Working Paper Series 703
(ISSN 1211-3298)

Environmental Regulations, Air Pollution, and Infant Mortality in India: A Reexamination

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CERGE-EI
Prague, September 2021

ISBN 978-80-7343-510-3 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-605-5 (Národohospodářský ústav AV ČR, v. v. i.)

Environmental regulations, air pollution, and infant mortality in India: A reexamination†‡

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August 20, 2021

ABSTRACT

This paper reexamines empirical evidence on the effectiveness of environmental regulations in India from a recent study by Greenstone and Hanna (GH, 2014). GH report that air pollution control policies in India were effective in improving air quality but had a modest and statistically insignificant effect on infant mortality. These somewhat counterintuitive findings are likely to stem from the limited availability of ground-based air pollution data used in GH and the absence of critical meteorological confounders. I leverage recent advances in satellite technology and GH's methodology to test the sensitivity of their findings to revised air pollution outcomes, an extended number of observations, and meteorological controls. Despite striking differences between the two datasets, reexamination using satellite-based data confirms the conclusions drawn from GH's data. The effects of the policies are, however, substantially weaker. The paper urges further research on the effectiveness of environmental regulations in developing countries and the use of satellite imagery in the examination of this important question.

Keywords: Air Pollution, Infant Mortality, Environmental Regulation, India

JEL Codes: I12, J13, O13, Q53, Q58

I am grateful to Sangeeta Bansal, Randall Filer, Patrick Gaulé, Ludovica Gazze, Yana Jin, Štěpán Jurajda, Peter Nilsson, Cristobal Ruiz-Tagle, Wolfram Schlenker, Kathrine von Graevenitz, Ulrich Wagner for valuable comments and suggestions; participants of the EAERE-FEEM European Summer School, EfD Annual Meeting, SEEDS Annual Workshop, IAERE Annual Conference, CES Biennial Conference, AERE Annual Summer Conference, EAERE Annual Conference, *i*HEA World Congress for helpful feedback; I am especially grateful to Janet Currie for the invitation to visit Princeton University and Wangyal Shawa for invaluable assistance with spatial data used in this study.

† Supported by Charles University, GAUK project No. 696318.

‡ Supported by the H2020-MSCA-RISE project GEMCLIME-2020 GA No. 681228.

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1 INTRODUCTION

Substantial health and economic costs of air pollution have forced countries around the world to enact increasingly stringent environmental regulations (Botta & Koźluk, 2014). Whether such regulations have been effective remains an important policy question, particularly in developing countries that suffer from weak institutions, severe air pollution, and limited data availability.

An *American Economic Review* paper by Michael Greenstone and Rema Hanna (2014) – henceforth, GH – is an important piece of empirical evidence for this line of research. It examines the impact of air pollution control policies in India on two integral dimensions of effectiveness: policy-induced changes in air pollution and associated changes in infant mortality.[1,2] Interestingly, GH report somewhat counterintuitively that the policies have been effective in improving air quality but have had a modest and statistically insignificant effect on infant mortality.[3] A likely explanation for GH's findings might stem from the scarcity of reliable air pollution measures and the effects of unaccounted confounding factors. I show that GH's dataset, which was constructed using readings from a spatially sparse network of public air pollution monitors, suffers from high interannual variability in sample size, relatively inaccurate measures of air pollution, and the absence of critical meteorological confounders. I argue that ignoring these limitations could potentially lead to misleading conclusions about the effectiveness of air pollution mitigation efforts. Coupled with the prominence of GH's study, this conclusion motivates a reexamination of GH's findings using alternative data sources.

This paper reexamines the link between environmental regulations, air pollution, and infant mortality using new data that were unavailable to GH. I take advantage of satellite-based data to revise air pollution measures and to extract meteorological conditions that proved to be important confounders. Maintaining GH's methodology, I test the sensitivity of their findings to the revised air pollution outcomes, extended number of observations, and meteorological controls. Thus, comparing results using satellite-based to ground-based data used by GH, I present complementing empirical evidence on the effectiveness of air pollution control policies in India.

Based on a careful account of similarities and disparities in the results generated by two data sources, it seems reasonable to confirm GH's findings and interpret air pollution control policies in India as effective, although with substantially weaker effects on air pollution. Further research exploring the prospects for using satellite-based data will be particularly valuable, especially for developing countries. Such research will be critical in uncovering the effects of environmental regulations and recommending sensible interventions to mitigate the environmental burden of air pollution and to protect population health.

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1 GH also assess the effects of water pollution regulations, but I focus exclusively on the part of GH's paper that analyzes the effectiveness of air pollution regulations.

2 Matus et al. (2012) show that health costs account for 71.4% of total air pollution-induced welfare losses in China and that mortality captures around 86% of those losses. Others have shown that mortality impacts associated with air pollution are strongest for infants (Ebenstein et al.; 2015, Tanaka, 2015). Compared to adults, infants' deaths lead to larger losses in life expectancy.

3 GH's findings contradict the conclusions of others in the literature. There is a substantial body of causal evidence that the regulation-induced improvements in air quality in developing countries lead to a decline in infant mortality. For example, see Foster, Gutierrez, and Kumar (2009), Ebenstein et al. (2015), Tanaka (2015), He, Fan, and Zhou (2016), Cesur, Tekin, and Ulker (2016).

2 REVIEW OF GREENSTONE AND HANNA (2014)

Using a panel of 140 Indian cities for the years 1987-2007, GH assess the impact of the Supreme Court Action Plans (SCAP) and the Mandated Catalytic Converters (CAT) on air pollution and infant mortality. Both policies belong to the command-and-control instruments and were at the forefront of India's environmental regulation since the 1970s. SCAP are a suite of policy actions aimed at reducing pollution in the cities identified by the Supreme Court of India as critically polluted. SCAP typically vary across cities and can take different forms depending on the type of targeted air pollutant.[4] CAT requires new cars to be equipped with a catalytic converter – an exhaust emission control device aimed at reducing toxic gases and pollutants in the exhaust gas by converting them into less harmful pollutants using catalyzing reaction. There are two distinctive features of this regulation. First, its enforcement is stringent as vehicle registrations are tied to the installation of catalytic converters. Second, its impact obviously increases over time with the increase in the share of newer vehicles (Greenstone, Harish, Pande, & Sudarshan, 2017).

SCAP and CAT policies can plausibly affect air pollutants analyzed in GH: nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and suspended particulate matter (SPM). NO_2 stands out as an indicator of vehicular pollution, SO_2 – as a by-product of thermal power generation, and SPM, particulate matter less than 100 micrometers (μm) in diameter, – as a general indicator of air pollution. All three are widely considered to cause serious health and economic costs.

GH's empirical strategy combines event study and difference-in-differences designs in a two-step econometric approach. At the first step, the approach measures average annual levels of air pollutants and infant mortality in the pre and post policies' adoption periods, while in the second step, it tests for the policies' impact. Equations (1) and (2) correspond to the first and second-step specifications. Together, these equations represent GH's preferred specification that controls for city fixed effects, year fixed effects, preexisting differential trends in the outcomes, and allows for a mean shift and trend break after the policies' implementation. Identifying variation comes from the variation in the timing of the policies' enactment across cities.

$$Y_{ct} = \alpha + \sum_{\tau} \sigma_\tau \boldsymbol{D}_{\tau,ct} + \beta \boldsymbol{X}_{ct} + \mu_t + \gamma_c + \epsilon_{ct} \tag{1}$$

where Y_{ct} is an outcome variable measuring either concentrations of air pollutants or infant mortality rate in city c in year t. $\boldsymbol{D}_{\tau,ct}$ is a vector of indicator variables for each year before and after a policy is in force. τ is normalized so that it is equal to zero in the year the policy was enacted; it ranges from -17 (for 17 years before a policy's adoption in a city) to 12 (for 12 years after its adoption). For the nonadopting cities, τs are equal to zero. $\boldsymbol{X}_{ct}$ is a set of additional control variables (consumption per

[4] Action plans for vehicular pollution include an odd-even program for private cars, compulsory retirement of old vehicles, or restrictions on the use of heavy vehicles, while plans that regulate industrial pollution include the mandated reallocation of heavily polluting industries, installation of specific abatement technologies, or bans on production processes.

capita and literacy rates). μ_t – year fixed effects to control for year-specific common shocks for all cities; γ_c – time-invariant city fixed effects to control for the permanent unobserved determinants of the outcome variable across cities. Equation (1) is weighted by the district-urban population in air pollution estimations and by the number of births in infant mortality estimations. The coefficients of interest σ_τ measure the levels of average annual outcomes in the pre- and postadoption periods. The estimated coefficients $\widehat{\sigma_\tau}$ are then fit into equation (2) that corresponds to the equation (2C) in GH.

$$\widehat{\sigma_\tau} = \pi_0 + \pi_1 1(Policy)_\tau + \pi_2 \tau + \pi_3 (1(Policy)_\tau \cdot \tau) + \epsilon_\tau \quad (2)$$

where $1(Policy)_\tau$ is a dummy variable that takes on the value 1 to indicate that the policy is in force; τ is a linear time trend to control for the differential preexisting trends in adopting cities. $1(Policy)_\tau \cdot \tau$ allows for the policies' effects to evolve over time; ϵ_τ – heteroskedastic-consistent standard errors. GH weight equation (2) by the inverse of the standard errors for the relevant σ_τ to account for differences in precision in the σ_τ's estimation. The specification tests for a policy impact after adjustment for the trend in outcome variable (π_2), and allows for both a mean shift (π_1) and trend break (π_3). From this equation, GH also report the policies' effects five years after implementation, $\pi_1 + 5\pi_3$. They then complement a two-step approach by its numerically identical one-step version.[5]

GH's central result is that the Mandated Catalytic Converters policy was strongly associated with air pollution reduction. Specifically, five years after the policy was in force, SPM and SO_2 concentrations declined by 48.6 μg/m^3 and 13.5 μg/m^3, or 19% and 69% of the 1987–1990 nationwide mean concentrations. The impact of the CAT policy on NO_2 was a statistically insignificant decline by 4.4 μg/m^3 or 19% of the 1987–1990 nationwide mean concentrations. In contrast, the Supreme Court Action Plans resulted in a marginally statistically significant decline in NO_2 concentrations without any evidence of an impact on SPM and SO_2. GH then proceed with the CAT policy, i.e. the one that was found to be the most strongly related to improvements in air quality, to show that the policy resulted in a modest and statistically insignificant decline in infant mortality.

[5] The specification below represents a one-step version of the two-step approach. GH include both policies into the one-step approach and limit the policies' dummies to the observed event years to preserve the comparability with the two-stage approach, specifically 20 city years for CAT and 15 city years for SCAP.

$$\begin{aligned} Y_{ct} = {} & \alpha + \theta_1 1(SCAP\ Range)_\tau + \theta_2 1(SCAP)_\tau * (SCAP\ Range)_\tau + \theta_3 1(SCAP\ Range)_\tau * \tau \\ & + \theta_4 1(SCAP)_\tau * \tau * (SCAP\ Range)_\tau + \theta_5 1(\tau Left)_\tau + \theta_6 1(\tau Right)_\tau + \rho_1 1(CAT\ Range)_\phi \\ & + \rho_2 1(CAT)_\phi * (CAT\ Range)_\phi + \rho_3 1(CAT\ Range)_\phi * \phi + \rho_4 1(CAT)_\phi * \phi * (CAT\ Range)_\phi \\ & + \rho_5 1(\phi Left)_\phi + \rho_6 1(\phi Right)_\phi + \beta \boldsymbol{X}_{ct} + \mu_t + \gamma_c + \epsilon_{ct} \end{aligned}$$

$1(SCAP\ Range)_\tau$ is a dummy variable for $-7 \leq \tau \leq 3$ and $1(CAT\ Range)_\phi$ is a dummy variable for $-7 \leq \phi \leq 9$; $1(SCAP)_\tau$ and $1(CAT)_\phi$ are the policy dummies that indicate whether $SCAP$ or CAT policies are in force and that take on the value 1 for the adopting cities with $\tau \geq 0$ and/or $\phi \geq 0$; $1(\tau Left)_\tau$ and $1(\tau Right)_\tau$ are dummies indicating that $\tau < -7$ or $\tau > 3$, respectively; by analogy, $1(\phi Left)_\phi$ and $1(\phi Right)_\phi$ indicate that $\phi < -7$ or $\phi > 9$, respectively; $1(SCAP\ Range)_\tau * \tau$ and $1(CAT\ Range)_\phi * \phi$ are a linear time trend variables interacted with a policy range dummies; $1(SCAP)_\tau * \tau * (SCAP\ Range)_\tau$ and $1(CAT)_\phi * \phi * (CAT\ Range)_\phi + \rho_5$ are policy*time-trend*policy-range interaction terms; ϵ_{ct} – standard errors clustered at the city-level (Bertrand, Duflo, & Mullainathan, 2004).

3 DATA

I reexamine the effectiveness of air pollution control policies combining GH's original datasets with new and improved data. GH undertook an extensive data-collecting exercise and made resulting datasets and Stata do-files publicly available.[6] I use GH's data on environmental regulations, infant mortality, and sociodemographic characteristics without modification. Instead, I revise data on air pollution outcomes and add key meteorological confounders absent in GH's paper.

3.1 GH's data limitations

A. Air pollution data

GH's air pollution data came from India's Central Pollution Control Board (CPCB), which operates a national network of ground-based monitoring stations. GH obtained monthly city-by-state monitor readings for NO_2, SO_2, and SPM concentrations from a spatially sparse network of 572 monitors in 140 cities.[7] To calculate the annual average concentrations for each city, GH took a simple average of the monthly average concentrations for the monitors within the city.

GH's final air pollution dataset has two major issues. First, the sample size is substantially restricted and highly variable. Column 1 of Table 1 tabulates the number of cities in GH's sample with at least one monitor reading in a particular year. Thus, the city counts in this column represent the maximum possible number of the cities available for the analysis in a given year. This number varies substantially because CPCB's monitor readings are not available for all years for most of the cities. Only 20 of 140 cities were covered by the monitoring network in 1987, while 115 cities were monitored by 2007. Another concern is that some of the monitors were not operating for a whole sample of cities, were not functioning appropriately, or were moved and reclassified over the years. These reasons may explain the substantial variability in GH's sample size over time. As column 1 indicates, the number of cities was steadily increasing until 1993 when it reached 65. Then, the sample size declined sharply to 42 cities in 1995, rapidly increased to 73 in 1997, dropped again to 54 in 2001, and continued growing until it peaked in 2007 with 115 cities. The variability appears high, although GH do not discuss this issue in detail. GH further restricted the sample of cities based on the availability of air pollution data. Policy-adopting cities were included in the analysis if they had at least one observation three or more years before the policy's implementation and at least one observation four or more years after. Non-adopting cities and adopting cites without post-policy pollution data were included if they had at least two air pollution readings.

[6] I downloaded GH's data and Stata code from the *AER* website.

[7] For comparison, the U.S. network of ground-based monitors that measure ambient PM concentrations consists of around 1200 monitors. This network covers 63% of the U.S. population in less than 20% of U.S. counties and is still considered spatially sparse by researchers (Sullivan & Krupnick, 2018; Fowlie, Rubin, & Walker, 2019).

Table 1 – Number of cities and prevalence of air pollution control policies

	Cities		Policies	
	GH sample	Full sample	SCAP	CAT
Year	1	2	3	4
1987	20	140	0	0
1988	25	140	0	0
1989	31	140	0	0
1990	44	140	0	0
1991	47	140	0	0
1992	58	140	0	0
1993	65	140	0	0
1994	57	140	0	0
1995	42	140	0	2
1996	68	140	0	4
1997	73	140	1	4
1998	65	140	1	22
1999	74	140	1	26
2000	66	140	1	24
2001	54	140	1	19
2002	63	140	1	22
2003	72	140	11	25
2004	78	140	15	24
2005	93	140	16	24
2006	112	140	16	24
2007	115	140	16	24

Notes: The table corresponds to GH's Table 1. SCAP and CAT stand for the Supreme Court Action Plans and the Mandated Catalytic Converters. Column 1 shows the number of the cities that have at least one air pollution reading in the particular year. Those numbers represent maximums out of 140 cities (column 2) used in GH. Columns 3 and 4 show the number of cities where the specified policy was implemented.

