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The Impact of Environmental Regulations on Air Pollution in India: the influence of industrial fuel intensity

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Section 1: Introduction

In this paper, I extend the analysis of "Environmental Regulations, Air and Water Pollution, and Infant Mortality in India" by Michael Greenstone and Rema Hanna (2014). Greenstone and Hanna collect what they call "the most comprehensive developing country dataset ever compiled on air and water pollution and environmental regulations", and assess the effectiveness of environmental regulations using a difference-in-differences design (2014, pg. 3038).

Using new data, I create a variable representing the prevalence of fuel intensive industries in a given state in 1987, and supplement it to Greenstone and Hanna's comprehensive dataset. The main policy regulations of focus in this article is Supreme Court Action Plans (SCAPs), which are discussed later in this paper. Like in Greenstone and Hanna (2014), I focus on the effect of the SCAP policy on pollution concentrations. My approach differs, however, in that I allow for the effects of the SCAP policy to vary with the 1987 prevalence of fuel intensive industries (Eip).

The main results show that if the 1987 prevalence of fuel intensive industries equals zero, the implementation of a SCAP policy in a state would result in an estimated reduction of 25.15-33.48 µg/m^3 in SO_2 levels, and 45.55 µg/m^3 in NO_2 concentrations. In addition, the impact of the SCAP policy on pollution levels would be reduced by 8.87-12.62 µg/m^3 for SO_2 levels, and 17.23 µg/m^3 for NO_2 levels for every standard deviation increase in the 1987 prevalence of fuel intensive industries measure. Finally, the average estimated impact of the SCAP policy on suspended particulate matter -(SPM) levels, with a mean 1987 prevalence of fuel intensive industries value, is between a 17.40 to 69.50 µg/m^3 reduction in SPM concentrations. The estimated reduction in SPM due to the policy increases by 114.58 to 180.38 μg/m^3 for each standard deviation increase in Eip. ~~Eip.~~ These results indicate that states with a higher prevalence of fuel intensive industries in 1987 would have more of a reduction in mean pollution concentrations following the implementation of SCAP policy in the case of SPM, but less in the case of SO_2 and NO_2. However, the NO2 results are insignificant in most specifications, and the SPM results are only significant in the reduced sample specifications.

The rest of the paper is ordered as follows: Section 2 reviews the related literature. Section 3 summarizes Greenstone and Hanna's study. Section 4 covers the background of SCAP. Section 5-7 describes the data, outlines the econometric approach, and analyzes the results respectively. Section 8 concludes.

Section 2: Literature review

There is ample literature covering the impact of regulations on pollution. Y. Chen et al (2013) use the 2008 Olympic Games in Beijing as a chance to test the effect of environmental regulations on air pollution. The cleanup involved in the Beijing Olympics was both temporary and targeted. Amongst the policies implemented, Beijing cut coal usage, shut down thermal power plants, renovated furnaces, and instituted odd-even driving restrictions based on license plate numbers. The temporary nature of the policy measures provided Y. Chen et al the opportunity to test the efficacy of these air pollution regulations. Y. Chen et al compare 28 non-Olympic cities before, during and after the games, while incorporating a variety of controls. By taking a benchmark period of one and a half years before the establishment of the Beijing Organizing Committee for the Games of the XXIX Olympiad (BOCOG), they could detect treatment effects in three windows: the 7-year preparation period, the one month of the Olympic and Paralympic Games, and 13 months after the Games.

Using Air Pollution Index (API), satellite, meteorological, socio-economic, and motor vehicle data, Y. Chen et al show that the average (API) of Beijing dropped from 109.01 before the setup of the BOCOG to 54.88 during the games and then rose back to 81.93 after the Games. In comparison, Aerosol Optical Depth (AOD) of Beijing started to decrease starting from the preparation period, reached the lowest level 2-6 months after the Games, and then increased thereon. Both the API and AOD data suggest that air quality improvement in Beijing was “real but temporary” (Y. Chen et al 2013, pg. 425).

In a similar article focused on Beijing, Sun et al (2014) analyze the effect of Beijing's odd-even traffic policy restriction on air pollution and traffic congestion. Due to the cultural distaste of the number "four", the very limited availability of vehicles with four as the last digit of the license plate provides an opportunity to test the marginal effect of driving restrictions on air quality. Sun et al stray away from conventional before-and-after comparison methods, and instead, consider what they call "high frequency exogenous treatments" to highlight how air quality is affected by stringent driving conditions (Sun et al. 2014, pg. 36). Using city-level daily records of the odd-even cycle, average traffic speed, a measure for traffic called the Traffic Performance Index (TPI), and average PM_{10} concentration[1], they can observe the inter-relationship of driving restrictions, traffic congestion, and air quality given the exogenous variation in the stringency of driving restrictions. The authors find that days when license plates ending with the number 4 are restricted, have worse traffic than days with all other restrictions. This is because there are not many vehicles with license plates ending in the number 4. The magnitude of the difference, they show, is quite significant (at 20% of TPI)~~.~~ highlighting the improvements to congestion caused by driving restrictions. On the other hand, their data did not

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[1] PM10 is defined as particulate matter that are less than 10 microns in diameter, which includes fine and coarse particles (WHO 2003)

support a similar relationship between driving restrictions and air quality (Sun et al. 2014, pg. 37). Their results suggest that positive traffic and environmental effects may not always go hand in hand.

Foster et al (2009) also use aerosol optical depth (AOD) data gained from satellite imagery to substitute for directly collected air pollution data in Mexico. They examine Mexican plants' voluntary participation in a program promoting pollution reduction. Firms volunteer to reach pollution reduction targets to receive Clean Industry Certificates. Their analysis measures differences in changes in pollution and infant mortality (due to respiratory diseases and other causes) in municipalities where more firms received the Clean Industry Certificate relative to where firms received less of this certification. The effects suggest the voluntary program resulted in lower pollution levels of roughly 3.6 percent as measured by AOD improvements. Their estimates also imply that certification translated to a 16 percent decrease in infant mortality due to respiratory illnesses. Combining both results, Foster et al. find that "a 1 percent increase in AOD results in a 4.4 percent increase in respiratory mortality" (2009, pg. 195).

While not always clear, the link between pollution and mortality is at least made more apparent with Y. Chen et al's Huai River policy analysis. Y. Chen et al (2013) take advantage of a peculiar policy from the Chinese government. During the 1950-1980 period of central planning in China, the Chinese government declared winter heating of homes and offices through the provision of free coal as a basic right. When encountered with budgetary limitations, the Chinese government determined that the free coal should only be provided to areas in Northern China, which have an average temperature of below freezing. This divide was defined by the line formed by the Huai River and Qinling Mountain range.

Using mortality data collected from China's Disease Surveillance Points (DPSs) system, Y. Chen et al classify causes of death as either cardiorespiratory or noncardiorespiratory. They define cardiorespiratory causes as those that have been linked to ambient air quality and include heart disease, stroke, lung cancer and respiratory illness. They also collect a range of determinants of life expectancy, which were used as control variables in their statistical analysis. Y. Chen et al attempt to expose a relation between ambient total suspended particles (TSPs) and life expectancy by leveraging "the regression discontinuity design implicit in the Huai River" (2013, pg. 12937). Y. Chen et al test whether the winter heating policy caused a discontinuous change in TSPs at the north-south division, and a discontinuous change in life expectancy. Using a two-stage least-squares regression (2SLS), they produce estimates of the impact of TSPs on life expectancy. Their paper's findings suggest that the winter heating policy greatly increases TSPs in northern China and causes reductions in life expectancy. Y. Chen et al found that ambient concentrations of TSPs are about 184 μg/m^3, or 55% higher in areas in northern China. They also find that life expectancies are reduced in the north by about 5.5 years due to a spike in incidences of cardiorespiratory mortality. The paper suggests that long-term exposure to an additional 100 μg/m^3 of TSPs is linked to a lower life expectancy of around 3.0 years. Ultimately, the policy to provide winter heating for homes had the adverse effect of lowering life expectancy due to cardiorespiratory illnesses.

