Seminar

Applied Methods in Environmental and Development Economics

Environmental Regulations, Air and Water Pollution, and Infant Mortality in India

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Abstract

In this paper we use a difference-in-differences approach together with a large city-level panel dataset to investigate the impact of environmental pollicies on pollution levels and human health in India. We find a significant improvement in air pollution levels caused by one air pollution policy. However, we did not find the water pollution regulations to significantly improve water quality. In fact, our results imply a decrease in water quality correlated to the introduction of the policy. We discuss why the effectiveness of the air pollution regulations might be caused by a high public demand for a better air quality and why this public support lead to the success of the policy, even in a weak institutional setting.

1 Introduction

With climate change becoming more and more apparent and being known to have significant impacts on different environments (Kløve et al., 2014; Lindner et al., 2010; Doney et al., 2012; Mora et al., 2018) global attention shifts to finding solutions for stopping it. It is evident that greenhouse gases are the main cause of climate change and rising temperatures (European Commission, n.d.; IPCC, 2013) and action needs to be taken. But not only globally does pollution pose significant threats. Many studies have shown that air pollution can have some major negative effects on health (Brook et al., 2004; Lin et al., 2013). In India it is expected that the life expectancy could be increased by 3.2 years if national air pollution standards would be fulfilled (Greenstone et al., 2015). However, air pollution is not the only environmental pollution factor linked to a theoretical loss of life. Water pollution is another local problem, in developing countries as well as in developed countries (Kumar Reddy and Lee, 2012; Abbaspour, 2011).

In this paper we want to asses whether or not it is possible for countries considered to have weak institutions to implement the local changes needed to decrease environmental pollution levels and thus increase the general health of its population. The question of what factors imply the success of policies in weak institutional settings has already been tried to be answered by some other studies. However, they did not manage to find conclusive results. Gonchar, Kuznetsov and Wade (2017) found success of policies and environmental regulations to be a byproduct of the national or global success of private institutions, whereas Hill and Menon (2013) state external help as another supplementary factor.

For our analysis we use India as its population accounted for 16% to 18% of the world population in the last several decades (Worldometer, n.d.; Macrotrends, n.d.). In addition to this, Indias rapid economical growth has severe impacts on the environment (Mani et al., 2012). Today, India is one of the worlds most polluted nations, with only Bangladesh and Pakistan surpassing its mean $PM_{2.5}$ levels (IQAir, 2022). Additionally, India is generally regarded to have large problems in the success with their policies. We want to try to identify some factors that might help India have more success with their policies. The fact that the water pollution regulations and the air pollution policies were introduced in different manners in India will be especially helpful with this identification. These insights might then be able to be generalised to other contries with weak institutions. Lastly, as India has a long history of different environmental policies, there is plentyful opportunity to compare different policies and their successes to another.

This paper largely follows the analysis done by Greenstone and Hanna (2014). We will assess three of Indias environmental policies using the data set compiled and provided by Greenstone and Hanna

(2014). The data set is based on city-level panel data from 1986 to 2007, consisting of meassurements for air pollution, water pollution and infant mortality. The air pollution data includes measurements from about 140 cities, whereas the water pollution measurements are gathered over 424 cities along 162 rivers.

We will examine the impact of three different policies on emissions. For air pollution we will take a closer look at the Supreme Court Action Plan (SCAP) and the Catalytic Converters. For water pollution we will focus on the National River Conservation Plan (NRCP). These policies are rather similar to policies from Europe and the United States and therefore can be used to compare the force of the different insitutions. We test for the effect the different policies have on pollution concentrations using a difference-in-differences approach to account for potential differential regulation. By doing this, we also control for other different trends in the control and the treatment group.

Our analysis suggests that even in countries with weak institutions policies can be succesful. Still, not all policies will be successful. We found showed that while one of the air pollution policies was successful in decreasing air pollution levels, one other policy designed to decrease air pollution concentrations did not succeed in its goal. We also found the one policy designed to reduce water pollution to be ineffective in achieving its goal. In our analysis we used a regression model controlling for city and year fixed effects as well as other preexisting trends. We find that the mandate of catalytic converters for vehicles caused significant reductions in air pollution levels. We estimated a reduction of about 27% in particulate matter (PM) with a diameter less than 100 micrometers (μm) and a reduction of 40% in sulfur dioxide SO_2 concentrations, both over a five year period after the policy was introduced. We did not find sufficient evidence for the CatConv policy to have an impact on NO_2 concentrations. Conversely, we did not find any statistically sufficient impact of the SCAP on air pollution levels. While there are some indications of a small impact on NO_2 levels, none of our results are statistically significant.

