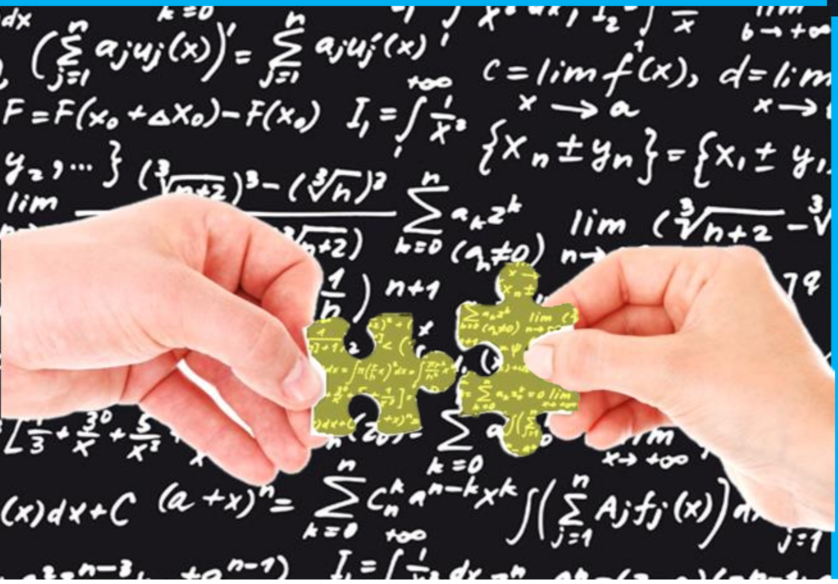
The impact of odd-even transportation policy and other factors on pollution in Delhi: A spatial and RDD analysis



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ASIA-PACIFIC RESEARCH AND TRAINING NETWORK ON TRADE

WORKING PAPER

The impact of odd-even transportation policy and other factors on pollution in Delhi: A spatial and RDD analysis

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Abstract

We study the impact of the odd-even transportation policy (environmental regulation), among other controlled factors on Delhi's pollution levels using panel data. We have daily data on five different pollutants from 9th April 2015 through 29th July 2018 and also pollutant's data over nine different locations of Delhi averaged over different years from 2014 onwards. We consider explanatory variables ranging from the dummy for introduction of the odd-even transportation policy adopted by Delhi Government in 2015 and 2016, along with polynomial terms of time; climatic factors like wind speed, average temperatures, relative humidity and rainfall; fringe factors like ban on sale of crackers, dummy for Deepawali and parallel build-up of highway for movement of trucks at the outskirts of Delhi, burning of agricultural residue in surrounding states, price of fossil fuels, spatial dependence among nine different locations of Delhi, number of CNG/electric cars plying in Delhi, number of registered public and private vehicles, among others. We use spatial regression and parametric RDD (Regression Discontinuity Design) for our study. The RDD exercise would help us to know through the impact of the dummy of the new transportation policy (with and without polynomial terms), its impact on the short- and long-term pollution levels in Delhi. Pollution data is gathered from Central Pollution Control Board (CPCB) offices of Delhi. At the end, we suggest some policy measures which should be undertaken for reducing pollution levels in Delhi. We have used time as the running variable for each pollutant with a treatment date as the threshold.

Keywords: RDD (Regression Discontinuity Design), Spatial Regression, Odd-even Transportation Policy, I Moran's statistics, Panel data

JEL Codes: Q51, Q52 and Q57

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1. Introduction and motivation of the study

An environmental problem in Delhi, India, is a serious threat to the well-being of the city. An air pollutant is a material in the air that can have adverse effects on humans and the ecosystem. The major reasons for rise in pollution in Delhi that have been identified in this study are as follows: industrial emissions, climatic factors and average temperatures prevailing in the months of summer and winter, anthropogenic factors like motorization and vehicular traffic, policy induced prices of fossil fuels, burning of agricultural residue in surrounding states, traffic congestion, population density, industrial activity, housing and type and nature of housing, clustering and spatial interdependence, among others. Delhi for instance has one of the country's highest volumes of particulate matter (especially PM 2.5 and PM 10) pollution. Sources of PM2.5 are mainly from vehicular traffic and grinding operations, while sources of PM10 are from all types of combustion, including motor vehicles, power plants, residential wood burning, forest fires, agricultural burning and some industrial processes, further SO_2 (Sulphur dioxide) is mainly emitted from fossil fuel at power plants and other industrial facilities, as well as fuel combustion in mobile sources such as locomotives, ships, and other equipment. Source of NO_2 is mainly due to traffic while the source of CO (Carbon monoxide) are the incomplete combustion of carbon-containing fuels, such as gasoline, natural gas, oil, coal, and wood. In urban area, its major source is vehicular emission.

Exposure to particulate matter for a long time can leads to respiratory and cardiovascular diseases such as asthma, bronchitis, lung cancer and heart attack (Key facts by WHO, 2018). In 2015, the Global Burden of Disease study by IHME (Institute for Health Metric and Evaluation) pinned outdoor air pollution as the fifth largest killer in India, after high blood pressure, indoor air pollution, tobacco smoking, and poor nutrition. (WHO, 2018) CPCB (Central Pollution Control Board) runs nationwide programs of ambient air quality monitoring known as National Air Quality Monitoring Programme (NAMP). The information on Air Quality at ITO is updated every week. Efficient pollution control requires well-grounded knowledge concerning emission sources and their effect on air quality. Although the physical and chemical processes behind pollution usually are too complex to be drawn in a simple model, some further knowledge of fundamental interrelations can be gained by application of mathematical and econometric models.

In this paper, we use a statistical approach to quantify the relationship between new transportation policy adopted by the Delhi Government, other controlled factors like meteorological conditions, price of fossil fuel, ban on crackers, burning of agriculture residue, among others on the concentration of various gaseous pollutants and air pollution levels at certain measurement stations in Delhi. Moreover, we try to rank multiple factors affecting the air pollution with the help of spatial econometrics and RDD (Regression Discontinuity Design). The RDD exercise would help us to know whether the odd-even transportation policy has been able to reduce pollution in Delhi both in short & long run and its impact on pollution levels existing in Delhi. Odd-even transportation policy were first introduced for five days in November 2015, then again from Jan 1st, 2016 through Jan 15th, 2016 and once again in the summer month of April 16th through April 30th, 2016. (Please see the plots of pollutants against time along with odd-even transportation policy intervention given below). The plots seem to indicate that there may be other variables besides odd-even rule which may have significantly impacted the pollution levels in Delhi (Climatic factors, among others). The new transportation policy meant that odd numbered vehicles would move on odd numbered days, while even numbered vehicles would move on even numbered days. Trucks usually run in the night and early morning. On Sundays, this rule would not apply. Followings were exempted from odd-even scheme

1. Two wheelers
2. Trucks
3. Women driven cars
4. VIP and emergency vehicles
5. Student driven vehicles
6. Public transport buses CNG operated passenger/private cars

The idea was to reduce vehicular pollution in Delhi. In Delhi, we have 3 million cars, 6 million scooters and motorbikes and 0.2 million private vehicles. Odd-even transportation policy would apply only for four-wheeler vehicles.

1.1 Motivation of the study

The motivating factor which has led to this research is the depiction of the data in the CPCB assessment report, 2016, which seem to indicate that odd-even scheme may be responsible for the rise of pollution in different locations in Delhi during and after the adoption of such transportation policy (appendix table A 1).

The tables give an impression that the frequency and the usage of tax's like Uber and Ola may have led to rise in pollution level during the adoption of odd-even scheme.

More specifically, the tables (1 through 6) of the CPCB report, Jan 2016, and table 1 through 3 of the CPCB report, April 2016, analyzing data 15 days prior to the introduction of odd-even policy, during the introduction of odd-even scheme and 15 days after the end of the odd-even scheme, indicate that the odd-even policy of pollution control may have led to increase in pollution levels in different locations in Delhi.

Econometrically speaking, this may mean that the estimate of the dummy for introduction of odd-even rule may turn out to be positive. This may indicate that pollution in Delhi has gone up entirely due to the new transportation policy introduced in Delhi. This is a myopic view of the various reasons for the rise in pollution in Delhi.

Our study using the appropriate RDD model identifies the various explanatory factors explaining rise in pollution in Delhi both in the short and in the long run, extending model and data much beyond 15 days after the introduction of the new transportation policy. The above is the major motivation behind the research study.

The paper is divided into nine sections including introduction and motivation of the study, objectives, some initial remarks on pollution in Delhi, literature review, methodology, data description and structure, discussion of results and policy implications, policy suggestions for abatement of air pollution in Delhi and conclusions. References and appendix tables are given at the end.

2. Objectives

In recent years, the National Capital Delhi and adjoining areas have experienced alarmingly poor air quality and therefore it is becoming necessary to come out with an analysis to look at such factors explaining pollution in Delhi. As per CPCB 2016 assessment report, pollutant data in different location in Delhi during and after the implementation of odd-even scheme have gone up. In our study, we wish to understand the impact of odd-even scheme along with all possible factors explaining pollution in Delhi.

In the first analysis, we use spatial data to understand the impact of climatic factors only on pollution levels existing in different locations in Delhi.

In the second part, we perform RDD exercise with an extended model on panel data of concentration of pollutants. In this way, we work out the contribution of odd-even Scheme, among other factor to analyse its role in impacting air pollution in Delhi both in short and in the long run.