In a different article, Randy Becker and Vernon Henderson ~~and Randy Becker~~ (2000) employ a similar attainment vs non-attainment status strategy to determine the effect of regulations on polluting industries. Using United States plant data for 1963-92, ~~Henderson and~~ Becker and Henderson examine the unintended effects of the Clean Air Act from 1970 on "firm decisions concerning plant locations, births, sizes, and investment patterns in major polluting industries" (2000, pg. 380). In order to curb air pollution, certain air pollution targets were to be met by counties. Counties belonged to the list of attainment areas, if they had reached their targets. Likewise, ~~countries~~ counties belonged to the list of non-attainment areas, if they did not reach their targets. Plants in the U.S were subject to much stricter controls in nonattainment areas relative to attainment areas. The authors considered four major volatile organic compounds (VOC) and nitrogen oxides (NO_x) emitting industries as the treatment group, and eight industries where there should not be treatment effects of nonattainment status as the control group. They then examined whether there was an effect of nonattainment status on firms' decisions and investment patterns.

Their findings showed a significant relocation of highly polluting industries from more to less polluted areas to avoid stricter regulation. This influenced relative pollution between these two areas. While the reduction of polluting plants in nonattainment areas helps bring those into attainment, the opposite effect is shown for attainment areas as environmental degradation follows the relocation of polluting industries. The effect on air quality is influenced by grandfathered industries, which slows the improvement/degradation of air quality as older dirtier plants are not affected by regulation. They also found smaller plants more prevalent in attainment areas, as there was a cost advantage of not being inspected by the Environmental Protection Agency (EPA) to smaller plants. Finally, they found that nonattainment status reduced the expected number of new plants in a county by 26-45 percent, depending on the industry. The largest impacts were on industries with the largest plant sizes. Their results suggest nonattainment counties experience a 45 percent reduction in new plants, should there be no change for attainment counties. The unintended consequences of the Clean Air Act were costly, by shifting plants to less productive locations, having them operate at smaller scales, and changing investment decisions.

Other articles have explored the link between industrial characteristics and air pollution. The aim of M.A. Cole et al’s (2008) paper is to “identify industrial characteristics that determine industry-level emissions intensity in China, thereby providing a greater understanding of the linkages between industrial characteristics, environmental regulations and pollution intensity” (pg. 394). The authors work with a framework of demand and supply of environmental services. Characteristics of industries determine the demand for environmental services, while society supplies environmental regulations at a price. The equilibrium level of emissions for each industry will thus represent demand and supply considerations. Through this framework, the authors can explore possible determinants of industry specific emissions intensity. M.A. Cole et al gather pollution intensity data covering SO_2, Soot, and Dust, and energy use data covering coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas and electricity from the China Statistical yearbook from 1998 to 2004. Their panel of industries covers 15 industries over the years of 1997-2003.

The authors find that all three pollutants (SO_2, Soot, and Dust) have a positive relationship with energy consumption by industry and have a negative relationship with total factor productivity (TFP). M.A. Cole et al's results suggest that increasing energy use by 10% will lead to a similar increase of 11.09% in soot intensity of 55.6 tons per unit of value added. On the other hand, a 10% rise in TFP would translate to a reduction in soot intensity of 36.14% to 181.17 tons per unit of value added. Also, physical capital has a positive relationship with soot and dust intensity. This suggests that machinery and equipment-intensive industries are typically more polluting. The authors find that this result remains consistent, even while controlling for energy use; suggesting that physical capital intensive firms are high pollution emitters for reasons other their use of energy. Regarding policy, the authors do not find a significant effect of pollution regulations on pollution intensity.

M.A. Cole et al (2005) uses the same empirical design in a paper concerning UK manufacturing industries. Their paper attempts to quantify and examine the complex linkages between industrial activity, environmental regulations, and air pollution. Using the same framework as the previous article of demand for and supply of environmental services, the authors utilize an industry specific emissions dataset covering a variety of pollutants from 1990 to 1998. The authors use this data to examine air pollution emissions caused by industries by using regional characteristics to take account of regional differences in the strictness of regulations. The authors utilize a panel of 22 manufacturing industries covering the years 1990-1998. They also gather data on pollution emissions by industry such as SO_2, NO_x, total acid, CO, PM_{10}, and CO_2 from the UK Office for National Statistics. TFP data is gathered from the Annual Business Inquiry from the Office for National Statistics. M.A. Cole et al find that pollution intensity is positively related to energy use and physical capital intensity. This was the case in all 12 models: energy intensity was a statistically significant determinant of pollution intensity. Quantitatively, M.A. Cole et al found that a 1% increase in energy use is associated with a 0.25% to 1.1% increase in pollution intensity, depending on the pollutant being measured. A similar result as the previous article is found regarding TFP and its negative relation with pollution intensity. M.A. Cole et al found that physical capital intensity had a statistically significant impact on $S0_2$, acid rain precursors, and CO_2, despite energy use being controlled for. This, again, suggests that industries that are capital-intensive tend to be more polluting for reasons other than their choice of energy use. Unlike in the previous article, however, M.A. Cole et al are successful in showing that regulations have an effect in reducing pollution intensity. The sign of the coefficient attached to the regulations variable was consistently negative, but not always significant. In their analysis, M.A. Cole et al showed that the change in their regional regulation variables over the 1990-1998 period reduced pollution intensity by 3.0% to 15.1% relative to 1990 levels, and depending on the pollutant.

Section 3: Summary of Greenstone and Hanna

Motivation

Greenstone and Hanna (2014) determine India to be an optimal setting to study the efficacy of environmental regulations. First, India's population of over 1.3 billion people constitutes nearly 18% of the world's population. Second, India has been the beneficiary of rapid economic growth, averaging around 6.9 percent annually in the last two decades (1996-2015). This rapid economic growth, Greenstone and Hanna suggests, places an environmental burden on the country. Further, a recent study by Yale University ranked India 178th out of 180 countries in respect of air quality (Environmental Performance Index 2016). Third, India is generally regarded to have sub-optimal institutions.[2] Greenstone and Hanna believe that "identifying which regulatory approaches succeed in this context would be of great practical value" (pg. 3039). Lastly, India has a rich history of environmental regulations and extensive air pollution data, which makes studying the effectiveness of environmental policy implementation possible. It is known that "air pollution in India is mainly caused from three sources namely vehicles, industrial and domestic sources" (CPCB 2006, pg. 4). While Greenstone and Hanna's article focused mainly on the vehicular sources, my article will seek to uncover some of the industrial dimensions of pollution.

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[2] For example, nearly seven out of 10 people who had accessed public services such as the police, public schools, and hospitals had paid a bribe, according to a survey by Transparency International (2017).

Data

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Greenstone and Hanna’s paper uses city-level panel data for 1986-2007 covering 140 cities, which are compiled from a myriad of data sources. The relevant data Greenstone and Hanna collect for the purposes of this article are environmental regulation data, air pollution data, and demographic data. The environmental regulation data that both Greenstone and Hanna and I use are documents obtained from the Indian government, the Central Pollution Control Board (CPCB), the Department of Road Transport and Highways, the Ministry of Environment and Forests (MoEF), and several Indian State Pollution Control Boards (SPCBs). Some of the secondary sourced information we use come from the World Bank, the Emission and Controls Manufacturers Association, and Urbantrail.net. For air pollution data, Greenstone and Hanna gather readings of NO_2, SO_2, and SPM from India’s CPCB. India’s SPCBs are tasked with collecting pollution readings from monitor stations spanned across India and providing the readings to the CPCB for “checking, compilation, and analysis” (2014, pg. 3046). The demographic data come from two sources: first, district-level data on literacy rates and population come from the 1981, 1991, and 2001 Censuses of India. Second, district-level expenditure per capita data come from the survey of household consumer expenditure conducted by India’s National Sample Survey Organization in 1987, 1993, and 1999. Greenstone and Hanna also compile data regarding water pollution, infant mortality, corruption, and media references; but these are irrelevant for the purposes of this research paper. The scope of this research paper is focused on the analysis of air pollution regulations conducted in Greenstone and Hanna’s paper.

