



Health effects of air quality regulations in Delhi, India

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ABSTRACT

This, the first systematic study, quantifies the health effects of air quality regulations in Delhi, which adopted radical measures to improve air quality, including, for example, the conversion of all commercial vehicles to compressed natural gas (CNG), and the closure of polluting industries in residential areas from 2000 to 2002. Air pollution data, collected at 113 sites (spread across Delhi and its neighboring areas) from July–December 2003, were used to compute exposure at the place of residence of 3989 subjects. A socio-economic and respiratory health survey was administered in 1576 households. This survey collected time-use, residence histories, demographic information, and direct measurements of lung function with subjects. The optimal interpolation methods were used to link air pollution and respiratory health data at the place of their residence. Resident histories, in combination with secondary data, were used to impute cumulative exposure prior to the air-quality interventions, and the effects of recent air quality measures on lung function were then evaluated. Three important findings emerge from the analysis. First, the interventions were associated with a significant improvement in respiratory health. Second, the effect of these interventions varied significantly by gender and income. Third, consistent with a causal interpretation of these results, effects were the strongest among those individuals who spend a disproportionate share of their time out-of-doors.

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1. Introduction

A well-established body of literature documents strong linkages between respiratory health and air pollution in both developed (Cohen et al., 2005; Dockery and Pope, 1994; EPA, 2001; Pope et al., 2002; Samet et al., 2000) and developing countries (Chhabra et al., 2001; Cropper et al., 1997; Katsouyanni et al., 1997; Pande et al., 2001). While the short-term effects, such as hospital admission and mortality caused by cardiovascular and respiratory diseases, and long-term effects of exposure that include lung-cancer and decay in lung function have been subject to research scrutiny, little is known about the health effects of air quality regulations, especially in developing countries. In the US, there is some evidence that policies targeting air quality can have significant impacts on health. Some of the most compelling evidence of policy effects comes from studies of the impact of the 1970 Clean Air Act (CAA) in the US in which there were large differences in policy responses in counties that were compliant with a set of air quality standards and otherwise similar counties that were not in compliance. In particular,

Chay and Greenstone (2003) find that infant mortality in these counties declined significantly after the CAA. There is less clear evidence of effects on adults, however, Greenstone and Gayer (2009) suggest that preexisting differences in mortality between attainment and non-attainment areas make inference here less compelling.

It is also not clear how well results from the developed world carry over to the developing world, given background differences in economic circumstance, access to health services, and overall exposure to adverse environmental conditions. Duflo et al. (2008) provide a short survey on the recent literature that uses natural variation in ambient air quality to examine the effects of air quality on health. Of particular interest are studies of the effects of 1997 forest fires in Indonesia, which were found to lead to higher infant mortality, higher respiratory-related hospitalizations (Emmanuel, 2000), and lower in terms of measures of health status that are shown to correlated with lung capacity (Frankenberg et al., 2005).

An important limitation of most existing studies exploiting natural or policy-induced variation in air quality is that they have made use of aggregated data. As a consequence, these studies have not incorporated information on the level of exposure faced by individuals, do not allow one to distinguish differences in effects by socio-economic status and have not included direct measures of respiratory health in a representative population. An ideal

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experiment in terms of measuring the effects of a policy-induced change in ambient air quality would be to examine two otherwise identical individuals, one exposed to the policy and one who is not. But given that ambient air quality is highly correlated across space, this implies that individuals who are exposed to the policy must live at some distance from those who are not exposed. As a result, we cannot know for sure whether there are other important sources of variation in respiratory health other than current ambient air quality that happen to be correlated with exposure to the policy. For infants, who do not have differences in previous exposure to ambient air quality, this may be less of an issue, but it is likely to be critical in adult populations.

Those studies that have made use of individual-level health data have often not been linked to air quality data at an appropriate scale. For example, Chhabra et al. (2001) is particularly relevant to the present study, given its focus is on Delhi, India. They examine the respiratory health of 4000 working-age adults living in the areas around nine air pollution monitoring sites in Delhi, India. They did not find an overall relationship between air quality at the nearest air pollution monitoring site and lung function, although such a relationship was found in some strata of the population. But these sites are carefully selected sentinel sites, and it is unclear how air quality at these sites relates to that in the neighborhoods of the study population. Frankenberg et al. (2005) do make use of individual data and employ differences in health over time to control for fixed individual-level variation among individuals exposed and not-exposed to the fires in Indonesia. They also employ satellite data to evaluate the extent of exposure. However, they do not have systematically collected ground-data on ambient air quality, do not consider effects of variation in exposure across individuals, and do not have access to a direct measure of respiratory health.

The present work aims to address the above identified gaps in the literature, and examines the overall health effects of a series of new air quality regulations that have differentially-affected air quality in Delhi, relative to its outlying areas (Kumar and Foster, 2009). Utilizing the rich air pollution data collected at spatially dispersed 113 sites (in and around Delhi) and respiratory health and socio-economic data, from 1576 households (covering respiratory health data on 3989 subjects), this paper examines the effects of air quality regulations in Delhi on respiratory health, measured by lung function.

2. Materials and methods

2.1. Study area

This study focuses on Delhi and its neighboring areas. Delhi is the second largest metropolitan in India, and its population has increased from 9.4 million in 1991 to 13.2 million in 2001 (at the rate of 3.34% annual exponential growth rate). The number of industrial units in Delhi increased from 8000 in 1951 to 125,000 in 1991; automobile vehicles increased from 235,000 in 1975 to 4,236,675 in 2003–04 (Government of Delhi, 2005; Government of India, 2006). Industries and automobiles are widely acknowledged to have been two important sources of air pollution in Delhi, with the transportation share growing rapidly in recent years (Narain and Krupnick, 2007). According to one set of estimates, the contribution of air pollution from vehicle emission increased from 23 percent in 1970–71 to 72 percent in 2000–01 (Table 1). At the turn of the millennium, air pollution in Delhi was at its peak: the city was ranked as the tenth most polluted city in the world in terms of total suspended particulate matter (PM) (Government of NCT of Delhi 2005). The burden of pollution in Delhi was such that it called for public attention, and triggered judiciary intervention to check the unabated increase in the ambient air pollution.

