc11_pca_tot_p	Total population count for 2011 census	PCA
2.	pc11_pca_p_sc	Total Scheduled Castes population	PCA
3.	pc11_pca_p_st	Total Scheduled Tribes population	PCA
4.	pc11_pca_p_lit	Literate Population Total	PCA
5.	pc11_pca_tot_work_p	Total Workers	PCA
6.	pc11_vd_t_p	Total Population of Village	VD
7.	pc11_vd_land_fores	Forest Area (in Hectares)	VD
8.	pc11_vd_area	Total Geographical Area (in Hectares)	VD
9.	pc11_td_max_temp	Maximum Temperature (in C)	TD
10.	pc11_td_min_temp	Minimum Temperature (in C)	TD
11.	pc11_td_avg_rain	Rainfall (mm)	TD

Notes. Similarly, pc01 for 2001 census.

Since we need to interpolate controls for 2018, the 2001 and 2011 variables have to be merged. We can use the more granular shrid to merge them and then aggregate back to the subdistrict level. We remove any observation with NAs in the desired fields and remove all duplicated shrids (a shrid is a village/town level data estimation with consistent geometries since 1991) before merging. The aggregation at the subdistrict level was done by summing all controls variables for shrids within the same subdistrict. Next, the two subdistrict level shapefiles (one obtained by this merging exercise and the other SoI Masterfile) are overlayed and any subdistrict which does not get assigned controls is dropped from further analysis.

Once we have our master shapefile with controls for both 2001 and 2011, we can use them to interpolate controls for 2018. This was done in the following manner. First, we calculate the growth rate of the controls between 2001 and 2011:

$$Growthrate_{ij} = \frac{PC11_{ij} - PC01_{ij}}{PC01_{ij}} \times 100$$

Here, $Growthrate_{ij}$ is the rate of growth in control j for subdistrict i. Since this is for a period of 10 years, the annual growth rate is estimated as:

$$AGR_{ij} = \frac{Growthrate_{ij}}{10}$$

Then, controls for 2018 are estimated using the classic population growth formula:

$$PC18_{ij} = PC11_{ij} \left(1 + \frac{AGR_{ij}}{100}\right)^7$$

Once we have the 2018 control values, we use base values (total population or total area) to convert them into % shares. Accordingly, the final set of controls used in this study are presented in the table below.