Pollutants

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The three pollution measures Greenstone and Hanna analyze are suspended particulate matter (SPM), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). Suspended particulate matter is a mixture of solid or liquid particles suspended in the air (WHO 2003). These SPM particles vary in size, make-up, and origin. The CPCB uses SPM as an overall indicator of pollution. SPM contributions mainly derive from the burning of fossil fuels, industrial activities, and vehicular pollution. Air quality monitor stations were placed in areas “where vehicle density is high” in areas where SPM levels are high (NAAQM 2003, pg. 25).

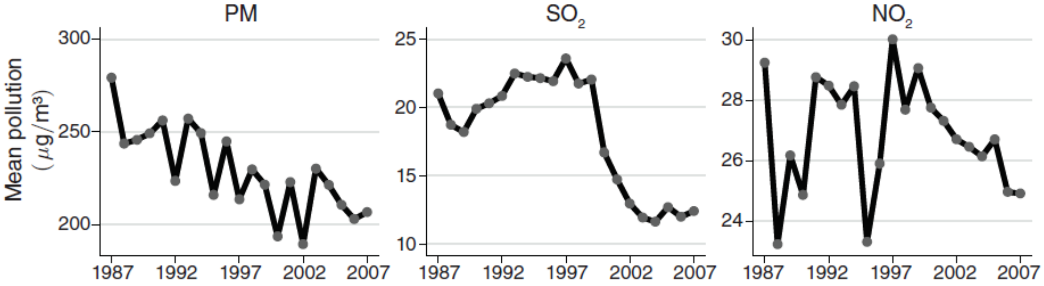
SO_2, or Sulfur Dioxide, is a “colorless toxic gas which is produced when any fuel or any product containing sulfur compounds is burnt” (Petropedia 2017). SO_2 is used in many industrial processes, predominantly in sulfuric acid manufacturing, and results from the burning of fossil fuels (SO2 2011). As part of the National Ambient Air Quality Monitoring (NAAQM), SO_2 culprits are highlighted as “domestic emissions from fossil fuel burning, industrial emissions, and diesel vehicles” (NAAQM 2003, pg. 25). Therefore, air quality monitor stations were placed in locations "where populations are large and where pollution levels are high" (NAAQM 2003, pg. 25).

Nitrogen dioxide (NO_2), finally, is primarily emitted by vehicles, thus making it a strong overall indicator of vehicular pollution (WHO 2003). NO_2 is also a precursor for several very harmful air pollutants, including nitric acid (WHO 2003). Although it is predominantly known for its significance in vehicular pollution, NO_2 is also “produced in almost all combustion reactions” (Greenstone and Hanna 2014, pg. 3046). Air quality monitor stations for NO_2 were placed in “areas with high population and traffic” (NAAQM 2003, pg. 25).

Air Pollution Trends

Greenstone and Hanna identify some air pollution trends in India from 1987 to 2007. Overall, Greenstone and Hanna highlight that air pollution concentrations have fallen over the 1987 to 2007 period (2014, pg. 3048). Ambient PM concentrations fell roughly 17 percent from 252.1 micrograms per cubic meter (μg/m^3) in 1987-1990 to 209.4 μg/m^3 in 2004-2007. Average $S0_2$ levels remained roughly constant up until the late 1990s, then declined sharply by 37 percent. SO_2 levels decreased from 19.4 μg/m^3 in 1987-1990 to 12.2 μg/m^3 in 2004-2007. Finally, NO_2 levels were very volatile up until a peak in 1997, then fell after this peak (Greenstone and Hanna 2014, pg. 3049).

Panel A. Air pollution ("Figure 4" Greenstone and Hanna 2014, pg. 3049)



"The figures depict annual mean pollution levels. There are no restrictions on the sample. Annual means are first taken across all monitors within a given city, and then across all cities in a given year. (…) Pollution data were drawn from Central Pollution Control Board's online and print sources" (Greenstone and Hanna 2014, pg. 3049).

Regulation

In their paper, Greenstone and Hanna examine the impact of the Supreme Court Action Plans (SCAP) and the mandatory use of catalytic converters on specific types of vehicles. SCAPs were a series of Supreme Court mandated actions, which were to be taken to reduce ambient air pollution in key polluting cities. The catalytic converter policy was also meant to reduce pollution in cities by mandating the use of lower fuel-emitting catalytic converters on specific vehicles. The focus of this paper is on the SCAP policy and its effect on air pollution. I will return to a more in-depth discussion of SCAP later in this paper.

Empirical Approach

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Greenstone and Hanna use both a one-step and two-step economic approach to testing whether regulatory policies have an impact on air pollution levels. Since this paper only deals with the one-step approach, I will focus only on Greenstone and Hanna's one-step approach. Greenstone and Hanna formulate three specifications to test the effect of policy regulation on pollution levels.

Greenstone and Hanna's first specification includes a dummy for policy implementation and measures the variation in pollution level occurring because of the policy. Greenstone and Hanna limit the dummy for policy implementation to equal to one in cases exceeding a minimum number of city-year observations, which is 15 years for the SCAP policy studied here. The equation representing the first specification is as follows:

$$Yct = \alpha + \vartheta_1 1(SCAPRange)_\tau + \vartheta_2 1(SCAP)_\tau * (SCAPRange)_\tau + \vartheta_3 1(\tau Left)_\tau + \vartheta_4 1(\tau Right)_\tau + \rho_1 1(CCRange)_\emptyset + \rho_2 1(CC)_\emptyset * (CCRange)_\emptyset + \rho_3 1(\emptyset Left)_\emptyset + \rho_4 1(\emptyset Right)_\emptyset + \mu t + \gamma c + \beta Xct + \epsilon ct$$

(EQUATION 1A)

For Greenstone and Hanna, Yct is one of the three measures of pollution by city c and year t. γc are the city fixed effects, which control for all unobservable and permanent determinants of pollution across cities. μt, year fixed effects, adjust for trends in pollution across time. Year fixed effects are important to control for because the overall decline in pollution levels observed in the data would overestimate the effectiveness of the policy. Xct is the per capital consumption and literacy rates included to adjust for the differential rates of growth across districts. τ and $\emptyset$ represent the number of years since a SCAP policy and catalytic converter policy are implemented, respectively. $1(\text{SCAPRange})_{\tau}$ is a dummy variable indicating that $-7 \leq \tau \leq 3$ and $1(\text{CCRange})_{\emptyset}$ is a dummy variable indicating that $-7 \leq \emptyset \leq 9$. Negative values represent years before the implementation of said policies, counting backwards from the year of implementation. $1(\text{SCAP})_{\tau}$ and $1(\text{CC})_{\emptyset}$ are dummy variables indicating whether the SCAP or Catalytic converter policies are adopted in a city ($\tau \geq 0$ and/or $\emptyset \geq 0$). The dummy variables $1(\tau\text{Left})_{\tau}$ and $1(\tau\text{Right})_{\tau}$ indicate whether $\tau < -7$ or $\tau > 3$, respectively. The dummy variables $1(\emptyset\text{Left})_{\emptyset}$ and $1(\emptyset\text{Right})_{\emptyset}$ indicate whether $\emptyset < -7$ or $\emptyset > 9$, respectively (Greenstone and Hanna 2014). The key coefficient to be studied here is ϑ_2, which measures the impact of a SCAP policy on air pollution within three years of its implementation. The catalytic converter variables are listed as controls in other to capture the variation in air pollution that would otherwise be attributable to the implementation of this policy.