Table 1

Sources of pollution in Delhi.

Source	1970–71	1980–81	1990–91	2000–01
Industrial	56	40	29	20
Vehicular	23	42	64	72
Domestic	21	18	7	8

Source: Government of India, 1997.

Ultimately, a series of rulings by the Indian Supreme Court put in place a series of regulations that were unprecedented in terms of their scope and mandated speed of implementation (Bell et al., 2004; Narain and Krupnick, 2007). Chief among these new regulations was a mandate to convert all public vehicles, inclusive of buses, taxis, and three-wheel scooters to compressed national gas (CNG) over a two-year period, and to substantially limit the flow of diesel trucks through Delhi during working hours. The virtual absence of CNG infrastructure prior to this announcement, coupled with the rapid rise in CNG vehicles following the announcement, is a testament to the extent to which these changes may be thought of as unanticipated. Bell et al. (2003) chronicles the remarkable story of how these interventions were put in place.

There remains some debate about how to attribute the various trends in various measures of air quality in Delhi and its surroundings to the various Court-induced policies, particularly given the rapid rise in the total number of vehicles in the area over the same period. A recent study (Narain and Krupnick, 2007) shows that there have been significant declines in carbon monoxide and sulfur dioxide in Delhi that may be attributable to the mandated conversion of all public vehicles to CNG. Suspended particulates, on the other hand, have been relatively stable over the period 1997–2005 for the city as a whole, with the CNG-induced declines from public vehicles being countered by the substantial rise in diesel powered private vehicles. However, as Kumar and Foster (Kumar and Foster, 2007) show, using the present data, there is substantial within-region variation with those areas with high levels of bus traffic, and those in the center of the city, having low levels relative to those areas at the boundaries and outside of the city. There was also a movement of non-CNG vehicles to outside of the city limits as a consequence of the law. While this movement is useful because it likely increases differences in ambient air between center city and other areas it complicates policy evaluation in the sense that one of the unintended consequences of the policy was that it likely reduced air quality outside of the regulated area.

2.2. Data

The analysis in this research is based on a number of datasets: air pollution, health, and socio-economic. Since the data collected by the Central Pollution Control Board (CPCB) were inadequate to develop spatially detailed estimates of exposure and to compute current and cumulative ambient exposure at household locations, air pollution was monitored at 113 sites, spread across Delhi and its neighboring areas from July–December 2003 (Fig. 1). Sampling design, sampling duration and frequency for air pollution monitoring are discussed elsewhere (Kumar and Foster, 2007, 2009). Aerocet 531 passive air samplers (Met One Inc., 2008) were deployed to record particulate matter (PM) in a range of 1, 2.5, 5, 7 and 10 μm in aerodynamic diameters. The Aerocet 531 uses right angle light scattering method at 780 nm. The source light travels at a right angle to the collection system and detector. The instrument uses the information from the scattered particles to calculate a mass-per-unit volume. Each of the 5 different sizes has a mean particle diameter calculated. This mean particle diameter is used to calculate a volume (cubic meters). It is then multiplied by the

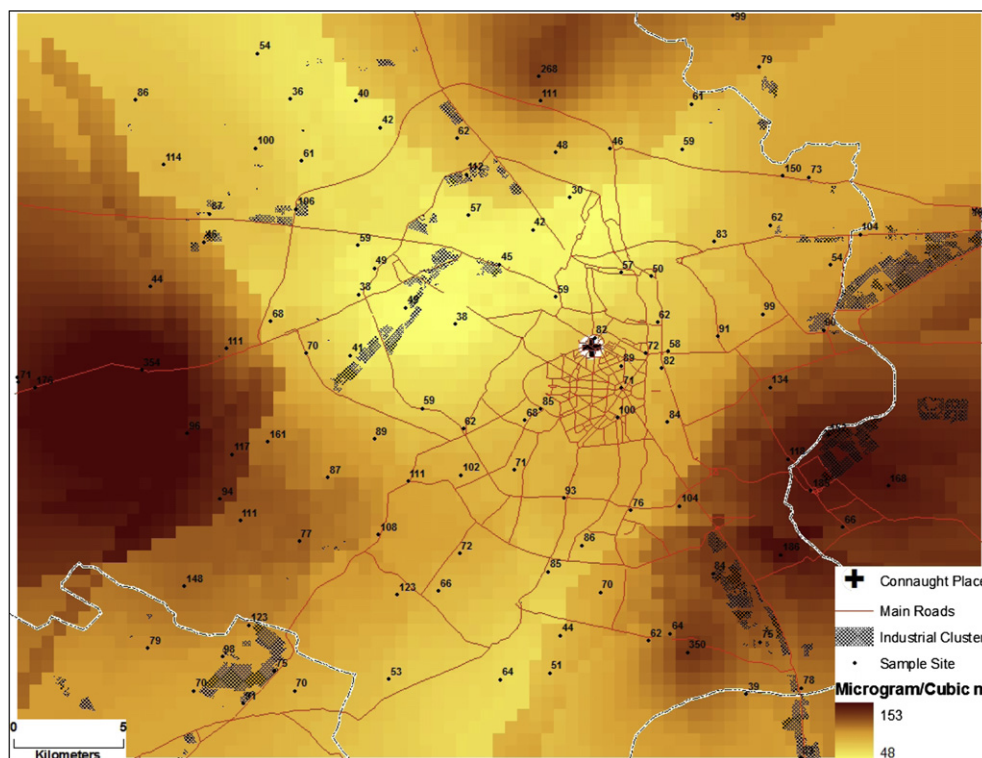


Fig. 1. Air quality sampling points and interpolated estimates of $PM_{2.5}$ in Delhi and its surrounding areas, July–December, 2003.

number of particles, and then a generic density ($\mu g m^{-3}$) that is a conglomeration of typical aerosols. The resulting mass is divided by the volume of air sample for a mass per unit volume ($\mu g m^{-3}$) measurement.