In addition to our difference-in-differences style analysis we used a Chow test to test for validity of these results. We specifically test for structural breaks in the effects of the pollution policies over time between adopting and non-adopting cities. While our analysis suggests some structural breaks in PM and SO_2 concentrations right around the time of the adoption of the CatConv policy, these findings are not statistically significant. We do not find evidence for structural breaks in water pollution levels.

Our analysis and some additional evidence gathered suggests that the difference of the success of the air and water regulations in India are largely due to a higher public attention to air quality, which is in line with the findings of Bonilla-Mejía and Higuera-Mendieta (2019). With regular smog clouds covering parts of India (Shabbir, Junaid and Zahid, 2019) it is not surprising that air pollution gets a lot of attention. In addition to this, high levels of air pollution are linked to many health risks, such as respiratory diseases (Orellano, Reynoso and Quaranta, 2021). While water pollution also can have significant impacts on ones health, it is much easier to prevent infections and other health problems from water pollution, while it is much harder to protect oneself from air pollution. Additionally, the problem of air pollution is much more present in the Indian media. Our data shows that in the years 1986 to 2007 total mentions of 'air pollution' in the Times of India are abouth three times as many as mentions of 'water pollution'. Especially after 1995 the coverage on air pollution increases drastically, which mostly is in line with the start of the environmental policies we are looking at. Another factor supporting the success of the air pollution policies is the high level of engagemet of the public by Indias supreme court. The policy aimed to reduce water pollution did not receive as much media coverage and had a much worse starting point. It was not clearly written, had less funds and was mostly implemented by agencies that had failed in the implementation of previous regulations as well. As there are many similarities betwee the air pollution regulations and the water pollution policies, it is especially interesting to investigate these differences and the impact they had on the respective policies.

Lastly, we tested whether or not the Catalytic Converter (Cat Conv) policy had an effect on infant mortality rates. Our results indicate that the adoption of the policy is correlated with a rise in infant mortality and therefore a loss in human health. As discussed below, our results are not significant for this part of the analysis.

This paper generally follows the analysis done by (Greenstone and Hanna, 2014). Section 2 gives a short summary of the data used and the overall time trends in pollution levels as well as infant mortality. Section 3 explains the theory of the economic approach we took for our analysis. Section 4 reports our results. In section 5 we present some qualitative evidence for our results while section 6 concludes the paper.

2 Data

As our analysis follows the paper by (Greenstone and Hanna, 2014) we also use the data set provided there. They compiled a large panel data file including air and water pollution concentrations as well as environmental policies. To supplement this data they also provide city level data on infant mortality. In this section we will take a closer look at the different data sources as well as provide a short overview of the data with some summary statistics.

2.1 Regulation Data

In the years between 1986 and 2007 India implemented and amended many different environmental policies (International Centre for Environment and Sustainable Development, n.d.). Greenstone and Hanna (2014) used multiple sources to assemble a dataset to systematically document these policy changes at the city-year level. They used print and web documentation from the Indian government, including the CPCB, the Department of Road Transport and Highways, the Ministry of Environment and Forests, and several Indian SPCB's. In addition to this the authors also used data from the World Bbank, the Emission Controls Manufacturers Association and Urbanrail.net.

Table 1: Prevalence of air and water pollution.

Policies	All Cities (1A)	SCAP (1B)	Cat Conv (1C)	All Cities (2A)	NRCP (2B)
1986				111	0
1987	17	0	0	121	0
1988	25	0	0	188	0
1989	31	0	0	219	0
1990	43	0	0	271	0
1991	46	0	0	265	0
1992	57	0	0	284	0
1993	63	0	0	304	0
1994	64	0	0	324	0
1995	43	0	2	325	27
1996	66	0	4	325	29
1997	70	1	4	335	29
1998	64	1	22	334	29
1999	72	1	26	322	29
2000	69	1	24	310	29
2001	66	1	24	372	29
2002	73	1	26	382	29
2003	72	11	26	386	28
2004	81	15	26	405	27
2005	93	16	26	304	24
2006	113	16	26		
2007	116	16	26		

In Table 1 we summarize the prevalence of the policies we will analyse from the provided dataset. In our analysis we only included cities that adopt a policy if there was data available from at least three years before the policies implementation and four years after. A city that did not adopt the policy was only included into our analysis when there were at least two data points available.

Column (1A) and (2A) of Table 1 display the number of all cities we included into our analysis whereas (1B), (1C) and (2B) display the number of cities included in our analysis where the policy was in place in that year.