Table 2: Control variables

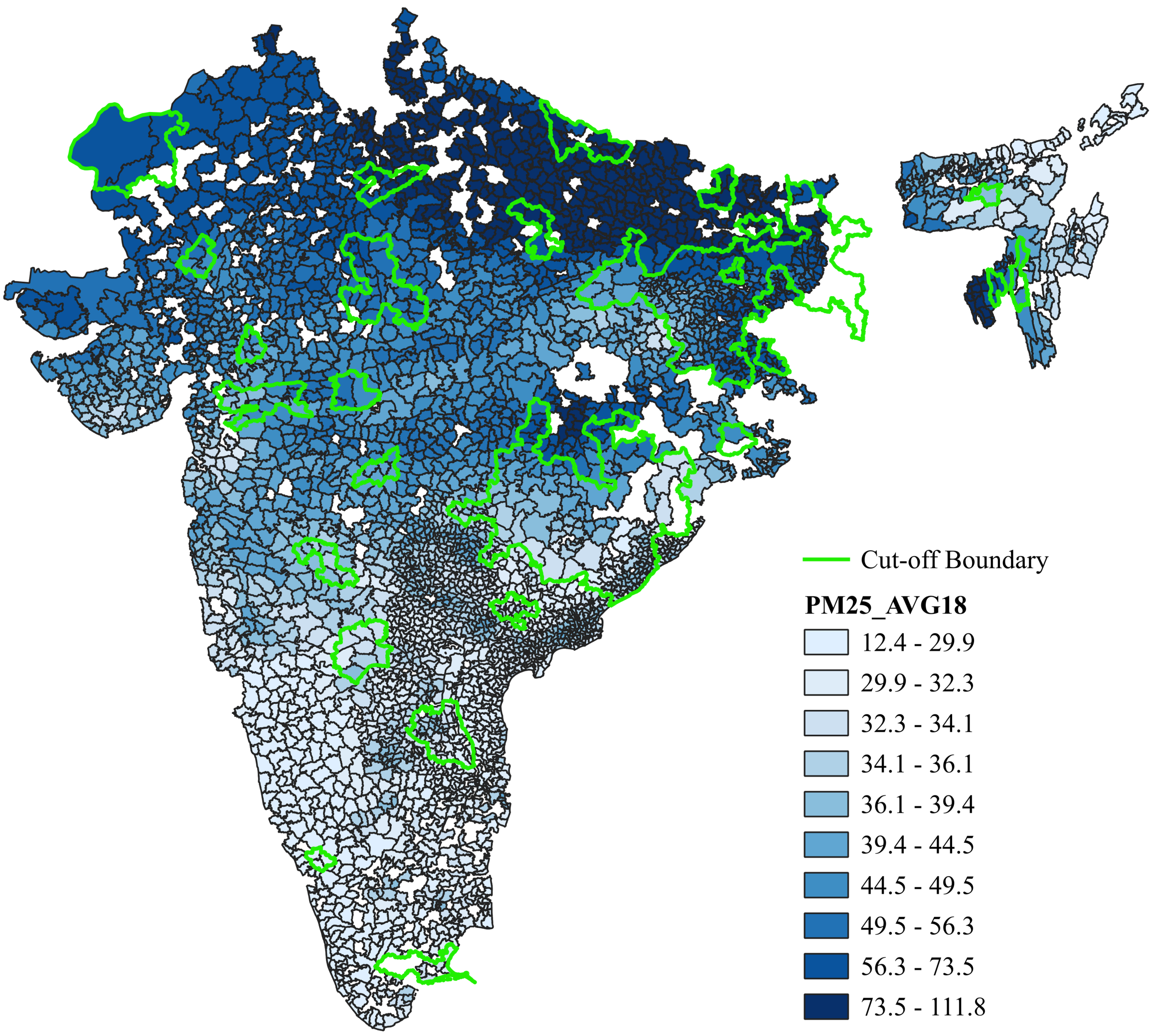
S. No	**Controls**	**Description**
1.	pc18_sc_share	Scheduled castes population share
2.	pc18_st_share	Scheduled tribes population share
3.	pc18_lit_share	Literate population share
4.	pc18_rural_share	Rural population share
5.	pc18_work_share	Working population share
6.	pc18_forest_share	Forest cover share

3.5 AQI Data

To measure subdsitrict level air quality, we used PM2.5 pollution from the SHRUG dataset Asher et al. (2021). The name of the variable on the dataset is Surface PM2.5 and it is described as "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 with the GEOS-Chem chemical transport model". We have access to the minimum, maximum and mean levels of PM2.5 in a subdistrict polygon across 1998 to 2020, however for the purpose of this study we will restrict our attention to the mean.

Figure 3 plots a heatmap of the subdistrict AQI levels with treatment boundaries. Any missing values are subdistricts that get lost in the cleaning process.

Figure 3: AQI heatmap with treatment boundaries



4 Empirical Strategy

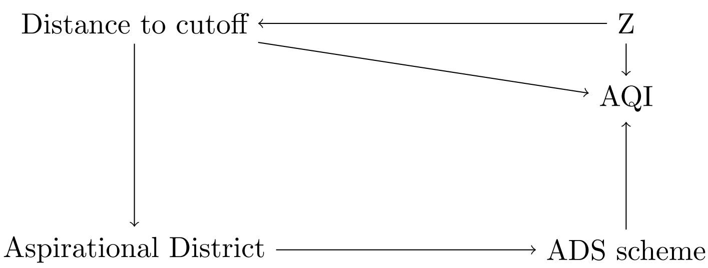
4.1 Identifying Strategy

In this paper, our attempt is to capture the effect of a geographically assigned treatment on air quality. Though the treatment is assigned at the district level, we cannot compare differences in AQI across districts as it would suffer from selection bias. Treating one district over another is a choice made by the government and not a random selection. Comparing districts in this regard is plagued by 'reverse causality', wherein it is difficult to isolate the effect of being treated on AQI from the effect the level of AQI had on the probability of being treated.