3. Some initial remarks on pollution in Delhi

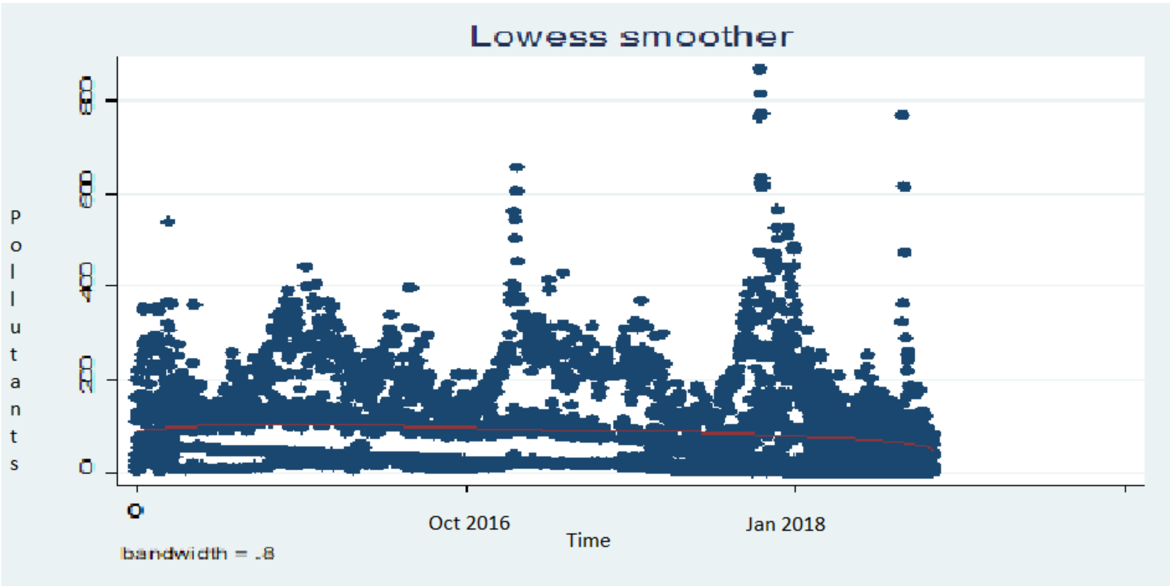
Comprehensive Study on Air Pollution and Green House Gases (GHGs) in Delhi by Mukesh Sharma, et al (2016) focused on addressing the air pollution problem in the city of Delhi by identifying major air pollution sources. Their study found that the two most consistent sources for PM10 and PM2.5 in winter and summer seasons are secondary particles and plying of vehicles. Consistent presence of secondary and vehicular PM10 and PM2.5 across all sites suggests that these particles encompass entire Delhi region as a layer. Similar to the point above, in summer, consistent presence of soil and road dust and coal and fly ash particles encompass entire Delhi region as a layer. Coal and fly ash and road and soil dust in summer contribute 26-37% to PM2.5 and PM10.

According to the World Air Quality Report by IQAir Air-Visual (2018) and WHO Survey of 1600 world cities, air pollution in Delhi is the worst of any major capital city in the world. As of November 2017, air quality plunged down to what is termed as the Great

Smog of Delhi. Levels of PM2.5 and PM 10 particulate matter hit 999 micrograms per cubic meter, while the safe limits for those pollutants are 60 and 100 respectively.

We plot the non-parametric Kernel regression function connecting pollutants with time (the daily data on 1208 observations of all five pollutants-PM10, PM 2.5, NO2, CO2 and CO from 2015 through 2018, figure 1). We see a systematic pattern with peaks being reached in the months of winters.

Figure 1. Non-parametric Kernel regression function connecting pollutants with time

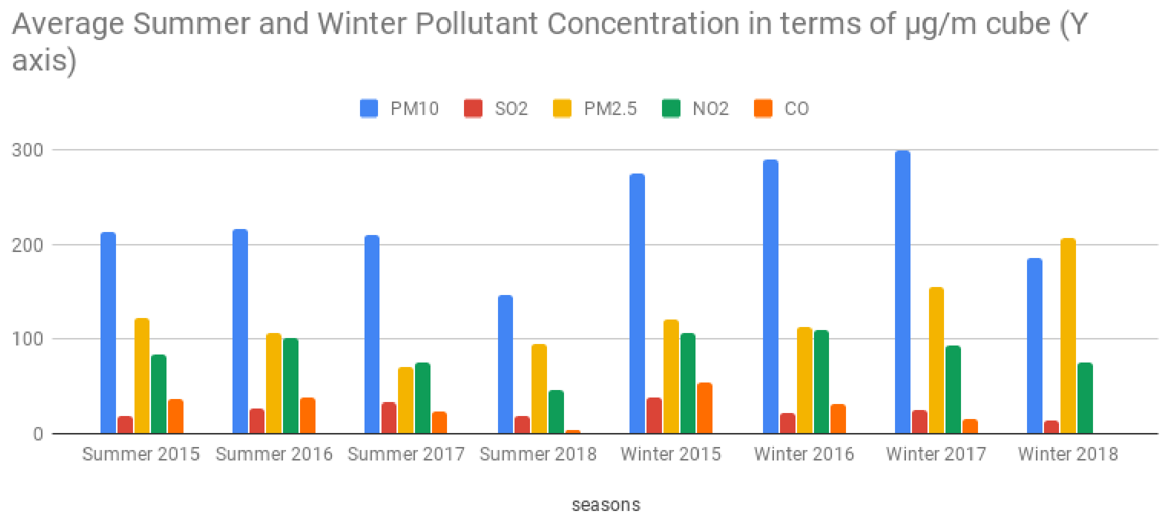


Note: The above figure depicts the non-parametric regression line (Lowess Smothers) relating five different pollutants Concentration in µg/m^3 against time (1208 observations for each pollutants). The pollutants considered in this study are SO2, NO2, CO, PM2.5 and PM10.

Source: Author's estimation using Stata

Figure 2 plots pollutants month/season wise. We find that pollution is higher in the winter months than what exists in summers. PM 10 followed by PM2.5 are responsible for high pollution in Delhi. Scientifically, vehicular pollution causes emissions of these two pollutants (World Air Quality Report 2018).

Figure 2. Average summer and winter pollutant's concentration



The summary statistics in Table 1 clearly observes that mean PM 10 is highest followed by mean PM 2.5 levels followed by NO2, CO and NO levels. In winter 2018, the average PM2.5 concentration crosses severe level of 200 micrograms where safe limit is 60 and PM 10 always comes in the severe level after crossing the limit of 100 micrograms.

Table 1. Summary statistics

Summary Statistics of Concentration					
	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
PM10 Concentration(in micrograms/m3)	1208	211.46	99.35	34.62	868.48
SO2 Concentration(in micrograms/m3)	1208	22.05	17.97	1.51	183.36
PM2.5 Concentration(in micrograms/m3)	1208	106.63	48.67	14.38	474.9
NO2 Concentration(in micrograms/m3)	1208	87.4	27.71	3.88	209.49
CO Concentration(in micrograms/m3)	1208	25.03	22.73	0.05	90.51

The figures 3 to 8 plot each of the five pollutants over daily data from 2015 through 2018 with transportation policy interventions. The figures seem to indicate that odd-even policy may not had significant impact on different pollutants, except maybe in the short run. Our regression exercise below would indicate the long-term and short-term impact of odd-even transportation policy, among other control factors on the pollution in Delhi. We see an upsurge in pollution in the winter months.

Figure 3. CO concentration over the period of time with transportation policy interventions

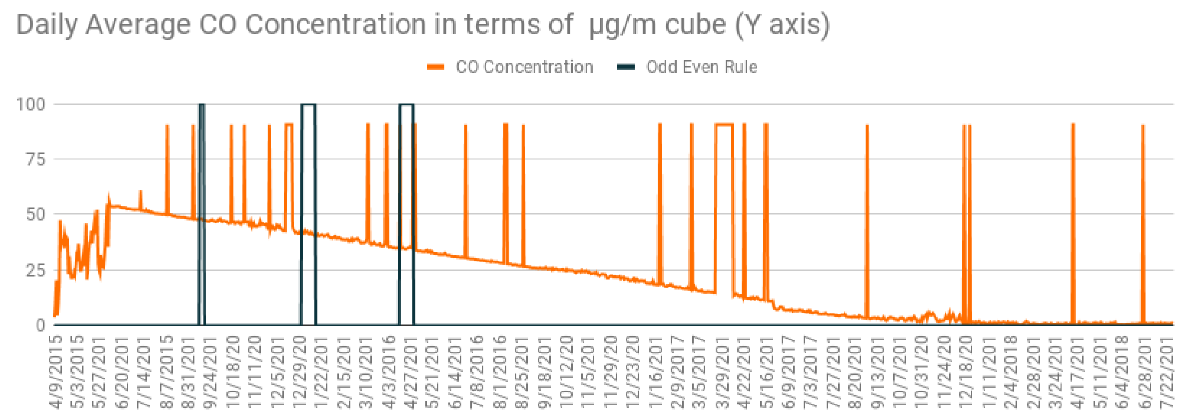


Figure 4. NO2 concentration over the period of time with transportation policy interventions

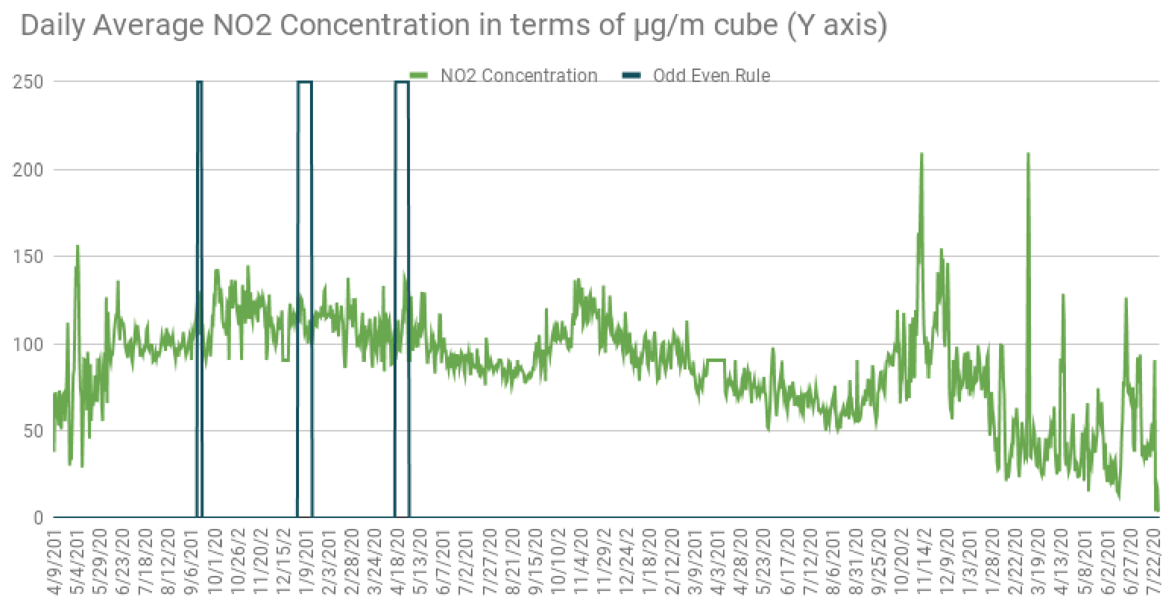


Figure 5. PM 2.5 concentration over the period of time with transportation policy interventions