The photometric technique used by the instrument (Aerocet 531) is sensitive to aerosol size, which can easily inflate with an increase in relative humidity. Therefore, using the standard relationship among relative humidity, photometric, and gravimetric measurements, as discussed in Ramachandran et al. (2003), air pollution data were calibrated as $D/D_0 = 1 + (0.25 (RH_2/(1 - RH)))$; where D (photometric measurement) and D_0 (gravimetric measurement) are the wet and dry particle diameters respectively, and RH is relative humidity (proportion). Sioutas et al. (2000) suggest the correction for relative humidity, using particle characteristics, including molecular weight of dry particles. Since these data were not available for the study area, the standard equation (3) was used to compute PM of different sizes.

The Kriging method (that minimizes prediction error) was employed to compute spatially-detailed air pollution surface (Cressie, 1993), and using the GPS coordinates all subjects included in the study, were linked to the air pollution surface (Fig. 1). Kriging, which resulted in the least-average variance between actual and estimated values at 113 sites, was employed to estimate air pollution at household locations. Since the spatial interaction of housewives and children is restricted within their neighborhood, the average air pollution within different distance intervals (including 250, 500, and 1000 m) from each household location was computed. Among these, the average air pollution within 250 m of a household location, which registered the highest impact on respiratory health, was used in the final analysis as a proxy of ambient exposure to air pollution. 95% of the households were within 4.4 km distance to a monitoring station and on average we utilized values from the closest eight monitoring stations to impute continuous surface. The robustness of these interpolation are

discussed elsewhere (Kumar and Foster, 2009). Since all 113 sites covered the study area adequately and Kriging utilizes multiple stations, the prediction error of PM is likely to be minimal for most household locations. The prediction error is likely to be high with the increase in the average distance between monitoring stations and household locations, but this distance did not vary significantly.

To collect respiratory health and socio-economic data, 1576 households were surveyed in Delhi and its surroundings from January to April, 2004. The households were selected using a spatial sampling approach to capture representative ambient air pollution exposure from different emission sources (Kumar, 2007). First, the study area was stratified using air pollution levels and proximity to emission sources, and the identified strata were partitioned into residential and non-residential areas. A sample of area weighted 2000 random points, was selected from the residential areas of the identified strata. These points were transferred to GPS to identify households the random locations and their consents to participate in the survey. If a random location was placed on a multi-story building, one household was selected randomly from the list of all households in that building. Finally, of the 2000 random locations, 1576 were found suitable and agreed to participate in the survey. The procedure for selection and robustness of exposure at the selected households are discussed elsewhere (Kumar, 2007). In order to minimize the gender-specific bias in the selection of subjects, we conducted interviews during the weekends (and for longer hours (9AM to 8PM) and break during the week days.

A questionnaire schedule was adopted for the survey, which had three components: (a) household, (b) individual, and (c) lung-function test. The household part covered all members of the household, duration of residence, household structure, type, and location (in terms of land-use zoning – industrial or residential), morbidity and mortality, and socio-economic details. The individual part included details on respiratory health related symptoms, air quality awareness, smoking habits, willingness to pay for

clean air, etc., a time diary (that included time spent at different places in a routine day), and building and place characteristics, residential history over the life-course, etc. It was administered to those individuals who were present in the household at the time of the survey and were 15 or older. A MicroDL spirometer was used to examine the lung-function objectively; each individual was given three trials, and the highest values of forced expiratory volume after one second (FEV₁) and forced vital capacity (FVC), were used in the analysis. The lung-function test was administered to all household members who were five or older and present in the household at the time of survey. Since this instrument was not configured for each individual, FVC was estimated using age, height, and race. The European Community for Coal and Steel (ECCS) method (Cogswell et al., 1975) was employed to estimate FVC with 12 and 15% ethnic correction for child and adult population, respectively. The lung function was computed using the FEV₁ recorded by the spirometer and FVC, computing using ECCS method, as given below:

For pediatric < 17 years (ESSC using Cogswell et al., 1975)

$$FVC_{\text{Male}} = \frac{\exp((2.936 \log(\text{Height})) - 2.9236)}{1000} \quad (1)$$

$$FVC_{\text{Female}} = \frac{\exp((2.8181 \log(\text{Height})) - 2.704)}{1000} \quad (2)$$

For adult ≥ 17 years (ESSC using Cogswell et al., 1975)

$$FVC_{\text{Male}} = (5.76(\text{Height}/100)) - (0.026\text{Age}) - (4.34) \quad (3)$$

$$FVC_{\text{Female}} = (4.43(\text{Height}/100)) - (0.026\text{Age}) - (2.89) \quad (4)$$

Our approach can be characterized in terms of a health production function as proposed by Grossman (1972), which is a central concept in the literature on the economics of health. A key application of this approach in the development literature is Cebu Study Team (1992). The idea is that health at any given time reflects the history of past health inputs. In our case we focus specifically on ambient air quality as an input to health. As we do not specifically condition on other inputs our estimates reflect the consequences of exposure to poor air quality net of any actions (such as treatment for respiratory conditions) as a response to past exposure. In general, of course, the consequences of exposure may be different at different ages and effects at any given age may tend to decline over time. It also may be the case that more recent exposure has a different effect than exposure in previous years. Given data limitations and the fact that our primary goal is to estimate the effects of the policy we simply divide the history of exposure into two components: recent exposure and average exposure over an individual's life time. Obviously the latter is going to be an imperfect measure of the life-history of exposure and coefficients on this variable must be interpreted with caution. Note, however, that in order to increase the validity of our estimates of the effects of the policy this measure of exposure need not be a perfect predictor of an individual's respiratory health; it need only serve as a control in the sense that it remove variation in lagged exposure that both predicts current respiratory health and is correlated with exposure to this policy. Our primary input of interest, recent exposure, is measured by PM_{2.5} at the point of household residence in 2003. Because air pollution regulations in Delhi were implemented during the 2000–2002 period, and air quality was measured in late 2003, this measure reflects post-regulation exposure. As noted, the air pollution data collected subsequent to the regulation change cannot be used to compute exposure before the regulation period or exposure at other places subjects have lived before moving to the study area. Therefore, residential history (with place

characteristics) and air pollution in the surrounding areas, unaffected by the regulations, were used to compute the average long-term exposure (to ambient air pollution) of the *i*th individual who was resident in household *j* at the time of the survey.