The authors found their study revealed trends in air population that predate policy implementation. As a result, they include a control for the linear time trend of the policy "to adjust for differential pre-existing trends in adopting cities" (Greenstone and Hanna, 2014, pg. 3054). In the second specification, Greenstone and Hanna interact the linear time trend variable with the policy-range dummy. Thus, $1(\text{SCAPRange})_{\tau}*\tau$ and $1(\text{CCRange})_{\emptyset}*\emptyset$ are added into the second specification. The key coefficients in this study are now ϑ_2, and ϑ_3. With this, we are capturing the immediate impact of the SCAP policy implementation on air pollution, while allowing for the pre-trend in air pollution to vary across cities. The equation for the second

$$\begin{gathered}
Yct = \alpha + \vartheta_1 1(\text{SCAPRange})_{\tau} + \vartheta_2 1(\text{SCAP})_{\tau}*(\text{SCAPRange})_{\tau} + \vartheta_3 1(\text{SCAPRange})_{\tau}*\tau + \\
\vartheta_4 1(\tau\text{Left})_{\tau} + \vartheta_5 1(\tau\text{Right})_{\tau} + \rho_1 1(\text{CCRange})_{\emptyset} + \rho_2 1(\text{CC})_{\emptyset}*(\text{CCRange})_{\emptyset} + \rho_3 1(\text{CCRange})_{\emptyset}*\emptyset + \\
\rho_4 1(\emptyset\text{Left})_{\emptyset} + \rho_5 1(\emptyset\text{Right})_{\emptyset} + \mu t + \gamma c + \beta Xct + \epsilon ct \qquad \textbf{(EQUATION 1B)}
\end{gathered}$$

specification is as follows:

To allow the full impact of the policy to evolve over time, Greenstone and Hanna include a Policy*Time-Trend*Policy-Range interaction term. The variables added are $1(SCAP)_\tau*\tau*(SCAPRange)_\tau$ and $1(CC)_\emptyset*\emptyset*(CCRange)_\emptyset$. These variables measure the change in the trend in air pollution through time. The coefficients of interest in this third specification are ϑ_2, ϑ_3, and ϑ_4. The equation representing the third specification is as follows:

$$Yct = \alpha + \vartheta_1 1(SCAPRange)_\tau + \vartheta_2 1(SCAP)_\tau*(SCAPRange)_\tau + \vartheta_3 1(SCAPRange)_\tau*\tau + \vartheta_4 1(SCAP)_\tau*\tau*(SCAPRange)_\tau + \vartheta_5 1(\tau Left)_\tau + \vartheta_6 1(\tau Right)_\tau + \rho_1 1(CCRange)_\emptyset + \rho_2 1(CC)_\emptyset*(CCRange)_\emptyset + \rho_3 1(CCRange)_\emptyset*\emptyset + \rho_4 1(CC)_\emptyset*\emptyset*(CCRange)_\emptyset + \rho_5 1(\emptyset Left)_\emptyset + \rho_6 1(\emptyset Right)_\emptyset + \mu t + \gamma c + \beta Xct + \epsilon ct \qquad \textbf{(EQUATION 1C)}$$

Greenstone and Hanna state that this third specification is their preferred estimation strategy, due to the list of controls it contains. In all regressions, the standard errors are clustered at the city-level to be consistent to what is done with difference-in-differences designs. To capture differences in the precision of estimates due to variation in city size, all regressions are weighted by the district-urban population.

Results

Greenstone and Hanna's results for the efficacy of policies on air pollution are mixed. The authors find little evidence to suggest an impact of SCAP policies on SPM or SO_2 levels. However, SCAP is shown to have an impact on NO_2 levels after controlling for pre-existing trends in pollution levels. Results for SCAP will be discussed further below.

Regarding the catalytic converter policy, their regressions confirm a strong impact on air pollution reduction. The third specification, which controls for the mean shift and trend break in pollution levels seems to be the most reliable. The authors show that the declines in pollution trends are quantitatively large, reflecting the fast rates in which air pollution concentrations were increasing in cities that adopted the policy. Their results suggest that five years after a policy is implemented, SPM, SO_2, and NO_2 decreased by 48.6 $\mu g/m^3$, 13.5 $\mu g/m^3$, and 4.4 $\mu g/m^3$, respectively. While these SPM and SO_2 declines are statistically significant, NO_2 declines are not. Greenstone and Hanna suggest that “if the pretrends had continued then pollution concentrations would have reached levels much higher than those recorded in the 1987-1990 period” (2014, pg. 3058).

Section 4: Background

India’s most comprehensive air quality policy comes in the form of the Air Act in 1981, which was enacted to “arrest the deterioration in air quality” (CPCB 2006, pg. 2). The Air Act formed the creation of the Central Pollution Control Board (CPCB) and the State Pollution Control Boards (SPCBs). These boards are responsible for planning, advising, and researching to control or abate air pollution (CPCB 2). The boards are also responsible for the monitoring and collection of environmental data, and developing compliance procedures (Greenstone and Hanna 2014, pg. 3042). To do so, the CPCB started the National Ambient Air Quality Monitoring (NAAQM) program in 1984 at the national level (CPCB 2006, pg. 1). This program was tasked with determining the status and trends of ambient air quality, determine whether violations occur, identify attainment status, and related tasks (CPCB 2006, pg. 4).

The 2003/2004 National Ambient Air Quality Monitoring (NAAQM) report highlights many major cities in India for which the major sources of air pollution are “vehicles and small/medium scale industries” (NAAQM 2003, pg. 4). A study carried out in Delhi shows the distribution of industrial, vehicular, and domestic pollution (NAAQM 2003, pg.4). While Delhi is not regarded as one of the most industry-intensive sources of pollution in India, industry is shown to still play a significant role in contributing to air pollution there:

Table 2.1 Contribution of air pollution from various sources in Delhi (NAAQM 2003, pg.4)

Source	**1970-71**	**1980-81**	**1990-91**	**2000-01 (E)**
Industrial	56%	40%	29%	20%
Vehicular	23%	42%	64%	72%
Domestic	21%	18%	7%	8%

Supreme Court Action Plans

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The CPCB, SPCBs, and the Supreme Court played a significant role in the monitoring and implementation of Supreme Court Action Plans (SCAPs). SCAPs were a series of Supreme Court mandated actions, which were to be taken to reduce ambient air pollution in key polluting cities. SCAP policies were drafted by the individual cities to reduce air pollution. The focus of SCAPs was to reduce vehicular and industrial pollution by instituting not only regulation, but also other measures, such as the widening of roads to reduce airborne dust particles. In 1996, Delhi was the first city to develop an action plan to curb their pollution. Narain and Bell (2005) say that “the first interventions by the Courts were to force relocation of hazardous, noxious, heavy, and large polluting industries, also called ‘category H,’ from Delhi” (pg. 3). Soon after, 16 highly polluted cities were selected by the supreme courts, and were mandated to develop action plans. These cities were Agra, Ahmedabad, Bangalore, Chennai, Faridabad, Hyderabad, Jharia, Jodhpur, Kanpur, Kolkata, Lucknow, Mumbai, Patna, Pune, Solapur, and Varanasi. These cities implemented SCAPs in 2003 and 2004. Due to the variation in the time of adoption by cities as well as the existence of cities that did not adopt such plans, the SCAP policies provide a basis for empirical i~~I~~nvestigation.

SCAPs presented a list of prioritized abatement measures to improve air quality in the short and medium run. SCAPs outlined the necessary regulations to achieve these lower emissions targets. There were provisions regarding vehicular pollution, industrial pollution, and other measures. For the purposes of this paper, we will only discuss the industrial plans below. While there were differences in regulations by city, some of the common regulations targeting industrial air pollution were as follows:

- Switching from coal or coke to natural gas use in production processes, with a strict focus on compliance by the Supreme Court (CPCB 2006, pg. 28).
- New zoning requiring new industries using coal or coke to avoid establishing in municipalities (CPCB 2006, pg. 28).
- Retrofitting older technologies with newer ones by installing wet scrubbers, electrostatic precipitators, and more (CPCB 2006, pg. 36-129).
- Mandating the use of 0.05% Sulfur by industries in diesel generation sets and boilers (CPCB 2006, pg. 49).
- Renewal of consent to operate based on compliance with new measures (CPCB 2006, pg. 58).
- Inspection of industries periodically, and monitoring sources of air pollution emissions for compliance (CPCB 2006, pg. 58).
- Industries using fuel to have Air Pollution Control Devices installed (CPCB 2006, pg. 83).
- Reusing waste from thermal power generations for cement manufacturing (CPCB 2006, pg. 38).
- Closure and relocation of industries. For example, in Delhi, “all stone crushers have been closed down in Delhi and shifted to Pali in Rajasthan”; “all the hot mix plants have been closed down and shifted to other states”; and “as per the directions of the Hon’ble Supreme Court, 168 hazardous industries have been closed down in Delhi” (CPCB 2006, pg. 75).