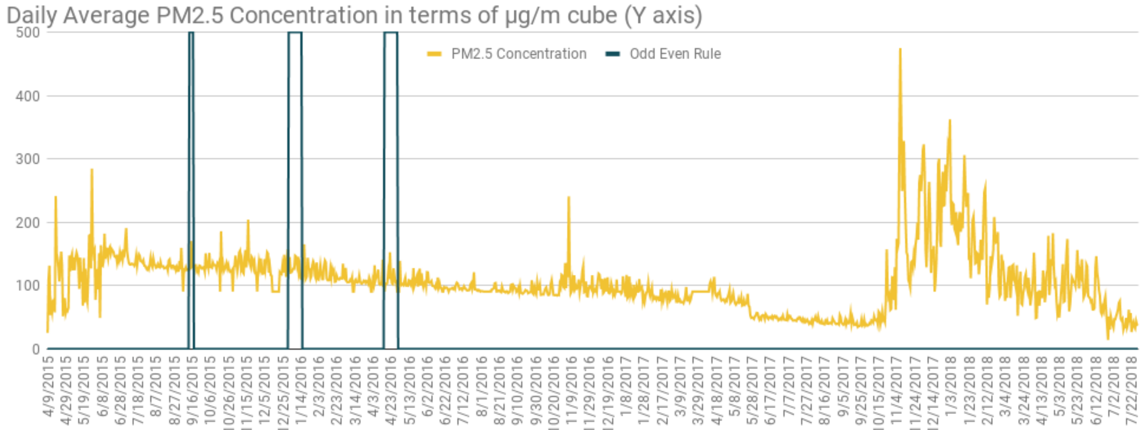


Figure 6. PM 10 concentration over the period of time with transportation policy interventions

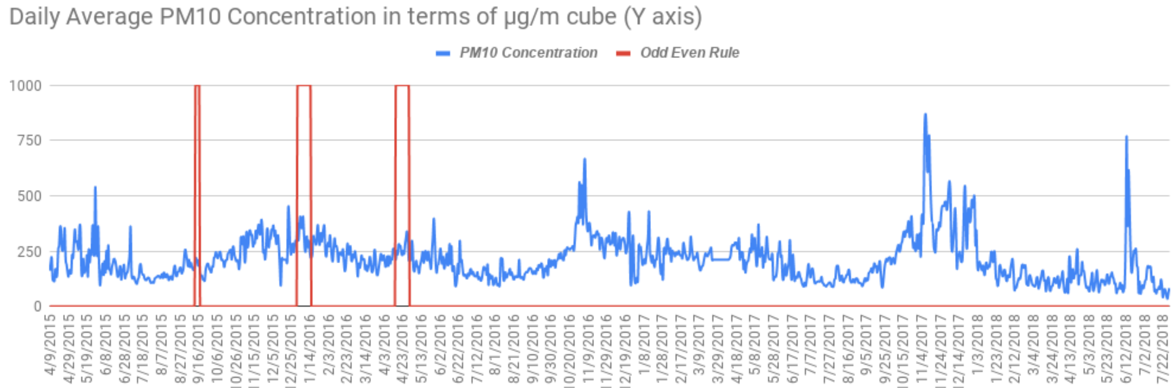


Figure 7. SO2 concentration over the period of time with transportation policy interventions

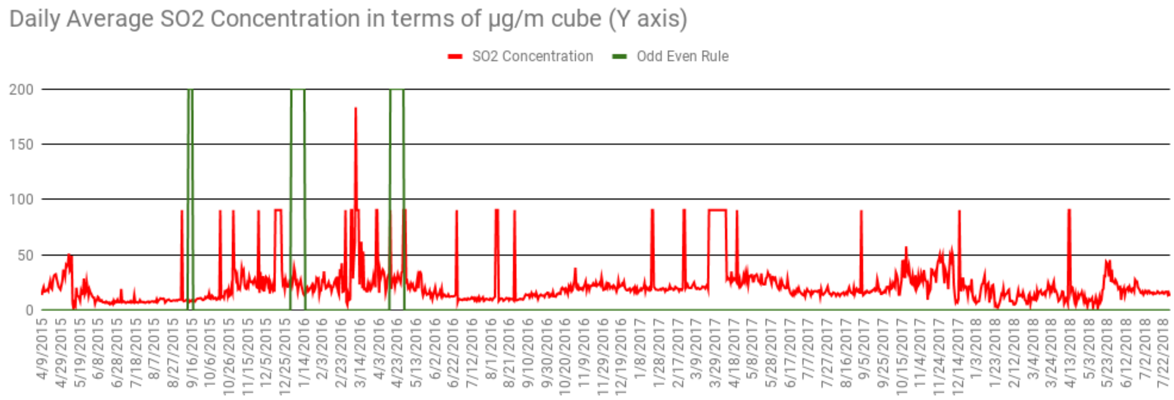
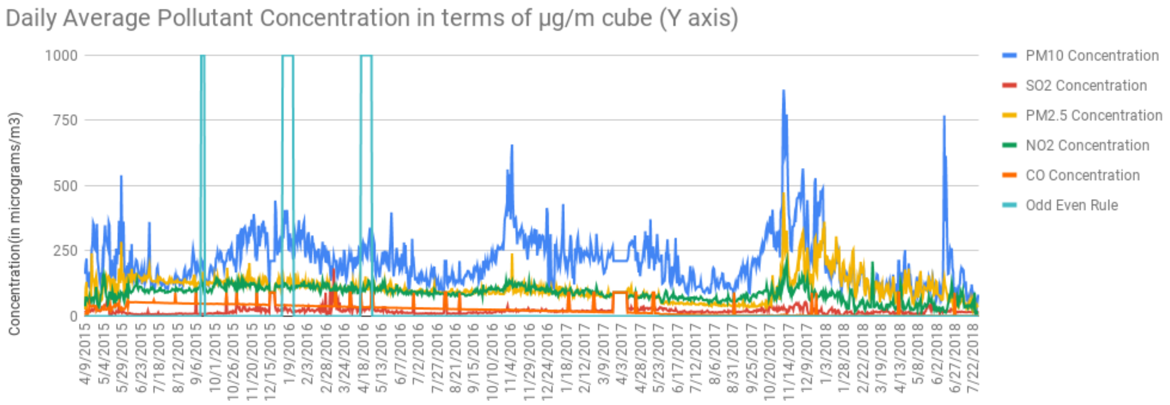


Figure 8. All pollutant's concentration over the period of time with transportation policy interventions



4. Literature review

There are several studies that analyze the impact of the transportation policies and factors on pollution levels. Chandrasiri (1999) analyzes policy variables and air pollutants namely PM, Pb, SO2 NOx and non-methane volatility covering data for the period of 37 years (1960-1997) based on Ordinary Least Squares (OLS). Based on existing theoretical and empirical evidence, paper hypothesized that vehicle prices, fuel prices, and user charges are key primary factors for vehicle ownership. The study concludes with providing policy suggestions for fuel pricing and vehicle imports that can help in controlling pollution and as well make people informative on economic costs of air pollution.

Giovanis et al. (2014), studies the effectiveness of policy mechanisms in the context of the Clean Air Works program in the Charlotte Area of North Carolina State, US, which aims to motivate individuals to follow practices that reduce ozone pollution, especially on the smog alert days. By using quadruple Differences (DDDD) estimator Giovanis et al. (2014) concluded that there was significant reduction in ground-level ozone.

The impact of license-plate-based driving restriction transportation policy in Mexico City was studied by Guerra et al. (2017). By using regression discontinuity design, the study conclude that the policy has done little to reduce overall vehicle travel and reject the hypothesis that lack of success is due to perverse incentives for households to buy second cars or other less costly ways that people adjust behavior to avoid the restrictions. Another study using Regression Discontinuity Design methodology by Percoco (2015) aimed to evaluate the causal effect of the London Congestion Charge on the level of pollution. By using a regression discontinuity design in time series; with thresholds centered on the dates of the introduction of the charge and of the beginning and end of Western Expansion, a negligible and adverse impact of the charge is documented. While the spatially analysis with disaggregated model is estimated, it emerges that the road pricing scheme has induced a decrease in the concentration of NO, NO2 and NOX in the charged area and an increase in surrounding areas. The estimates of the RDD model also suggests that the London congestion charge increases pollution in the long run. This was due to deviant behavior of the motorist in London who took circuitous routes to reach the destination, thereby increasing the time on road leading to higher pollution in London.

Agglomeration of economic activities, fast expanding cities and a rapid increase in number of automobiles has led to traffic congestion. Jerrett et al. (2010) reviewed the use of Geographic Information Systems (GIS) and spatial analysis in environmental epidemiology and public health research. Their study created a spatial weight matrix based on the neighboring relation and checked out for spatial auto-correlation using Moran's I stat. In examining the trends, there has been a remarkable growth in the use of advanced spatial modeling that appears an essential component of spatial epidemiology and public health. Jerrett et al. (2005), using spatial analysis, found the specificity in cause of death; with PM2.5 associated more strongly with ischemic heart disease than with cardiopulmonary or all-cause mortality in Los Angeles, US.

Considering the literature on Delhi’s pollution level, the study by Sharma et al (2017) on the marker elements and isotopic analysis of PM2.5 and PM10 samples indicated that vehicle exhaust is one of the major sources of PM2.5 and PM10 at the sampling site of Delhi. Another study by Goyal et al (2006) focus at understanding the problem of vehicular pollution vis-a-vis ambient air quality for a highly traffic affected megacity Delhi. The Study found that contribution of transport sector was estimated to be as high as 72% of the total pollution in Delhi.

There are several measures taken by Delhi government to reduce the policy level like ban on crackers, construction of Peripheral highway, building up of metro rail network in Delhi and odd-even scheme. Goel and Gupta (2015) analyzed whether the Delhi metro (DM) led to reductions in localized pollution measured in terms of NO2; CO; and PM2:5 and found that one of the larger rail extensions of the DM led to a 34 percent reduction in localized CO at a major track intersection in the city. Greenstone et al. (2017) study DID technique in comparison with neighboring cities of Delhi (Faridabad, Gurgaon and Rohtak). Fine particulate concentrations in Delhi's air were lower by roughly 24-36 μg/m3 during the January odd-even scheme. These reductions were largest in the mid-morning (11am – 2pm) and they saw no gains in air quality at nights (when rationing was not in effect). In contrast, Delhi's air did not show any quality gains relative to its neighboring cities during the April phase of the program in their study.