$$e_{ij} = \left(p_{jt} \sum_{k=0}^{\text{age}_i} \sum_s k_{st-k} r_{ist-k} \right) / \text{age}_i \quad (5)$$

p_{jt} = PM₂₅ μg m⁻³ at location household *j* and time *t*, k_{st} = PM concentration at time *t* – *k* at location *s* relative to that in Delhi post-intervention, r_{ist-k} = dummy variable indicating if *i* was at location *s* at time *t* – *k*.

As noted earlier, the exposure in Delhi during the previous two years is reasonably measured based on the 2003 air measurements. The areas surrounding Delhi, however, were largely unaffected by the air quality regulations, and the exposure in these areas can be considered the same for the previous several years. In the absence of spatially detailed air pollution, we relied on satellite based aerosol optical depth (AOD), corrected for meteorological condition, to evaluate the trend of air pollution before and after the regulations inside and outside Delhi. We computed 2 km AOD using the satellite data (Remer et al., 2006), and corrected them for meteorological conditions, because meteorological conditions can bias AOD estimates (Kumar et al., in press). Our analysis suggests that areas bordering Delhi but outside Delhi recorded 9.7% increase from 2000–01 to 2003–04 (Fig. 2); the increase in areas inside Delhi that included all rural and urban areas in Delhi was 7.3%. Fig. 3 clearly shows a decline in AOD in central parts of the city after the regulations, and increase in built up area in areas near Delhi border, especially southern borders of the city. Based on these empirical evidences, we assume that the air quality inside Delhi was worse before the regulations than that in areas outside Delhi.

On average, the air pollution at household locations (most of them were located within 15 km of Delhi Border) outside Delhi was 1.147 times higher than that located in Delhi. Multiplying the current exposure by 1.147 can help compute exposure before the regulations at the current location. Residential history and place characteristics were used to estimate air pollution at previous residential locations. Since the spatially detailed air pollution data were not available for those places except for Delhi, place-characteristics were used to assess the location constants (k_{st}). Based on the degree of urbanization, which is positively associated with the levels of ambient air pollution, places were grouped into five categories, namely City, City Suburban, Town, Town Suburban, and Rural, and air pollution at these places were computed by

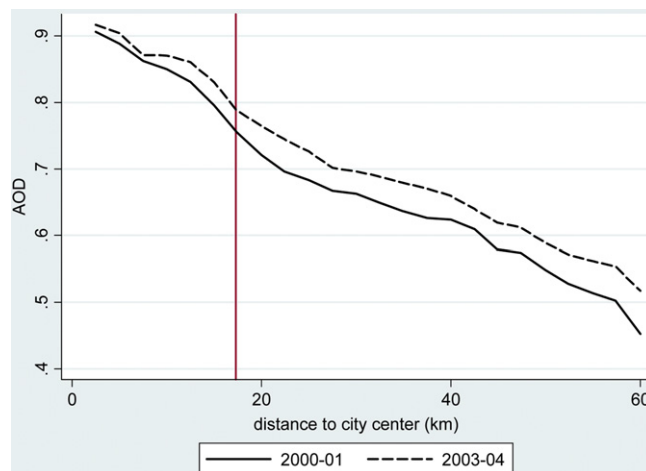


Fig. 2. Change in AOD with respect to distance to the city center (Connaught Place, i.e., central business district of Delhi).