We will only include a city in the following regressions, if there is sufficient data for that specific dependent variable of the regression. Therefore, the numbers in Table 1 only give a maximum for the numbers of cities included in the regression. However, most cities have measurements for all pollutants studied here.

2.2 Pollution Data

Air Pollution Data Greenstone and Hanna (2014) took advantage of the growth of environmental monitoring stations in Inda. The Central Pollution Control Board (CPCB) began in 1987 to collect air pollution levels, including NO_2, SO_2 and SPM measurements. This was done as part of the National Air Quality Monitoring Program (NAMP), whose purpose it is to assess trends in air quality as well es to check whether or not national stadards are violated. The NAMP is also tasked with understanding the keys for decreeing successful policies to reduce air pollution (Central Pollution Control Board, n.d.). The CPCB hereby aided in identifying and assessing the need for pollution crontrols and potential pollution sources and hazards. Further, state pollution control boards (SPCB) were tasked with collecting pollution measurements in their states and analysing them. Greenstone and Hanna (2014) used a collection of CPCB online and print sources from the years 1986-2007.

The complete dataset compiled by Greenstone and Hanna (2014) in total includes 572 air pollution monitoring stations in 140 cities. However, most of these stations only operated for a short period of time and not for all cities data is available in every year. In 1987 there are measurements only from 21 cities, whereas in 2007 the coverage of air pollution monitors increased to 132 cities.

In this paper we will mainly focus on three different air pollutants: PM, SO_2 and NO_2. This is in line with the pollutants the CPCB deems most important to measure (Central Pollution Control Board, n.d.). All of these three pollutants have severe impacts on health, as found by multiple papers. PM is directly linked to cardiovascular diseases as well as lung cancer and various other health problems (Turner et al., 2011; Martinelli, Olivieri and Girelli, 2013; Polichetti et al., 2009; Brook et al., 2010). It is mostly caused by combustion processes, emissions from vehicles and tobacco smoke (Anderson, Thundiyil and Stolbach, 2012). SO_2 emissions are mostly caused by geothermal acitivities and the combustion of fossil fuels such as coal and petroleum (Cullis and Hirschler, 1980). As is PM, SO_2 is also found to cause respiratory problems (Orellano, Reynoso and Quaranta, 2021). Lastly, NO_2 emissions are mostly caused by vehicular traffic (Kurtenbach et al., 2012) and are also found to have numerous negative health effects (Pandey, Kumar and Devotta, 2005; Khaniabadi et al., 2017).

Water Pollution Data Water pollution monitoring is another task of the CPCB. In the last years they have seen some massive growth in their monitoring network, with around 200 monitoring stations for surface and groundwater in 1986, about 870 in 2005 and 4111 monitoring stations in 2019 within the National Water Monitoring Programme (NWMP) (Central Pollution Control Board, 2020). The data set comprised by Greenstone and Hanna (2014) focuses on data from river monitoring stations as they argue that there the pollution ist most serious, the measurements are most consistent and they have the best coverage by public policy. The dataset provided includes 489 monitoring stations in 425 cities along 162 rivers in the years between 1986 and 2005.

In our analysis we focused on three main measurements for pollution: biochemical oxygen demand (BOD), dissolved oxygen (DO) and fecal coliforms (FColi). These three parameters were also chosen by Greenstone and Hanna (2014) because of their prevalence in other studies (Karn and Harada, 2001; Sharma et al., 2020) as well as the consistent reports of these pollution levels by the CPCB.

BOD is generally used to measure overall water quality. It describes the amount of biodegradable organic matter in water (Jouanneau et al., 2014). High levels of BOD can cause DO depletion and fishkills, thus having severe impacts on the environment (Penn, Pauer and Mihelcic, 2009). As BOD can have an impact of DO, we also look at the concentration levels of DO. Low levels of DO are a direct cause of high pollution levels (Waziri and Ogugbuaja, 2010), thus making DO a good indicator for general pollution as well. Lastly, FColi is a good indicator for waste water pollution with human feces (Hazen, 1988). FColi are also correlated with other pollution parameters, therefore making them a good candidate for a measure of domestic pollution as well. Greenstone and Hanna (2014) provide FColi as ln(number of bactria per 100ml) as the distribution of FColi is approximately ln normal.

Trends in Pollution Concentrations In figure 1 we visualized the overall trends of the different pollution measures as well as of the infant mortality rate. The first row shows the yearly means of the air pollution from 1987 to 2007, whereas the second row visulaizes the yearly means of the water pollution indicators in years from 1986 to 2005. Table 2 gives some summary statistics for the data we based our regression on.