Second, measures of the city-level concentrations might be relatively inaccurate. Several problems can emerge when using a sparse network of monitors to infer air pollution levels. First, there can be significant discrepancies between the monitor's readings and surface concentrations because of air pollution's physical properties. The fundamental issue is that air pollution can both vary sharply over short distances with higher concentrations downwind of the source of emission and travel long distances from its source being dispersed by wind or washed away by rain. Therefore, the further a particular location is from a monitor, the less accurate is the measure of concentration inferred from this monitor for this location (Sullivan, 2016; Sullivan & Krupnick, 2018). Second, evidence shows that local officials can manipulate ground-based pollution readings, particularly in developing countries (Andrews, 2008; Chen, Jin, Kumar, & Shi, 2012; Ghanem & Zhang, 2014). Such manipulations can take the form of strategically placing monitors in less polluted parts of the cities, relocating monitors from locations downwind of polluters to locations upwind, or even spraying water over monitors to decrease local pollution concentrations (Fan & Grainger, 2019). Third, the aggregation method used in GH can also cast doubt on the accuracy of measurements. A monitor measures concentration from a single point in space to represent a concentration over a city, in which neighborhoods can have a varying landscape, wind pattern, population density, and emission sources. However, in 2007, 18% of sample cities did not have a SPM monitor, 21% had one monitor, 31%

had two monitors, and 16% had three. Thus, an aggregation by a simple averaging can be highly misleading. Ideally, the computation of air pollution levels that relies on data obtained from ground-based monitors should include the interpolation of monitor-level data into the surface.[8] The outcomes of this procedure, i.e. average concentrations at every grid point, can then be temporally and spatially aggregated by averaging concentrations at all grid points that fall within the cities' administrative boundaries. Following these steps, one can accurately measure the city-level pollution concentrations over time.

B. Meteorological data

Additionally, GH's dataset does not include meteorological conditions. Not controlling for these conditions can potentially confound GH's findings because of the significant impact of meteorological conditions on air pollution and infant mortality. Apart from anthropogenic emissions, meteorological forces are the primary factors that shape air pollution trends over cities around the world.[9] They play a critical role in dispersion, transformation, transport, removal of air pollutants in the atmosphere and can exacerbate or mitigate their concentrations (Zhong et al., 2018; Li et al., 2019; He at al., 2019; Zhou et al., 2020). Rain can wash air pollutants away and high wind speeds disperse them, lowering concentrations. Low wind speeds coupled with low winter temperatures and thermal inversions tend to worsen air quality, increasing concentrations. In turn, these processes also affect infant mortality, indirectly through the impact on air pollution or directly (Goyal, 2002). Many studies find statistically significant effects of extreme air temperature, rainfall, and humidity on infant mortality in developed and developing countries (Deschênes & Greenstone, 2011; Kudamatsu, Persson, & Strömberg, 2012; Gasparrini et al., 2015; Barreca, 2016; Heutel, Miller, & Molitor, 2017; Burgess et al., 2017; Geruso & Spears, 2018). Thus, ignoring considerable fluctuations in meteorological conditions can lead to misleading conclusions about the effectiveness of air pollution mitigation efforts. In line with this argument, Sullivan (2016) formally shows that economic studies underestimate the effects of changes in air pollution exposure, including those induced by exogenous shock, because of the bias that arises when researchers do not account for meteorological confounders, specifically for wind speed. It has been shown that at the time of writing GH, publicly available in-situ monitor readings of meteorological conditions in India were highly sparse and erratic (Burgess et al., 2017). That likely explains the absence of these data in GH's dataset, despite an extensive data collection exercise.

Nevertheless, high variability in the interannual sample size, relatively accurate measures of air pollution concentrations, and the absence of important meteorological confounders motivate a reexamination of GH's findings using alternative data sources.

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8 This can be usually achieved using spatial interpolation methods such as inverse distance weighting or Kriging.

9 For example, variation in meteorological conditions explains more than 70% of daily variations in five air pollutants in major Chinese cities during the 2014-2015 period (He et al., 2017) and up to 50% of daily $PM_{2.5}$ variation in the US during the 1998-2008 period (Tai, Mickley, & Jacob, 2010).

3.2 New and revised data

A. Revised air pollution outcomes

To address the issues with GH's air pollution data, I leverage recent advances in satellite technology. I construct air pollution outcomes, i.e. annual city-level averages of fine particulate matter ($PM_{2.5}$) and sulfur dioxide (SO_2), from the satellite-based Aerosol Optical Depth (AOD) retrievals.[10] AOD measures the amount of sunlight absorbed, reflected, and scattered by particles suspended in the air. Satellite observations of AOD make it possible to estimate surface $PM_{2.5}$ and SO_2 concentrations at granular spatial resolution and with comprehensive geographical and temporal coverage. AOD-based estimates are a good proxy of air pollution over India (Dey et al., 2012).

I replace GH's SPM by the satellite-based estimates for $PM_{2.5}$, also particulate matter but with a diameter less than 2.5 µm. $PM_{2.5}$ is a fraction of SPM and is a more sophisticated exposure indicator.[11] An increasing number of social scientists focus on $PM_{2.5}$ to study the effectiveness of environmental regulations, health effects, and the economic impacts of pollution exposure (Voorheis, 2016; Chen, Oliva, & Zhang, 2017; Fu, Viard, & Zhang, 2017; Sullivan & Krupnick, 2018; Fowlie, Rubin, & Walker, 2019). $PM_{2.5}$ data were unavailable to GH as $PM_{2.5}$ monitoring in India started only in 2009 after the second revision of the national air quality standards.

I obtained satellite-based estimates for $PM_{2.5}$ and SO_2 concentrations from NASA's Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2; GMAO, 2015).[12] MERRA-2 data result from atmospheric reanalysis that combines satellite-based measurements of AOD, ground-based monitor readings, and other sources with sophisticated chemical-transport and climate modeling to create gridded estimates for surface air pollution variables. MERRA-2 reanalysis data are widely used in various studies due to their high quality, granular spatial and temporal resolutions, and diverse atmospheric variables (Chen et al., 2017; Fu et al., 2017; He et al., 2019). MERRA-2 is the only alternative that provides estimates for $PM_{2.5}$ and SO_2 concentrations for GH's sample years, 1987-2007. For comparison, another source of air pollution data popular among social scientists, van Donkelaar et al. (2019), provides estimates for $PM_{2.5}$ concentrations starting only from 1998. Therefore, MERRA-2 is my preferred source of data for air pollution outcomes.

MERRA-2 provides global gridded data of monthly means at 0.5° x 0.625° spatial resolution (approximately 56km x 69km at the equator). Estimates for SO_2 concentrations are readily available, while $PM_{2.5}$ concentrations need to be calculated using estimates for $PM_{2.5}$ components: dust ($DUST_{2.5}$), sea salt ($SS_{2.5}$), black carbon (BC), organic carbon (OC) and sulfate particulate (SO_4).[13] I follow the literature from atmospheric science, Buchard et al. (2016), and apply equation (3) to

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[10] Data on NO_2 concentrations are not readily available for the temporal and geographic scope required for GH's reexamination.

[11] Smaller $PM_{2.5}$ particles penetrate the deeper alveolar region of the respiratory tract and thus could more likely to cause premature mortality and severe morbidity than GH's SPM (Schwartz, Dockery, & Neas, 1996; U.S. EPA, 2004; WHO, 2006a).

[12] M2TMNXAER product, version 5.12.4.

[13] Sources of SO_4 (sulfate), BC and OC (carbonaceous) are emissions from power plants, vehicle exhaust, and biomass burning. $Dust_{2.5}$ comes from local arid sources or transported from abroad by dust storms. $SS_{2.5}$ penetrates the land from the seas and oceans.

calculate $PM_{2.5}$ concentrations at every grid point. Figure 1 maps the resulting spatial distribution of MERRA-2 $PM_{2.5}$ and SO_2 pollution in India. Panels A and B show long-run average $PM_{2.5}$ and SO_2 concentrations in $\mu g/m^3$ for 1987-2007. The figure depicts higher levels of air pollution with the shades of red color. For $PM_{2.5}$, broad areas in North-West India, Gangetic Plains, and northern regions of Central India are well above national and WHO air quality guidelines, which are annual averages of 40 $\mu g/m^3$ and 10 $\mu g/m^3$, respectively. Even though there are observable SO_2 hot spots, most of India is in rough compliance with the national standard, which is 50 $\mu g/m^3$.

$$PM_{2.5} = DUST_{2.5} + SS_{2.5} + BC + 1.4 * OC + 1.375 * SO_4 \tag{3}$$

Panel A. Average $PM_{2.5}$, 1987-2007 | Panel B. Average SO_2, 1987-2007

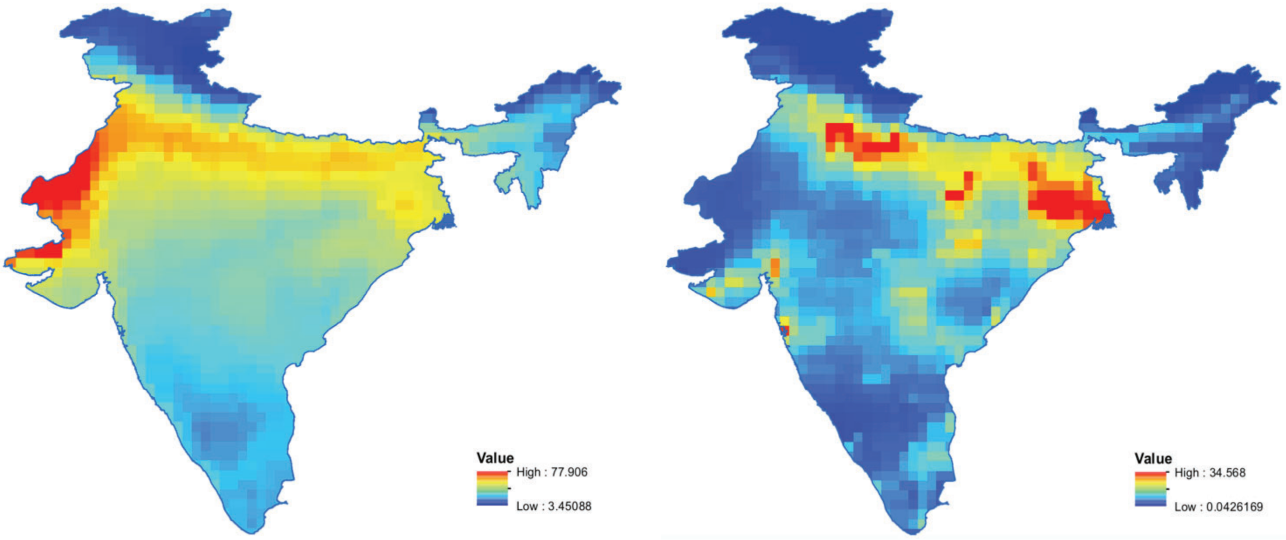


Figure 1. Spatial distribution of air pollution concentrations in India, 1987-2007

Notes: The figure maps spatial distributions of $PM_{2.5}$ and SO_2 concentrations constructed using MERRA-2 reanalysis products. Panels A and B show long-run average $PM_{2.5}$ and SO_2 concentrations in $\mu g/m^3$ for 1987-2007, respectively. Shades of red color depict higher concentrations of the specific air pollutants.

To map MERRA-2 air pollution concentrations to the city level, I construct urban extent polygons that correspond to the cities' administrative boundaries using 2011 ML InfoMap's digital maps.[14] The definition of what to consider a city is a major challenge as GH do not provide any information about this. I rely on the operational definition of an urban area (town) adopted by the Office of the Registrar General & Census Commissioner of India as, I believe, GH also did by default.[15] They

[14] State-wise ML InfoMap village (and town) boundary polygons represent a digital map that provides socio-demographic and economic census data in GIS file format. I downloaded ML InfoMap's shapefiles from the Princeton University Digital Maps & Geospatial Data Library during my research visit.

[15] The Office of the Registrar General & Census Commissioner of India is the central authority in charge of the population (Census) and vital statistics. The Census statistics for urban areas (towns) comprises two types of towns, namely Statutory towns and Census towns. Statutory towns are all places with a municipality, corporation, cantonment board or notified town area committee. Census towns are defined as a place satisfying three criteria simultaneously: (i) a minimum population of 5000; (ii) at least 75% of the male working population engaged in non-agricultural activities; (iii) a density of population of at least 400 persons per km^2 (Census of India 2011).

retrieved data from the official administrative sources, and I assume that Indian government agencies, including CPCB, define administrative units uniformly. The list of the cities was obtained from GH's Stata do-files and Vital Statistics of India, while the cities' geometry from the maps in the India District Census Handbooks 2011.[16] ML InfoMap's digital maps depict cities' administrative boundaries as of 2011, a year that is outside of GH's study period of 1987-2007. Whenever possible, I adjust the resulting polygons so that they correspond to the cities' administrative boundaries as they were at the time of the 2001Census. Most of the District Census Handbooks contain Table 3 that provides a list of new towns, denotified, declassified, and merged during the decade of 2001-2011. Exploiting this information, I retrieve ML InfoMap's administrative boundaries polygons net of 2001-2011 changes. In rare cases in which the ML InfoMap's digital maps do not contain cities' boundaries, I geo-reference and digitize them using maps from the District Census Handbooks. For some of the larger cities, their administrative boundaries consist of several ML InfoMap polygons, which I merge to obtain a single polygon for each city.

Overall, I selected the final sample of 140 polygons from about 619,000 across 28 Indian states. Appendix Figures 1 through 5 highlight the construction of the resulting cities' administrative boundaries. Finally, I average monthly MERRA-2 $PM_{2.5}$ and SO_2 concentrations to annual levels and then take an average of annual average concentrations at all MERRA-2 grid points that fall within the cities' administrative boundaries. The final dataset represents city-by-year annual $PM_{2.5}$ and SO_2 average concentrations for the years 1987-2007. Figure 2 shows the exact geometry and location of the constructed urban extent polygons and examples of cities with already assigned concentrations of $PM_{2.5}$ and SO_2 air pollution.

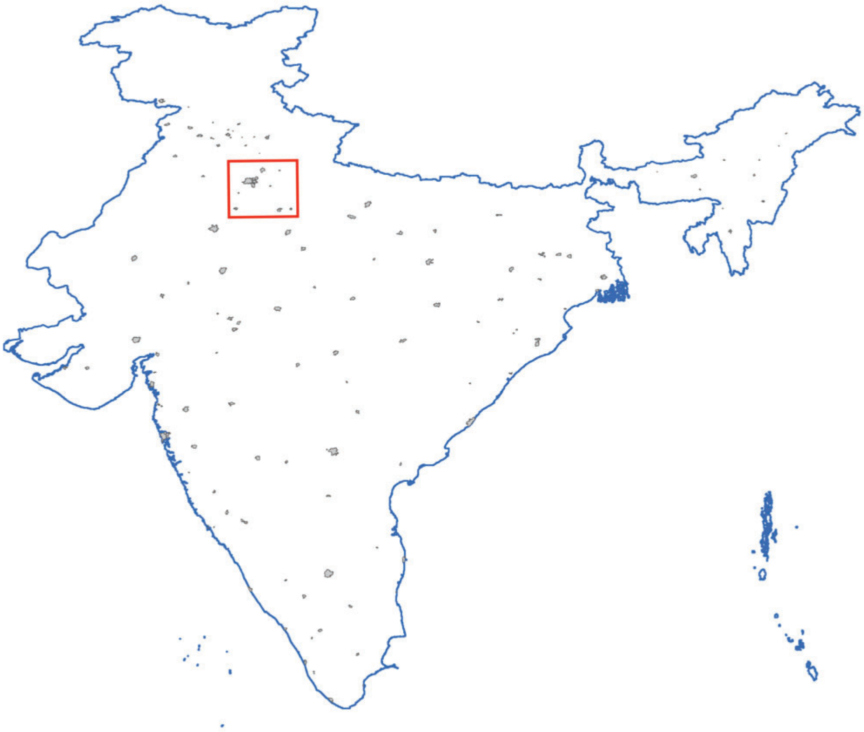
B. Concerns about revised air pollution outcomes

Resulting estimates of the city-level average concentrations of air pollution are not immune to plausible concerns. The first two pertain to MERRA-2 data and the approach I use to construct the cities' administrative boundaries, while the last one is common to all satellite-based estimates.

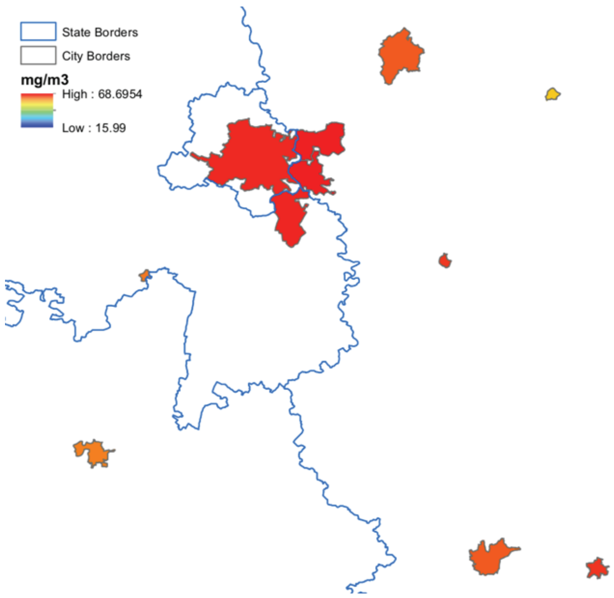
MERRA-2 $PM_{2.5}$ data lack nitrate particulate matter, an important $PM_{2.5}$ component and precursor, primarily emitted by vehicle exhaust and industrial activities (Buchard et al., 2016; He et al., 2019). Thus, resulting from the equation (3), estimates of $PM_{2.5}$ concentrations can underestimate ground-based $PM_{2.5}$ measurements. As a sensitivity test, I construct estimates for $PM_{2.5}$ concentrations for the years 1998-2007 using van Donkelaar et al. (2019) and compare them with MERRA-2 $PM_{2.5}$ concentrations. Previous studies point on a good match between van Donkelaar's $PM_{2.5}$ estimates and ground-based $PM_{2.5}$ observations (van Donkelaar et al., 2013; He et al., 2019). Therefore, a high correlation coefficient between MERRA-2 and van Donkelaar's $PM_{2.5}$ estimates (91%) provides evidence for high consistency between them and relaxes the MERRA-specific concern.