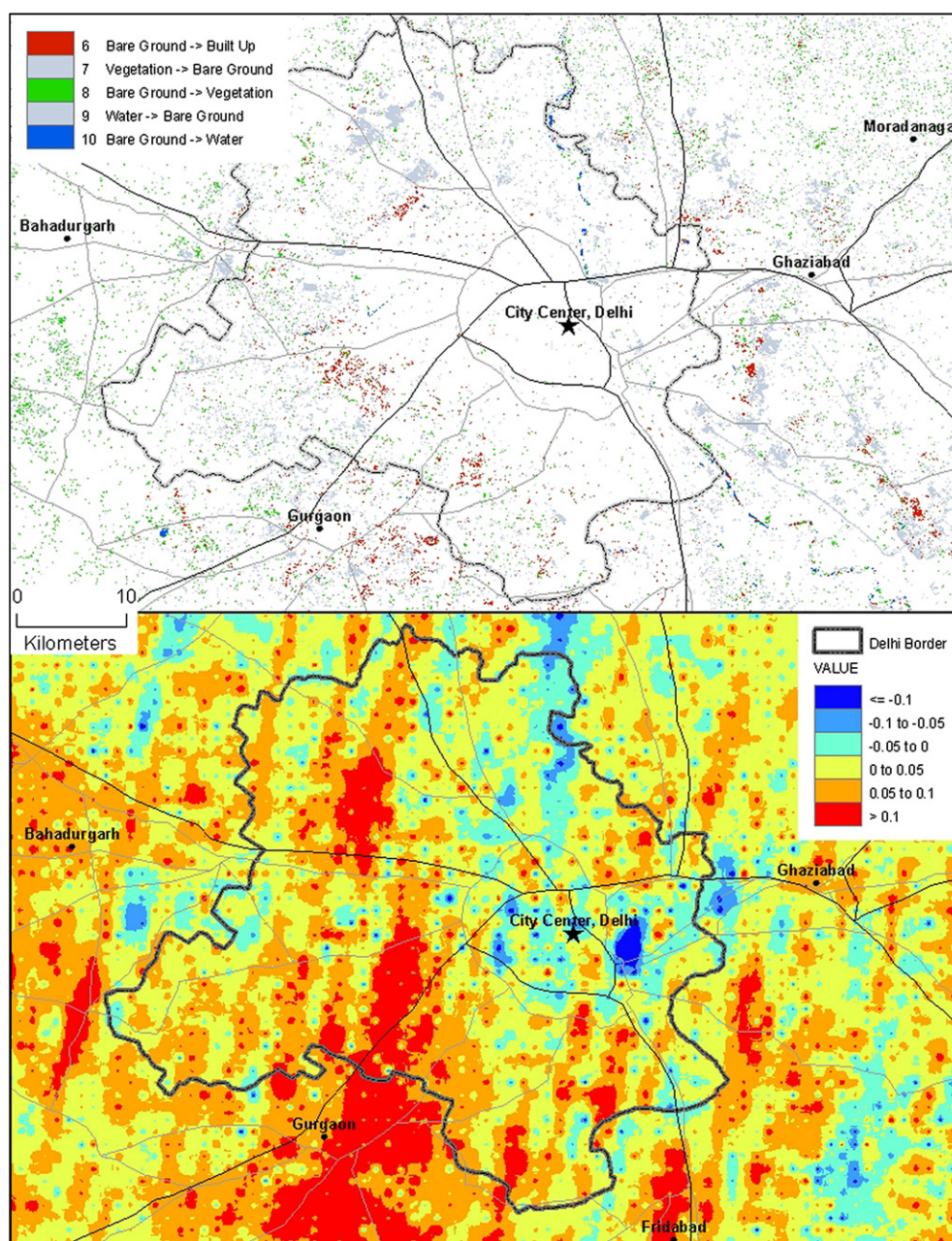


Fig. 3. Change in AOD and Land Use and Land Cover in and around Delhi from 2000–01 to 2003–04.

multiplying the air pollution at the present household location by the location constants of 1, 0.85, 0.75, 0.5, and 0.25, respectively; these constants were estimated using the air pollution data monitored by the Central Pollution Control Board at different locations in Delhi and its neighboring states. Again while we note that these estimates are only approximations we believe they provide a reasonable mechanism for controlling for past exposure to adverse air quality so that we can obtain valid estimates of the effects of exposure in the last two years as a consequence of the policy.

2.3. Estimation

We estimate a linear approximation to the respiratory health production function for individual i in household j , which can be expressed as (*xtreg* function in *STATA*, 2010)

$$l_{ij} = \alpha + \beta p_j + \gamma e_{ij} + \lambda w'_{ij} + \delta_j + \varepsilon_{ij} \quad (6)$$

where l_{ij} = lung-function of i th individual in j th household; p_j = current exposure to ambient air pollution; e_{ij} = average lifetime exposure to ambient air pollution; w'_{ij} = a vector of household and individual level variables; δ_j = household-level effect; ε_{ij} = individual-level effect.

There are two potential difficulties that arise in the estimation of (6). First, the current and cumulative measures of exposure to ambient air pollution based on point of residence are likely to be a noisy estimate of the true exposure. For example, if an individual lives at point A, but spends equal amounts of time within a radius r of point A, then his exposure will be the air quality over this circle and thus the point estimate at A is a noisy estimate of the true exposure. In the absence of data explicitly evaluating where an individual is at each point in time, this problem can be addressed as

a measurement error problem, assuming one has available an instrument that predicts ambient air quality, but is otherwise uncorrelated with lung function given (6). As we will show, residence inside the city meets the first of these criteria.

The second criterion is related to a second estimation problem. To what extent is it reasonable to take location as given with respect to lung function, given (6)? While we have argued above that the introduction of air quality regulations was unanticipated and it is thus unlikely that those in the survey (at least those resident for at least two years) did so in direct response to the introduction of the CNG-regulations, there may well be other factors that attracted certain types of people to the city prior to the regulation that otherwise affect lung function. To gain some insight into this possibility as well as to help validate our measures of lifetime exposure we make use of a differencing argument. The idea is that the coefficient γ in (6) can be estimated in two different ways and the resulting estimates can be compared. First, we can use ordinary least squares in which case the estimate of both β will, in general, be downwardly biased if, say people with poor respiratory health are more likely to be living in areas impacted by the regulations. Moreover, because current and past exposure are negatively correlated (as we will show below), a bias in β induces a bias in γ of the same sign. Second we can use household fixed-effects, in which case we are comparing respiratory health of people that are coresident. In this case we cannot estimate β because p_j will not vary for people within the same household. But if people in the same household have different average past exposures (because they lived in different places before moving to Delhi) then we can obtain an estimate of γ that is not biased. Thus if the two estimates of γ are similar we can reasonably presume that this particular sort of bias is not present and thus that the least squares estimates of β , our parameter of interest, are not importantly biased as a result of endogenous residential choice.

3. Results

Table 2 reports estimates of the means and standard deviations of the variables used in the analysis, stratified by whether the individual is a resident inside or outside of Delhi. Of particular interest is the fact that there is no significant difference in lung function by location inside Delhi. Given the fact that regulations on air quality were only imposed within the city, this may appear to suggest that the regulation had little effect on lung function. However, this would presume that the population within and outside Delhi had similar lung function prior to the introduction of the regulations.

There are two reasons to believe that lung function within and outside Delhi differed prior to the introduction of regulation. While there were not significant differences by age, sex, or smoking status in the two populations, there was a significant difference in household expenditure per capita. In particular, those living outside

of Delhi were better off than those living inside the city and thus, perhaps had better lung function because they were just healthier overall or had better access to medical services. A second explanation is that exposure to adverse ambient air prior to the regulations was significantly higher in Delhi. Because our imputation was done under the assumption that the prior air quality within the city was comparable to that outside the city, any difference between those inside and outside the city limits is attributable to differences in prior living arrangements (e.g., time spent in more rural areas or small cities) rather than to the imputation per se. Indeed, as might be expected from this perspective, those living outside of the city had a significantly shorter duration of residence in their current house than those inside the city. Because people currently living outside the city limits were more likely to have lived for some time in rural areas or smaller cities then, all else being equal, their overall lung function should have been better than those resident inside the city limits. As it was not better, one may infer that “all else” was not equal—that is those outside the city were exposed to poor air quality following the introduction of the regulations.