In this paper, we want to include the impact of not only environmental and transportation policy measures on impacting pollution in Delhi, but also factors like policy induced variables like prices of fossil fuels, burning of agricultural residue in surrounding states, plying of electricity driven vehicles, registration of public and private vehicles operation of Western & Eastern Peripheral Highway, among others. This study uses high frequency data for three years (daily data) ranging from 9th April 2015 through 29th July 2018, which would help us in analyzing the impact on pollution level in both short and long run by applying RDD in panel/ RDiT (Regression Discontinuity in Time). Another novelty of the paper is to consider the unobserved spatially correlated factors like traffic congestion, crop residual burning during harvesting season in the regions near to Delhi, industrial activity in different location in Delhi, green cover, among others. These factors affecting the pollution level were going to be captured by Spatial Econometric Analysis.

5. Methodology

5.1 Spatial model

Our first concern is on regression (econometric) analysis—estimation of the regression model which will reflect the dependence of the concentration of the pollutants at different locations in Delhi. SAR (Spatial Autoregressive) model is suitable in case of the interdependence among the spatial data of the dependent variable, while the SEM (Spatial Error Model) examines spatial dependence in the error term.

This type of analysis has usually been applied to the cross-sectional data or panel data. Since the cross-sectional data analysis deals with the data for individual regions in one defined time, the panel data analysis considers also the development of the cross-sectional data in time. Moreover, in this particular spatial exercise, we will firstly deal with the pooled data and then apply to the cross-sectional data. As mentioned by Anselin (1988), SAR model is suitable in case of the spatial dependence in the dependent variable, and the SEM model in case of spatial dependence in the regression disturbance term. The specifications of the SAR model are as follows

$$Y = \rho \mathrm{WY} + \mathrm{X}\beta + \mathrm{u}$$

ρ = scalar spatial autoregressive parameter (measuring the degree of dependence)

W = spatial weight matrix of dimension (n×n)

WY = (Nx1) dimensional vector of spatially lagged dependent variable

β = coefficient for independent variable i.e. Wind speed, Rainfall

u = (n x1) dimensional vector of error terms

Since the value $\rho \neq 0$ implies the existence of spatial dependence across neighboring locations (endogenous interaction effects), a zero indicates no spatial effect between observations of the considered dependent variable.

The SEM model is expressed as:

$$Y = X\beta + \varepsilon$$

$$\varepsilon = \lambda W\varepsilon + u$$

λ = Spatial error parameter

$W\varepsilon$ = Vector of spatially lagged error terms with (nx1) dimension

λ replicate the intensity of spatial auto-correlation between regression residuals. Both the SAR and the SEM model can be estimated by maximum likelihood (ML) method (Anselin, 1988, Lesage and Pace 2003). The suitable form of spatial model, that is, SAR or SEM, can be chosen based on the Lagrange Multiplier (LM) test results and their robust modifications (Anselin & Florax, 1995). Both tests use OLS residuals in order to test the null hypothesis of no spatial dependence against the alternative hypothesis of spatial dependence. These tests are asymptotic and follow a $\chi 2$ distribution with one degree of freedom. In our study we have quoted both SAR and SEM results.

Spatial autocorrelation is characterized by a correlation in a signal among nearby locations in space. Spatial autocorrelation is more complex than one-dimensional autocorrelation because spatial correlation is multi-dimensional (i.e. 2 or 3 dimensions of space) and multi-directional. Moran's I is defined as

$$I = \frac{N}{W}\frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})}$$

Where N is the number of spatial units indexed by i and j; x is the variable of interest, $\bar{x}$ is the mean of x; w_{ij} is a matrix of spatial weights with zeros on the diagonals (i.e., w_{ij} =0); and W is the sum of all w_{ij}. We constructed a Spatial weight matrix (9*9) below based on the inverse distance between the two stations using R codes for our cross-sectional work (data on each pollutant over nine different locations averaged over three year data). Spatial weight matrix (36*36) below (Appendix table A3) is based on inverse distance between the two stations using Stata code for our pooled data (data on each pollutant for nine different location in Delhi).

Table 2 W matrix of nine locations

	1	2	3	4	5	6	7	8	9
1	0	0.0809	0.0982	0.0354	0.0271	0.0665	0.2245	0.0586	0.4083
2	0.0984	0	0.0889	0.0971	0.1528	0.3491	0.0988	0.0468	0.0677
3	0.087	0.0648	0	0.1156	0.0214	0.1866	0.0419	0.4429	0.0394
4	0.0471	0.1061	0.1736	0	0.0452	0.4537	0.0388	0.105	0.0298
5	0.0775	0.3586	0.0691	0.0971	0	0.144	0.1352	0.0466	0.0715
6	0.0587	0.2534	0.1859	0.3011	0.0445	0	0.0492	0.0738	0.033
7	0.226	0.0963	0.0561	0.0346	0.0561	0.066	0	0.035	0.3894
8	0.0701	0.0459	0.5973	0.0946	0.0195	0.0999	0.0353	0	0.0371
9	0.4283	0.0584	0.0467	0.0235	0.0262	0.0392	0.3447	0.0326	0

The Spatial exercise, especially SEM and SAR Models, are relevant because there may be other factors beside the climatic factor which may be spatially auto correlated. These can be like burning of agricultural residual, traffic congestion dependent on nearby locations, green cover at different location in Delhi, industrial activities at different locations, plying of metro at different locations, population density, among others. SAR and SEM Models are the most suitable models as the pollutant concentrations at a station are more likely to get in sequenced by neighboring stations than the meteorological factors; hence we have not included the spatial-correlation of meteorological factors (Spatial Durbin Model).

5.2 RDD design

A regression discontinuity design (RDD) is a quasi-experimental pretest-posttest design that elicits the causal effects of interventions by assigning a cutoff or threshold above or below which an intervention is assigned. First, the coefficients are estimated by applying panel estimation technique. The following equation is used to describe the relation of each pollutant with the policy parameter:

$$Y_{it} = \Theta + \rho D_t + \varepsilon_{it}$$

The goal is to estimate the parameter ρ on treatment of this form in order to capture the effect of transportation policy through the dummy. Where $\mathbf{Y_{it}}$ is the concentration of a given pollutant i in day t whose treatment status is T, Θ is a constant, $\mathbf{X_{it}}$ variable (Treatment date) properly normalized. The expresses impact of the treatment at $\mathbf{X_{it}}$ = $\mathbf{X_0}$. Lastly $\boldsymbol{\varepsilon_{it}}$ is an error term. D is our treatment variable taking the value of 1 after the effective time period of the policy and zero otherwise. We further add control variables to the above equation.

$$Y_{it} = \Theta + \rho D_t + Z_{kit}\beta_k + \varepsilon_{it}$$

Here $\boldsymbol{Z_{kit}}$ is the matrix of control variables introduced in the model and $\boldsymbol{\beta_k}$ is the vector of the coefficients of control variables. To proceed with estimation, the following model is considered:

$$Y_{it} = \Theta + f(X_{tT}) + \rho D_t + Z_{kit}\beta_k + \varepsilon_{it}$$

Here $f(\boldsymbol{X_{tT}})$ is the p-th order parametric polynomial to account for non linearity of the relationship between the time trend and pollution and thus to control that the eventual break at $\mathbf{X_{it}}$ = $\mathbf{X_0}$ is not due to unaccounted non-linearity. For our analysis p is taken to be 4 i.e. $f(\boldsymbol{X_{tT}})$ term is 4-th order parametric polynomial. Therefore,

$$f(X_{tT}) = \tau_1 X_{tT} D + \tau_2 X_{tT}^2 D + \tau_3 X_{tT}^3 D + \tau_4 X_{tT}^4 D + +\alpha_1 T + \alpha_2 T^2 + \alpha_3 T^3 + \alpha_4 T^4$$

$f(\boldsymbol{X_{tT}})$ Can be further expressed as:

$$f(X_{tT}) = \tau_1 T * D + \tau_2 T^2 * D + \tau_3 T^3 * D + \tau_4 T^4 * D + \alpha_1 T + \alpha_2 T^2 + \alpha_3 T^3 + \alpha_4 T^4$$

Major advantage of RDD is that when properly implemented and analyzed, the RDD yields an unbiased estimate of the local treatment effect and it can be almost as good as a randomized experiment in measuring a treatment effect. Hausman & Rapson (2017) formalized some of the differences between time-based regression discontinuity (RDiT) applications, which are similar to event studies, and other uses of the regression discontinuity framework. It is argued that the most common deployment of RDiT faces an array of challenges due primarily to its reliance on time-series variation for identification. This is an entirely different source of identifying variation than is used in the canonical cross-sectional RD, rendering the traditional RD toolkit (for example, as described in Lee and Lemieux (2010). Following this, we have used RDD in panel setting (having features of RDiT methodology) to examine the impact of odd-even Transportation policy on Delhi's Pollution levels.

5.2.1 Model 1: without polynomial terms

Below we mentioned the linear RDD model specification where the right- and left-hand side variables are as follows:

Left hand side: Concentration of pollutants

Right hand side: Odd-even policy dummy, rainfall, wind speed, average temperature, relative humidity, time, Crackers ban dummy, daily petrol price, daily diesel price, highway dummy, agriculture residue burning, number registered public and private Vehicles and number of electric cars in Delhi.

$$
\begin{aligned}
Y_{it} = \alpha + \rho Oddevenrule + \beta_1 rainfall + \beta_2 windspeed + \beta_3 avgtemp \\
+ \beta_4 rh + \beta_5 highway + \beta_6 crackerban + \beta_7 petrol + \beta_8 diessel \\
+ \beta_9 agriresidual + \beta_{10} electriccar + \beta_{11} privatevehicles \\
+ \beta_{12} Publicvehicles + \varepsilon_{it}
\end{aligned}
$$

5.2.2 Model 2: With polynomial terms

This is the nonlinear RDD wherein the right- and left-hand side variables are as follows:

Left hand side: Concentration of pollutants

Right hand side: Odd-even policy dummy, rainfall, wind speed, average temperature, relative humidity, time(t), time$(t)^2$, time$(t)^3$, time$(t)^4$, interaction of time polynomials with odd-even dummy, Crackers ban dummy, daily petrol price, daily diesel price, highway dummy and agriculture residue burning, number registered public and private Vehicles and number of electric cars in Delhi.