[16] Princeton University also granted access to the annual issues of the Vital Statistics of India. India District Census Handbooks depicting district-wise village and town administrative boundaries as of 2011 were downloaded from the website of the Census of India.

Panel A. City-level administrative boundaries



Panel B. Average $PM_{2.5}$, a closer look



Panel C. Average SO_2, a closer look

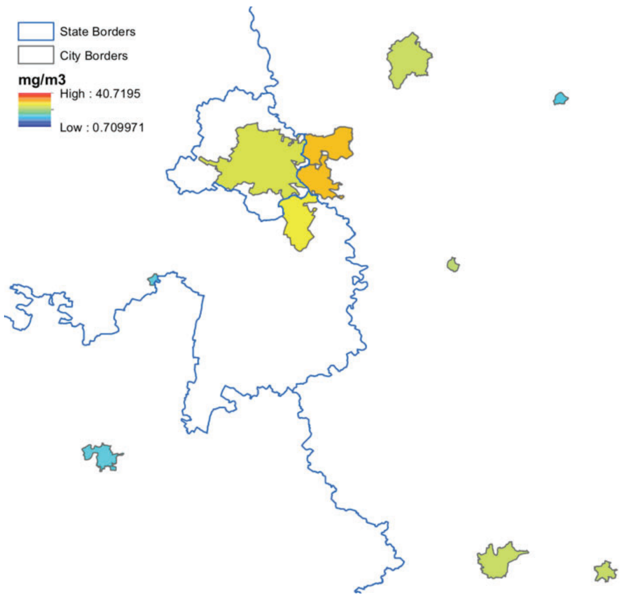


Figure 2. Cities' administrative boundaries with assigned air pollution levels

Notes: The figure denotes all cities from the full sample with the resulting administrative boundaries. Panel A depicts the cities preserving their exact geometry and location across India. Panels B and C show examples of the cities with already assigned levels of $PM_{2.5}$ and SO_2 pollution in $\mu g/m^3$ for randomly selected year 2004. Shades of red color depict higher concentrations of the specific air pollutants. The cluster of four cities at the center represents the capital city of Delhi (National Capital Territory), Ghaziabad and Noida (Uttar Pradesh), and Faridabad (Haryana). Despite the spatial proximity of these cities, the approach that I use to construct their exact urban extent polygons allows me to assign air pollution to each of these cities and to analyze them as separate administrative units. $PM_{2.5}$ and SO_2 pollution measures are constructed using the MERRA-2 reanalysis product and represent annual average concentrations at the city's level.

The approach I use to construct the cities' administrative boundaries might also be subject to concern. As I use ML InfoMap's digital maps with administrative boundaries as they were at a single year, the resulting urban extent polygons do not trace the cities' spatial expansion at different points in time. However, Seto et al. (2011) show that Indian cities were expanding at an average annual rate of 4.84% between 1970 and 2000. This evidence raises the possibility that the approach I adopt in this paper can potentially lead to measurement error. Generally, too narrowly or too broadly defined boundaries of urban footprints may affect an assignment of air pollution. Nevertheless, I believe that this is not a major concern, and my approach is preferable to other available alternatives. I pursued the goal of constructing urban extent polygons separately for each city in GH's sample and preserving consistency with GH's default definition of a city. However, the most commonly used alternative approach for the delineation of urban areas, night-time lights satellite imagery, fell short in achieving this goal. Appendix Figure 6 provides an illustration. The figure compares urban extent polygons defined by the cities' administrative boundaries in this study with those defined by the combination of the night-time lights and buffered settlement centroids in the Global Rural-Urban Mapping Project (GRUMP).[17]

Two apparent observations arise. First, urban areas retrieved from the night-time lights dataset do not correspond to their Census counterparts, making it impossible to obtain a single polygon for each city. For example, the cluster of four cities at the center of the figure includes the capital city of Delhi, Ghaziabad, Noida, and Faridabad. Despite spatial proximity, the approach I use allows me to analyze these cities as separate administrative units. In contrast, GRUMP's output is a single polygon, a multi-city agglomeration that extends beyond the administrative boundaries of these four cities and additionally includes the city of Meerut 70 kilometers away from Delhi to the North-East.[18]

Second, even if both approaches result in a single polygon for each city, the polygons retrieved from the night-time lights are larger than the polygons represented by the cities' administrative boundaries. This observation suggests that GRUMP polygons overestimate the extent of the cities. The GRUMP relies on the 1994/1995 stable city night-time lights dataset, meaning that the resulting output exhibits boundaries of urban areas as of 1995. However, given the evidence above of Seto et al. (2011), it is highly unlikely that the ML InfoMap polygons of the adjusted cities' administrative boundaries as of 2001 were smaller than the corresponding GRUMP polygons as of 1995. Thus, I believe that the approach used in this paper performs well and matches the goal better.

Finally, a limitation common to all satellite-based estimates is that such estimates are just a reflection of the actual air pollution concentrations and are prone to prediction and forecast errors. Fowlie et al. (2019) highlight the importance of accounting for these errors. In this study, however, it is difficult to perform such a check because of the limited availability of reliable ground-based air pollution

17 More information about the GRUMP can be found at https://sedac.ciesin.columbia.edu/data/collection/grump-v1/about-us.

18 This is because the approach based on the night-time lights satellite imagery delineates urban areas by considering spatially contiguous lighted pixels surrounding a city's coordinates, with luminosity above a pre-defined threshold.

measurements for India. In general, a comprehensive analysis of this issue is yet to be discussed in the literature and is beyond the scope of this paper.

C. New meteorological data

To control for the effects of the meteorological conditions on air pollution and infant mortality, I collect data on air temperature, precipitation, and wind speed.[19] Specifically, I obtain raw data on these covariates from various MERRA-2 reanalysis products and process them the same way as air pollution data to construct variables at the city-by-year level.[20] MERRA-2 temperature and precipitation data have been successfully validated against the observation-based Indian Meteorological Department data, indicating that MERRA-2 products are reliable substitutes to the observed weather indicators (Ghodichore et al., 2018; Gupta et al., 2020).

I control flexibly for meteorological confounders by including $f(\boldsymbol{W}_{ct})$ into equation (1) and a one-step version of GH's two-step approach. $\boldsymbol{W}_{ct}$ is a set of meteorological covariates that includes a count of the number of days each year in which the average daily temperature falls into 10 temperature bins, precipitation calculated as the annual sum from daily observations and its quadratic, and a count of the number of days each year in which the average daily wind speed falls into 12 wind speed bins.

In particular, to estimate the effects of daily temperatures on annual outcomes, I follow a widely-used method that transforms an annual distribution of daily temperatures into a set of temperature bins (Deschênes & Greenstone, 2011; Deryugina & Hsiang, 2014; Cheng & Yang, 2017; Zhang et al., 2018). This approach allows flexible estimation of nonlinear temperature effects across daily temperature values. In practice, a vector of temperature bins, $Temp_{ct}^{m}$, denotes the number of days in year t with daily average temperatures in city c that fall into the mth temperature bin, $m = 1,2,\ldots,10$. Following Burgess et al. (2017), I divide daily average temperatures, measured in °C, into ten bins, each of which is 3 °C wide. For example, $Temp_{ct}^{1}$ is the number of days in city c during year t with daily temperature below 12 °C. Then, $Temp_{ct}^{10}$ is the number of days with temperature above 35 °C. To avoid collinearity, the temperature bin [21°C, 23 °C) is set as an omitted, reference category.

A vector of wind speed bins, $Wind_{ct}^{m}$, is constructed similarly, but bins are defined as a Beaufort wind scale. I distributed daily average wind speeds, measured in knots, between 12 categories that characterize wind force from calm to hurricane.

3.3 Comparison of trends

Figure 3 compares trends in air pollution outcomes constructed using CPCB data exploited by GH and the data obtained from MERRA-2 products. Panels A and B plot the city-level average

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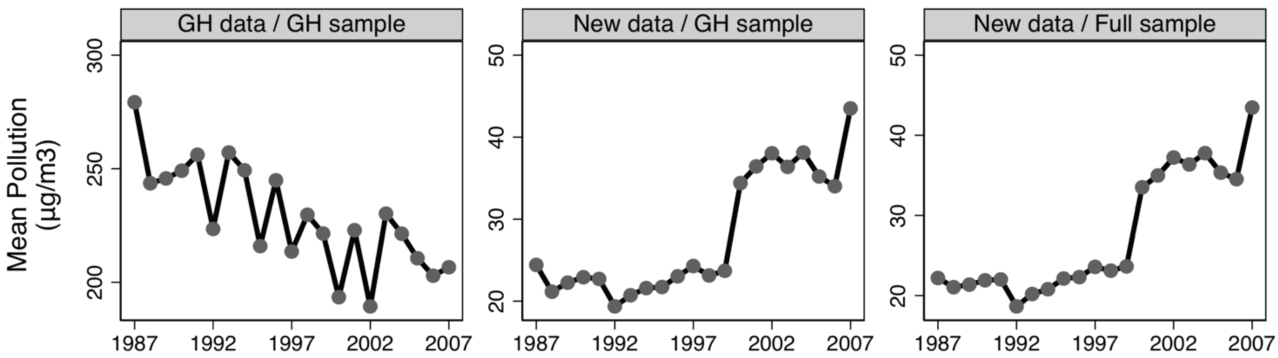
[19] Most of the relevant studies in economic literature control at least for air temperature and precipitation. However, Sullivan (2016) and Zhang, Zhang, and Chen (2017) demonstrate the importance of additional meteorological covariates, especially humidity and wind speed.

[20] M2I1NXLFO product for air temperature and wind speed; M2T1NXLND product for precipitation

concentrations of particulate matter and SO_2 for the years 1987-2007. Left-hand graphs in both panels show SPM and SO_2 trends in GH's data for the restricted sample of cities used in GH.[21] Right-hand graphs show trends in MERRA-2 $PM_{2.5}$ and SO_2 for the full sample of 140 cities, while the middle graphs plot the trends for the same pollutants across GH's sample of cities. Compared to GH's data, revised air pollution outcomes yield substantially more city-by-year observations: 2,940 against 1,370 and 1,344 for GH's particulate matter and SO_2, respectively. I refer to these observations as the GH sample and the full sample. Table 2 provides the corresponding sample statistics for both ground-based and satellite-based data. The table reports the city-level averages, the number of observations, the tenth and ninetieth percentiles of air pollution outcomes, meteorological variables, and infant mortality rate, broken down by the whole of GH's study period, early (1987-1990), and later (2004-2007) periods of the sample.

Panel A: Particulate air pollution



Panel B: Sulfur dioxide pollution

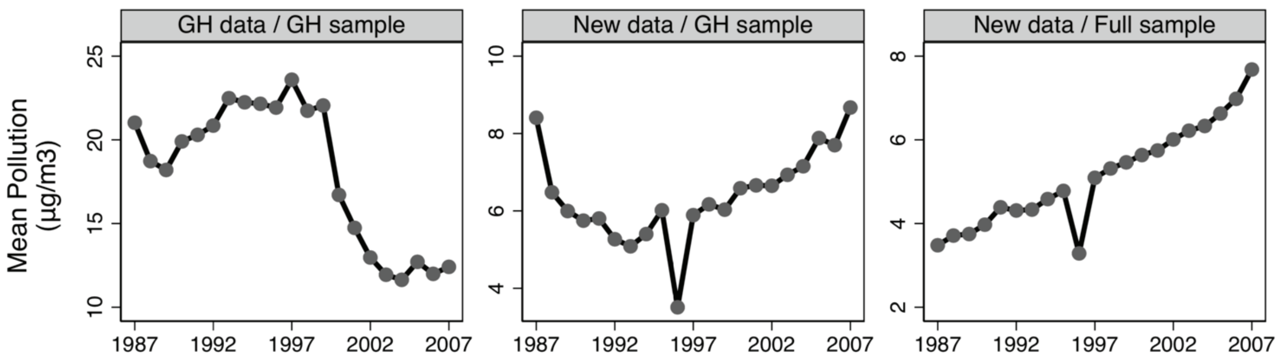


Figure 3. Trends in air pollution, 1987-2007

Notes: The figure plots annual city-level average concentrations of particulate air pollution (Panel A) and SO_2 (Panel B). Left-hand graphs show SPM and SO_2 trends in GH's data for their restricted sample of cities. Right-hand graphs in Figure 3 show trends in $PM_{2.5}$ and SO_2 estimates for the full sample of 140 cities, while the middle graphs plot the trends for the same pollutants across GH's sample of cities. GH's air pollution data were drawn from the CPCB ground-based monitoring network, while the revised air pollution data - from the MERRA-2 satellite-derived estimates.

[21] These graphs correspond to the first two graphs in panel A of GH's Figure 4.

The striking finding that immediately emerges from Figure 3 is the opposite air pollution trends in GH's data relative to MERRA-2 data. While SPM and SO_2 levels were falling in GH, concentrations of the revised air pollution outcomes are continuously increasing. As Table 2 indicates, concentrations of GH's SPM fall steadily from 252.13 $\mu g/m^3$ during 1987-1990 to 209.42 $\mu g/m^3$ during 2004-2007, or a 17% reduction. SO_2 concentrations are quite stable until the late 1990s but then decline sharply from the 1987-1990 levels, overall, by 37% during 2004-2007, from 19.36 to 12.19 $\mu g/m^3$. In contrast, the concentrations of MERRA-2 $PM_{2.5}$ increase by 68% in 2004-2007 compared to 1987-1990, from 22.63 to 37.92 $\mu g/m^3$ for GH's sample of cities. Similarly, MERRA-2 SO_2 concentrations increase by 24%, from 6.36 to 7.89 $\mu g/m^3$. The increase in the revised air pollution outcomes is even more pronounced for the full sample of cities, 75% and 85% for $PM_{2.5}$ and SO_2, respectively.

Table 2 – Comparison of Summary Statistics

	Air Pollution							Meteorological Variables			Infant Mortality
	GH data GH sample			New data GH sample		New data Full sample		New data Full sample			GH data GH sample
	SPM	PM2.5	SO2	PM2.5	SO2	PM2.5	SO2	Temp-ture	Precip-tion	Wind speed	IM Rate
Period	1	2	3	4	5	6	7	8	9	10	11
Full Period											
Mean	223.23	49.41	17.26	29.89	6.49	27.44	5.13	25.57	1152.02	4.86	23.46
Standard deviation	113.99	25.23	15.17	13.16	7.35	12.14	5.67	1.85	562.64	0.79	22.09
Observations	1370	1370	1344	1370	1344	2940	2940	2940	2940	2940	1247
Tenth percentile	90.51	20.03	4.00	16.47	1.63	14.93	1.34	23.40	547.81	3.84	3.36
Ninetieth percentile	378.44	83.76	35.37	50.15	13.23	45.17	10.39	27.28	1947.70	5.86	46.23
1987-1990											
Mean	252.13	55.8	19.36	22.63	6.36	21.64	3.73	25.60	1078.50	4.94	29.60
Standard deviation	126.35	27.96	13.28	5.52	8.46	5.91	4.54	2.24	541.13	0.80	31.44
Observations	120	120	116	120	116	560	560	560	560	560	358
Tenth percentile	101.55	22.48	4.40	14.01	1.17	13.77	1.10	23.34	460.77	3.90	4.79
Ninetieth percentile	384.30	85.05	38.23	29.21	29.41	29.16	7.10	27.47	1888.23	5.87	56.20
2004-2007											
Mean	209.42	46.35	12.19	37.92	7.89	37.78	6.90	25.59	1315.35	4.79	16.70
Standard deviation	97.13	21.5	8.09	14.66	7.52	14.18	6.76	1.54	681.19	0.76	14.09
Observations	420	420	381	420	381	560	560	560	560	560	216
Tenth percentile	92.01	20.36	4.00	21.17	2.10	21.22	1.69	23.41	625.60	3.75	2.73
Ninetieth percentile	366.59	81.13	22.95	59.83	15.84	58.83	14.41	27.12	2328.06	5.74	36.15

Notes: This table provides summary statistics on air pollution, meteorological variables, and infant mortality. GH's air pollution data are the annual city-level average SPM and SO_2 concentrations constructed using CPCB ground-based monitoring network, and $PM_{2.5}$ converted from SPM using SPM-PM_{10}-$PM_{2.5}$ ratios. New air pollution data are the revised $PM_{2.5}$ and SO_2 air pollution outcomes derived using MERRA-2 satellite-based estimates. GH's sample corresponds to the number of cities used in GH. The number is restricted by the availability of the ground-based air pollution monitor readings. The full sample contains a panel of 140 cities used in the GH reexamination. Columns with meteorological variables provide summary statistics on city-level air temperature, precipitation, and wind speed constructed using various MERRA-2 products. Construction of GH and revised air pollution outcomes, as well as meteorological covariates, is described in detail in the text. Infant mortality data are taken from GH without modification. The sources of infant mortality data include the Vital Statistics of India from various years and some offices of the state registrar.