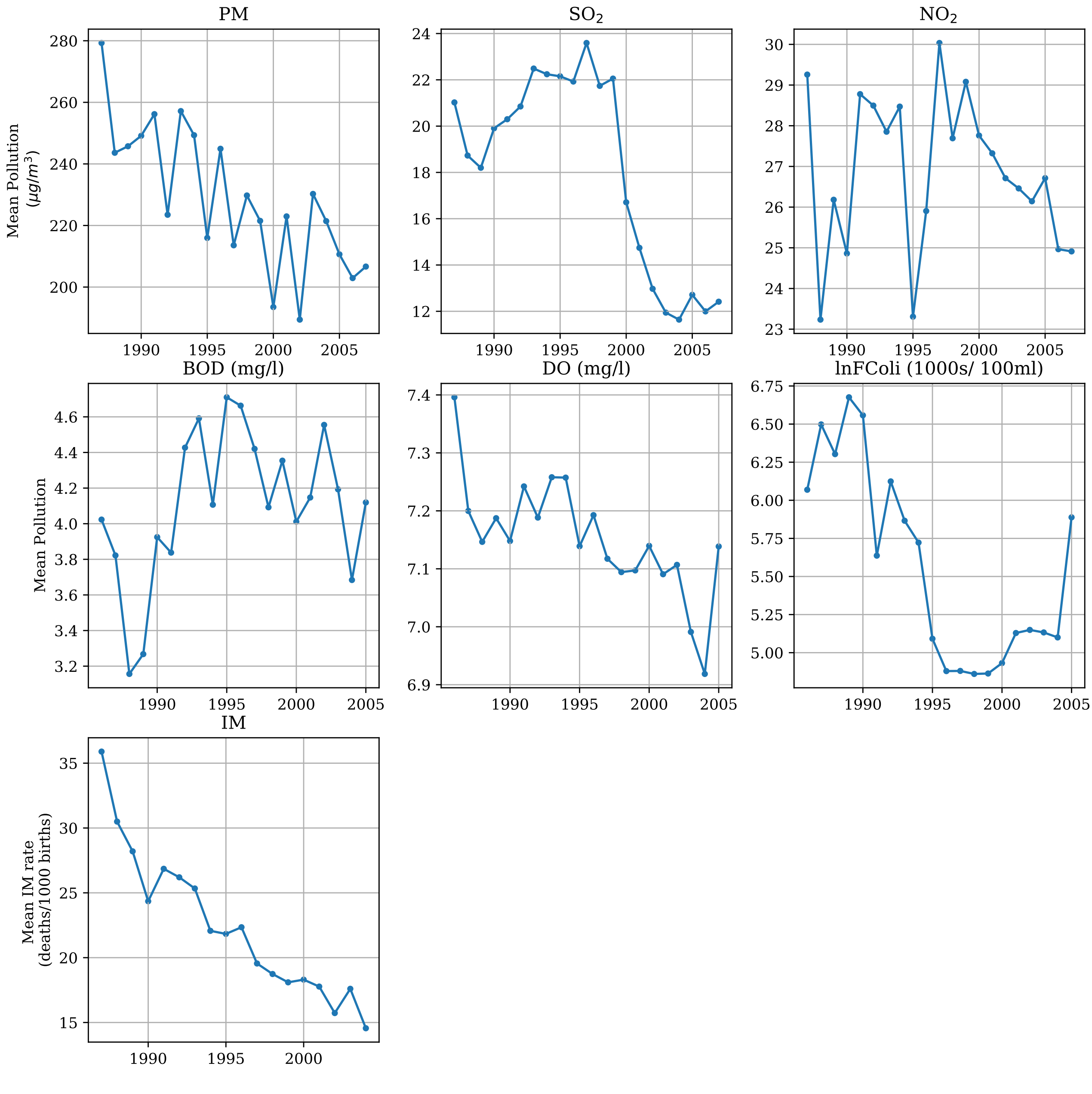

Figure 1: Overview of the time trends of all measurements

From the first row in Figure 1 we can see that the overall air pollution levels were generally on a downward trend. All of the air pollutants measured clearly reduced in the time frame from 1987 to 2007. While the mean of PM pollution in 1987-1990 was at around 252.1 microgram per cubic meter ($\mu g/m^3$), the mean of PM pollution levels in 2004 to 2007 reduced to about $209.4 \mu g/m^3$, a total reduction of around 17% in 17 years. SO_2 levels were rather constant in the first half of the time frame with a significant drop in 2000. In the first few years of our analysis mean SO_2 levels were