Section 5: Data

In addition to the data from Greenstone and Hanna (2014), this article utilizes a measure (Eip) which represents the 1987 prevalence of fuel intensive industries in a state. This measure is created using India's Annual Survey of Industries (ASI) data from 1987. India's ASI contains data on relevant industry characteristics at the state level such as inputs, outputs, value added, fuel consumed, capital stock, employees, and more. The measure is a snapshot of the prevalence of fuel intensive industries at the beginning of the sample. The Eip measure is calculated as follows:

$$Fi = \frac{Fuels\ Value\ Nationwide\ in\ Industry\ i}{Input\ Value\ Nationwide\ in\ Industry\ i}$$

$$Eip = \sum Fi * \frac{Total\ Output\ in\ Industry\ i, State\ p, 1987}{Total\ Output\ in\ State\ p, 1987}$$

Eip is calculated by first finding the fuel's share of total input nationwide by industry (Fi). This idea is derived from M.A Cole et al's results, who find that energy inputs are the main determinant of pollution concentrations in the United Kingdom and in China (M.A Cole et al. 2008; M.A Cole et al. 2005). Fuels are also more generally known as pollution emitting, compared to other input sources. As such, fossil fuels, coal, oil, natural gas, and solvents, are known to be more pollution-emitting than other, less polluting inputs. The industry share of output in each state is then calculated and multiplied by Fi. This gives us the fuel intensity of each industry by state. By summing this result up by industry, we arrive at the 1987 prevalence of fuel intensive industry in a state.

The Eip variable proxies for the 1987 prevalence of polluting industries in each state. Eip values range from 0.053 to 0.277. Higher values of Eip represent higher shares of pollution-intensive industries in a state. Eip has a mean value of 0.144 and a standard deviation of 0.046. I assign this state-level variable to cities in Greenstone and Hanna's data. There are 1310 city-year observations of Eip. The cities Dimapur in Nagaland, and Silvassa in Dadra & Nagar Haveli are not contained in the 1987 ASI data, thus are not assigned a Eip measure. These cities combined only account for 10 city-year observations, and removing them should not have a measurable impact on the results.

There are 21 distinct values of Eip after removing Manipur, Andaman, Meghalaya, and Jammu & Kashmir from the sample, as Greenstone and Hanna's dataset did not contain data on these states. Also, Goa and Daman & Diu are given the same Eip measure because they were considered one state in the 1987 ASI data, but are considered separate states in Greenstone and Hanna's dataset. Daman and Diu only contain four observations in the final dataset, so it should not have a measurable impact either. Below is a summary of Eip measures by state, with the number of city-year observations in each case:

State	**Eip**	**Frequency**	**Percent**
Assam	0.053156	25	1.9%
Chandigarh	0.057584	16	1.21%
Delhi	0.089789	21	1.59%
Haryana	0.103339	37	2.81%
Andhra Pradesh	0.107940	43	3.26%
Punjab	0.110785	53	4.02%
Kerala	0.111115	85	6.44%
Maharashtra	0.114549	129	9.78%
Tamil Nadu	0.115603	71	5.38%
West Bengal	0.127081	58	4.4%
Karnataka	0.127791	46	3.49%
Uttar Pradesh	0.131056	131	9.93%
Gujarat	0.142793	98	7.43%
Bihar	0.143692	94	7.13%
Pondicherry	0.152817	18	1.36%
Rajasthan	0.161942	56	4.25%
Daman and Diu	0.171293	4	0.3%
Goa	0.171293	35	2.96%
Madhya Pradesh	0.175029	149	11.3%
Orissa	0.216071	77	5.84%
Himachal Pradesh	0.276989	73	5.53%
~~Total~~	~~2.861707~~	~~1,319~~	~~100%~~

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This measure may be used as a proxy for industrial pollution. I run correlations of the three pollutants on the EIP measure. Since the Eip measure is based on 1987 data, I keep only those observations that are between 1987 and 1990. Then, I collapse the pollution data by city, giving the mean pollution for each city between 1987 and 1990. I then remove the influential observations with Eip measures > 0.17 or < 0.08 to work as a robustness check in some of my later regressions. ~~This is consistent with what I do in my later regressions~~This is explained in more detail later. Finally, I correlate the three pollution measures with the Eip measure. The correlation of Eip with SPM, SO_2, and NO_2 *before* removing the influential values are -0.0536, -0.1326, and -0.1851, respectively. The correlation of Eip with SPM, SO_2, and NO_2 *after* removing the influential values ~~are~~ 0.2836, 0.3286, and 0.3077, respectively. ~~My results show that the~~These results show that the Eip measure is positively correlated with all three pollutant concentrations~~, indicating that the measure works as~~ only when influential values are removed. The measure seems to work as a good proxy for industrial pollution only in this case.~~.~~

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Section 6: Econometric Approach

The econometric approach used in this paper stems from what Greenstone and Hanna have done. I start by using the same specifications they created, equations (1A) to (1C), but then add the Eip measure into the specifications to measure how the impact of a SCAP policy implementation on pollution levels varies with the prevalence of fuel intensive industries in 1987. By adding the Eip variable into the specifications, I come up with equations (2A) to (2C), described below.

I first run the first set of equations on Greenstone and Hanna's full sample of cities to arrive at the first set of three regressions.[3] Next, I run the second set of equations on this full

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[3] Greenstone and Hanna drop Delhi from their sample. I choose to retain Delhi, which means my first set of regressions differ slightly from Greenstone and Hanna's.

sample of cities, arriving at the second set of three regressions. Finally, I run the second set of equations on a reduced sample of cities (discussed below), thus arriving at the third set of three regressions. These three sets of regressions are run using each of the three pollutants as the outcome measure. As a result, we run a total of 27 different regressions. While this paper focuses on the SCAP regulation as opposed to the catalytic converter regulation (discussed in Section 2 above), catalytic converter variables remain in the regression equations to control for the deviation in air pollution that would otherwise be attributable to the catalytic converter policy. What follows is a description of equations (1A) to (1C) and (2A) to (2C), followed by our results.

To recap, equation (1A) measures the impact of a SCAP policy three years after its implementation on pollution levels. Equation (1B) measures the impact of a SCAP policy on pollution concentrations, while adjusting for the time trend in pollution levels. In other words, it allows for the pre-existing trend in pollution concentrations to deviate across cities. Equation (1C) measures the impact of a SCAP policy on pollution concentrations, not only by allowing for the time trend in pollution concentrations to vary, but by also allowing for the change in the trend (trend break) in pollution concentrations to vary as well. The trend break of pollution levels is added to the regression to allow for factors which may delay the direct influence of the SCAP policy; such as the time it takes for the policy to become fully communicated and implemented.