Appendix Figure 7 provides additional evidence on the opposite trends. It compares kernel density estimates of GH's and revised air pollutant distributions across Indian cities for two periods, 1987-1990 and 2004-2007. While GH's entire SPM and SO_2 distributions shifted to the left, the opposite shift is apparent for the pollutants derived using MERRA-2 reanalysis data. The shift to the right is particularly substantial for MERRA-2 $PM_{2.5}$. As Table 2 reports, the tenth and the ninetieth percentiles of GH's SMP and SO_2 concentrations demonstrate a decline between two periods: about 10% in the tenth percentiles for both pollutants, 5% in the ninetieth percentile for SPM and 40% in the ninetieth percentile for SO_2. In contrast, the distributions of MERRA-2 $PM_{2.5}$ and SO_2 concentrations worsened substantially, with striking increases in the tenth percentiles by about 50% and in the ninetieth percentiles by 100% for the full sample.

The difference in trends between GH's SPM and MERRA-2 $PM_{2.5}$ cannot be explained by the fact that SPM and $PM_{2.5}$ are not directly comparable pollutants. I convert GH's SPM concentrations into $PM_{2.5}$ concentrations applying SPM/PM_{10} and $PM_{10}/PM_{2.5}$ ratios used in Nilekani (2014) and Greenstone et al. (2015).[22] Column 2 of Table 2 demonstrates the summary statistics for GH's $PM_{2.5}$ air pollution. The results are qualitatively similar in terms of the difference in trends between GH's SPM/$PM_{2.5}$ and MERRA-2 $PM_{2.5}$.

Several potential explanations for such a dramatic difference in the observed air pollution trends relate to the arguments summarizing issues with GH's data and highlighting the advantages of the satellite-derived estimates relative to ground-based measures. Specifically, the limited availability of air pollution data and the problems with using a sparse ground-based monitoring network can explain an unusual year-to-year spike-and-drop pattern in GH's SPM/$PM_{2.5}$ concentrations (left-hand graph in panel A of Figure 3). MERRA-2 reanalysis products have been compiled consistently during GH's study period and potentially provide a more reliable air pollution measure. Indeed, the trends in the revised air pollution outcomes correspond well with the similar trends documented in other recent studies and perfectly reflect numerous concerns about increasingly deteriorating air quality in China and India over the past decades (Greenstone et al., 2015; Ebenstein et al., 2015; Chen et al., 2017). A similar trend in particulate air pollution is also indicated by $PM_{2.5}$ estimates constructed for the period 1998-2007 using van Donkelaar et al. (2019).

However, sharp increases in the trend of MERRA-2 $PM_{2.5}$ in 2000 and 2007 look suspicious. Appendix Figure 8 shows the trends in the components of this pollutant that shed some light on the developments in $PM_{2.5}$ air pollution. The left-hand graph of panel B shows that the first episode of the substantial increase in $PM_{2.5}$ concentrations in 2000 can be explained by the spike in $DUST_{2.5}$ that was likely caused by dust storms (Prasad & Singh, 2007). The second episode in 2007 is likely attributable to the mutually magnifying effects of the simultaneous increase in concentrations of SO_4, Organic and Black Carbons. With the peak in $PM_{2.5}$ air pollution in 2008, the worsening of air quality in 2007 could be associated with the accelerating economic growth during the pre-crisis wave of globalization accompanied by the increasing trends in industrialization, fast-growing population and deterioration of the natural environment (CPCB, 2014). During other years, a continuously rising

[22] PM_{10} is a fraction of SPM; PM_{10} is particulate matter with a diameter less than 10 μm. PM_{10} = 0.5053SPM, $PM_{2.5}$=0.438PM_{10}

trend in MERRA-2 $PM_{2.5}$ was predetermined by Black and Organic Carbons, the products of the anthropogenic emissions.

The comparisons in Figure 3 and Table 2 indicate that the trends in particulate and SO_2 air pollution outcomes constructed using GH and MERRA-2 data differ substantially. This conclusion suggests that the reexamination of the empirical evidence on the effectiveness of environmental policies using revised air pollution outcomes, extended number of observations, and meteorological controls may lead to different results than those estimated by GH.

4 THE EFFECTS OF REVISED AIR POLLUTION OUTCOMES

In this section, I maintain GH's methodology to test the sensitivity of their findings to the revised air pollution outcomes and the extended number of observations. Table 3 demonstrates the effects of these revisions by reporting the estimated impacts of the SCAP and CAT policies on $PM_{2.5}$ and SO_2 air pollution. For each policy-pollutant and data-sample combination, the table reports estimates from fitting equation (2) and its one-step analog. Exactly following GH's methodology ensures that the differences in the results stem only from the differences in air pollution data.

Columns 1-2 replicate GH's results using their data. The outcome variables in these columns are the city-level annual average $PM_{2.5}$ and SO_2 concentrations. $PM_{2.5}$ here is an indicator of particulate air pollution converted from GH's SPM using SPM-PM_{10}-$PM_{2.5}$ ratios. I use GH's $PM_{2.5}$ for consistency as I focus on MERRA-2 $PM_{2.5}$ in the following reexamination. Appendix Table 1 compares replication results using GH's SPM and $PM_{2.5}$ as the outcome variables. The results are qualitatively similar in terms of the sign and statistical significance of the coefficients. Relying on this comparison, I use GH's $PM_{2.5}$ in the rest of the analysis. I successfully reproduce GH's results, confirming that the CAT policy is strongly associated with the reduction in $PM_{2.5}$ and SO_2 concentrations five years after the policy implementation by 10.75 $\mu g/m^3$ and 13.45 $\mu g/m^3$, or 19% and 69% of the 1987–1990 nationwide mean concentrations. The coefficients on policy dummy are not statistically significant and suggest a decline only in the case of SO_2 pollution. However, panels C and D point to a negative and statistically significant break in $PM_{2.5}$ and SO_2 trends caused by the CAT policy.

Columns 3-4 use the same sample of cities as in GH but replace original air pollution outcomes by MERRA-2 $PM_{2.5}$ and SO_2. The effects of this substitution are quantitively captured by the column-wise differences between the coefficients in columns 1-2 and 3-4 (i.e., column 1 - column 3, column 2 - column 4). Revised air pollution outcomes yield remarkable changes in the estimated effects of the SCAP and CAT policies. In contrast to GH, the significance of the CAT policy's effects on $PM_{2.5}$ and SO_2 five years after its implementation vanish. Not only that, but also the magnitude of the estimated effects is substantially smaller. For $PM_{2.5}$, another notable change in the CAT policy's effects includes the significance of the positive coefficients on a policy dummy in panel C.[23] For SO_2,

[23] One possible reason for the positive sign of the coefficients is that the binary variable that captures the effects of the CAT policy enactment might fail to account for some of the policy's features. Specifically, for the fact that the impact of the CAT policy evolves in line with the higher proportion of newer vehicles subject to the mandatory installation of catalytic converters (Greenstone et al., 2017). Negative coefficient on the policy's effects five years after its implementation seems to support this hypothesis.

the revised air pollution data indicate a higher magnitude of the policy dummy coefficient, which remains negative but, in contrast to GH, turns statistically significant in the one-step specification. The coefficient in column 4, panel D, suggests that SO_2 concentrations decrease by 0.88 $\mu g/m^3$ or 13.8% of the 1987–1990 nationwide mean concentrations. Another change is that the coefficients on the break in SO_2 trend turn positive, small, and statistically insignificant. The effects of the SCAP policies on $PM_{2.5}$ are also substantially different from those found in GH. In contrast to GH, the effects of the SCAP policies five years after implementation enter positively, large, and significantly. Thus, the SCAP policies do not appear to have helped reduce $PM_{2.5}$ concentrations but are rather associated with their increase.[24] The policy dummy coefficients in panel A turn negative but remain statistically insignificant. Column 4, panel A, based on estimating the one-step version of equation (2), shows a positive and statistically significant break in $PM_{2.5}$ trend. The general pattern of the SCAP policies' effects on SO_2 is similar to those in GH. However, their magnitudes are much smaller than those estimated using GH's data.

Finally, columns 5-6 take full advantage of MERRA-2 air pollution data and report coefficients estimated from fitting GH's specifications to the revised air pollution outcomes and the extended number of observations. The column-wise differences between the estimates in columns 3-4 and 5-6 capture the effects of the full sample (i.e., column 3 - column 5, column 4 - column 6). Of all the changes attributable to the extended number of observations, the most prominent change occurs with the impact of the CAT policy on SO_2. Alongside the negative and statistically significant coefficient on the policy dummy already observed in column 4, panel D, the results from the one-step specification in column 6, panel D, show that the policy is associated with a statistically significant decline in SO_2 concentrations five years after its implementation. Although substantially larger than in columns 3-4, -0.75 $\mu g/m^3$ against -0.28 $\mu g/m^3$, the effect remains considerably smaller than that obtained by GH, 20% against 69% of the 1987–1990 nationwide mean concentrations. The effects of the SCAP policies on SO_2, panel B, also change considerably compared to those in columns 3-4. The coefficients on the break in SO_2 trend enter with the opposite sign, while the policies' effects five years after implementation become almost indistinguishable from zero and change the sign in the one-step specification. The SCAP and CAT policies' effects on $PM_{2.5}$ change moderately compared to those in columns 3-4. The general pattern of these impacts in terms of the sign and significance of the coefficients does not change, but their magnitudes do. Notably, the size of the column-wise coefficients based on the numerically identical equation (2) and its one-step version in columns 5 and 6 becomes more similar compared to the size of the coefficients in other columns, perhaps due to the increase in the sample size and less noise in MERRA-2 data. These reasons are also behind the decrease in standard errors.

[24] It may well be that the coefficients on the SCAP policies' effects five years after implementation capture some other changes. Some blame lies with the energy generation by power plants, on which GH focus to a lesser degree than on vehicular pollution. Energy generation is the major contributor to air pollution in many developing countries and is certainly the driving force behind the rapid economic growth in China and India. At the city level, Goyal (2002) refers to the fossil fuel burning power plants in Delhi as the primary source of SO_2 and SPM air pollution, with the respective shares of 56.8% and 60.4%. For comparison, vehicular emissions contribute a modest 4.8% and 6.7% to SO_2 and SPM air pollution in Delhi. Thus, any increase in the power plant emissions increases levels of particulate air pollution. This can happen directly through the SPM channel and indirectly because of the conversion of SO_2 to sulfate particulates (SO_4), a $PM_{2.5}$ component.

Table 3 – Effectiveness of air quality policies: Effects of MERRA-2 air pollution data

	Replication		Reexamination		Reexamination	
	GH data / GH sample		New data / GH sample		New data / Full sample	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6
			Supreme Court Action Plans			
			Panel A. PM2.5			
π1: 1(Policy)	1.66	0.07	-0.69	-1.70	-1.41	-1.85
	(4.56)	(4.76)	(2.79)	(1.90)	(2.18)	(1.74)
π2 : time trend	-0.80	-0.63	0.67	0.58	0.55	0.54
	(0.61)	(0.95)	(0.38)	(0.54)	(0.29)	(0.50)
π3: 1(Policy)*time trend	-0.34	0.03	1.83	2.28*	2.11**	2.21*
	(1.58)	(1.32)	(0.97)	(1.33)	(0.76)	(1.26)
5-year effect: π1+5π3	-.05	.20	8.46*	9.68**	9.12**	9.19*
p-value	[.99]	[.98]	[.07]	[.05]	[.02]	[.06]
Observations	11	1,165	11	1165	11	2720
1987–1990 mean	55.8		22.63		21.64	
			Panel B. SO2			
π1: 1(Policy)	-1.44	-1.25	-0.27	-0.12	-0.34	-0.14
	(0.88)	(2.13)	(0.30)	(0.44)	(0.33)	(0.45)
π2: time trend	0.20	0.09	0.12**	0.09	0.07	0.05
	(0.12)	(0.55)	(0.04)	(0.14)	(0.04)	(0.12)
π3: 1(Policy)*time trend	-0.06	0.10	-0.03	-0.03	0.07	0.04
	(0.31)	(0.98)	(0.10)	(0.12)	(0.11)	(0.10)
5-year effect: π1+5π3	-1.74	-.78	-.4	-.28	-.01	.04
p-value	[.21]	[.87]	[.37]	[.71]	[.98]	[.94]
Observations	11	1158	11	1158	11	2720
1987–1990 mean	19.36		6.36		3.73	
			Mandated Catalytic Converters			
			Panel C. PM2.5			
π1: 1(Policy)	1.23	1.69	2.26*	1.96*	2.15**	1.95**
	(2.82)	(2.71)	(1.24)	(1.15)	(0.84)	(0.97)
π2 : time trend	1.72***	1.73**	0.32	0.23	0.19	0.15
	(0.55)	(0.73)	(0.24)	(0.25)	(0.17)	(0.11)
π3: 1(Policy)*time trend	-2.40***	-2.48**	-0.95***	-0.79**	-0.82***	-0.73***
	(0.64)	(1.01)	(0.28)	(0.39)	(0.19)	(0.27)
5-year effect: π1+5π3	-10.75**	-10.71*	-2.48	-1.99	-1.93	-1.71
p-value	[.04]	[.06]	[.25]	[.19]	[.19]	[.15]
Observations	17	1,165	17	1165	17	2720
1987–1990 mean	55.8		22.63		21.64	
			Panel D. SO2			
π1: 1(Policy)	-0.53	-0.76	-0.75	-0.88***	-0.89**	-0.86***
	(1.52)	(2.56)	(0.49)	(0.22)	(0.38)	(0.19)
π2: time trend	2.02***	1.91***	-0.03	-0.03	0.06	0.06
	(0.29)	(0.70)	(0.09)	(0.07)	(0.07)	(0.04)
π3: 1(Policy)*time trend	-2.58***	-2.39**	0.11	0.12	0.03	0.02
	(0.34)	(0.98)	(0.11)	(0.10)	(0.09)	(0.07)
5-year effect: π1+5π3	-13.45***	-12.69**	-.22	-.28	-.73	-.75*
p-value	[.00]	[.02]	[.79]	[.62]	[.27]	[.07]
Observations	17	1158	17	1158	17	2720
1987–1990 mean	19.36		6.36		3.73	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to the revised air pollution outcomes and the extended number of observations. It reports estimates from fitting the second-step equation (2), odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) levels. Columns 1-2 use GH's original data to replicate their results. I substitute GH's SPM by GH's $PM_{2.5}$ converted from GH's SPM using SPM-PM10-PM2.5 ratios for comparability with the policies' effects on MERRA-2 $PM_{2.5}$. Columns 3-4 exploit the same sample of cities as in GH and revised $PM_{2.5}$ and SO_2 air pollution outcomes to reexamine GH findings. Columns 5-6 reexamine GH results by taking full advantage of the revised outcome variables and fitting equation (2) and its one-step version to all available city-by-year observations. Standard errors are reported in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effect 5 years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

5 THE EFFECTS OF METEOROLOGICAL CONTROLS

A. Air pollution

This subsection explores the effects of meteorological conditions on the robustness of GH's findings by estimating a two-step approach and its one-step version with air temperature, precipitation, and wind speed as control variables.[25] Table 4 summarizes the regression results. For brevity, it reports only estimates from the regressions that are based on the most complete data-sample combination, the same as in columns 5-6 of Table 3, and control for a complete set of the meteorological variables. Paralleling analysis in section 4, appendix Table 2 shows the results for other data-sample combinations from Table 3. Appendix Tables 3-5 document a detailed, data-sample combination-specific breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed.

Columns in Table 4 report results from the regressions that incorporate all changes in the data, particularly revised air pollution outcomes, extended number of observations, and a full set of the meteorological controls. Altogether, these changes yield the most striking result of reexamination. Negative coefficients on the CAT policy's effects on $PM_{2.5}$ five years after implementation turn statistically significant (panel C). However, the magnitudes of the effects are smaller compared to the policy's five-year effects on GH's $PM_{2.5}$ and correspond to a decline of 2.28 $\mu g/m^3$ to 2.53 $\mu g/m^3$ against 10.7 $\mu g/m^3$, or 11% against 19% of the 1987–1990 nationwide mean concentrations. Further, the pattern of the estimates in column 6 of panel C, based on estimating the one-step version of equation (2), is the most similar to that in GH.