Table 3 presents estimates of the effects of current and lifetime exposure to adverse ambient air quality on lung function, using both household-random and household-fixed effects. The estimates show a remarkably clear and consistent pattern, in terms of adverse effects of both current and lifetime exposure to adverse air quality on lung function. In the first pair of regression, the point-estimate of current and lifetime average $PM_{2.5}$ are significant at the 5% and 1% levels, respectively, but quite small in magnitude. In particular, the first column of estimates indicates that a one standard deviation increase in estimated average lifetime ambient $PM_{2.5}$ exposure results in a .79 point decline in lung function, which represents 0.05 standard deviations. The coefficient estimate for current ambient exposure is similarly small. A one standard deviation increase in current $PM_{2.5}$, results in a .628 point decline in lung function, which represents .04 standard deviations. Controlling for household-fixed effects slightly lowers the average lifetime exposure in absolute value. Introducing controls for age, sex, and expenditures reduces the estimated effects of ambient air quality slightly. It is evident that there is a positive effect of per-capita expenditures with a doubling of household expenditure, resulting in a 1.659 point increase in lung function or .11 standard deviations. Men have lower lung function than do women, and lung function is declining with age, but at a diminishing rate.

One potential concern is that our air quality estimates are measured with error. In particular while this study is unusual in the sense that the estimates of air quality were systematically collected on the ground, it is still the case that we are sampling data at particular points in time and space. Thus the actual exposure of an individual is being measured with significant error. One way to approach this problem is to use instrumental variables that predict exposure but are not themselves subject to the sampling error associated with measuring air quality. Thus we instrument using

Table 2
Means and standard deviations by residence.

	Total		Inside Delhi		Outside Delhi		Different by location
	Mean	S.D.	Mean	S.D.	Mean	S.D.	P-Value
Lung function ($100 \times (FEV1/FVC)$)	70.30	15.31	70.44	15.35	69.85	15.17	.287
Current $PM_{2.5}$ ($\mu g m^{-3}$)	35.31	4.14	34.14	4.06	38.95	1.37	.000
Average Life time $PM_{2.5}$ ($\mu g m^{-3}$)	38.14	10.35	39.86	10.43	32.78	7.99	.000
Per Capita Exp expenditure (Rs)	1328	9523	1272	889	1501	1112	.000
Male	.449	.497	.446	.497	.458	.499	.486
Age	31.22	18.25	31.20	18.32	31.30	18.03	.876
Duration of residence (year)	14.50	11.37	15.36	11.62	11.81	10.08	.000
N	4015		3040		975		

Table 3Estimates of the effects of current and estimated average lifetime PM_{2.5} exposure on lung function using household random and fixed effects.

	I		II		III		IV		V	
	Panel estimates using exposure variables		I+ Variables and controls		II + Instruments for measurement error		III for PC expend < 1224 Rs		III for PC expend < 1224 Rs	
	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects	Random effects	Fixed effects
Current PM _{2.5} ^a	−0.15 2 (2.24)**		−0.12 2 (1.82)*		−1.023 (2.92)***		−1.828 (2.85)***		−0.298 −0.75	
Av. Life PM _{2.5} ^a	−0.076 (3.15)***	−0.059 (1.75)*	−0.059 (2.48)**	−0.042 −1.28	−0.628 (2.75)***	−1.025 (1.89)*	−0.67 (2.27)**	−2.626 (1.71)*	−0.261 −0.88	0.34 −0.68
log(PC Exp)			1.659 (3.77)***		1.05 (2.04)**		−2.271 −1.4		0.673 0.66	
Male			−2.258 (4.83)***	−2.454 (4.45)***	−2.375 (4.65)***	−2.905 (4.21)***	−1.177 −1.45	−4.213 (1.81)*	−3.144 (4.93)***	−3.713 (4.75)***
Age (year)			−0.348 (7.23)***	−0.338 (5.75)***	−0.188 (2.28)**	−0.084 −0.54	−0.25 (1.75)*	0.253 −0.55	−0.143 −1.48	−0.263 (1.75)*
Age(year) ²			0.002 (3.55)***	0.002 (2.58)***	0 (5.99)***	−0.001 −0.64	0.001 −0.51	−0.007 −1.03	0 −0.11	0.001 −0.73
Constant	78.317 (29.23)***	72.539 0	74.041 (17.44)***	80.801 0	129.552 (5.99)***	115.083 (6.06)***	181.635 (4.55)***	172.548 (3.18)***	92.483 (3.76)***	66.264 (3.85)***
# of subjects	3989	3989	3989	3989	3989	3989	1994	1994	1995	1995
# of households	1550	1550	1550	1550	1550	1550	679	679	871	871
Random vs Fixed Effects		X2(1) = 0.57 P = 0.452		X2(4) = 1.54 P = 0.819		X2(4) = 1.96 P = 0.744		X2(4) = 4.12 P = 0.391		X2(1) = 1.96 P = 0.744

*Significant at 10%; ** significant at 5%; *** significant at 1%; PC Exp = per capita expenditure (Rs); PM_{2.5} = $\mu\text{g m}^{-3}$; T-value in parenthesis.^a Treated for measurement error in specifications II–V, instruments are location, duration, and interaction.

location (inside/outside the Delhi city limits), duration of residence, and the interaction of the two. The estimates of the first stage (regress of current and lifetime exposure on the instrumental variables) are presented in Table 4. These estimates show that the instruments are strongly significant and that those residents outside the Delhi city limits have higher current but lower lifetime exposure, and that those who have been resident in the same households for longer have higher lifetime exposure. The instrumented random-effects estimates indicate that a one standard deviation increase in current PM_{2.5} results in a .28 standard deviation reduction in lung function. An increase in overall PM_{2.5} results in a .42 standard deviation reduction in lung function. Combining

these two effects, one might conclude that the difference in lung function between an individual who spent his entire life exposed to the PM_{2.5} currently inside Delhi compared with one who spent his life exposed to the PM_{2.5} currently outside Delhi, would on average have a difference in lung function of 7.624 points: a difference that is comparable, given the corresponding coefficients on age between the average lung function of a 65 year-old and that of a 20 year-old.