The second set of equations (2A) to (2C) are an extension of the first set of equations (1A) to (1C), in that they contain all the same variables. However, equations (2A) to (2C) are supplemented by the Eip measure, which is interacted with all the variables used in the first set

$$\begin{aligned}
&Yct = \alpha + \vartheta_1 1(\text{SCAPRange})_\tau + \vartheta_2 1(\text{SCAP})_\tau*(\text{SCAPRange})_\tau + \vartheta_3 1(\tau\text{Left})_\tau + \vartheta_4 1(\tau\text{Right})_\tau + \\
&\rho_1 1(\text{CCRange})_\emptyset + \rho_2 1(\text{CC})_\emptyset*(\text{CCRange})_\emptyset + \rho_3 1(\emptyset\text{Left})_\emptyset + \rho_4 1(\emptyset\text{Right})_\emptyset + \mu t + \gamma c + \beta Xct + \\
&\pi_1 1(\text{SCAPRange})*Eip + \pi_2 1(\text{SCAP})_\tau*(\text{SCAPRange})_\tau*Eip + \pi_3 1(\tau\text{Left})_\tau*Eip + \pi \\
&{}_4 1(\tau\text{Right})_\tau*Eip + \rho_5 1(\text{CCRange})_\emptyset *Eip + \rho_6 1(\text{CC})_\emptyset*(\text{CCRange})_\emptyset *Eip + \rho_7 1(\emptyset\text{Left})_\emptyset *Eip + \\
&\rho_8 1(\emptyset\text{Right})_\emptyset *Eip + \mu t*Eip + \gamma c*Eip + \beta Xct*Eip + \epsilon ct \qquad \textbf{(EQUATION 2A)}
\end{aligned}$$

of equations. By introducing the Eip measure into the equations, we can estimate the added impact of the prevalence of fuel intensive industries in 1987 on pollution levels. The equations

$$Yct = \alpha + \vartheta_1 1(\mathrm{SCAPRange})_\tau + \vartheta_2 1(\mathrm{SCAP})_\tau \ast (\mathrm{SCAPRange})_\tau + \vartheta_3 1(\mathrm{SCAPRange})_\tau \ast \tau + \vartheta_4 1(\tau\mathrm{Left})_\tau + \vartheta_5 1(\tau\mathrm{Right})_\tau + \rho_1 1(\mathrm{CCRange})_\emptyset + \rho_2 1(\mathrm{CC})_\emptyset \ast (\mathrm{CCRange})_\emptyset + \rho_3 1(\mathrm{CCRange})_\emptyset \ast \emptyset + \rho_4 1(\emptyset\mathrm{Left})_\emptyset + \rho_5 1(\emptyset\mathrm{Right})_\emptyset + \mu t + \gamma c + \beta Xct + \pi_1 1(\mathrm{SCAPRange}) \ast Eip + \pi_2 1(\mathrm{SCAP})_\tau \ast (\mathrm{SCAPRange})_\tau \ast Eip + \pi_3 1(\mathrm{SCAPRange})_\tau \ast \tau \ast Eip + \pi_4 1(\tau\mathrm{Left})_\tau \ast Eip + \pi_5 1(\tau\mathrm{Right})_\tau \ast Eip + \rho_6 1(\mathrm{CCRange})_\emptyset \ast Eip + \rho_7 1(\mathrm{CC})_\emptyset \ast (\mathrm{CCRange})_\emptyset \ast Eip + \rho_8 1(\mathrm{CCRange})_\emptyset \ast \emptyset \ast Eip + \rho_9 1(\emptyset\mathrm{Left})_\emptyset \ast Eip + \rho_{10} 1(\emptyset\mathrm{Right})_\emptyset \ast Eip + \mu t \ast Eip + \gamma c \ast Eip + \beta Xct \ast Eip + \epsilon ct$$

(EQUATION 2B)

$$Yct = \alpha + \vartheta_1 1(\mathrm{SCAPRange})_\tau + \vartheta_2 1(\mathrm{SCAP})_\tau \ast (\mathrm{SCAPRange})_\tau + \vartheta_3 1(\mathrm{SCAPRange})_\tau \ast \tau + \vartheta_4 1(\mathrm{SCAP})_\tau \ast \tau \ast (\mathrm{SCAPRange})_\tau + \vartheta_5 1(\tau\mathrm{Left})_\tau + \vartheta_6 1(\tau\mathrm{Right})_\tau + \rho_1 1(\mathrm{CCRange})_\emptyset + \rho_2 1(\mathrm{CC})_\emptyset \ast (\mathrm{CCRange})_\emptyset + \rho_3 1(\mathrm{CCRange})_\emptyset \ast \emptyset + \rho_4 1(\mathrm{CC})_\emptyset \ast \emptyset \ast (\mathrm{CCRange})_\emptyset + \rho_5 1(\emptyset\mathrm{Left})_\emptyset + \rho_6 1(\emptyset\mathrm{Right})_\emptyset + \mu t + \gamma c + \beta Xct + \pi_1 1(\mathrm{SCAPRange})_\tau \ast Eip + \pi_2 1(\mathrm{SCAP})_\tau \ast (\mathrm{SCAPRange})_\tau \ast Eip + \pi_3 1(\mathrm{SCAPRange})_\tau \ast \tau \ast Eip + \pi_4 1(\mathrm{SCAP})_\tau \ast \tau \ast (\mathrm{SCAPRange})_\tau \ast Eip + \pi_5 1(\tau\mathrm{Left})_\tau \ast Eip + \pi_6 1(\tau\mathrm{Right})_\tau \ast Eip + \rho_7 1(\mathrm{CCRange})_\emptyset \ast Eip + \rho_8 1(\mathrm{CC})_\emptyset \ast (\mathrm{CCRange})_\emptyset \ast Eip + \rho_9 1(\mathrm{CCRange})_\emptyset \ast \emptyset \ast Eip + \rho_{10} 1(\mathrm{CC})_\emptyset \ast \emptyset \ast (\mathrm{CCRange})_\emptyset \ast Eip + \rho_{11} 1(\emptyset\mathrm{Left})_\emptyset \ast Eip + \rho_{12} 1(\emptyset\mathrm{Right})_\emptyset \ast Eip + \mu t \ast Eip + \gamma c \ast Eip + \beta Xct \ast Eip + \epsilon ct$$

(EQUATION 2C)

are specified as follows:

The key coefficients in equation (2A) to (2C) are ~~the interaction terms~~ π_2, π_3, and π_4, attached to the interaction terms $1(\mathrm{SCAP})_\tau \ast (\mathrm{SCAPRange})_\tau \ast Eip$, $1(\mathrm{SCAPRange})_\tau \ast \tau \ast Eip$ and $1(\mathrm{SCAP})_\tau \ast \tau \ast (\mathrm{SCAPRange})_\tau$, respectively. The coefficient of interaction π_3 represents the added impact of a SCAP policy on pollution levels by allowing for the 1987 prevalence of fuel intensive industries to vary. A positive estimate would indicate that the SCAP policy would have less of an impact on air pollution in cities with a higher prevalence of fuel intensive industries in 1987. Like equation (1A), equation (2A) measures the impact of a SCAP policy three years after its implementation on pollution levels; however, equation (2A) allows for the variation in the 1987 prevalence of fuel intensive industries to have an added impact on pollution concentrations via the variable $1(SCAP)_{\tau}*(SCAPRange)_{\tau}*Eip$. Equation (2B) goes further by allowing for the 1987 prevalence of fuel intensive industries to influence the effect of the pre-existing time trend on pollution levels via the variable $1(SCAPRange)_{\tau}*\tau*Eip$. Finally, equation (2C) measures the impact of a SCAP policy on pollution concentrations, allowing the 1987 prevalence of fuel intensive industries to influence not only the time trend, but also the trend break in pollution concentrations via the variable $1(SCAP)_{\tau}*\tau*(SCAPRange)_{\tau}$.

In the third set of regressions, we remove influential observations of Eip ($Eip < 0.08$ or $Eip > 0.17$) before running equations (2A) to (2C). These influential values of Eip are removed from the sample to see whether the cities with the highest and lowest prevalence of fuel intensive industries are affecting the results. Substantial changes in the estimates and/or their significance would suggest that this is, in fact, the case. It may be worthwhile to note that the general direction is for the significance to decrease due to the reduced sample lowering the degrees of freedom and data variability. Nevertheless, the cities removed from the sample in these regressions are those in the states belonging to Assam, Chandigarh, Goa, Daman & Diu, Madhya Pradesh, Orissa, and Himachal Pradesh.