Do meteorological controls matter? The column-wise differences between the estimates in columns 5-6 in Tables 3 and 4 (i.e., column 5 in Table 3 - column 5 in Table 4) isolate the impacts of the meteorological confounders on the policies' effects net of the impacts of the extended number of observations (i.e., column 3 - column 5 in Table 3).[26] Substantially larger impacts of the meteorological confounders compared to the impacts of the extended number of observations indicate that the changes in the CAT policy's effects on $PM_{2.5}$ are driven by controlling for meteorological conditions. Wind speed makes a major contribution to improvements in air quality, while the size and significance of the policy's effects are mostly unchanged after controlling for air temperature and precipitation (appendix Table 5, panel C).

Likewise, meteorological conditions are important factors behind the changes in the SCAP policies' effects on SO_2. Panel B of Table 4 indicates that meteorological controls alter the magnitude and

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[25] I control for a set of meteorological covariates by including $f(\boldsymbol{W}_{ct})$ into Equation (1) of a two-step econometric approach.

[26] I illustrate this point on the example of the effects of the CAT policy on $PM_{2.5}$ estimated using a two-step approach. The difference between the coefficients on policy dummy that captures the combined effect of the sample extension and inclusion of the meteorological controls is equal to 0.68 $\mu g/m^3$ (2.26 - 1.58 or column 3 in Table 3 - column 5 in Table 4, panel C). The difference that captures the effect of the sample extension alone is equal to 0.11 $\mu g/m^3$ (2.26 - 2.15 or column 3 - column 5 in Table 3, panel C). Then, the effect of the inclusion of the meteorological controls is equal to 0.57 $\mu g/m^3$ (0.68 - 0.11). This is exactly the difference between the policy dummy coefficients that captures the effect of meteorological covariates described above, i.e., column 5 in Table 3 - column 5 in Table 4, panel C, or 2.15 - 1.58 = 0.57 $\mu g/m^3$.

significance of the policies' impacts. The policy dummy coefficient from estimating the two-step approach doubled compared to that in Table 3 to statistically significant -0.71 $\mu g/m^3$ (19% of the 1987–1990 nationwide mean concentrations), while the five-year policies' effects increase from -0.01 $\mu g/m^3$ and 0.04 $\mu g/m^3$ to -0.32 $\mu g/m^3$ and -0.36 $\mu g/m^3$ (10% of the 1987–1990 nationwide mean concentrations) and remain insignificant. Although substantially different from those in columns 5-6 of Table 3, these effects are similar to those reported in columns 3-4 of appendix Table 2. Panel B of appendix Table 5 indicates that wind speed plays a major role in magnifying the effects of SCAP policies on SO_2 and improving air quality.

Table 4 – Effectiveness of air quality policies: Effects of meteorological controls

	Reexamination: *Full set of meteorological controls* New data / Full sample							
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans				*Mandated Catalytic Converters*			
	Panel A. PM2.5		*Panel B. SO2*		*Panel C. PM2.5*		*Panel D. SO2*	
π1: 1(Policy)	-1.41	-1.63	-0.71**	-0.43	1.58**	1.52	-1.07**	-0.98***
	(2.35)	(1.65)	(0.29)	(0.38)	(0.72)	(0.93)	(0.38)	(0.17)
π2 : time trend	0.50	0.48	0.07	0.05	0.30*	0.25**	0.08	0.07*
	(0.32)	(0.47)	(0.04)	(0.11)	(0.14)	(0.12)	(0.08)	(0.04)
π3: 1(Policy)*time trend	1.57*	1.64*	0.08	0.01	-0.82***	-0.76***	0.02	0.01
	(0.81)	(0.91)	(0.10)	(0.09)	(0.16)	(0.23)	(0.09)	(0.07)
5-year effect: π1+5π3	6.42*	6.55*	-.32	-.36	-2.53**	-2.28*	-.96	-.95**
p-value	[.09]	[.06]	[.47]	[.49]	[.05]	[.09]	[.15]	[.03]
Observations	11	2720	11	2720	17	2720	17	2720
1987–1990 mean	21.64		3.73		21.64		3.73	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to additional controlling for meteorological confounders. It reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) concentrations. Both specifications include a full set of meteorological controls, specifically air temperature, precipitation, its quadratic, and wind speed. The table reports only estimates from the regressions that are based on the most complete data-sample combination, the same as in columns 5-6 of Table 3. Specifically, the columns use new air pollution outcome variables and fit equation (2) and its one-step version to full sample of cities. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effect five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

For the remaining policy-pollutant pairs, the impact of the meteorological controls is weaker. Although the magnitude of the CAT policy's effects on SO_2 increases (panel D), the general pattern of the estimates is comparable to those in columns 5-6 of Table 3. In this case, the effect of the inclusion of meteorological covariates is equivalent to the effect of the extended number of observations. However, the significance of the CAT policy's impact five years after implementation is attributed to the increase in the sample size as the policy's impact first becomes significant in Table 3. Appendix Table 5, panel D, documents that all three meteorological covariates are beneficial for the effects of the CAT policy on SO_2. Air temperature and precipitation alter mainly the magnitude of the policy' effects five years after implementation, while wind speed also changes the coefficients on the policy dummy. In the case of the SCAP policies' effects on $PM_{2.5}$ (panel A), the effects of the inclusion of meteorological controls substantially reduces the positive and significant effects of the SCAP policies on $PM_{2.5}$ five years after implementation. Appendix Table 5, panel A, suggests that all meteorological conditions are beneficial for the five-year policies' effects. In contrast, meteorological controls change the coefficients on policy dummy minimally. Air temperature and precipitation are harmful to the policies' effects, while wind speed is beneficial. However, meteorological controls do not change the significance of the policy dummy coefficients, which remain statistically insignificant.

B. Infant mortality

This subsection reexamines the effects of the CAT policy on infant mortality. Following GH, I apply a two-step econometric approach with infant mortality rate as the outcome variable. As air pollution concentrations do not enter this equation directly, I test the sensitivity of GH's findings solely to the inclusion of the meteorological controls. Table 5 reports the resulting estimates.

Table 5 – Effectiveness of air quality policies: Infant mortality

	Replication	Reexamination		
		GH data / GH sample		
	No Meteo Vars	Air temperature	Add precipitation	Add wind speed
	Eq. 2	Eq. 2	Eq. 2	Eq. 2
	1	2	3	4
		Mandated Catalytic Converters		
		Infant Mortality Rate		
π1: 1(Policy)	3.57**	3.19**	3.30**	3.81**
	(1.49)	(1.43)	(1.43)	(1.59)
π2 : time trend	-0.26	-0.26*	-0.27*	-0.28
	(0.15)	(0.14)	(0.14)	(0.16)
π3: 1(Policy)*time trend	-0.84**	-0.71*	-0.72*	-0.64
	(0.36)	(0.34)	(0.34)	(0.38)
5-year effect: π1+5π3	-.64	-.36	-.29	.59
p-value	[.71]	[.83]	[.86]	[.74]
Observations	16	16	16	16
1987–1990 mean		29.60		

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach that tests for the effects of the CAT policy on infant mortality rate. Column 1 uses GH's original data to replicate their results. Columns 2-4 reexamine GH's findings by reporting a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation and its quadratic, and wind speed. Standard errors are reported in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policy's effect five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

I begin by successfully reproducing GH estimates of the CAT policy's effects on infant mortality rate using GH's original data. Column 1 of Table 5 indicates that the policy is associated with a modest and statistically insignificant decline in the infant mortality rate of 0.64 per 1000 live births five years after implementation. This result corresponds to that reported by GH in column 3 of Table 6. However, the policy dummy coefficient is positive and statistically significant at the 5 percent level. GH do not report the significance of this coefficient. The estimates in the column also indicate a negative and statistically significant break in infant mortality trend.

In the second column, I report estimates after controlling for air temperature. The general pattern of the results is little changed. However, the evidence of a negative and insignificant policy's effect five years after implementation is substantially weaker using this specification, with a reduction in the infant mortality rate of 0.36 per 1,000 live births. In the third column, I additionally control for precipitation and its quadratic. Inclusion of these meteorological variables reduces the estimated impact of the CAT policy on infant mortality further to -0.29 per 1,000 live births, which is about a third of the size of GH's original estimate. Other results are largely unchanged, including a positive and statistically significant policy dummy coefficient and negative and significant trend break.

Finally, in the last column of Table 5, I add wind speed as a control variable. In contrast to the results in previous columns, the estimated effect of the policy five years after implementation turns positive but remains insignificant. CAT policy is associated with a statistically insignificant increase in the infant mortality rate of 0.59 per 1,000 live births five years after implementation. Controlling for wind speed reduces the size of the trend break coefficient and eliminates its significance. However, the sign and significance of the policy dummy coefficient are robust to the inclusion of meteorological controls, although its magnitude increases compared to those reported in previous columns.

6 DISCUSSION

How should the evidence in Sections 4 and 5 be interpreted in terms of the policies' effectiveness?

The analysis in Section 4 indicates that GH's findings are highly sensitive to the revised air pollution outcomes and the extended number of observations. The changes in the patterns of the policies' effects include changes in the size, significance, sign of the estimates, and reinforce the conclusion made in Section 3 based on the observation of the opposite trends in air pollution outcomes.

GH's findings do not generally hold after replacing original air pollution outcomes by those constructed using satellite-derived data. Environmental regulations found in GH to be strongly associated with air quality improvements do not appear to have helped reduce air pollution. The only exception pertains to the CAT policy's effect on SO_2. The statistically significant policy dummy coefficient from the one-step specification suggests a modest reduction in SO_2 pollution. The policy's effects five years after implementation, however, remain insignificant. Thus, adding revised data casts doubts on the effectiveness of air pollution control policies.

Nevertheless, GH's findings seem somewhat less fragile after extending the sample size to the full number of observations from the satellite-derived data. Alongside the coefficient on the policy dummy, the estimate from the one-step specification indicates that the CAT policy is associated with a statistically significant decline in SO_2 concentrations five years after implementation. However, the effect remains substantially smaller than that obtained by GH. There is still little empirical support for the effectiveness of air pollution control policies for other policy-pollutant pairs.

Estimates from the richest specifications in Section 5 that additionally incorporate a complete set of meteorological controls point to further convergence in the policies' effects estimated using GH's and satellite-based data. Similarly to GH, the CAT policy induces reductions in $PM_{2.5}$ and SO_2 concentrations five years after implementation. Although weaker than those found using GH's data, the CAT policy's effects five years after implementation estimated using satellite-based data point to a decline of 11% against 19% of the 1987–1990 nationwide mean concentrations for $PM_{2.5}$ and 25% against 69% for SO_2. The fact that this study finds a similar pattern of the CAT policy's effects using alternative data is particularly remarkable given substantive differences between data sources and differential trends in air pollution. Likewise, the estimated impact of the CAT policy on infant mortality confirms GH's finding that regulation-induced improvements in air quality need not improve infants' health.

A natural question that arises from these findings is whether GH's and satellite-based data lead to the same results. Analysis of the disparities in the outcomes generated by two data sources provides a reasonable basis for answering this question. At least two of them deserve attention.

First, the qualitative patterns of the policies' effects estimated using GH's and satellite-based data differ considerably. For the CAT policy's effects on SO_2, GH's data indicate insignificant coefficients on policy dummy and negative and significant breaks in SO_2 trend, whereas satellite-based data point to the opposite effects. Estimates suggest that GH might overlook the effectiveness of the SCAP policies. The policy dummy coefficient turns statistically significant after estimating the two-step approach using satellite-based data, indicating a reduction in SO_2 pollution by 19% of the 1987–1990 nationwide mean concentrations. For the CAT policy's effects on infant mortality, the estimates point to the opposite conclusion from that reached by GH. The policy is associated with a modest and insignificant increase in infant mortality five years after implementation.

Second, the policies' effects estimated using satellite-based data are not always robust across various data-sample combinations and across two-step and one-step specifications that are supposed to return numerically identical estimates. For the CAT policy's effects on $PM_{2.5}$, the coefficients that quantify the policy's effects five years after implementation turn significant only in the richest combination but across both GH's specifications. In contrast, for the CAT and SCAP policies' effects on SO_2, the coefficients on policy dummy and five-year effect become significant in several data-sample combinations but only in one of the GH's specifications. For example, the CAT policy's effect on SO_2 five years after implementation turns significant in the one-step specification, whereas the estimate from the two-step specification remains insignificant. Not only does the significance of the estimates vary dramatically but also their sign and size. The CAT policy's effects on infant mortality are similarly sensitive to the inclusion of additional controls. After controlling for wind speed, the five-year effect reverses the sign from all previous specifications using GH's and satellite-derived data.

Observed disparities do not provide strong empirical support for a complete similarity in the results based on the findings from two data sources. Therefore, reexamination using satellite-based data can confirm the conclusions drawn from GH's data, but with reservations. Equally, it seems unreasonable to interpret the results from satellite-derived data as sufficiently compelling.

7 CONCLUSION

This paper reexamines empirical evidence on the effectiveness of environmental regulations in India from a recent study by Greenstone and Hanna (2014). GH demonstrate that air pollution control policies have been effective in improving air quality but arrive at the surprising conclusion that the policy-led reductions in air pollution need not improve infants' health. These somewhat counterintuitive findings are likely due to the limited availability of air pollution data and the absence of critical meteorological confounders. This conclusion motivated a reexamination of GH's findings using alternative data sources.

Using satellite-based estimates for air quality and meteorological conditions, I test the sensitivity of GH's findings to revised air pollution outcomes, an extended number of observations, and meteorological controls. Three findings emerge. First, air pollution outcomes constructed using GH's and satellite-based data demonstrate opposite trends. While concentrations of air pollutants were falling in GH, concentrations of the revised air pollution outcomes are continuously increasing. Second, GH's findings are highly sensitive to the revised air pollution outcomes and the extended number of observations. There is little empirical support in satellite-derived data for the effectiveness of the air pollution control policy found in GH to be strongly associated with air quality improvements. Third, meteorological controls matter. Additionally controlling for meteorological confounders revealed similar effects of policies on air pollution to those reported in GH. Likewise, the estimated impact on infant mortality confirms that regulation-induced improvements in air quality do not necessarily result in improved health. However, the qualitative patterns estimated using GH's and satellite-derived data differ substantially. Further, the effects of policies estimated using satellite-derived data are not robust across various data-sample combinations and specifications. Thus, based on the complementary empirical evidence from satellite-derived data, it seems reasonable to confirm GH's findings and interpret air pollution control policies in India as effective, although with substantially weaker effects on air pollution.

The next important empirical step in this line of research will be to explore further the prospects for using satellite-based data in a meaningful examination of important issues related to the effectiveness of environmental regulations. Such research would be particularly valuable for developing countries where air pollution control policies are especially contentious, and their effectiveness is hampered by weak institutions and limited data availability. Understanding whether and to what extent satellite-based estimates can be reliable complements to the observed indicators will be critical in uncovering the effects of environmental regulations and recommending sensible interventions aimed at mitigating air pollution and protecting population health.