Polynomial terms in time i.e time(t), time$(t)^2$, time$(t)^3$, time$(t)^4$ follows the mathematical axiom that any function can be depicted by any p^{th} order polynomial

$$
\begin{aligned}
Y_{it} = \alpha + \rho Oddevenrule + \beta_1 rainfall + \beta_2 windspeed + \beta_3 avgtemp \\
+ \beta_4 rh + \beta_5 highway + \beta_6 crackerban + \beta_7 petrol + \beta_8 diessel \\
+ \beta_9 agriresidual + \beta_{10} electriccar + \beta_{11} privatevehicles \\
+ \beta_{12} Publicvehicles + \alpha_1 time + \alpha_2 time^2 + \alpha_3 time^3 \\
+ \alpha_4 time^4 + \tau_1 oddeven * time + \tau_2 oddeven * time^2 \\
+ \tau_3 oddeven * time^3 + \tau_4 oddeven * time^4
\end{aligned}
$$

Tests: Durbin- Wu Hausman test: To decide between fixed effect and random effect models.

The major benefit of using the RDD method is that when properly implemented and analyzed, the RDD yields an unbiased estimate of the local treatment effect. That is the RD design is seen as a useful method for determining whether the program or treatment was effective or not.

6. Data description and structure

The Air Quality of Delhi is monitored by the National Air Monitoring Programme (NAMP) run by CPCB. It is the most suitable source of yearly data of various stations from CPCB and some meteorological parameters from climate manual monitoring sites. The analysis report is based on the available data of 9 manual monitoring stations of Delhi. We created a pooled data (for spatial regression) of pollutants of these stations and other control factors averaged over a time interval from 2014 to 2018. The stations are:

1. N.Y school -Sarojini Nagar
2. Town hall-Chandni chowk
3. Mayapuri Industrial area
4. Pitampura
5. Shahadra
6. Shahzada Bagh
7. Nizamuddin
8. Janakpuri
9. Siri Fort

In the RDD model, we have used panel data of 5 pollutants during the period 2015-18 (Using daily data) and following that we have used Durbin-Wu Hausman test to determine whether to use Fixed Effects or Random Effects on model with polynomial terms and the other without polynomial terms, respectively.

The table 3 gives the description of the variables used in the RDD Model along with its data source and the hypothesis impacting the pollutant in Delhi.

Table 3. Variable name and description, data source and hypothesis

Variable	Description	Source	Hypothesis
Pollutant Concentration	Daily Concentration of Pollutants like SO_2, NO_2, PM 2.5, PM 10 and CO	Central Pollution Control Board websites	This is the Dependent variable
Temp	Average Daily Temperature of Delhi	Central Pollution Control Board websites	Affect Negatively
Rainfall	Average Daily Rainfall	Central Pollution Control Board websites	Affect negatively
Relative Humidity	Average Relative Humidity of Delhi	Central Pollution Control Board websites	Affect Negatively
Wind speed	Average Wind Speed of Delhi	Central Pollution Control Board websites	Affect negatively

Odd-even Rule Dummy	Dummy for the day odd-even rule was introduced	Central Pollution Control Board websites	Affect negatively
Highway Dummy	Dummy for Eastern and Western Peripheral highway: Eastern is Kundli-Ghaziabad-Palwal (KGP) Expressway and Western is Kundli-Manesar–Palwal (KMP) Expressway (one for the time period after the construction of the both expressways and zero prior to this).	Central Pollution Control Board websites	Affect negatively
Agricultural Residual	Dummy for the post harvesting period of Rabi and Kharif crop for capturing the crop residual burning	Arthapedia	Affect positively
Cracker ban	Dummy for the time when crackers are ban Delhi	Times of India	Affect negatively
Diwali	Dummy for the Diwali period (5 day around the Diwali festival)	Google Calendar	Affect positively
Petrol Prices	Petrol prices for the prevailing in Delhi	Website of Indian Oil	Affect positively
Diesel Prices	Diesel prices for the prevailing in Delhi	Website of Indian Oil	Affect negatively
Electric Cars	Number of Electric cars in Delhi	Website of Government of Delhi	Affect negatively

Private Vehicles	Number of Private Vehicles registered in Delhi	Website of Government of Delhi	Affect positively
Public Vehicles	Number of Public Vehicles registered in Delhi	Website of Government of Delhi	Affect positively

7. Hypotheses

CPCB assessment reports on odd-even policy have shown that this policy was not effective to reduce the pollution level of Delhi and this assessment also seems to conclude that the policy is responsible for increasing pollution level in Delhi. If we see the impact assessment of this transportation policy by applying RDD methodology (with polynomials and interactive terms), it turns out to be appropriate in defying the CPCB claims based on their data assessment. Odd-even dummy in the RDD model is hypothesized to have a negative impact on pollution in Delhi.

Climatic factors like wind speed and rainfall would reduce the level of pollution as they carry away the pollution particulates. Other climatic factors, temperature and humidity act as catalyst in decreasing the pollution level. Spatial regression and RDD regression may show mixed result of the impact of climatic factors on pollution levels as contiguity, spatial analysis and clustering may negate the impact of the climatic factors on pollution levels.

Policies for reducing the Delhi's pollution level like ban on crackers, building up of Eastern and Western Peripheral highways are hypothesized to have significant impact on reducing pollution. Burning of agricultural residuals in the regions located near to Delhi is also responsible for increasing pollution. The dummy for this might show positive and significant coefficient. Bursting of crackers at the time of Diwali is hypothesized by creating huge amount of pollution in Delhi.

Price of Petrol and Diesel price are hypothesized to have positive and negative impact on pollution levels. This may be since petrol and diesel may be substitutes for each other, leading to replacement of petrol driven cars by diesel driven cars once the price of petrol goes up, which in turn would lead to rise in pollution levels. If the price of diesel goes up, then people may reduce consumption of diesel driven cars leading to reductions in pollution levels. The above arguments are based on the fact that diesel causes more pollution than petrol.

If there are large numbers of vehicles registered in Delhi (both public and private), they are likely to increase the pollution level in Delhi. But one can also infer that the registration of new vehicles, which might replace the old technology cars may reduce pollution as they might be confirming to the international pollution norms. Number of electric cars registered are hypothesized to reduce pollution level. Dummy for winter month is hypothesized to have positive impact on pollution level in Delhi.

8. Discussion on results & policy implications

8.1 Spatial analysis

The I Moran statistics given in the appendix Table A 2 shows negative spatial autocorrelation for the pollutant SO2, NO2, PM10 and positive spatial autocorrelation for PM2.5. It seems that pollution due to agriculture residual SO2 and NO2 tend to have negative spatial autocorrelation across nine different locations in Delhi, while Vehicular pollution (PM2.5) tend to have positive autocorrelation across nine different locations in Delhi. The same appendix table gives LM and robust LM statistic; the two statistics indicate that spatial dependence is statistically not present among pollutant in different locations. This may be due to limited data on spatial units. We have run spatial dependence models so that we understand the impact of climatic factors on pollutants in Delhi using spatial pooled data having two dimensions, namely pollutant data over nine different locations averaged over four year’s data from 2014 onwards.

The Spatial exercise especially SEM and SAR Model are relevant because there may be other factors beside the climatic factor which may be spatially auto correlated. These may range from burning of agricultural residue, traffic congestion dependent on nearby locations, green cover at different locations, intensity of industrial activities at different locations in Delhi, population density, plying of metro at different locations, elevated road corridor at different locations in Delhi, population density at different locations in Delhi, type of houses built and infrastructure at different locations in Delhi, among others. SEM model may indicate the impact of spatial explanatory factors (omitted from the set of explanatory variables and aligned with error terms) on the pollution at different locations in Delhi.

Table 4. Pooled spatial results of all pollutants

VARIABLES	Pooled OLS	SAR	SEM
AT	-0.237 (7.312)	-0.235 (6.786)	-0.237 (6.806)
Rainfall	-0.476 (2.591)	-0.475 (2.405)	-0.477 (2.412)
WS	1.172 (27.11)	1.181 (25.17)	1.169 (25.21)
RH	37.49 (192.2)	37.40 (178.4)	37.38 (178.8)
rho		-0.0170 (0.850)	
lambda			-0.0133 (0.849)
sigma2_e			
Constant	120.6 (307.8)	122.5 (300.3)	120.7 (286.6)
Observations	36	36	36
R-squared	0.004		
Number of station panel	9	9	9

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The first analysis (Table 4) shows the estimation by linear model using pooled data of pollutants over nine different locations in Delhi. The coefficient shows that increase in temperature and rainfall leads to reduction in pollution. Moreover, the increase in wind speed and relative humidity is likely to increase the pollution levels. SAR and SEM estimates have shown similar results as pooled OLS results. It may be noted that none of the climatic factor are having significant impact on pollution in Delhi using spatial analysis.

Table 5. Spatial results of different pollutants

	SEM Model				SAR Model			
Variables	SO2	NO2	PM10	PM2.5	SO2	NO2	PM10	PM2.5
AT	-0.401*** (0.111)	-3.599 (1.842)	17.55*** (5.852)	8.326*** (2.688)	-0.117 (0.0907)	-1.602 (1.297)	8.030* (4.176)	-7.917*** (2.009)

Rainfall	0.00579 (0.0422)	0.975 (0.706)	-0.945 (1.872)	-1.573** (0.684)	0.0375 (0.0346)	0.743 (0.473)	-1.545 (1.447)	-1.619** (0.688)
WS	2.020*** (0.373)	22.03*** (6.326)	-37.83** (15.34)	20.03*** (7.181)	1.422*** (0.444)	13.62** (5.687)	-31.81* (17.28)	21.03*** (7.152)
RH	-5.100* (2.762)	-45.43 (46.87)	226.1** (110.6)	-86.58* (49.66)	2.576 (2.453)	22.74 (34.83)	149.2 (110.8)	-86.88* (50.94)
Constant	17.53*** (5.251)	114.2 (86.79)	-199.2 (252.1)	405.3*** (98.55)	15.88** (7.746)	181.3** (73.96)	321.5 (276.3)	388.3*** (77.01)
Lamda	-2.547*** (0.264)	-2.449*** (0.359)	-2.293*** (0.541)	-0.46 (1.391)	-1.423* (0.794)	-1.959*** (0.606)	-0.797 (0.684)	0.0752 (0.605)
Sigma	0.433*** (0.13)	7.656*** (2.35)	19.69*** (6.378)	13.62*** (3.395)	0.707*** (0.192)	10.07*** (2.898)	31.90*** (7.793)	13.91*** (3.281)
Observations	9	9	9	9	9	9	9	9

Standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

The above results (Table 5) are based on pooled data of four pollutants over nine different locations in Delhi. However, when each pollutant is regressed on climatic factors existing in nine different location in Delhi, rainfall, wind speed, temperature and relative humidity tends to have significant impact on individual pollutants (Table 5). It seems that average temperature tends to have a positive and significant impact on vehicular pollution leading to larger emissions of PM10 and PM 2.5 (in SEM Model). Wind speed on the other hand tend to have negative and significant impact on vehicular pollution (PM10). Relative humidity tends to have a positive and significant impact on PM 10 and a negative and significant impact on PM 2.5.