Therefore, to establish causality we look at the air quality for finer geographical units namely 'Tehsils/Taluks'. The idea is to consider the district boundaries as a cutoff and compare subdistricts on both sides that are 'just treated' and 'just not treated' within a bandwidth. This is called a regression discontinuity design (RDD), specifically a spatial RDD. Three recurrent terminologies for this design should be discussed– running variable, cutoff and bandwidth. The value of the running variable with respect to the cutoff determines the treatment status for each unit. The running variable in this study is the distance to cutoff for each subdistrict, centered at 0 (cutoff). The bandwidth would be the equidistant region on both sides of the cutoff within which we will compare subdistricts. It will be discussed in greater detail in the next section.

The identifying assumption of an RDD is that the units close to the cutoff are 'randomly assigned' and cannot choose their own treatment status. If these conditions are met, we can isolate variation along Treatment $\longrightarrow$ Outcome by controlling all variation in the running variable except for being above the cutoff (Huntington-Klein, 2021). In our case, being above cutoff is the same as being treated and resultantly we have a sharp regression discontinuity design, as shown in the figure below.

Figure 4: DAG



Here, Distance to cutoff is the running variable and Aspirational District indicates being above cutoff. Those who are above the cutoff get the treatment (SRE scheme) which we suspect affects AQI. Z refers to the unobservable confounders.

4.2 Model

In an RDD, the empirical measure for the local average treatment effect (LATE) is the difference in intercepts of two regressions across the cutoff. As a result our model takes the following structure–

$$pm25\_avg18_i = \beta_0 + \beta_1 A_i + \beta_2 D_i + \beta_3 A_i D_i + \mu_i$$

Here, $pm25\_avg18_i$ is the mean PM2.5 of 2018 for subdistrict i. A_i is a dummy variable indicating treatment status. It takes value 1 if subdistrict i lies in the ADS treated area and 0 otherwise. D_i is the running variable- distance which is centred at the cutoff. Thus, it reflects the distance from cutoff for subdistrict i. The coefficient of interest is β_1, which is the difference between the intercepts of two local linear regression just across the cutoff. The above model is assumed to be a linear regression. However, it is not always the case that straight lines are a good fit for the data across the cutoff. In this case we may need to check for nonlinear functional forms like a second-order polynomial. In that case, our model becomes–

$$pm25\_avg18_i = \beta_0 + \beta_1 A_i + \beta_2 D_i + \beta_3 {D_i}^2 + \beta_4 A_i D_i + \beta_5 A_i (D_i)^2 + \mu_i$$

Once again, β_1 is the coefficient of interest and represents the discontinuity in the two fitted parabolas. Following the recommendations of Gelman and Imbens (2019), we do not test for higher order polynomials greater than two. We use a package in R called **rdrobust** which allows for estimation of bias-corrected robust rd estimates Calonico et al. (2014). The rdrobust package also helps to take the decision regarding bandwidth size out of the researcher's hands and effectively prevent cherry picking. It selects that size of bandwidth as optimal which minimizes mean squared error (MSE). Lastly, since proximity of a subdistrict to the cutoff implies higher similarity between the controlled and treated units, a weight function is generally used in spatial regression discontinuity designs. By default, rdrobust uses a triangularly weighted kernel, i.e., observations right at the cutoff are given the highest weight and the weights linearly decrease as we move to either side of the cutoff reaching 0 at the bandwidth max and min.

4.3 Controls

An RDD by the nature of its assumptions does not require controls. Including controls would imply that we do not expect the treatment to be randomly assigned around the cutoff. This section will provide justifications for the use of controls and will discuss the nature of controls to be included.

Our approach to the spatial RDD uses a single running variable (distance to cutoff) instead of two running variables (latitude and longitude). This simplification however implies a reduction in dimensionality and a loss of valuable spatial information. To better understand how this impacts our study, consider an example. Let there be two subdistricts located far from each other but equidistant to a cutoff boundary. In the multiple running variable approach, the lack of proximity between them is evident as we have exact coordinates. But, in the single running variable approach the two can have the exact same distance to cutoff. Information regarding their vicinity vis-a-vis each other is lost Keele and Titiunik (2015). To account for this, we include pre-treatment controls in the RD estimation. Additionally, adding controls reduces the unexplained variation which can help increase the precision of the RD estimates Huntington-Klein (2021).