The fixed-effects instrumental variables estimates yield a coefficient on average life exposure that is 63% larger and, not surprisingly, less precisely measured than that for the random-effects estimates. This provides some evidence that households that have been co-resident longer tend to have unobserved household-specific attributes that, on average, result in lower lung function. However, a Hausman test comparing the specifications indicates that the differences between the random and fixed-effects coefficients are not significantly different ($\chi^2(4) = 1.96$, $P = .74$). This suggests that the problem of endogenous location choice with respect to lung function is not large.

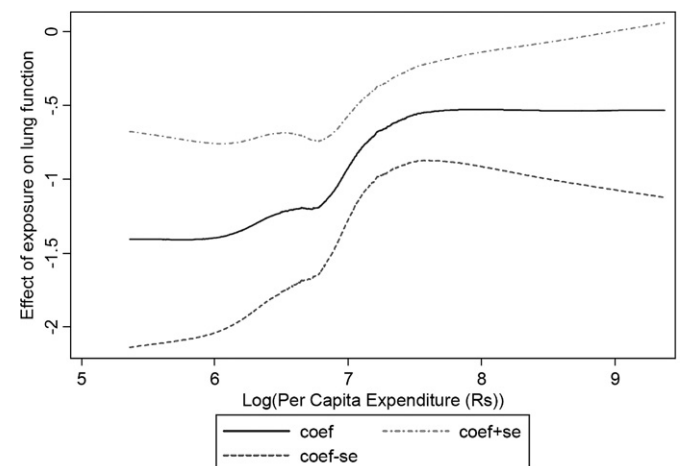
Table 4

First stage estimates.

	PM _{2.5} random effects	Average lifetime PM _{2.5} random effects	Average lifetime PM _{2.5} fixed effects
log(Per Capita Expenditure (Rs))	1.072 (6.61)***	0.756 (2.47)**	
Male	−0.042 −0.36	−0.464 −1.57	−0.653 (1.92)*
Age (years)	0.003 −0.24	0.247 (8.17)***	0.235 (6.52)***
Age (years) ²	0 −0.01	−0.004 (9.27)***	−0.004 (7.19)***
Out of Delhi	5.307 (20.29)***	−7.287 (11.35)***	
Duration in current residence (years)	0.014 −1.29	0.107 (5.81)***	0.102 (3.33)***
Out of Delhi × duration	−0.026 (1.96)*	0.033 −0.9	−0.029 −0.52
Constant	41.305 (35.04)***	30.329 (13.92)***	34.31 (54.87)***
Observations	4015	4015	4015
Number of group(H1)	0.27	1555	1555
R-squared			0.03
Test of excluded instruments Chi ² (3)	X2(3) = 253.51 P = .000	X2(3) = 316.43 P = .000	X2(2) = 6.05, P = .002

Absolute value of z statistics in parentheses.

* Significant at 10%; ** significant at 5%; *** significant at 1%; t-value in parenthesis.

**Fig. 4.** Lowess estimates of effects of current exposure by PC expenditure.

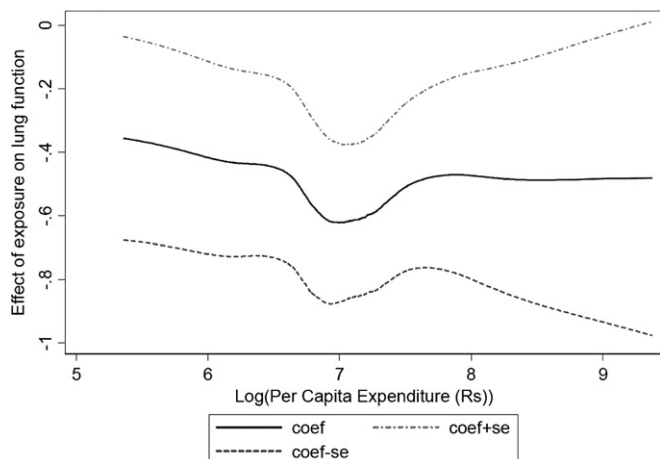


Fig. 5. Lowess estimates of effects of average lifetime exposure by PC expenditure.

To examine whether there are differences in the effects of lung function by economic strata, the dataset was divided at the median-household expenditures, 1142 Rs. Given the potential endogeneity of expenditures with respect to health, we also considered the use of levels of education as a stratifying variable. Results were very similar. Again the random effects specification was not rejected with respect the fixed-effects specification in either strata. Using the preferred random-effects specification, we find that the effects are significant and negative among the lower-expenditure households, while they are not significantly different from zero for the better-off households. Evidently, the better-off households are better protected from the adverse effects of exposure to ambient air pollution, perhaps reflecting differences in protection from air (e.g., air conditioning, houses better-protected from roads), or differences in overall health or nutritional status. A convenient way to summarize the different effects based on household economic status is to construct locally-weighted regressions (lowess) centered around each expenditure level and then to plot the result. A graphical portrayal of the differences are presented in Figs. 4 and 5, which shows the coefficients for current and average lifetime exposure, respectively, by log per-capita expenditure. The effects of current exposure are especially dramatic in the low-expenditure households, with a pronounced rise in the middle-range of the expenditure distribution. By contrast, there is little evidence of a trend in the effects of average lifetime exposure.