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APPENDIX

Appendix Figure 1: Vital Statistics of India 1995, example page with city names

Table 5 - Live births, deaths, infant deaths and maternal deaths

India/State/Union territory/Town	Birth 1991	1992	1993	Death 1994	1995	1995
1	2	3	4	5	6	7
INDIA (all towns)	**2,976,305**	**3,020,746**	**3,053,505**	**814,277**	**806,887**	**773,183**
Andhra Pradesh (all towns)	**281,283**	**300,049**	**284,283**	**66,022**	**63,407**	**63,370**
1. Adoni	2,680	2,824	3,202	720	692	714
2. Anantapur	4,485	6,203	5,959	1,480	1,309	1,595
3. Bheemavaram	3,232	3,820	4,003	526	480	478
4. Chirala	2,676	2,610	2,696	532	529	478
5. Chittoor	5,236	5,469	5,756	713	734	691
6. Cuddapah	4,692	4,795	5,287	994	851	947
7. Eluru	4,557	4,778	4,837	1,442	1,485	1,463
8. Gudivada	3,271	3,775	3,750	586	612	648
9. Guntakal	1,709	1,935	2,037	591	478	530
10. Guntur	12,428	12,350	12,452	4,866	4,775	4,545
11. Hindupur	1,602	16,006	1,456	393	403	403
12. Hyderabad	96,454	101,984	102,279	19,749	19,220	19,302
13. Kakinada	6,752	7,641	7,539	3,202	3,214	3,104
14. Karimnagar	8,128	8,889	8,826	1,234	1,138	1,156
15. Khammam	5,358	N.A.	N.A.	495	N.A.	N.A.
16. Kurnool	7,977	8,247	8,533	2,993	2,812	3,386
17. Machilipatnam	5,238	5,205	5,383	1,113	1,125	1,126
18. Mahabubnagar	1,644	1,526	N.A.	860	803	N.A.
19. Nandyal	4,033	4,487	4,446	463	455	472
20. Nellore	10,251	9,815	10,403	2,055	1,915	1,931
21. Nizamabad	6,845	N.A.	8,264	1,212	N.A.	1,112
22. Ongole	3,583	4,050	N.A.	564	725	N.A.
23. Prodatur	3,903	3,771	4,053	494	475	412
24. Qutubullapur	1,698	2,382	N.A.	142	131	N.A.
25. Rajahmundri	7,764	8,188	8,504	1,751	1,701	1,913
26. Ramagundam	3,297	5,643	N.A.	609	439	N.A.
27. Tenali	5,251	5,334	5,450	792	720	685
28. Tirupati	5,956	6,827	7,028	2,207	2,299	2,537
29. Vijaywada	15,784	15,871	16,322	3,859	4,037	4,211
30. Vishakhapatnam	14,730	15,123	15,590	4,738	5,202	4,686
31. Vizianagaram	2,592	2,449	2,471	1,181	1,312	1,111
32. Warangal	17,477	18,052	17,757	3,466	3,336	3,734

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in towns with population 100,000 and above during 1993-95

Infant Death 1993	1994	1995	Maternal Death 1993	1994	1995	India/State/Union territory/Town	
8	9	10	11	12	13	1	
66,783	**68,610**	**67,018**	**1,660**	**2,162**	**1,468**	**INDIA (all towns)**	
5,116	**4,322**	**4,700**	**155**	**98**	**87**	**Andhra Pradesh (all towns)**	
57	65	91	4	3	3	Adoni	1.
149	143	151	4	8	10	Anantapur	2.
13	8	6	-	-	-	Bheemavaram	3.
10	9	2	1	-	-	Chirala	4.
7	11	14	-	-	-	Chittoor	5.
93	38	39	-	-	-	Cuddapah	6.
68	45	52	3	-	-	Eluru	7.
27	34	21	-	-	-	Gudivada	8.
8	2	15	-	-	-	Guntakal	9.
551	40	520	-	10	19	Guntur	10.
27	36	39	-	-	-	Hindupur	11.
1,662	1,251	908	29	12	14	Hyderabad	12.
281	310	300	-	-	-	Kakinada	13.
216	184	184	31	27	12	Karimnagar	14.
16	N.A.	N.A.	-	N.A.	N.A.	Khammam	15.
357	312	460	-	-	-	Kurnool	16.
107	114	81	-	3	-	Machilipatnam	17.
75	-	N.A.	-	-	N.A.	Mahabubnagar	18.
2	-	9	-	-	-	Nandyal	19.
69	72	54	6	1	-	Nellore	20.
26	N.A.	69	1	N.A.	7	Nizamabad	21.
14	20	N.A.	2	4	N.A.	Ongole	22.
8	5	1	1	-	-	Prodatur	23.
-	12	N.A.	-	-	N.A.	Qutubullapur	24.
24	32	26	-	-	-	Rajahmundri	25.
108	7	N.A.	-	-	N.A.	Ramagundam	26.
11	-	8	-	-	-	Tenali	27.
312	324	358	2	4	2	Tirupati	28.
276	168	258	7	16	18	Vijaywada	29.
38	419	353	23	-	-	Vishakhapatnam	30.
4	8	4	39	10	2	Vizianagaram	31.
500	653	677	2	-	-	Warangal	32.

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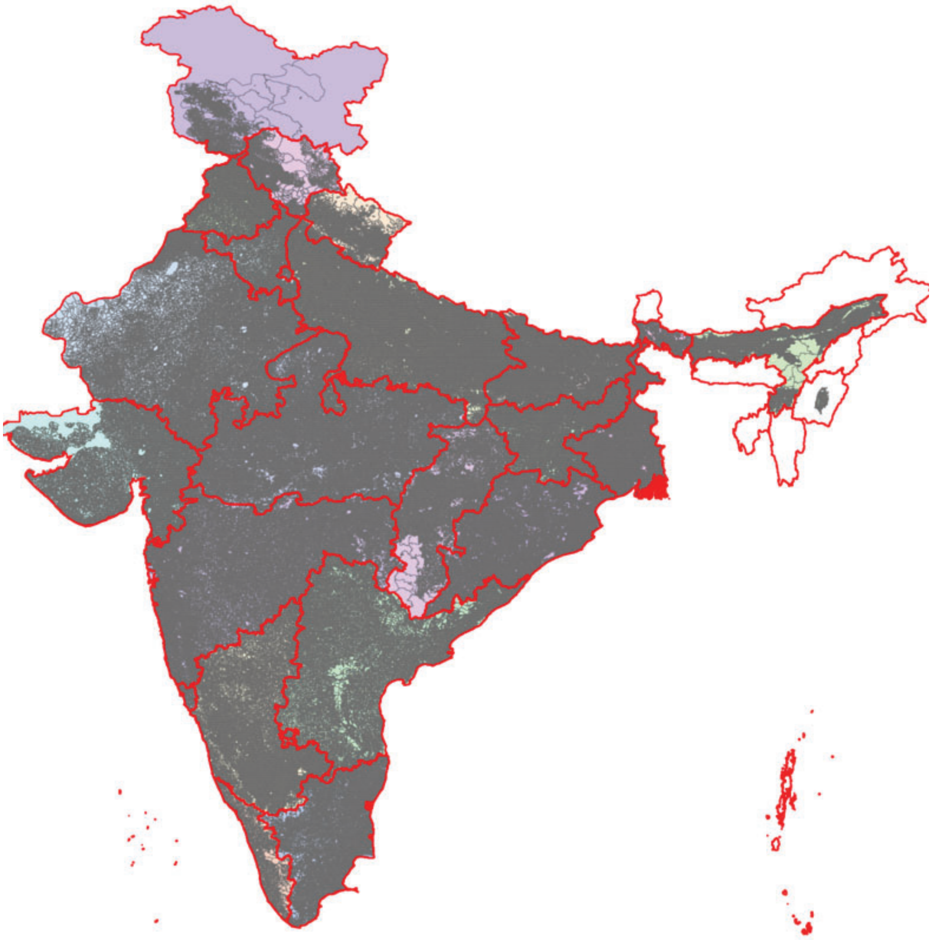
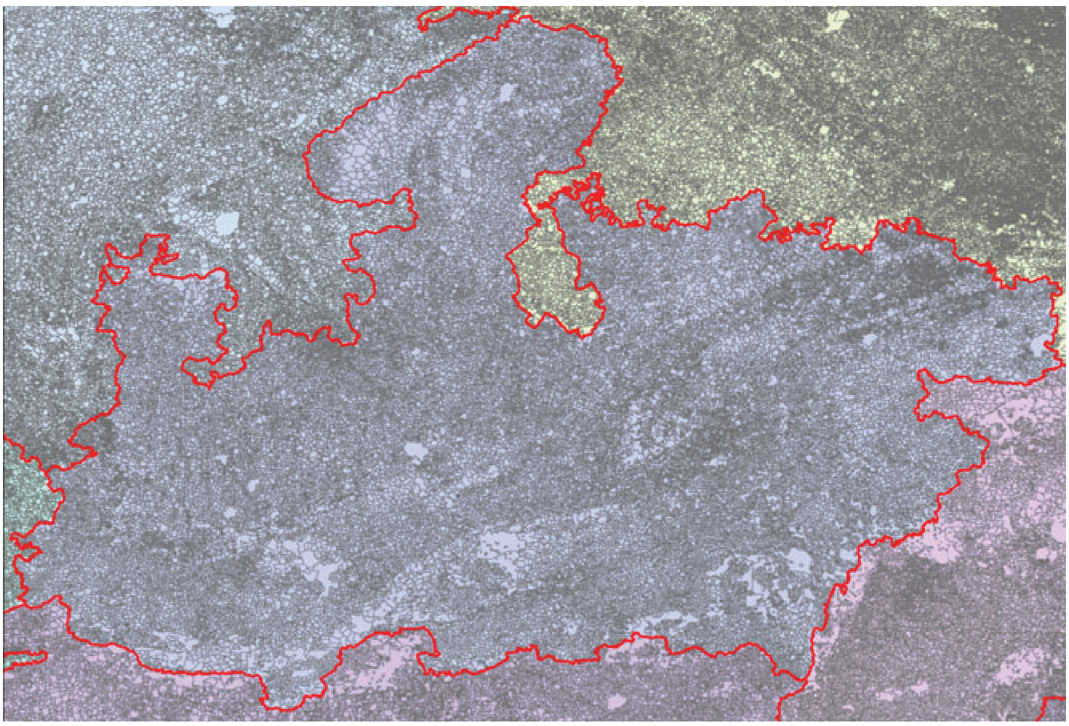
Appendix Figure 2: ML InfoMap digital maps with village and town borders as of 2011

Panel A: All India, 619000 polygons

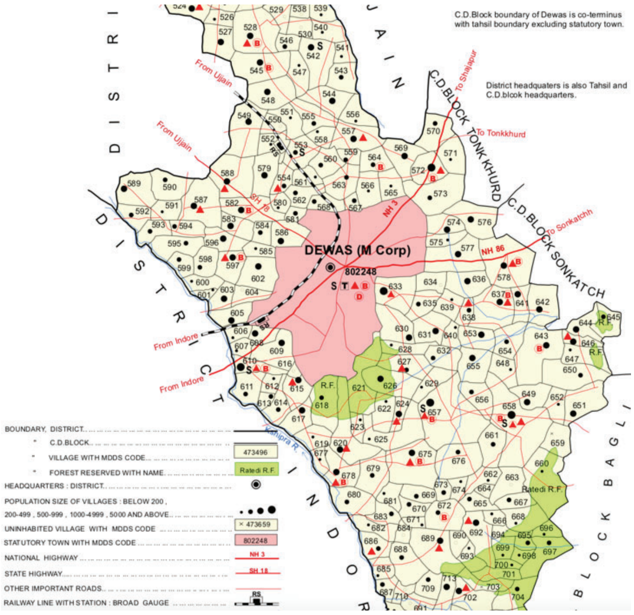


Panel B: State of Madhya Pradesh

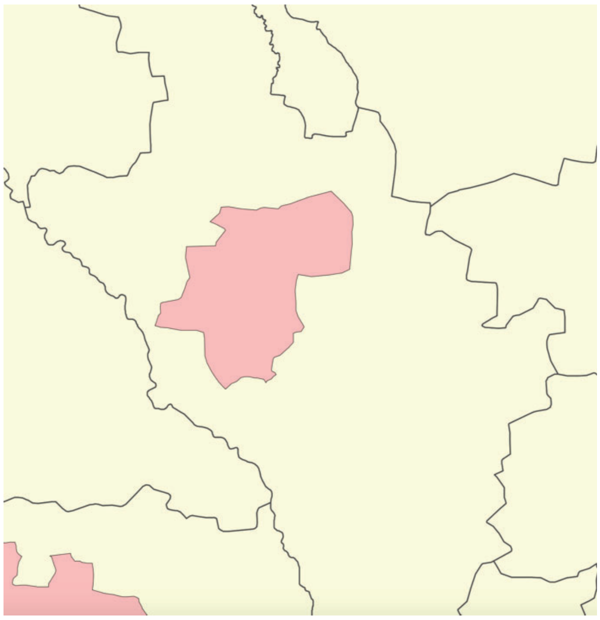


Appendix Figure 3: Example of city extent polygon selection

Panel A: District Census Handbook, Dewas city, Dewas district, Madhya Pradesh state

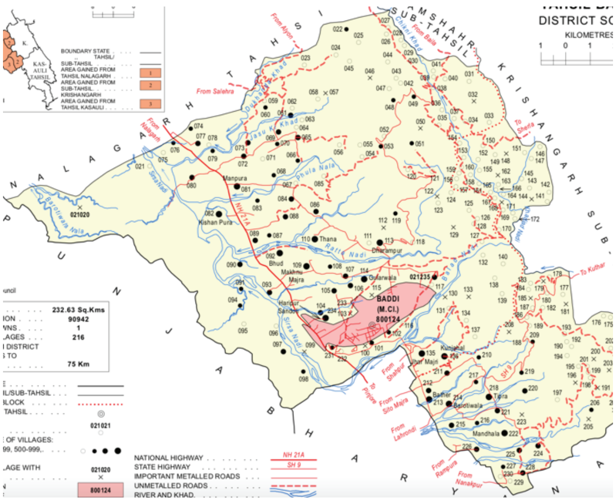


Panel B: Dewas city, selected urban extent polygon, ML InfoMap 2011 digital maps

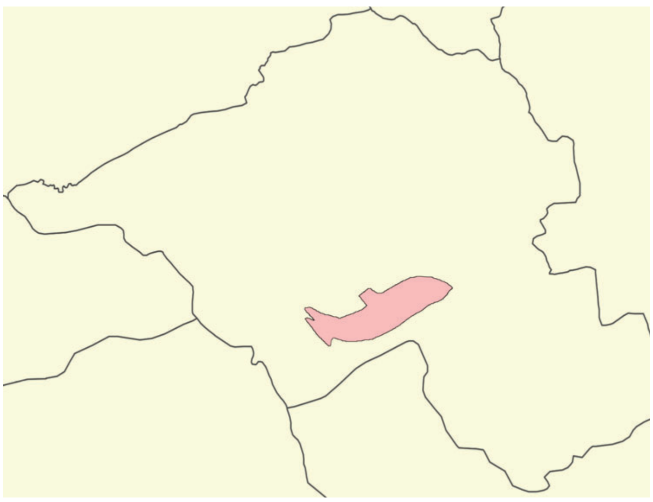


Appendix Figure 4: Example of digitized city extent polygon

Panel A: District Census Handbook, Baddi city, Solan district, Himachal Pradesh state



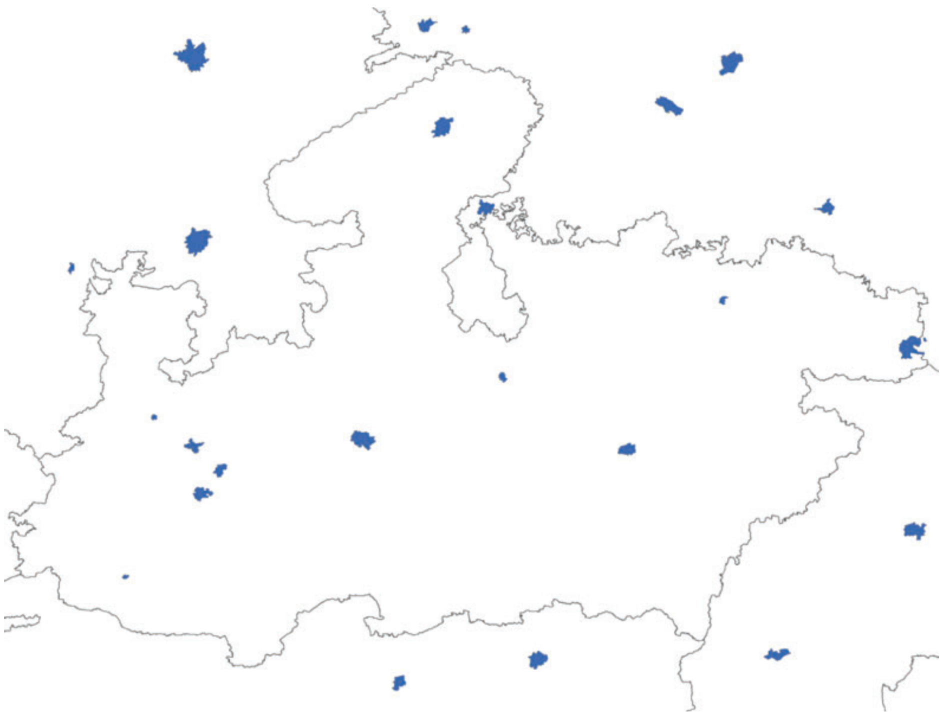
Panel B: Baddi city, selected urban extent polygon, digitized from the District Census Handbook