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Section 7: Results

Table 1 - The Effect of Supreme Court Action Plan Policy on Air SO_2 Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Eqn 1a	Eqn 1b	Eqn 1c	Eqn 2a	Eqn 2b	Eqn 2c	Eqn 2a	Eqn 2b	Eqn 2c
ϑ3: time trend		-0.08	0.09		1.28	2.51		-0.78	2.35
		(0.52)	(0.55)		(3.34)	(3.63)		(4.65)	(5.07)
ϑ2: 1(Policy)	-1.73	-1.52	-1.25	-25.15*	-33.48***	-26.59**	-49.85**	-46.42***	-33.84*
	(2.03)	(2.18)	(2.13)	(14.74)	(8.94)	(11.16)	(24.36)	(17.27)	(19.33)
ϑ4: 1(Policy)* time trend			0.10			-2.29			-11.17
			(0.98)			(5.31)			(8.39)
π3: Eip * time trend					-13.70	-21.89		4.22	-18.62
					(26.45)	(30.33)		(36.63)	(41.07)
π2: Eip*1(Policy)				192.77	274.40***	238.65***	382.72*	362.32***	353.63***
				(121.25)	(75.77)	(84.38)	(193.91)	(135.90)	(126.79)
π4: Eip*1(Policy)* time trend						17.35			83.84
						(46.80)			(67.30)
5-Year Effect			-.78			-38.05			-89.67***
p-value			[.87]			[.12]			[.01]
Eip*5-Year Effect						325.38			772.84**
p-value						[.20]			[0.02]
Observations	1,165	1,158	1,158	1,158	1,158	1,158	847	847	847

Notes: This table displays the results from the three sets of regressions using the one-step equations（1A)，(1B)，(1C), (2A), (2B), and (2C) for SO_2. The row indicating "5-year effect" report $\vartheta_2 + 5*\vartheta_4$, which estimates the effect of the SCAP policy 5 years after implementation from equation（1C) and (2C). The row indicating "Eip*5-year effect" report Eip*($\pi_2 + 5* \pi_4$), which estimates the additional effect of a SCAP policy with a rise in the 1987 prevalence of fuel intensive industries 5 years after the implementation of a SCAP policy from equation（1C) and (2C). The *p*-values report the significance tests of the linear combination five-year estimates above them, respectively. See the text for further details.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In the first set of regressions (1-3), none of the relevant coefficient estimates are statistically significant, which initially leads us to believe that there is no estimated impact of a SCAP policy implemented in a city on SO_2 levels, whether considering the mean shift (ϑ2), trend break (ϑ4), or both. In the second and third sets of regressions, we see that the first set of regressions conceals effects that vary according to the 1987 prevalence of fuel intensive industries. The “five-year effect” in column 3 sums both of these effects over five years, and is also insignificant.

In the second set of regressions (4-6), the Eip measure is interacted with all the regressors. The coefficient for the SCAP policy effect on SO_2 levels, while Eip is equal to zero ($\vartheta 2$), is negative and statistically significant for all three specifications (2A) to (2C). The coefficient interaction term for the added impact of the 1987 prevalence of fuel intensive industries on pollution levels ($\pi 2$) is positive statistically significant for equations (2B) and (2C), but not (2A). From this, we find that the estimated effect of the SCAP policy on SO_2 levels, when Eip equals zero, is between a 25.15 and 33.48 $\mu g/m^3$ reduction in mean SO_2 levels, depending on the specification used. The prevalence of fuel intensive industries measure in 1987 reduces the effect of the SCAP policy on SO_2 levels by 8.87 to 12.62 $\mu g/m^3$ for every standard deviation increase in the Eip measure.

Neither the pre-existing time trend ($\vartheta 3$), nor trend break ($\vartheta 4$) estimates, are statistically significant in their respective specifications, when allowing for the 1987 prevalence of fuel intensive industries to vary across states. In addition, the added impacts of the 1987 prevalence of fuel intensive industries on the time trend ($\pi 3$) and on the trend break ($\pi 4$) in SO_2 levels are not statistically significant in their respective specifications. The results show that a higher 1987 prevalence of fuel intensive industries in a state can counteract the mean shift in SO_2 caused by a SCAP policy implementation. The same cannot be said, however, for the Eip measure’s influence on the ~~and~~ trend break in SO_2 levels, as their coefficient of interaction estimates were statistically insignificant.

In the third set of regressions (7-9), with the influential observations in Eip values removed, the resulting estimates are generally larger in magnitude and more likely to be significant across the different specifications. Both the coefficients for the effect of the SCAP policy implementation ($\vartheta 2$), when Eip equals zero, and the added impact of the prevalence of fuel intensive industries in 1987 ($\pi 2$) on pollution levels are statistically significant for all three specifications (2A) to (2C). The reduction in SO_2 levels caused by the SCAP policy implementation when Eip equals zero becomes more pronounced, estimated at between 33.84 and 49.85 $\mu g/m^3$, depending on the specification used. In this set of regressions, the prevalence of fuel intensive industries measure in 1987 reduces the effect of the SCAP policy on SO_2 levels by 16.27 to 17.60 $\mu g/m^3$ for every standard deviation increase in the Eip measure. The insignificance of the time trend ($\vartheta 3$) and the trend break ($\vartheta 4$) coefficients do not change in this third set of regressions. Lastly, the 1987 prevalence of fuel intensive industries continues to have a statistically insignificant estimated impact on the effects of the time trend and trend break on SO_2 levels.

Unlike in the second set of regressions, specification (2C) in the third set of regressions has a statistically significant effect of a five-year effect of a SCAP policy on SO_2 levels when Eip equals zero; as well as the change of this impact due to the variability of the 1987 prevalence of fuel intensive. These effects are significant at the 1% and 5% levels of significance, respectively. The estimated five-year effect of a SCAP policy is a drop in SO_2 levels of 89.67 $\mu g/m^3$, when Eip is equal to zero. There is a reduction in the five-year effect of the SCAP policy on SO_2 levels of 35.55 $\mu g/m^3$ for every standard deviation increase in the Eip measure.

The regressions run on SO_2 return largely statistically significant estimates for the coefficients $\vartheta 2$, $\vartheta 4$, $\pi 2$, and $\pi 4$. It was found that the coefficient of interaction $\pi 4$ was, in fact, positive and significant for specifications (2B) and (2C). This suggests that the effect of the SCAP policy on SO_2 levels decreased in cities with a higher prevalence of fuel intensive industries in 1987. This result may require us to question these SCAP polices, as to their efficacy in targeting cities with the most fuel intensive industries.

Table 2 - The effect of Supreme Court Action Plan Policy on NO_2 Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Eqn 1a	Eqn 1b	Eqn 1c	Eqn 2a	Eqn 2b	Eqn 2c	Eqn 2a	Eqn 2b	Eqn 2c
ϑ3: time trend		1.23	1.61*		-4.19	-4.84		-8.06	-5.36
		(0.75)	(0.88)		(3.42)	(4.28)		(6.12)	(7.74)
ϑ2: 1(Policy)	0.02	-5.49	-2.61	-45.55**	-22.35	-28.01	-56.50*	-9.27	-0.37
	(3.32)	(3.98)	(4.41)	(18.40)	(21.96)	(21.60)	(32.32)	(43.75)	(33.12)
ϑ4: 1(Policy)* time trend			-1.74			3.84			-10.73
			(2.14)			(11.62)			(22.03)
π3: Eip * time trend					41.70	50.87		72.86	56.30
					(26.87)	(38.45)		(48.99)	(63.28)
π2: Eip*1(Policy)				374.51**	149.18	173.53	464.15*	48.25	73.39
				(151.97)	(196.47)	(179.44)	(251.95)	(358.37)	(304.57)
π4: Eip*1(Policy)* time trend						-52.58			57.13
						(103.86)			(170.30)
5-Year Effect			-11.32			-8.8			-54.03
p-value			[.22]			[.87]			[.62]
Eip*5-Year Effect						-89.36			359.05
p-value						[.88]			[.73]
Observations	1,184	1,177	1,177	1,175	1,175	1,175	844	844	844