In the spatial exercise, we have not included the impact evaluation variable as in RDD exercise below. The RDD model below shows that the climatic factors, among others may be more important in explaining pollution in Delhi, rather than the introduction of odd-even transportation policy. We expect higher pollution in nine different locations in Delhi due to congestion in traffic in that location, the number of factories operating in that particular location, availability of metro at that particular location, green cover, population density, climatic factors, among others. It is difficult to ascertain the impact of the introduction of odd-even transportation time dummy on the pollution in different region of Delhi using spatial regression except through reducing congestion in traffic in such regions.

We hope to include congestion in traffic, road size, green cover, population density, plying of metro in that location and number of factories operating in Delhi region in our future study. We also hope to get time series data on spatial units (different locations in Delhi). In this regression model, we would consider dummy for implementation of odd-even rule.

8.2 RDD results: extended model

Table 7 shows the random effect; ML random effect and fixed effect estimates of the odd-even rule dummy with and without polynomial terms controlling for the other explanatory variables impacting pollution in Delhi. The variant of the Hausman test shows evidence in favor of using the fixed effect panel estimates. The FE odd-even dummy shows a positive impact on pollution in Delhi when the regression model is used without the time trend polynomial terms. This model falsely indicate that the odd-even transportation policy is responsible for increasing pollution in Delhi. This result one may see in the short run. In the long run, policy implications are best seen using RDD model with full sample data and considering all the polynomial terms with its interactive effects on the odd-even dummy variables.

As soon as the polynomial terms are added and the extended model is used (showing long term results), the impact of odd-even scheme becomes negative and insignificant. This means at the threshold level introduction of transportation odd-even policy did reduce pollution but was statistically insignificant in impacting pollution levels in Delhi. Only climatic factors, price of fossil fuel, number of electric/CNG cars and number of public and private vehicles, operation of Western & Eastern Peripheral highway had statistically significant impact on pollution in Delhi.

Wind Speed, Temperatures and Relative humidity tend to have negative impact on pollution in Delhi, while price of petrol and price of diesel tend to have positive and negative impact on pollution, respectively. Registration of private and public vehicles and plying of electric/CNG vehicles tend to have negative impact on pollution in Delhi. Dummy for Diwali period, dummy for crackers ban and dummy for burning of agriculture residual (Harvesting) did not have any statistical impact on pollution in

Delhi. Dummy for Built up of peripheral highway tend to have a positive impact on pollution in Delhi as indicated in FE results with polynomial terms.

Table 6. Results of RDD with random effects and fixed effects

VARIABLES	FE without Polynomial	FE with Polynomial	RE without Polynomial	RE with Polynomial	RE MLE without Polynomial	RE MLE with Polynomial
oddevenrule	11.14*** (3.977)	-516.5 (394.5)	10.54 (7.118)	-331.4 (710.3)	11.14*** (3.972)	-516.4 (393.8)
Peripheral highway	-3.071 (3.423)	10.31** (5.140)	-3.395 (6.127)	8.666 (9.255)	-3.071 (3.419)	10.31** (5.131)
harvesting	1.176 (1.723)	-1.735 (1.796)	3.543 (3.084)	1.030 (3.234)	1.177 (1.721)	-1.734 (1.793)
diwali	11.35 (7.369)	9.371 (7.412)	11.03 (13.19)	9.532 (13.35)	11.35 (7.360)	9.371 (7.400)
crackerban	6.837 (9.937)	4.872 (9.916)	4.756 (17.79)	2.951 (17.85)	6.836 (9.925)	4.871 (9.899)
rainfall	-0.167 (0.118)	-0.194* (0.117)	-0.216 (0.211)	-0.239 (0.211)	-0.167 (0.118)	-0.194* (0.117)
ws	-13.57*** (1.271)	-12.25*** (1.286)	-13.55*** (2.275)	-12.43*** (2.316)	-13.57*** (1.270)	-12.25*** (1.284)
rh	-0.651*** (0.0525)	-0.785*** (0.0551)	-0.637*** (0.0940)	-0.758*** (0.0992)	-0.651*** (0.0525)	-0.785*** (0.0550)
temp	-1.853*** (0.116)	-2.287*** (0.127)	-1.791*** (0.207)	-2.181*** (0.229)	-1.853*** (0.115)	-2.287*** (0.127)
petrolprice	1.830*** (0.401)	0.659 (0.424)	1.317* (0.717)	0.327 (0.764)	1.830*** (0.400)	0.659 (0.424)
dieselprice	-0.747* (0.397)	-0.936** (0.412)	-0.470 (0.711)	-0.632 (0.741)	-0.747* (0.397)	-0.936** (0.411)
electriccng	-0.350*** (0.0869)	-0.724*** (0.111)	-0.424*** (0.156)	-0.814*** (0.200)	-0.350*** (0.0868)	-0.724*** (0.111)
privatevehicles	-0.183*** (0.0194)	-0.343*** (0.0265)	-0.187*** (0.0346)	-0.332*** (0.0478)	-0.183*** (0.0193)	-0.343*** (0.0265)
publicvehicles	-0.313*** (0.0898)	-0.572*** (0.135)	-0.367** (0.161)	-0.631*** (0.243)	-0.313*** (0.0897)	-0.572*** (0.135)
index		-0.00956 (0.0239)		0.00699 (0.0431)		-0.00956 (0.0239)
index2		-4.81e-05 (3.44e-05)		-7.58e-05 (6.20e-05)		-4.82e-05 (3.44e-05)
index3		8.54e-08*** (2.04e-08)		9.32e-08** (3.67e-08)		8.54e-08*** (2.04e-08)
oddindex		5.053 (3.830)		3.055 (6.895)		5.052 (3.823)
oddindex2		-0.0156 (0.0124)		-0.00872 (0.0223)		-0.0156 (0.0123)
oddindex3		1.56e-05		7.90e-06		1.56e-05

		(1.33e-05)		(2.39e-05)		(1.33e-05)
Constant	483.3*** (38.55)	903.2*** (66.99)	517.3*** (68.99)	896.4*** (120.6)	482.1*** (49.75)	902.0*** (73.93)
Observations	5,790	5,790	5,790	5,790	5,790	5,790
R-squared	0.176	0.189				
Number of panelid	5	5	5	5	5	5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's Calculations
Note: The variant of hausman test (with command sigmamore) was used in the light of the negative value obtained for the chi-square test statistics. This revised test indicated statistical evidence in favour of fixed effect panel model.

It seems climatic factors, price of fossil fuel and registration and plying of electric CNG Vehicles, have significant impact on pollution in Delhi. Also, odd-even rule in the long run does not tend to have any significant impact in reducing pollution in Delhi (Definitely it has not statistically increased pollution as indicated by the data given in CPCB reports, 2016). Maybe, if odd-even rule is introduced for longer time period with no exceptions, the same transportation policy may have had significant impact in reducing pollution in Delhi. The econometric model without polynomial terms may falsely indicate that odd-even rule may have had positive impact on pollution, meaning that running of OLA and Uber taxi's substituting for owner driven private vehicles may have increased pollution in Delhi. Thereby, the econometric model with polynomial terms (RDD Models: FE) is the most appropriate model in explaining pollution in Delhi.

8.3 Diagnostics

Panel unit root test indicate that all variables are integrated of order zero with no unit root problem. Therefore, all regression results are valid. It is submitted that data on price of fossil fuel may have non-stationarity in data at 10% level of significance. The modified Wald test for group wise heteroscedasticity and Woolridge test for first order serial correlation in panel setting indicate presence of heteroscedasticity and serial correlation in the RDD dataset, respectively. Therefore, we have also presented the RDD fixed effect estimates with robust standard errors (table appendix A4). The robust FE results seem to mimic the above FE results put in previous tables. Regression results correcting for first order serial correlation in panel setting are also given in Table A7.

Appendix Table A5 shows the diagnostics. The estimates are based on abridged dataset containing 540 observations covering 15-day window span of pollutant data, along with explanatory variables before, during, and after, the introduction of new transportation policy. The results seem to indicate that in short run (using econometrics model without polynomial term), odd-even rule has led to rise in pollution in Delhi. This seems to be inappropriate as there are many other variables which have significant impact on pollution and who’s impact one can study in the long run only (using econometric model with full sample data and polynomial terms).

The RDD regression with additional explanatory variable of winter time dummy, among other explanatory variables are also presented in table A6. The coefficient for winter dummy turns out to be significant. The extended model is used, showing long term results, the impact of odd-even scheme becomes negative, but insignificant. This means at the threshold level to introduction of transportation odd-even policy did reduce pollution, but was statistically insignificant in impacting pollution levels in Delhi (in the long run).

Only climatic factors, price of fossil fuel, number of electric/CNG cars and number of public and private vehicles had statistically significant impact on pollution in Delhi. Wind Speed, Temperatures and Relative humidity tend to have negative impact on pollution in Delhi, while price of petrol and price of diesel tend to have positive and negative impact on pollution, respectively. Registration of private and public vehicles and plying of electric/CNG vehicles tend to have negative impact on pollution in Delhi.

As per Hausman & Rapson (2017), we have run panel unit root test, checked for spatial and serial autocorrelation, performed regression with shorter window span, checked for model adequacy and plotted pollutant against time. CPCB 2016 plots pollutants against climatic factors (Table A1)

We use AIC and BIC criterions to check for model adequacy on the extended model having polynomial (time) trend term. It seems that extended model with polynomial term (time) of degree three is adequate. The results seem to mimic the model with polynomial terms of degree four, wherein coefficient of odd even dummy signifies that odd even transportation policy has a negative impact on pollution in the long run, although the impact is statistically insignificant.