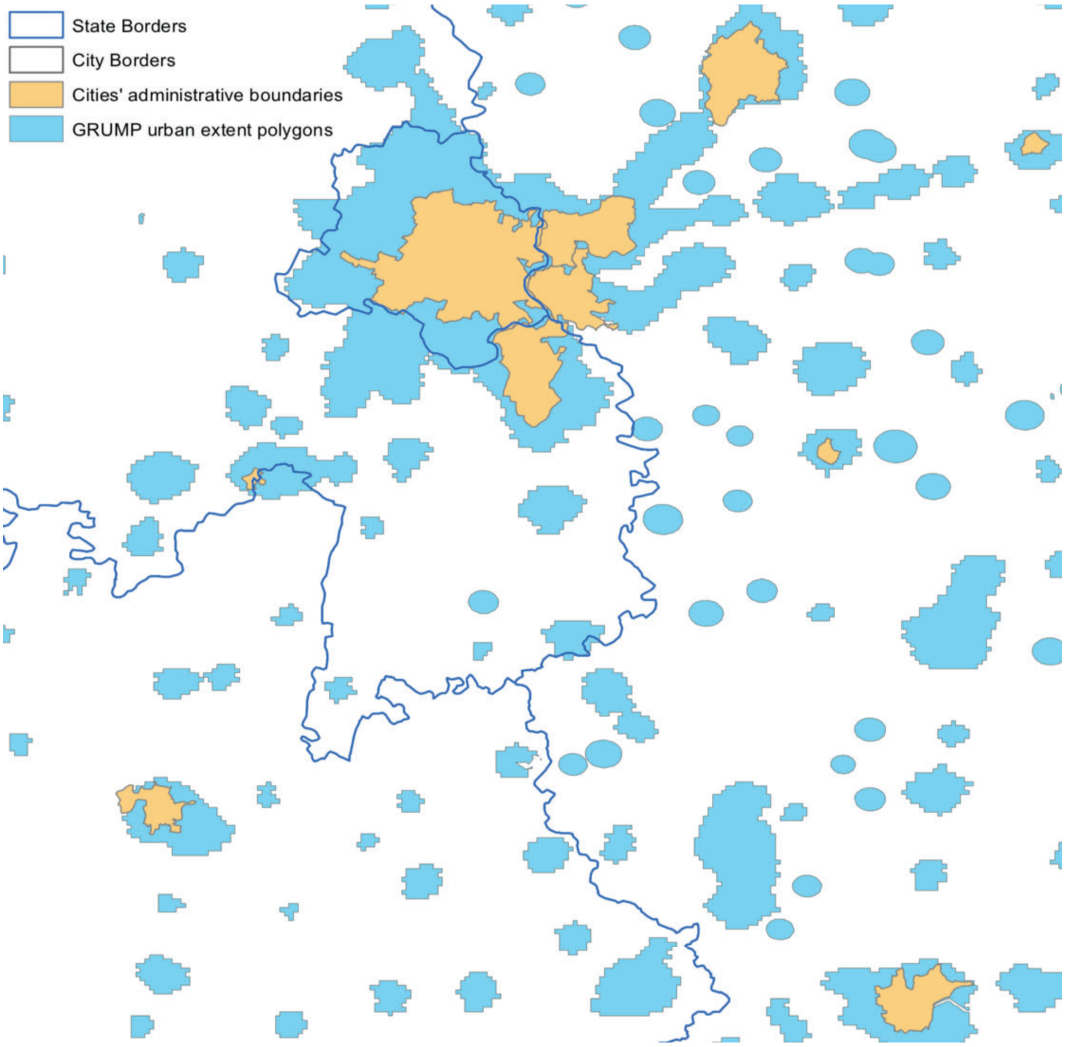
Appendix Figure 5: Selected city extent polygons

Panel A: All selected cities, 140 polygons

Panel B: Selected cities, a closer look



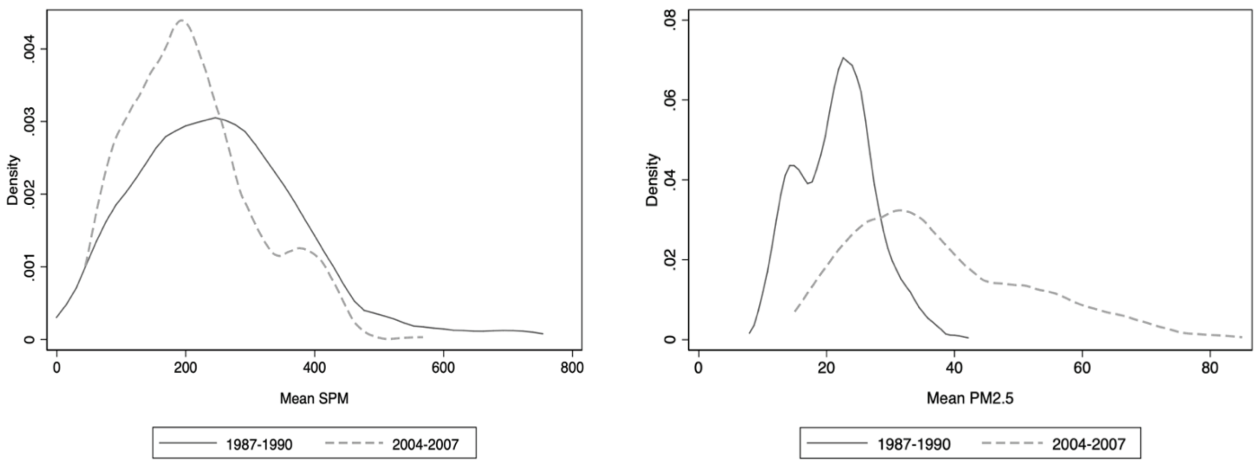
Appendix Figure 6: Comparison of the cities' administrative boundaries
with GRUMP urban extent polygons



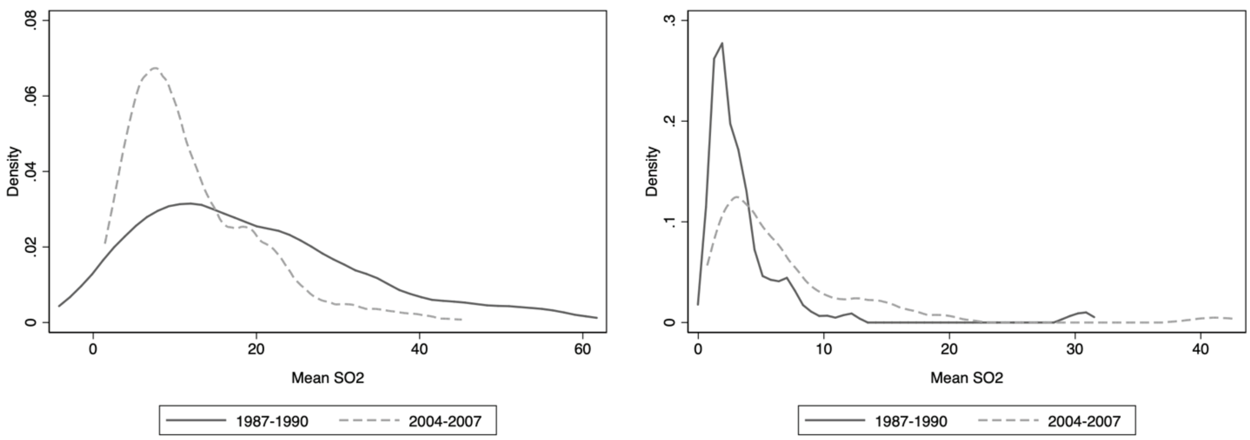
Notes: The figure compares urban extent polygons defined by the cities' administrative boundaries in this study with those defined by the combination of the night-time lights and buffered settlement centroids in the Global Rural-Urban Mapping Project (GRUMP). More information about the GRUMP can be found at https://sedac.ciesin.columbia.edu/data/collection/grump-v1/about-us.

Appendix Figure 7: Comparison of kernel density graphs of air quality

Panel A: Particulate air pollution: GH (left) vs. This study (right)



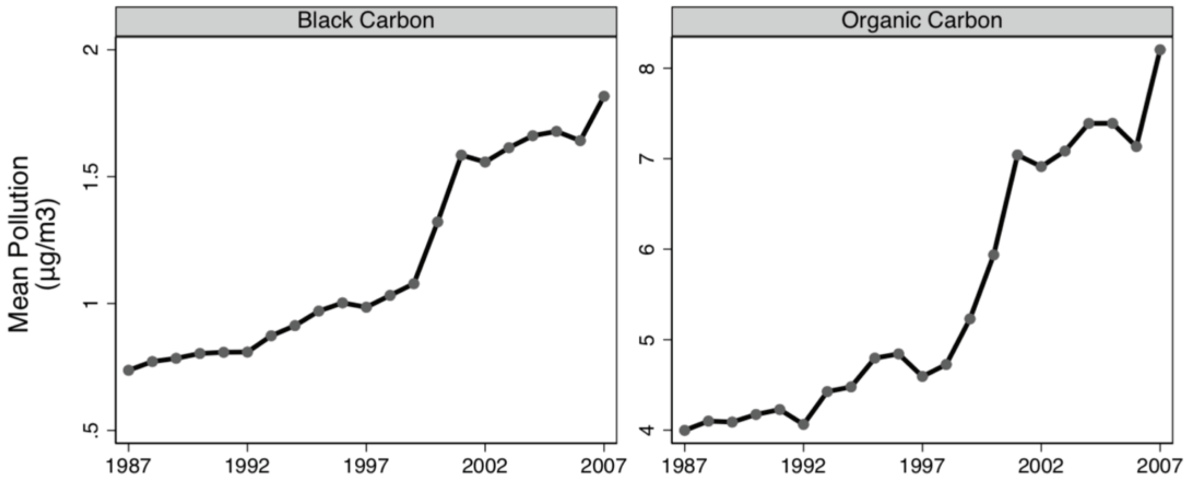
Panel B: SO_2 air pollution: GH (left) vs. This study (right)



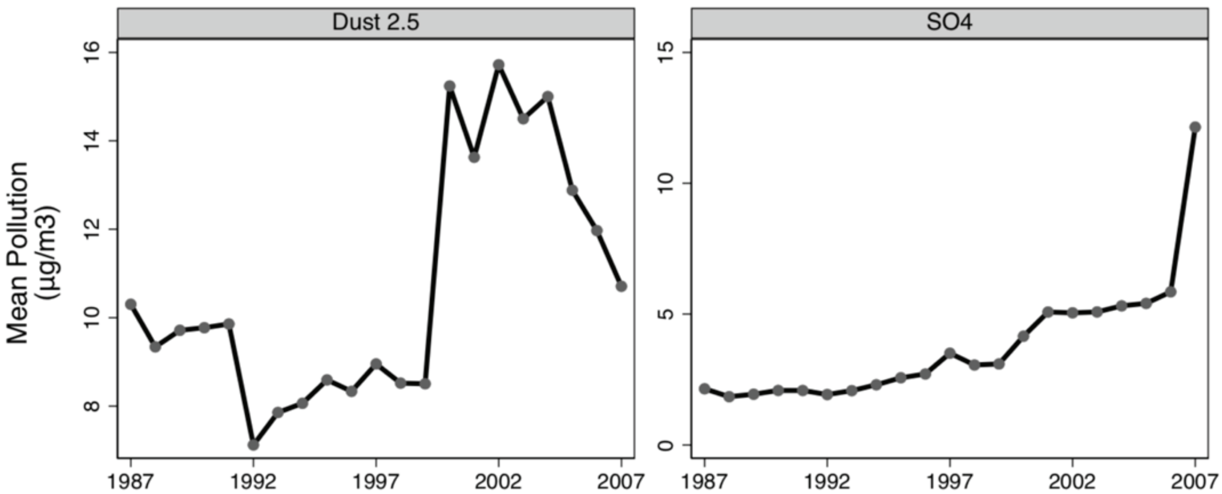
Notes: The figure provides additional evidence on the opposite trends. It compares kernel density estimates of GH's and revised air pollutant distributions across Indian cities for two periods, 1987-1990 and 2004-2007.

Appendix Figure 8: Trends in $PM_{2.5}$ components, 1987-2007

Panel A: $PM_{2.5}$ components 1



Panel B: $PM_{2.5}$ components 2



Notes: The figure shows the trends in the components of $PM_{2.5}$ that shed some light on the developments in the overall $PM_{2.5}$ air pollution.

Appendix Table 1 – GH replication: Comparison of outcome variables

	Replication GH data, GH sample			
	SPM		PM2.5	
	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4
	Panel A. Supreme Court Action Plans			
π1: 1(Policy)	7.50	0.30	1.66	0.07
	(20.59)	(21.51)	(4.56)	(4.76)
π2 : time trend	-3.60	-2.85	-0.80	-0.63
	(2.78)	(4.28)	(0.61)	(0.95)
π3: 1(Policy)*time trend	-1.54	0.12	-0.34	0.03
	(7.13)	(5.97)	(1.58)	(1.32)
5-year effect: π1+5π3	-.21	.92	-.05	.20
p-value	[.99]	[.98]	[.99]	[.98]
Observations	11	1,165	11	1,165
	Panel B. Mandated Catalytic Converters			
π1: 1(Policy)	5.55	7.62	1.23	1.69
	(12.76)	(12.26)	(2.82)	(2.71)
π2: time trend	7.75***	7.81**	1.72***	1.73**
	(2.50)	(3.29)	(0.55)	(0.73)
π3: 1(Policy)*time trend	-10.82***	-11.20**	-2.40***	-2.48**
	(2.89)	(4.57)	(0.64)	(1.01)
5-year effect: π1+5π3	-48.56**	-48.39*	-10.75**	-10.71*
p-value	[.04]	[.06]	[.04]	[.06]
Observations	17	1,165	17	1,165

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table replicates GH's results exactly using their data. It reports estimated coefficients from fitting the second-step equation (2), odd columns, and its one-step version, even columns, for the effects of SCAP (Panel A) and CC (Panel B) policies on particulate air pollution. The outcome variable in columns 1-2 is the original GH's SMP, while the outcome variable in columns 3-4 is $PM_{2.5}$ converted from GH's SPM using $SPM/PM_{10}/PM_{2.5}$ ratios: PM_{10} = 0.5053SPM, $PM_{2.5}$=0.438PM10. PM_{10} is particulate matter with a diameter less than 10 µm. Both PM_{10} and $PM_{2.5}$ are the fractions of SPM. Columns 1-2 correspond to panels A, columns 1-2 and 7-8 of Table 3 in the main text. Standard errors are in parentheses. The liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects 5 years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Appendix Table 2 – Effectiveness of air quality policies: Effects of meteorological controls

	Reexamination: Full set of meteorological controls					
	GH data GH sample		New data GH sample		New data Full sample	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6
	Supreme Court Action Plans					
	Panel A. PM2.5					
π1: 1(Policy)	3.94	1.17	-0.41	-1.05	-1.41	-1.63
	(5.07)	(4.30)	(2.78)	(1.76)	(2.35)	(1.65)
π2 : time trend	-0.45	-0.35	0.53	0.45	0.50	0.48
	(0.68)	(0.86)	(0.38)	(0.52)	(0.32)	(0.47)
π3: 1(Policy)*time trend	-1.60	-0.66	1.39	1.76*	1.57*	1.64*
	(1.75)	(1.41)	(0.96)	(1.06)	(0.81)	(0.91)
5-year effect: π1+5π3	-4.06	-2.13	6.55	7.77**	6.42*	6.55*
p-value	[.59]	[.79]	[.14]	[.05]	[.09]	[.06]
Observations	11	1165	11	1165	11	2720
	Panel B. SO2					
π1: 1(Policy)	-1.51	-1.70	-0.70**	-0.43	-0.71**	-0.43
	(0.91)	(2.28)	(0.27)	(0.42)	(0.29)	(0.38)
π2: time trend	0.24*	0.09	0.11**	0.09	0.07	0.05
	(0.12)	(0.61)	(0.04)	(0.12)	(0.04)	(0.11)
π3: 1(Policy)*time trend	-0.02	0.33	0.05	-0.01	0.08	0.01
	(0.32)	(0.94)	(0.09)	(0.11)	(0.10)	(0.09)
5-year effect: π1+5π3	-1.61	-.05	-.46	-.47	-.32	-.36
p-value	[.25]	[.99]	[.27]	[.47]	[.47]	[.49]
Observations	11	1158	11	1158	11	2720
	Mandated Catalytic Converters					
	Panel C. PM2.5					
π1: 1(Policy)	1.99	2.08	2.03*	1.85	1.58**	1.52
	(3.36)	(2.80)	(1.12)	(1.25)	(0.72)	(0.93)
π2 : time trend	1.69**	1.72**	0.42*	0.36	0.30*	0.25**
	(0.66)	(0.71)	(0.22)	(0.23)	(0.14)	(0.12)
π3: 1(Policy)*time trend	-2.62***	-2.64***	-0.98***	-0.88***	-0.82***	-0.76***
	(0.76)	(0.98)	(0.25)	(0.31)	(0.16)	(0.23)
5-year effect: π1+5π3	-11.13*	-11.1*	-2.86	-2.53	-2.53**	-2.28*
p-value	[.07]	[.06]	[.15]	[.14]	[.05]	[.09]
Observations	17	1165	17	1165	17	2720
	Panel D. SO2					
π1: 1(Policy)	0.09	-0.46	-0.87*	-0.89***	-1.07**	-0.98***
	(1.92)	(2.74)	(0.48)	(0.25)	(0.38)	(0.17)
π2: time trend	1.88***	1.75**	-0.00	-0.01	0.08	0.07*
	(0.38)	(0.73)	(0.09)	(0.08)	(0.08)	(0.04)
π3: 1(Policy)*time trend	-2.45***	-2.14**	0.09	0.09	0.02	0.01
	(0.43)	(0.98)	(0.11)	(0.10)	(0.09)	(0.07)
5-year effect: π1+5π3	-12.15***	-11.18**	-.41	-.43	-.96	-.95**
p-value	[00]	[.05]	[.61]	[.51]	[.15]	[.03]
Observations	17	1158	17	1158	17	2720