To further support the RD assumption, restrictions can be added to the geographic area in study. Since the treatment is assigned at the district level we cannot control for them. Otherwise, we would be comparing all treated units to other treated units and all control units to other control units which is incorrect. Thus, the largest geographic restriction we can add is at the state level. This was implemented in two ways. First, we filtered the dataset and ran our model on each individual state and reported their respective RD estimates. Second, we considered the entire dataset but included state fixed effects to report a single RD estimate for all states. In the latter case our regression equation becomes-

$$pm25\_avg18_{is} = \beta_0 + \beta_1 A_i + \beta_2 D_i + \beta_3 A_i D_i + X_i\gamma + \lambda_s + \mu_i$$

Here, $X_i\gamma$ are a set of subdistrict level controls and λ_s captures the state fixed effects. Note that these will be omitted when running the regression individually for each state.

5 Results

State-wise RD estimates and placebo tests show that the AQI (proxied by the average PM2.5 levels) in 2018 is lower for treated subdistricts in Jharkhand. In the aggregated model, no statistically significant difference in AQI can be found. For each model run, we report the bias-correct robust estimate of β_1, 95% confidence interval, standard error, robust p-value, number of observations, number of effective observations in bandwidth and the data-driven MSE-optimum bandwidth. All standard errors are heteroskedasticity robust and the level of clustering will be mentioned (if any). This chapter is divided into two sections. The first, discusses the main results and the second section provides results from a placebo test used to increase the robustness of our estimates for the state where the AQI is affected significantly in 2018.

4.1 Main RD estimates

We begin by estimating the spatial RD with as well as without controls for each individual state. Out of the 14 states, the results could not be estimated for Karnataka, Uttar Pradesh, Chattisgarh, Odisha and Assam on account of lower number of observations relative to the number of parameters to be estimated. This results in a short ranked matrix.[1] For the remaining 9 states, the results are presented in Table 4.1.

As suspected, including controls reduces the standard errors for almost all states, with the exception of Bihar and Madhya Pradesh. Statistically significant results are found only for Jharkhand. We find that average PM2.5 levels in 2018 are lower in the treated subdistricts of Jharkhand by roughly 19 units in the specification with controls and by about 22 units without controls. While the conventional RD estimate for several states appears large or imprecise, the bias-corrected robust estimates indicate that these effects are not statistically meaningful. For all remaining states, any difference in PM2.5 levels is likely driven by sampling variability rather than a true treatment effect. Lastly, although some states experience a reduction in standard errors after adding controls, the corresponding coefficients also shrink in magnitude, leaving the overall inference unchanged.

Table 4.1: State-wise Bias-corrected Robust RD Estimates

Outcome variable: Average PM2.5 in 2018

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
ANDHRA PRADESH	2.125	[−0.772, 5.021]	1.478	0.151	635	116	13.515	Yes
ANDHRA PRADESH	1.382	[−1.813, 4.577]	1.630	0.397	635	128	15.345	No
BIHAR	14.087	[−128.410, 156.585]	72.704	0.846	79	11	7.035	Yes
BIHAR	−39.645	[−110.808, 31.518]	36.308	0.275	79	5	5.643	No
GUJARAT	3.702	[−14.711, 22.115]	9.394	0.694	201	47	36.846	Yes
GUJARAT	−0.989	[−24.325, 22.346]	11.906	0.934	201	47	34.969	No
JHARKHAND	**-18.790**	**[-35.527,-2.054]**	**8.539**	**0.028**	**256**	**17**	**4.398**	**Yes**
JHARKHAND	−22.381	[−40.013, −4.749]	8.996	0.013	256	43	6.602	No
MADHYA PRADESH	3.868	[−4.513, 12.250]	4.277	0.366	259	77	24.041	Yes
MADHYA PRADESH	6.142	[−2.170, 14.454]	4.241	0.148	259	72	21.989	No
MAHARASHTRA	0.746	[−17.722, 19.214]	9.423	0.937	329	53	15.824	Yes
MAHARASHTRA	−2.357	[−28.844, 24.129]	13.514	0.862	329	54	16.327	No
MIZORAM	8.251	[1.925, 14.578]	3.228	0.011	16	15	124.220	Yes
MIZORAM	23.682	[14.480, 32.884]	4.695	0.000	16	15	124.220	No
RAJASTHAN	29.610	[−25.449, 84.670]	28.092	0.292	230	45	17.098	Yes
RAJASTHAN	31.702	[−26.159, 89.562]	29.521	0.283	230	63	25.969	No
TELANGANA	2.924	[−17.674, 23.522]	10.509	0.781	429	23	5.165	Yes
TELANGANA	−13.303	[−50.241, 23.636]	18.847	0.480	429	21	4.833	No