9. Policy suggestions for abatement of air pollution in Delhi

We can reduce Delhi's pollution level through the following ways

- Acid rain
- Elevated road corridor
- Connecting different location of Delhi with metro rail
- Improving Public Transportation running on CNG
- Use of alternative fuel based on Jethropha, mustard and Sarso plants.
- Use of Bio Fuel
- Electricity run vehicles
- Investment in Renewable energy
- Mono Rail
- Reducing industrial emissions by shifting industries out of Delhi
- Taxing the private vehicles
- Appropriate land allocation policies
- Reducing diesel run vehicles
- Investment in Climate SMART goods
- Improving Green cover to absorb carbon emissions

10. Conclusions

Recent upsurge in air pollution levels in Delhi has been major cause of concern for the Delhi government. Air pollution is not only the trigger for health issues such as cardiovascular disease, mortality rate, cancer and lung diseases; it is also a precursor of deterioration of economy.

Some of the primary factors identified for the rise of pollution in Delhi apart from the transportation policy are climatic factors, price of fossil fuel and operation of western & eastern peripheral highway, burning of crackers mainly during Diwali, agricultural (paddy) residue burnt in states around Delhi during winter, burning of fuels in large quantity, registration of public and private vehicles among others. Due to these reasons, the concentration of PM10 and PM2.5 along with gases like SO2, NO2 and CO have increased. Thus, in order to tackle this problem, government introduced many policies. One such policy is the odd-even rule. Under the scheme, cars with license plates ending in an odd number and even number are allowed to ply on alternate days. The scheme aims to cut down vehicular traffic by half, thereby reducing air pollution.

The study has shown that introduction of odd-even scheme may not be responsible for increasing pollution levels in Delhi, at least in the long run. This also defies the CPCB 2016 claim that odd-even scheme was responsible for increasing pollution in different locations in Delhi.

RDD helps us decipher whether there is statistically significant difference between treatment and control group in terms of outcome variable at threshold levels of the explanatory variable, where the threshold level is the time period during which the policy has been implemented.

If the odd-even scheme needs to be successful, it has to be implemented for longer time period with less exemptions like odd-even scheme should also apply to trucks, two wheelers, women, and student driven vehicles and VIP cars.

The study based on RDD result shows that all climatic factor (Rainfall, wind speed, temperature and relative humidity) operation of the peripheral highway, price of fossil fuel, plying of electric CNG car and registration of public and private vehicles has significantly impacted the pollution in Delhi.

Burning of agricultural residual (harvesting), ban on cracker, Diwali time period are not significantly impacting pollution in Delhi. Price of fossil fuel, climatic factors and operation of Western & Eastern Peripheral Highway tend to have significant impact of pollution in Delhi. Plying of electricity driven vehicles, CNG driven vehicles and registration of public and private vehicles (maybe complying with international pollution norms) tend to reduce pollution in Delhi. Odd-even dummy turns out to be negative but insignificant, clearly indicating that it has potential to reduce pollution in Delhi provided it is implemented in totality (with no exceptions) and for longer time period.

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Appendix

A1 Table from assessment report CPCB 206

Table-1: $PM_{2.5}$ µg/m^3

	PRE ODD EVEN			DURING ODD EVEN		
Stations	*Max*	*Min*	*Average*	*Max*	*Min*	*Average*
DMS Shadipur	135	111	126	146	103	123
NSIT Dwarka	147	96	121	192	103	137↑
IHBAS Dilshad Garden	182	92	143	157	97	121
ITO	147	46	87	252	76	143↑
DCE	188	49	95	190	78	145↑
Pitampura	82	55	69	NA	NA	NA
Nizamuddin	106	28	63	189	74	112↑
Sirifort	79	33	56	201	49	99↑
Shahzada Bagh	62	33	45	249	57	111↑
Janakpuri	115	49	74	328	124	182↑
Shadhara	NA	NA	NA	85	43	63
Parivesh Bhawan	63	32	45	151	42	87↑
DPCC Stations						
R.K. Puram	137	68	102	175	106	156↑
Mandir Marg	83	39	57	164	44	85↑
Punjabi Bagh	123	38	66	139	56	107↑
Anand Vihar	222	46	130	226	73	174↑
Average	125	54	85	190	75	123↑
Note: NA indicates non availability of Data						

Table-2: PM_{10} µg/m^3

	PRE ODD EVEN			DURING ODD EVEN		
Stations	*Max*	*Min*	*Average*	*Max*	*Min*	*Average*
Pitampura	173	89	132	414	217	271↑
Nizamuddin	236	189	206	421	206	303↑
Sirifort	405	270	316	696	279	434↑
ShahzadaBagh	300	253	276	464	257	361↑
Janakpuri	324	226	255	423	191	304↑
Shadhara	441	246	343	701	235	387↑
Parivesh Bhawan	260	194	226	411	241	311↑
ITO BSZ Marg	199	120	146	389	170	270↑
Average	292	198	238	490	225	330↑

Table-3: NO_2 µg/m^3						
	PRE ODD EVEN			DURING ODD EVEN		
Stations	*Max*	*Min*	*Average*	*Max*	*Min*	*Average*
DMS Shadipur	72	36	51	87	38	66↑
NSIT Dwarka	26	12	18	39	13	23↑
IHBAS Dilshad Garden	42	21	33	78	26	52↑
Pitampura	41	31	37	84	21	48↑
Nizamuddin	47	43	45	83	31	55↑
Sirifort	48	47	47	72	31	54↑
ShahzadaBagh	61	51	55	95	46	65↑
Janakpuri	57	47	52	75	42	52
Shadhara	66	56	60	63	31	49
PariveshBhawan	35	23	28	72	28	46↑
ITO BSZ Marg	66	38	57	112	35	74↑
DPCC Stations						
R.K. Puram	109	50	69	138	45	87↑
Mandir Marg	66	25	41	102	27	59↑
Punjabi Bagh	96	56	80	131	59	91↑
Anand Vihar	109	50	82	163	67	109↑
Average	63	39	50	93	36	62↑

Table-4: SO_2 µg/m^3						
	PRE ODD EVEN			DURING ODD EVEN		
Stations	*Max*	*Min*	*Average*	*Max*	*Min*	*Average*
DMS Shadipur	30	13	22	38	14	23↑
NSIT Dwarka	19	9	13	24	3	11
IHBAS Dilshad Garden	17	8	13	18	9	13
Pitampura	5	4	5	31	4	17↑
Nizamuddin	4	4	4	15	5	8↑
Sirifort	4	4	4	26	5	10↑
ShahzadaBagh	9	6	7	25	9	14↑
Janakpuri	5	4	4	20	7	11↑
Shadhara	12	7	9	30	7	18↑
PariveshBhawan	29	5	16	50	14	31↑
ITO BSZ Marg	17	7	13	37	6	17↑
DPCC Stations						
R.K. Puram	74	21	47	62	28	47
Mandir Marg	29	13	21	81	14	38↑
Punjabi Bagh	58	19	31	62	16	43↑
Anand Vihar	118	18	39	69	11	36
Average	29	9	16	39	10	34↑

Central Pollution Control Board
Air Quality Profile (Daily average in µg/m^3)
(CAAQM Stations of CPCB in Delhi)

Stations (CPCB Stations)	Parameters	Pre Odd Even (25-31 December, 2015						During Odd-Even (1-15 January, 2016)						Post Odd-Even 16-21 January, 2016)					
		PM2.5	CO	NO2	O3	Benzene	SO2	PM2.5	CO	NO2	O3	Benzene	SO2	PM2.5	CO	NO2	O3	Benzene	SO2
DMS Shadipur	*Max*	141	1244	72	48	3	31	270	1990	126	45	8	26	165	604	47	34	4	13
	Min	65	114	35	34	1	22	79	280	14	2	1	7	76	278	20	13	1	7
NSIt Dwarka	*Max*	298	698	12	40	7	28	261	1061	33	66	11	8	235	675	28	32	7	7
	Min	52	484	5	18	3	8	93	438	9	4	2	5	160	502	17	13	3	4
IHBAS Dilshad Garden	*Max*	221	1006	71	NA	NA	19	295	1610	148	NA	NA	12	229	1316	44	NA	NA	8
	Min	85	321	51			7	107	371	29			6	103	363	27			7
Parivesh Bhawan	*Max*	NA	NA	NA	NA	NA	NA	408	NA	NA	NA	NA	NA	237	NA	NA	NA	NA	NA
	Min							119						114					

Central Pollution Control Board

Air Quality Profile (Daily average values in µg/m^3)
(Manual Monitoring Stations in Delhi)

Manual Stations (CPCB Stations)	Parameters & data range	Pre Odd Even (25-31 December, 2015				During Odd-Even (1-15 January, 2016)			
		PM10	PM2.5	NO2	SO2	PM10	PM2.5	NO2	SO2
Pitampura	*Max*	420	NA	44	9	541	429	98	17
	Min	142	NA	43	5	207	116	15	4
Sirifort	*Max*	Data inadequate				548	286	98	39
	Min					301	168	33	4
Janakpuri	*Max*					614	259	97	34
	Min					367	102	24	4
Nizamuddin	*Max*	270	NA	71	13	294	185	81	11
	Min	253	NA	51	13	161	84	31	4
Shazada Bagh	*Max*	309	233	93	17	607	166	93	15
	Min	301	193	52	5	172	81	50	4
Shahdara	*Max*	Data inadequate				629	231	106	42
	Min					217	82	26	4
BSZ-Marg	*Max*	454		116	4	516		159	17
	Min	254		77	4	169		64	4

A2 Diagnostics test for spatial dependence

Pollutant	Model	Test	Statistic	df	p-value
SO2	Spatial error	Moran's I	**-0.106**	1	1.085
		Lagrange multiplier	0.293	1	0.588
		Robust Lagrange multiplier	2.2	1	0.138
	Spatial lag	Lagrange multiplier	0.854	1	0.355
		Robust Lagrange multiplier	2.761	1	0.097
NO2	Spatial error	Moran's I	**-0.955**	1	1.661
		Lagrange multiplier	0.973	1	0.324
		Robust Lagrange multiplier	1.583	1	0.208
	Spatial lag	Lagrange multiplier	1.385	1	0.239
		Robust Lagrange multiplier	1.995	1	0.158
PM10	Spatial error	Moran's I	**-0.972**	1	1.669
		Lagrange multiplier	0.991	1	0.32
		Robust Lagrange multiplier	0.349	1	0.554
	Spatial lag	Lagrange multiplier	0.803	1	0.37
		Robust Lagrange multiplier	0.162	1	0.687
PM2.5	Spatial error	Moran's I	**0.507**	1	0.612
		Lagrange multiplier	0.049	1	0.825
		Robust Lagrange multiplier	1.138	1	0.286
	Spatial lag	Lagrange multiplier	0.013	1	0.911
		Robust Lagrange multiplier	1.101	1	0.294