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table tests the sensitivity of GH's findings to additional controlling for meteorological confounders. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) concentrations. Both specifications include a full set of meteorological controls, specifically air temperature, precipitation, its quadratic, and wind speed. The enumeration of columns corresponds to that of columns in Table 3. Columns 1-2 use GH's data. I substitute GH's SPM by GH's $PM_{2.5}$ for comparability with the policies' effects on MERRA-2 $PM_{2.5}$. GH's $PM_{2.5}$ is converted from GH's SPM using SPM-PM10-PM2.5 ratios. Columns 3-4 exploit the same number of cities as in GH and modified $PM_{2.5}$ and SO_2 air pollution outcomes. Columns 5-6 use new outcome variables and fit equation (2) and its one-step version to full sample of cities. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Appendix Table 3 – Detailed effects of meteorological controls, GH data/GH sample

	GH data, GH sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
π1: 1(Policy)	1.66	0.07	4.18	2.23	4.71	2.59	3.94	1.17
	(4.56)	(4.76)	(4.89)	(4.21)	(4.96)	(4.22)	(5.07)	(4.30)
π2 : time trend	-0.80	-0.63	-0.71	-0.54	-0.81	-0.61	-0.45	-0.35
	(0.61)	(0.95)	(0.66)	(0.92)	(0.67)	(0.92)	(0.68)	(0.86)
π3: 1(Policy)*time trend	-0.34	0.03	-1.23	-0.72	-1.23	-0.72	-1.60	-0.66
	(1.58)	(1.32)	(1.69)	(1.44)	(1.72)	(1.40)	(1.75)	(1.41)
5-year effect: π1+5π3	-.05	.20	-1.98	-1.37	-1.44	-.99	-4.06	-2.13
p-value	[.99]	[.98]	[.78]	[.87]	[.84]	[.90]	[.59]	[.79]
Observations	11	1165	11	1165	11	1165	11	1165
	Panel B. SO2							
π1: 1(Policy)	-1.44	-1.25	-1.09	-1.20	-1.49**	-1.53	-1.51	-1.70
	(0.88)	(2.13)	(0.87)	(2.17)	(0.63)	(2.13)	(0.91)	(2.28)
π2 : time trend	0.20	0.09	0.29**	0.18	0.31***	0.19	0.24*	0.09
	(0.12)	(0.55)	(0.12)	(0.59)	(0.08)	(0.59)	(0.12)	(0.61)
π3: 1(Policy)*time trend	-0.06	0.10	-0.28	-0.03	-0.13	0.10	-0.02	0.33
	(0.31)	(0.98)	(0.30)	(0.92)	(0.22)	(0.89)	(0.32)	(0.94)
5-year effect: π1+5π3	-1.74	-.78	-2.49*	-1.36	-2.12**	-1.05	-1.61	-.05
p-value	[.21]	[.87]	[.08]	[.77]	[.05]	[.83]	[.25]	[.99]
Observations	11	1158	11	1158	11	1158	11	1158
	Mandated Catalytic Converters							
	Panel C. PM2.5							
π1: 1(Policy)	1.23	1.69	1.57	1.72	1.23	1.46	1.99	2.08
	(2.82)	(2.71)	(2.90)	(2.66)	(2.97)	(2.65)	(3.36)	(2.80)
π2 : time trend	1.72***	1.73**	1.61**	1.68**	1.67**	1.74**	1.69**	1.72**
	(0.55)	(0.73)	(0.57)	(0.71)	(0.58)	(0.70)	(0.66)	(0.71)
π3: 1(Policy)*time trend	-2.40***	-2.48**	-2.43***	-2.51**	-2.46***	-2.55***	-2.62***	-2.64***
	(0.64)	(1.01)	(0.66)	(0.97)	(0.67)	(0.96)	(0.76)	(0.98)
5-year effect: π1+5π3	-10.75**	-10.71*	-10.59**	-10.82*	-11.05**	-11.29**	-11.13*	-11.1*
p-value	[.04]	[.06]	[.05]	[.06]	[.04]	[.05]	[.07]	[.06]
Observations	17	1165	17	1165	17	1165	17	1165
	Panel D. SO2							
π1: 1(Policy)	-0.53	-0.76	-0.38	-0.80	-0.36	-0.88	0.09	-0.46
	(1.52)	(2.56)	(1.56)	(2.64)	(1.55)	(2.67)	(1.92)	(2.74)
π2 : time trend	2.02***	1.91***	1.98***	1.88***	1.94***	1.85**	1.88***	1.75**
	(0.29)	(0.70)	(0.30)	(0.71)	(0.30)	(0.72)	(0.38)	(0.73)
π3: 1(Policy)*time trend	-2.58***	-2.39**	-2.50***	-2.28**	-2.44***	-2.22**	-2.45***	-2.14**
	(0.34)	(0.98)	(0.35)	(0.96)	(0.35)	(0.96)	(0.43)	(0.98)
5-year effect: π1+5π3	-13.45***	-12.69**	-12.86***	-12.21**	-12.58***	-11.95**	-12.15***	-11.18**
p-value	[.00]	[.02]	[00]	[.03]	[00]	[.03]	[00]	[.05]
Observations	17	1158	17	1158	17	1158	17	1158

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It uses original GH data like in Columns 1-2 of Table 3 to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) concentrations. I substitute GH's SPM by GH's $PM_{2.5}$ for comparability with the policies' effects on MERRA-2 $PM_{2.5}$. GH's $PM_{2.5}$ is converted from GH's SPM using SPM-PM10-PM2.5 ratios. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. p-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Appendix Table 4 – Detailed effects of meteorological controls, New data/GH sample

	New data, GH sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
π1: 1(Policy)	-0.69	-1.70	-0.40	-1.22	-0.12	-1.04	-0.41	-1.05
	(2.79)	(1.90)	(2.45)	(1.86)	(2.56)	(1.75)	(2.78)	(1.76)
π2 : time trend	0.67	0.58	0.53	0.44	0.55	0.46	0.53	0.45
	(0.38)	(0.54)	(0.33)	(0.55)	(0.34)	(0.55)	(0.38)	(0.52)
π3: 1(Policy)*time trend	1.83	2.28*	1.59	1.97*	1.49	1.92*	1.39	1.76*
	(0.97)	(1.33)	(0.85)	(1.11)	(0.89)	(1.12)	(0.96)	(1.06)
5-year effect: π1+5π3	8.46*	9.68**	7.55*	8.65**	7.31*	8.55**	6.55	7.77**
p-value	[.07]	[.05]	[.07]	[.04]	[.08]	[.05]	[.14]	[.05]
Observations	11	1165	11	1165	11	1165	11	1165
	Panel B. SO2							
π1: 1(Policy)	-0.27	-0.12	-0.34	-0.17	-0.36	-0.20	-0.70**	-0.43
	(0.30)	(0.44)	(0.27)	(0.42)	(0.22)	(0.44)	(0.27)	(0.42)
π2 : time trend	0.12**	0.09	0.10**	0.07	0.11***	0.09	0.11**	0.09
	(0.04)	(0.14)	(0.04)	(0.13)	(0.03)	(0.13)	(0.04)	(0.12)
π3: 1(Policy)*time trend	-0.03	-0.03	0.04	0.03	0.03	0.02	0.05	-0.01
	(0.10)	(0.12)	(0.09)	(0.12)	(0.08)	(0.12)	(0.09)	(0.11)
5-year effect: π1+5π3	-.4	-.28	-.12	-.03	-.2	-.08	-.46	-.47
p-value	[.37]	[.71]	[.75]	[.97]	[.55]	[.90]	[.27]	[.47]
Observations	11	1158	11	1158	11	1158	11	1158
	Mandated Catalytic Converters							
	Panel C. PM2.5							
π1: 1(Policy)	2.26*	1.96*	2.39*	2.07	2.41*	2.11	2.03*	1.85
	(1.24)	(1.15)	(1.23)	(1.45)	(1.22)	(1.50)	(1.12)	(1.25)
π2 : time trend	0.32	0.23	0.41	0.34	0.40	0.33	0.42*	0.36
	(0.24)	(0.25)	(0.24)	(0.23)	(0.24)	(0.24)	(0.22)	(0.23)
π3: 1(Policy)*time trend	-0.95***	-0.79**	-1.03***	-0.89***	-1.01***	-0.88***	-0.98***	-0.88***
	(0.28)	(0.39)	(0.28)	(0.32)	(0.28)	(0.32)	(0.25)	(0.31)
5-year effect: π1+5π3	-2.48	-1.99	-2.74	-2.38	-2.64	-2.31	-2.86	-2.53
p-value	[.25]	[.19]	[.20]	[.22]	[.21]	[.24]	[.15]	[.14]
Observations	17	1165	17	1165	17	1165	17	1165
	Panel D. SO2							
π1: 1(Policy)	-0.75	-0.88***	-0.74	-0.86***	-0.70	-0.81***	-0.87*	-0.89***
	(0.49)	(0.22)	(0.48)	(0.21)	(0.47)	(0.22)	(0.48)	(0.25)
π2 : time trend	-0.03	-0.03	0.01	0.00	-0.00	-0.01	-0.00	-0.01
	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.08)
π3: 1(Policy)*time trend	0.11	0.12	0.07	0.08	0.08	0.09	0.09	0.09
	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)
5-year effect: π1+5π3	-.22	-.28	-.41	-.48	-0.32	-.38	-.41	-.43
p-value	[.79]	[.62]	[.61]	[.42]	[.69]	[.52]	[.61]	[.51]
Observations	17	1158	17	1158	17	1158	17	1158

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It exploits the same number of cities as in GH and MERRA-2 $PM_{2.5}$ and SO_2 air pollution outcomes, like in Columns 3-4 of Table 3, to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) concentrations. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. *p*-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Appendix Table 5 – Detailed effects of meteorological controls, New data/Full sample

	New data, Full sample							
	No Meteo Vars		Add air temperature		Add precipitation		Add wind speed	
	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step	Eq. 2	One-step
	1	2	3	4	5	6	7	8
	Supreme Court Action Plans							
	Panel A. PM2.5							
$\pi1$: 1(Policy)	-1.41	-1.85	-0.71	-1.15	-0.60	-1.07	-1.41	-1.63
	(2.18)	(1.74)	(1.92)	(1.79)	(2.02)	(1.74)	(2.35)	(1.65)
$\pi2$: time trend	0.55	0.54	0.41	0.40	0.44	0.43	0.50	0.48
	(0.29)	(0.50)	(0.26)	(0.52)	(0.27)	(0.51)	(0.32)	(0.47)
$\pi3$: 1(Policy)*time trend	2.11**	2.21*	1.80**	1.92*	1.72**	1.86*	1.57*	1.64*
	(0.76)	(1.26)	(0.67)	(1.06)	(0.70)	(1.05)	(0.81)	(0.91)
5-year effect: $\pi1+5\pi3$	9.12**	9.19*	8.30**	8.45**	7.98**	8.21**	6.42*	6.55*
p-value	[.02]	[.06]	[.02]	[.05]	[.03]	[.05]	[.09]	[.06]
Observations	11	2720	11	2720	11	2720	11	2720
	Panel B. SO2							
$\pi1$: 1(Policy)	-0.34	-0.14	-0.45	-0.23	-0.46	-0.25	-0.71**	-0.43
	(0.33)	(0.45)	(0.30)	(0.42)	(0.27)	(0.42)	(0.29)	(0.38)
$\pi2$: time trend	0.07	0.05	0.05	0.03	0.06	0.04	0.07	0.05
	(0.04)	(0.12)	(0.04)	(0.11)	(0.04)	(0.11)	(0.04)	(0.11)
$\pi3$: 1(Policy)*time trend	0.07	0.04	0.11	0.08	0.11	0.07	0.08	0.01
	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)	(0.09)
5-year effect: $\pi1+5\pi3$	-.01	.04	.12	.15	.08	.11	-.32	-.36
p-value	[.98]	[.94]	[.78]	[.80]	[.84]	[.84]	[.47]	[.49]
Observations	11	2720	11	2720	11	2720	11	2720
	Mandated Catalytic Converters							
	Panel C. PM2.5							
$\pi1$: 1(Policy)	2.15**	1.95**	1.95**	1.76	1.98**	1.81	1.58**	1.52
	(0.84)	(0.97)	(0.74)	(1.15)	(0.75)	(1.16)	(0.72)	(0.93)
$\pi2$: time trend	0.19	0.15	0.24	0.21	0.24	0.21	0.30*	0.25**
	(0.17)	(0.11)	(0.14)	(0.13)	(0.15)	(0.13)	(0.14)	(0.12)
$\pi3$: 1(Policy)*time trend	-0.82***	-0.73***	-0.81***	-0.74***	-0.82***	-0.74***	-0.82***	-0.76***
	(0.19)	(0.27)	(0.17)	(0.25)	(0.17)	(0.25)	(0.16)	(0.23)
5-year effect: $\pi1+5\pi3$	-1.93	-1.71	-2.1	-1.95	-2.1	-1.92	-2.53**	-2.28*
p-value	[.19]	[.15]	[.11]	[.20]	[.11]	[.21]	[.05]	[.09]
Observations	17	2720	17	2720	17	2720	17	2720
	Panel D. SO2							
$\pi1$: 1(Policy)	-0.89**	-0.86***	-0.90**	-0.87***	-0.90**	-0.85***	-1.07**	-0.98***
	(0.38)	(0.19)	(0.39)	(0.16)	(0.39)	(0.17)	(0.38)	(0.17)
$\pi2$: time trend	0.06	0.06	0.07	0.07*	0.07	0.07*	0.08	0.07*
	(0.07)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)
$\pi3$: 1(Policy)*time trend	0.03	0.02	0.02	0.00	0.02	0.01	0.02	0.01
	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)	(0.09)	(0.07)
5-year effect: $\pi1+5\pi3$	-.73	-.75*	-0.83	-.85**	-0.82	-.83**	-.96	-.95**
p-value	[.27]	[.07]	[.22]	[.04]	[.22]	[.05]	[.15]	[.03]
Observations	17	2720	17	2720	17	2720	17	2720

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table further tests the sensitivity of GH's findings to additional meteorological confounders. It uses the full sample of cities and MERRA-2 $PM_{2.5}$ and SO_2 air pollution outcomes, like in Columns 5-6 of Table 3, to provide a detailed breakdown of the changes in the estimates after the sequential inclusion of air temperature, precipitation, and wind speed. The table reports regression results from estimating the second-step equation (2) of a two-step econometric approach, odd columns, and its one-step version, even columns, for the effects of SCAP and CAT policies on $PM_{2.5}$ (panels A and C) and SO_2 (panels B and D) concentrations. Standard errors are in parentheses. Liner combination of the coefficients $\pi_1 + 5\pi_3$ is an estimate of the policies' effects five years after implementation. p-value of a hypothesis test for the significance of this linear combination is reported below the estimates in square brackets.

Abstrakt

Tento článek zkoumá empirické výsledky o efektivnosti enviromentální regulace v Indii uvedené v nedávné studii Greenstona a Hanna (2014). Greenstone a Hann zjišťují, že politika pro kontrolu znečištění ovzduší v Indii byla efektivní ve zlepšení kvality ovzduší, ale měla jen mírný a statisticky nevýznamný efekt na kojeneckou úmrtnost. Tyto do určité míry neintuitivní výsledky pravděpodobně pramení z omezené dostupnosti pozemních dat o znečištění ovzduší použitých ve studii a ignorování důležitých meteorologických faktorů. Využívám nedávného pokroku v satelitní technice a metodologie Greenstona a Hanna k testování citlivosti jejich výsledků na revidované míry znečištění, vyšší počet pozorování a meteorologické kontrolní proměnné. Navzdory zásadním rozdílům mezi těmito dvěma datovými soubory shodně potvrzuji závěry Greenstona a Hanna. Nicméně, efekt enviromentální politiky je významně slabší. Tento článek vyzdvihuje význam dalšího výzkumu efektivity enviromentální regulace v rozvojových zemích a využití satelitních snímků ve zkoumání důležitých enviromentálních otázek.

Klíčová slova: znečištění vzduchu, kojenecká úmrtnost, enviromentální regulace, Indie

Working Paper Series
ISSN 1211-3298
Registration No. (Ministry of Culture): E 19443

Individual researchers, as well as the on-line and printed versions of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the CAS, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute of the CAS, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Printed by CERGE-EI, Prague
Subscription: CERGE-EI homepage: http://www.cerge-ei.cz

Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: http://www.cerge-ei.cz

Editor: Byeongju Jeong

The paper is available online at http://www.cerge-ei.cz/publications/working_papers/.

ISBN 978-80-7343-510-3 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-605-5 (Národohospodářský ústav AV ČR, v. v. i.)