Next, we estimate the spatial RD model for the full dataset by pooling all subdistricts together and including state fixed effects. The aggregated estimate is not statistically significant, as shown in Table 4.2. This is expected, since only one state - Jharkhand, exhibits a significant treatment effect, and the remaining states show estimates close to zero. When these heterogeneous state-level

[1] More variables compared to the number of equations.

effects are combined, the overall impact naturally averages out. For inference, *rdrobust* already reports heteroskedasticity-robust nearest-neighbour standard errors (based on the three closest units), which effectively behaves like subdistrict-level clustering. Therefore, clustering at the subdistrict level does not change the results, and we do not report it separately. Since treatment effects differ across states, clustering at the state level is more appropriate. Although state-clustered standard errors are slightly smaller than the unclustered ones, they are still not small enough to make the pooled estimate statistically significant.

Table 4.2: Aggregated Bias-corrected Robust RD Estimates

Outcome variable: Total PM2.5 in 2018

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
ALL STATES	1.829	$[-1.561, 5.220]$	1.730	0.290	3456	889	20.572	Yes
ALL STATES	−1.916	$[-17.619, 13.787]$	8.012	0.811	3456	1194	30.659	No

Notes. Standard errors are clustered by state.

4.2 Placebo test

As discussed earlier, many schemes and policies that already existed were implemented more effectively under the Aspirational Districts Programme in 2018. However, to establish that the significant results we observe for Jharkhand are caused by the 2018 intervention and not the effect of any previously existing treatment, we conducted a placebo test which checks for discontinuity using 2018 boundaries for "dummy" pre-2018 PM2.5 data (2017). If the novel treatments did not exist before 2018, then there should be no difference in PM2.5 across the control and treated units. The same was confirmed and results are presented in Table 4.3.

Table 4.3: Placebo Test

Outcome variable: PM2.5 in 2017 (before policy implementation)

	Estimate	95% CI	Std. Error	Robust P-Value	Obs	Eff. Obs	Bandwidth	Covs
JHARKHAND	−17.297	$[-36.163, 1.568]$	9.626	0.072	256	29	5.261	Yes

Notes. Standard errors are heteroskedasticity robust.

To understand why Jharkhand displays a statistically significant improvement in PM2.5 levels after the launch of the Aspirational Districts Scheme (ADS), it is important to consider how districts were selected and how the scheme interacts with the state's baseline conditions. The ADS identifies districts using a composite deprivation index covering five sectors: health, education, agriculture, financial inclusion and basic infrastructure. Jharkhand performs poorly across several of these dimensions, particularly in basic infrastructure, which resulted in 19 out of its 24 districts being classified as aspirational. Because the ADS measures incremental progress relative to a district's starting point, states beginning from very low baselines tend to show rapid improvements once interventions are introduced. Jharkhand's low initial levels therefore created substantial scope for early gains, reflected in the immediate reductions in PM2.5 in 2018. This is consistent with the sharp rise in its Delta Ranking, where Ranchi moved from rank 106 to rank 10 within a few months of the scheme's launch.