Notes: This table displays the results from the three sets of regressions using the one-step equations（1A）,（1B）,（1C), (2A), (2B), and (2C) for NO_2. The row indicating “5-year effect” report $\vartheta_2 + 5*\vartheta_4$, which estimates the effect of the SCAP policy 5 years after implementation from equation（1C) and (2C). The row indicating “Eip*5-year effect” report Eip*($\pi_2 + 5*\pi_4$), which estimates the additional effect of a SCAP policy with a rise in the prevalence of fuel intensive industries 5 years after the implementation of a SCAP policy from equation（1C) and (2C). The *p*-values report the significance tests of the linear combination five-year estimates above them, respectively. See the text for further details.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In Greenstone and Hanna’s results, they had found no significant effect of the SCAP policy on the mean shift and trend break in NO_2 levels. In the second and third set of regressions, only specification (2A) has statistically significant estimates for the two coefficients of interest (ϑ2) and (π2). When I allow the 1987 prevalence of fuel intensive industries to vary, the estimated impact of SCAP policy three years after its implementation results in a reduction of

45.55 μg/m^3 in NO_2 concentrations, when Eip equals zero. Furthermore, this reduction in NO_2 levels is reduced by 17.23 μg/m^3 for every standard deviation increase in the 1987 prevalence of fuel intensive industries measure. The two coefficients mentioned are statistically significant at the 5% level in specification (2A). In the third set of regressions, the significance of these two coefficients is reduced. One probable reason why NO_2 estimates do not provide the same statistically significant coefficients as the SO_2 estimates can be because NO_2 concentrations are mainly vehicular emissions, while SO_2 emissions gain a significant share from industrial sources. it would make sense that the variability in the 1987 prevalence of fuel intensive industries would not cause the impact of the SCAP policy on NO_2 levels to vary, as NO_2 concentrations are more tied to vehicular pollution.

Table 3 - The effect of Supreme Court Action Plan Policy on SPM Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Eqn 1a	Eqn 1b	Eqn 1c	Eqn 2a	Eqn 2b	Eqn 2c	Eqn 2a	Eqn 2b	Eqn 2c
ϑ3: time trend		-3.64	-2.85		7.88	15.98		-35.94	-16.23
		(4.13)	(4.28)		(24.99)	(25.20)		(35.54)	(39.11)
ϑ2: 1(Policy)	-18.79	-1.39	0.30	165.83	108.76	165.88	291.61**	451.72*	547.28**
	(14.22)	(22.77)	(21.51)	(116.07)	(178.79)	(194.13)	(144.41)	(237.38)	(251.32)
ϑ4: 1(Policy)* time trend			0.12			-21.90			-59.84
			(5.97)			(40.37)			(90.61)
π3: Eip * time trend					-97.79	-161.47		251.28	93.53
					(214.97)	(225.85)		(289.05)	(324.08)
π2: Eip*1(Policy)				-1,565.2	-943.44	-1,237.6	-2,490.9**	-3,619.6*	-3,921.4**
				(958.74)	(1,520.57)	(1,532.71)	(1,173.39)	(1,929.52)	(1,894.13)
π4: Eip*1(Policy)* time trend						212.82			530.30
						(368.34)			(721.07)
5-Year Effect			.92			56.39			248.09
p-value			[.98]			[.80]			[.57]
Eip*5-Year Effect						-173.5			-1269
p-value						[.94]			[.76]
Observations	1,172	1,165	1,165	1,159	1,159	1,159	838	838	838

Notes: This table displays the results from the three sets of regressions using the one-step equations (1A), (1B), (1C), (2A), (2B), and (2C) for SPM. The row indicating "5-year effect" report $\vartheta_2 + 5*\vartheta_4$, which estimates the effect of the SCAP policy 5 years after implementation from equation (1C) and (2C). The row indicating "Eip*5-year effect" report Eip*($\pi_2 + 5* \pi_4$), which estimates the additional effect of a SCAP policy with a rise in the prevalence of fuel intensive industries 5 years after the implementation of a SCAP policy from equation (1C) and (2C). The *p*-values report the significance tests of the linear combination five-year estimates above them, respectively. See the text for further details.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Regarding SPM, none of the coefficients in the first set of regressions are statistically significant, which is in line with the results Greenstone and Hanna concluded with. In the second set of regressions, the main coefficients of interest ($\vartheta 2$) and ($\pi 2$) are not significantly different from zero. In the third set of regressions, however, the main coefficients of interest are statistically significant, but are of the opposite sign from the previous results for SO_2 and NO_2. The following interpretation can be drawn from these results: when the 1987 prevalence of fuel intensive industries is equal to 0.144 (the average) the impact of the SCAP is between a 17.40 and 69.50 $\mu g/m^3$ reduction in SPM, depending on the regression specification used. The estimated reduction in SPM due to the policy increases by 114.58 to 180.38 $\mu g/m^3$ for each standard deviation increase in Eip. Finally, the coefficients for the time trend, the trend break, and the added impact of these caused by the variability in the Eip measure were statistically insignificant in all sets of regressions. In this model, the impact of the 1987 prevalence of fuel intensive industries on SPM is made more apparent than for NO_2. This may be since SPM is a more general indicator of pollution that contains pollutants from industrial sources. Variation in the 1987 prevalence of fuel intensive industries seems to have resulted in a varying impact of the SCAP policy implementation on SPM levels. It is worthy to note that this impact, however, was statistically significant only after a reduced sample was used. This may raise heterogeneity treatment effects beyond linearity as a concern, but the coefficient standard errors already adjust.

To recap, our results show that there is a statistically significant reduction in the impact of a SCAP policy on SO_2 levels caused by increases in the 1987 prevalence of fuel intensive industries. This estimate is not statistically significant for NO_2. This estimate is, however, statistically significant for SPM, but only when the reduced sample is used, and goes in the other direction. By removing influential observations, we find that the statistical significance of some of our coefficient estimates rise for SO_2 and SPM, but not for NO_2. It may be the case that these influential observations were, in fact, affecting the results.

Section 8: Conclusion

This paper builds on Greenstone and Hanna's (2014) paper regarding the effectiveness of environmental regulations in reducing air pollution. I supplement Greenstone and Hanna's dataset with a variable measuring the 1987 prevalence of fuel intensive industries in a given state. Using this new dataset, I test for how the impact of a SCAP policy on air pollution varies with the 1987 prevalence of fuel intensive industries.

In my results, I find the coefficient of interaction for the prevalence of fuel intensive industries in 1987 and the SCAP policy implementation is generally more significant for the regressions run on SO_2, compared to those run on NO_2 and SPM. For the regressions run on SPM, the coefficient for interaction only becomes significant after reducing the sample. Since I estimated the impact of the SCAP policy in a state, while allowing the 1987 prevalence of fuel intensive industries to vary across states, the higher significance in the SO_2 regressions highlights the importance industrial emissions may have on SO_2 levels.

The results indicate further that the estimated effect of the SCAP policy in a state, with the 1987 prevalence of fuel intensive industries equalling zero, is between a 25.15 and 33.48 $\mu g/m^3$ reduction in mean SO_2 levels; and a 45.55 $\mu g/m^3$ reduction in mean NO_2 levels. Every standard deviation increase in the 1987 prevalence of fuel intensive industries measure reduces this effect by 8.87 to 12.62 $\mu g/m^3$ in SO_2 levels, and 17.23 $\mu g/m^3$ in NO2 concentrations. Further, the average estimated impact of the SCAP policy on SPM levels, with an average 1987 prevalence of fuel intensive industries value (.0144), is between a 17.40 to 69.50 $\mu g/m^3$ reduction in SPM concentrations. Finally, the estimated reduction in SPM due to the policy increases by 114.58 to 180.38 $\mu g/m^3$ for each standard deviation increase in Eip. My results indicate that the effectiveness of the SCAP policy does, in fact, vary with the 1987 prevalence of fuel intensive industries in a given state. These results indicate that states with a higher prevalence of fuel intensive industries in 1987 would have more of a reduction in mean pollution concentrations following the implementation of SCAP policy in the case of SPM, but less in the case of SO_2 and NO_2. However, the NO_2 results are insignificant in most specifications, and the SPM results are only significant in the reduced sample specifications.

That said, further research can be done to measure how the prevalence of fuel intensive industries in a given state varies through time as a result of environmental regulations. Such an endeavor would provide insights into how environmental regulations may affect an industry's choice to use fuels as inputs into the production process.

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