A3 W Matrix for spatial pooled regression

0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768	0.093725	0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768
0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392	0.028171	0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392
0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325	0.02156	0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325
0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838	0.028007	0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838
0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139	0.026114	0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139
0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188	0.051044	0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188
0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584	0.031243	0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584
0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0	0.024828	0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0
0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729	0	0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729
0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768	0.093725	0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768
0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392	0.028171	0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392
0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325	0.02156	0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325
0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838	0.028007	0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838
0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139	0.026114	0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139
0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188	0.051044	0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188
0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584	0.031243	0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584
0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0	0.024828	0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0
0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729	0	0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729
0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768	0.093725	0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768
0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392	0.028171	0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392
0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325	0.02156	0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325
0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838	0.028007	0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838
0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139	0.026114	0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139
0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188	0.051044	0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188
0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584	0.031243	0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584
0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0	0.024828	0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0
0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729	0	0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729
0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768	0.093725	0	0.015274	0.014925	0.021233	0.017091	0.044623	0.02336	0.019768
0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392	0.028171	0.026603	0	0.026247	0.023243	0.019124	0.040106	0.054112	0.032392
0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325	0.02156	0.018145	0.018321	0	0.041965	0.032113	0.019484	0.030087	0.068325
0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838	0.028007	0.021982	0.013816	0.035737	0	0.063662	0.01983	0.024128	0.042838
0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139	0.026114	0.022061	0.014172	0.034094	0.079369	0	0.019225	0.021826	0.033139
0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188	0.051044	0.050132	0.02587	0.018005	0.021518	0.016734	0	0.041509	0.025188
0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584	0.031243	0.025837	0.034363	0.027372	0.025776	0.018703	0.040865	0	0.04584
0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0	0.024828	0.019741	0.018572	0.056123	0.04132	0.02564	0.022389	0.041387	0
0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729	0	0.085684	0.014787	0.016213	0.024731	0.018496	0.041537	0.025824	0.022729

A4 FE results with robust standard errors

VARIABLES	(1) FE Robust without Polynomials	(2) FE Robust with Polynomials
oddevenrule	11.14 (7.761)	-496.6 (579.1)
peripheral_highway	-3.071 (7.438)	9.836 (10.18)
harvesting	1.176 (3.742)	-1.808 (2.334)
rainfall	-0.167 (0.145)	-0.194 (0.155)
ws	-13.57 (7.028)	-12.13 (5.727)
rh	-0.651 (0.383)	-0.783 (0.493)
temp	-1.853 (0.974)	-2.280 (1.229)
diwali	11.35 (16.26)	9.488 (13.81)
crackerban	6.837	4.661

	(11.00)	(10.63)
petrolprice	1.830 (1.221)	0.631 (0.368)
dieselprice	-0.747 (0.628)	-0.888 (0.596)
electriccng	-0.350 (0.515)	-0.683 (0.723)
privatevehicles	-0.183 (0.211)	-0.342 (0.301)
publicvehicles	-0.313 (0.791)	-0.544 (0.765)
index		-0.0106 (0.0612)
index2		-5.69e-05* (2.51e-05)
index3		1.12e-07 (9.85e-08)
index4		-0 (5.80e-11)
oddindex		4.877 (5.358)
oddindex2		-0.0152 (0.0154)
oddindex3		1.55e-05 (1.32e-05)
oddindex4		-5.22e-10 (2.67e-09)
Constant	483.3 (440.4)	894.1 (651.8)
Observations	5,790	5,790
R-squared	0.176	0.190
Number of panelid	5	5

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A5 FE results with Data confined to 15-day window before, during and after the introduction of odd-even scheme

VARIABLES	(1) FE without Polynomials 15 days	(2) FE with Polynomials 15 days
oddevenrule	5.637* (3.043)	-308.7 (428.6)
peripheral_highway	-1.590 (8.602)	-5.135 (10.64)
harvesting	-1.941 (3.881)	2.526 (7.085)
rainfall	3.420 (4.279)	3.083 (4.341)

ws	-15.76*** (3.415)	-14.62*** (3.689)
rh	-0.338* (0.204)	-0.480** (0.243)
temp	-0.601 (0.474)	-1.022** (0.515)
diwali	7.709 (6.810)	0.153 (7.794)
o.crackerban	-	-
petrolprice	1.288 (2.469)	-4.352 (4.218)
dieselprice	-4.381** (1.725)	-5.593** (2.261)
electriccng	-0.0844 (0.131)	0.118 (0.296)
o.privatevehicles	-	-
o.publicvehicles	-	-
index		-2.678 (2.835)
index2		0.00648 (0.00776)
index3		-6.18e-06 (5.73e-06)
index4		4.48e-09 (8.26e-09)
oddindex		3.242 (4.164)
oddindex2		-0.0121 (0.0124)
oddindex3		1.96e-05** (9.94e-06)
oddindex4		-1.20e-08 (1.35e-08)
Constant	294.6** (140.0)	1,037** (462.9)
Observations	492	492
R-squared	0.221	0.239
Number of panelid	5	5

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A6 RDD results with winter dummy

VARIABLES	(1) FE	(2) FE with polynomials	(3) RE	(4) RE with polynomials	(5) RE MLE	(6) RE MLE with Polynomials
oddevenrule	7.414* (3.927)	-461.1 (591.1)	6.955 (7.106)	-633.4 (1,075)	7.413* (3.922)	-461.1 (589.9)
peripheral_highway	-4.293 (3.373)	9.744* (5.104)	-4.572 (6.103)	8.638 (9.286)	-4.293 (3.368)	9.743* (5.093)
harvesting	0.0580 (1.700)	-2.734 (1.775)	2.469 (3.075)	0.157 (3.229)	0.0589 (1.697)	-2.733 (1.771)
rainfall	-0.0952 (0.116)	-0.132 (0.116)	-0.146 (0.210)	-0.179 (0.211)	-0.0952 (0.116)	-0.132 (0.116)
ws	-13.14*** (1.253)	-12.02*** (1.278)	-13.14*** (2.267)	-12.31*** (2.325)	-13.14*** (1.251)	-12.02*** (1.275)
rh	-0.583*** (0.0520)	-0.689*** (0.0549)	-0.571*** (0.0941)	-0.668*** (0.0999)	-0.583*** (0.0519)	-0.689*** (0.0548)
temp	0.0173 (0.180)	-0.451** (0.188)	0.00942 (0.326)	-0.415 (0.342)	0.0173 (0.180)	-0.451** (0.188)
diwali	10.08 (7.258)	10.13 (7.308)	9.807 (13.13)	10.14 (13.30)	10.08 (7.249)	10.13 (7.294)
crackerban	20.54** (9.840)	16.84* (9.823)	17.95 (17.81)	14.74 (17.87)	20.54** (9.828)	16.84* (9.803)
petrolprice	1.540*** (0.395)	0.345 (0.420)	1.037 (0.715)	0.0480 (0.765)	1.540*** (0.395)	0.345 (0.420)
dieselprice	-0.733* (0.391)	-0.887** (0.411)	-0.457 (0.708)	-0.632 (0.747)	-0.733* (0.391)	-0.887** (0.410)
electriccng	-0.376*** (0.0856)	-0.679*** (0.122)	-0.449*** (0.155)	-0.814*** (0.222)	-0.376*** (0.0855)	-0.679*** (0.122)
privatevehicles	-0.176*** (0.0191)	-0.332*** (0.0263)	-0.181*** (0.0345)	-0.323*** (0.0478)	-0.176*** (0.0190)	-0.332*** (0.0262)
publicvehicles	-0.357*** (0.0885)	-0.644*** (0.138)	-0.410** (0.160)	-0.728*** (0.251)	-0.357*** (0.0884)	-0.644*** (0.138)
winter	35.09*** (2.623)	34.42*** (2.636)	33.79*** (4.746)	33.24*** (4.797)	35.09*** (2.620)	34.42*** (2.631)
index		-0.0369 (0.0237)		-0.0181 (0.0431)		-0.0369 (0.0237)
index2		-2.70e-05 (3.59e-05)		-4.63e-05 (6.53e-05)		-2.70e-05 (3.58e-05)
index3		9.51e-08** (4.01e-08)		7.47e-08 (7.30e-08)		9.50e-08** (4.01e-08)
index4		-0 (0)		0 (0)		-0 (0)
oddindex		4.269		5.720		4.269

		(5.727)		(10.42)		(5.716)
oddindex2		-0.0127 (0.0170)		-0.0152 (0.0309)		-0.0127 (0.0170)
oddindex3		1.21e-05 (1.33e-05)		6.45e-06 (2.43e-05)		1.21e-05 (1.33e-05)
oddindex4		6.77e-10 (1.83e-08)		1.50e-08 (3.33e-08)		6.83e-10 (1.82e-08)
Constant	438.2*** (38.11)	855.0*** (67.17)	473.9*** (68.96)	859.0*** (122.2)	437.0*** (49.42)	853.8*** (74.08)
Observations	5,790	5,790	5,790	5,790	5,790	5,790
R-squared	0.201	0.213				
Number of panelid	5	5	5	5	5	5

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A7 RDD results correcting for first order autocorrelation

VARIABLES	(1) FE GLS regression with AR(1) disturbances	(2) RE GLS regression with AR(1) disturbances
oddevenrule	7.100 (5.429)	4.744 (5.432)
peripheral_highway	-2.053 (7.989)	-14.34* (8.447)
harvesting	-1.323 (3.066)	-1.417 (3.046)
rainfall	-0.0406 (0.0509)	-0.0388 (0.0508)
ws	-8.309*** (0.833)	-8.347*** (0.831)
rh	0.0176 (0.0623)	0.0164 (0.0620)
temp	0.475** (0.196)	0.500** (0.196)
diwali	-4.686 (5.533)	-4.651 (5.521)
crackerban	3.848 (6.512)	3.704 (6.499)
petrolprice	1.131 (0.761)	1.007 (0.758)
dieselprice	-1.149 (0.740)	-1.062 (0.715)
electriccng	0.265 (0.223)	-0.353 (0.264)

privatevehicles	-0.0110 (0.0210)	-0.191*** (0.0463)
publicvehicles	0.323*** (0.101)	-0.697*** (0.244)
Constant	48.61*** (3.323)	521.9*** (111.9)
Observations	5,785	5,790
Number of panelid	5	5

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

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