Jharkhand's administrative and political context further strengthened this effect. As a state affected by Left-Wing Extremism (LWE), it already operated within a strong centre–state coordination framework, facilitating tighter monitoring, targeted resource flows and better alignment with national priorities. This allowed the ADP's model of convergence, competition and collaboration to operate more effectively compared to many other states. Improvements in basic services, digital monitoring, Anganwadi strengthening, nutrition interventions and early action under the state's Clean Air Action Plans were implemented with greater coherence and speed. The combination of extensive district coverage, very low starting conditions, strong centre–state collaboration in LWE-affected regions and high administrative convergence explains why Jharkhand alone displays a statistically significant discontinuity in PM2.5 levels.

6 Conclusion

Our results indicate that the Aspirational Districts Programme had a statistically significant impact on air quality only in Jharkhand, where treated subdistricts experienced an improvement of roughly 18.8 units in PM2.5 in 2018. This aligns with the state's low baseline conditions, extensive coverage under the programme, and rapid early improvements documented in the Delta Rankings. The aggregate results provide evidence of a dual mechanism: development interventions can generate short-term pollution through construction and economic activity, yet simultaneously reduce pollution through improved public services, institutional strengthening, and cleaner infrastructure.

At the same time, the study has limitations, particularly regarding potential spatial spillovers and the use of Euclidean rather than network-based distances. Future work can enhance robustness by analysing outcomes at finer geographies such as villages or towns, and by incorporating a two–running variable design to better validate RD assumptions. Understanding how development shapes environmental outcomes remains essential for designing policies that promote growth while safeguarding public health.

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A Additional Tables

Table 4.4: State-wise 2018 ADS Districts

S. No	State	No. of Districts	Districts
1	Karnataka	2	Raichur, Yadgir.
2	Andhra Pradesh	3	Vizianagaram, Visakhapatnam, Cuddapah.
3	Telangana	3	Khammam, Jayashankar Bhoopalapally, Kumuram Bheem (Asifabad).
4	Uttar Pradesh	8	Chitrakoot, Fatehpur, Bahraich, Shravasti, Balrampur, Siddharthnagar, Chandauli, Sonbhadra.
5	Rajasthan	5	Dholpur, Karauli, Jaisalmer, Sirohi, Baran.
6	Jharkhand	19	Garhwa, Chatra, Giridih, Godda, Sahebganj, Pakur, Bokaro, Lohardaga, Purbi Singhbhum, Palamu, Latehar, Hazaribagh, Ramgarh, Dumka, Ranchi, Khunti, Gumla, Simdega, Pashchimi Singhbhum.
7	Chhattisgarh	10	Korba, Rajnandgaon, Mahasamund, Uttar Bastar Kanker, Bastar, Narayanpur, Dakshin Bastar Dantewada, Bijapur, Sukma, Kondagaon.
8	Madhya Pradesh	8	Chhatarpur, Damoh, Barwani, Rajgarh, Vidisha, Guna, Singrauli, Khandwa (East Nimar).
9	Mizoram	1	Mamit.
10	Maharashtra	4	Nandurbar, Washim, Gadchiroli, Osmanabad.
11	Bihar	13	Sitamarhi, Araria, Purnia, Katihar, Muzaffarpur, Begusarai, Khagaria, Banka, Sheikhpura, Aurangabad, Gaya, Nawada, Jamui.
12	Gujarat	2	Dahod, Narmada.
13	Odisha	10	Dhenkanal, Gajapati, Kandhamal, Balangir, Nuapada, Kalahandi, Rayagada, Nabarangpur, Koraput, Malkangiri.
14	Assam	7	Dhubri, Goalpara, Barpeta, Hailakandi, Baksa, Darrang, Udalguri.
15	Arunachal Pradesh	1	Namsai.
16	Jammu & Kashmir	2	Kupwara, Baramulla.
17	Punjab	2	Moga, Firozpur.
18	Sikkim	1	West Sikkim District.
19	Tamil Nadu	2	Virudhunagar, Ramanathapuram.
20	Manipur	1	Chandel.
21	Meghalaya	1	Ri Bhoi.
22	Nagaland	1	Kiphire.
23	Tripura	1	Dhalai.
24	Uttarakhand	2	Udham Singh Nagar, Haridwar.
25	West Bengal	5	Dakshin Dinajpur, Malda, Murshidabad, Birbhum, Nadia.
	Total	**117**	

Source- NITI Aayog