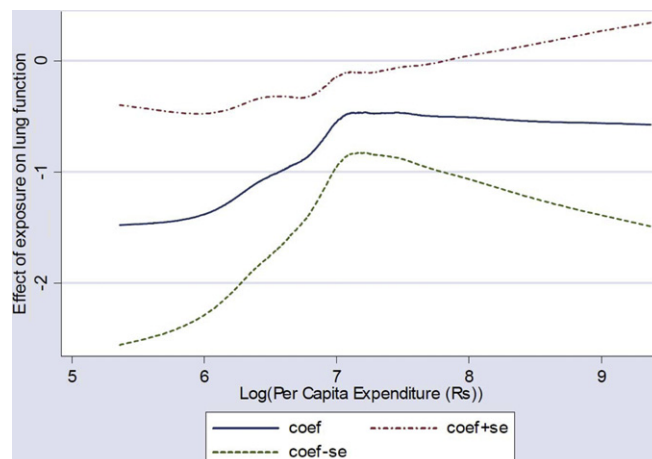


Fig. 7. Lowess estimates of effects of current exposure by per capita expenditure for adult men.

There are, of course, a variety of reasons that the poor may be differentially affected by air quality relative to the rich. One possible explanation is that the individuals in poor households spend more time exposed to ambient air than their better-off counterparts. Moreover, if this is indeed the case, one might expect to see differences by gender among adults, given that time spent outside is also likely to differ by gender as well as by economic status.

Fig. 6 confirms these differences in time spent outside. While the poorest men spend an average of 7 h per day outside and the poorest women spend 3 h per day outside, both male and female adult members who are above the median in terms of per capita expenditures, spend about an hour outside. In the richest households, adult members of both households spend almost no time outside. Figs. 7 and 8 provide lowess estimates of the $PM_{2.5}$ effects, stratified by gender and economic status. While the standard errors for the stratified estimates are too large to provide a compelling basis for statistical inference, the results correspond well to the time-allocation data. There is a strong gradient in terms of the male effects, with poorer men exhibiting a significant negative relationship between ambient air and respiratory health, and better-off men exhibiting an insignificant relationship. On the other hand, the relationship for women is relatively flat and bordering on statistical insignificance throughout the range.

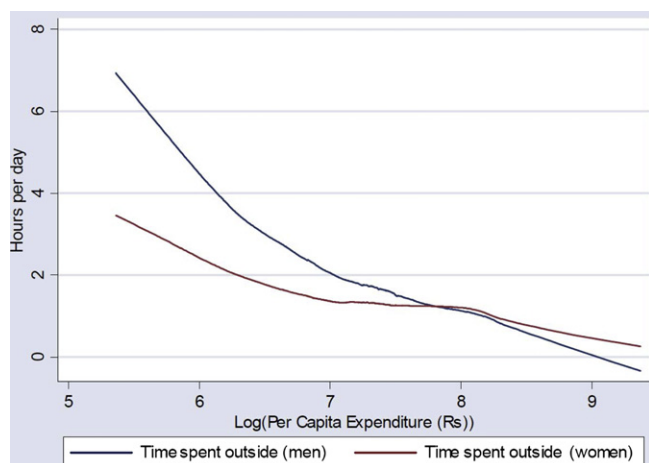


Fig. 6. Estimates of time spent outside the household by sex and Per Capita Expenditure.

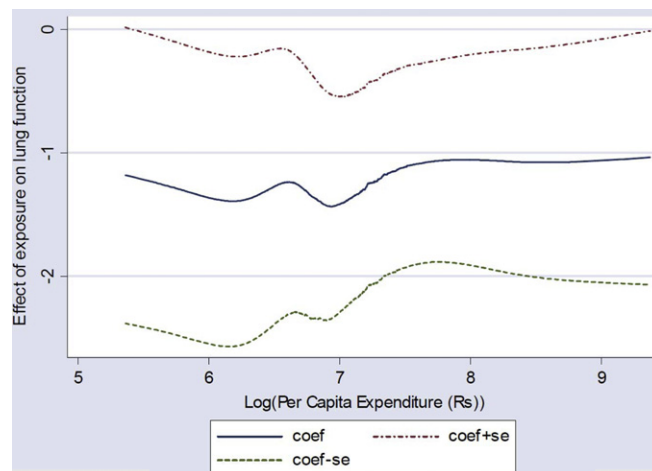


Fig. 8. Lowess estimates of effects of current exposure by per capita expenditure for adult women.

4. Conclusion

The results of this paper suggest that the changes in air quality regulations in Delhi that were put in place over the 1997–2002 period, had a substantial effect on respiratory health, and that this effect was concentrated among low-expenditure households. The results appear to be robust to the possibility of endogenous residence, but importantly affected by treatment for measurement error. There are important limitations to this analysis that may be addressed. First, we have constructed reduced-form estimates of the effects of ambient air quality. In particular, we have not considered the effects of variation in indoor air quality or smoking, which also may have important effects on lung quality. To the extent that individuals and households alter these behaviors in response to exposure to ambient pollution, we may be underestimating the direct-effect of ambient air. Second, while we have high-resolution estimates of current air quality, our measurements of lifetime exposure are imputed based on aggregate data. Obviously it is not possible, on a retrospective basis, to collect the kind of detailed air quality data that was collected for the post-regulation period. Our research suggests that we can capture a substantial fraction of local variation in $PM_{2.5}$ in 2003 using aerosol optical depth (AOD) from the satellite data. Application of these methods to satellite data from 2000 shows a slow negative trend, as might be anticipated using other available sources (Kumar et al., 2008). In this paper we utilized high resolution, i.e. 2 km, AOD to evaluate air quality in and around Delhi before and after the air quality regulations. The future work will be geared towards deriving $PM_{2.5}$ and PM_{10} estimates using these data to construct precise estimates of air pollution exposure at the place of residence of respondents before and after the regulations. To the extent that these methods may be used, it may be possible to get a much clearer sense of the overall impact of Delhi's air quality regulations on the health of her citizens. Finally, while it is not possible to obtain direct estimates of respiratory health estimates prior to the introduction of the regulation changes, it may be possible to use longitudinal data of this type to better control for the cumulative effects of past exposure. A second round of this survey to collect additional respiratory data was administered in 2009, and is currently being analyzed.

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