Table 2: Summary Statistics

Period	Air Pollution			Water Pollution			Infant Mortality
	SPM	SO_2	NO_2	BOD	DO	ln(FColi)	IM rate
Full Period							
Mean	223.2	17.3	26.8	4.2	7.1	5.4	23.5
Standard Deviation	114.0	15.2	18.0	8.0	1.3	2.7	22.1
Observations	1370.0	1344.0	1382.0	5948.0	5919.0	4985.0	1247.0
10th Percentile	90.9	4.0	10.0	0.8	5.7	1.9	3.4
90th Percentile	378.2	35.4	48.7	7.0	8.5	9.0	46.2
1987 – 1990							
Mean	252.1	19.4	25.5	3.5	7.2	6.5	29.6
Standard Deviationtd	126.4	13.3	21.5	6.7	1.2	2.3	31.4
Observations	120.0	116.0	117.0	806.0	813.0	634.0	358.0
10th Percentile	103.6	4.4	8.6	0.9	6.0	3.6	4.9
90th Percentile	383.5	38.2	42.6	5.7	8.4	9.5	55.3
2004 – 2007							
Mean	209.4	12.2	25.6	3.9	7.0	5.4	14.6
Standard Deviation	97.1	8.1	14.0	6.9	1.6	3.0	11.1
Observations	420.0	381.0	417.0	727.0	725.0	655.0	30.0
10th Percentile	92.8	4.0	10.4	0.9	5.4	1.6	2.1
90th Percentile	366.6	22.9	46.4	7.0	8.4	9.5	27.4

about $19.4\mu g/m^3$ with levels of about $12.2\mu g/m^3$ at the end of the period. This is a significant drop of more than 37%. Compared to the SO_2 measures the NO_2 levels were much more volatile. There are significant drops of pollution levels in 1988 and 1995. Therefore, the mean of the starting years of the period compared to the final years is not that significant. Comparing the years around the peak of NO_2 levels, 1996 to 1999, to the final years $2004 - 2007$ we get a drop of $2.6\mu g/m^3$ in total or 9%.

In addition to the declines in overall mean pollution levels we can also see changes in the 10th and 90th percentile. For SPM and SO_2 the 10th percentile declined by about 10% over the years from 1986 to 2007. However, the 90th percentile for SO_2 declined from $38.2\mu g/m^3$ to $22.9\mu g/m^3$, a staggering 40%, whereas the 90th percentile of the SPM pollution only declined by just over 4%, from $383.5\mu g/m^3$ to $366.6\mu g/m^3$. In opposition to this, the 90th percentile of the NO_2 pollution worsened and increased from $42.6\mu g/m^3$ to $46.4\mu g/m^3$, or by almost 10%, whereas the 10th percentile increased from $8.6\mu g/m^3$ to $10.4\mu g/m^3$ or about 21%.

For water pollution the trends are not as obvious. In Figure 1 we can see a increase in BOD levels in the first half of our time frame with a peak in 1995 and a slow downward trend in the years afterwards. Because of these two time trends, the comparison between the start and end period are not that meaningful. We see, however, that the mean increased from $3.5mg/l$ to $3.9mg/l$ or by 11%. This shows, that the decline in pollution levels after 1995 was not enough to combat the earlier rise. When comparing 1994 to 1997 with the final period, however, we see a decrease in BOD levels from $4.5mg/l$ to $3.9mg/l$ or by 13%. Nonetheless, the trend of the BOD levels is not that stable over the time period as can be seen by its very large standard deviation.

For the DO levels we observe a general downwards trend over time, which is in line with the overall rise of BOD, since they are negatively correlated and lower DO levels indicate a worse water quality. We are able to observe a decrease in the mean DO levels from $7.2mg/l$ to $7mg/l$ or by almost 3%. For FColi we see a much more significant drop than this, from 6.5 to 5.4.

Similar trends can be observed in the 10th and 90th percentile. The 10th percentile of the BOD measurements remained constant at $0.9mg/l$ at the beginning and the end of our time frame whereas the 90th percentile increased from $5.7mg/l$ to $7mg/l$ or about 23%. For DO the converse is true: While the 90th percentile stayed constant at $8.4mg/l$, the 10th percentile decreased from $6mg/l$ to $5.4mg/l$ or 10%. FColi has a similar behavior, with a constant 90th percentile amd a decrease on the 10th percentile from 3.6 to 1.6.

All of these ambiguous trends might rather suggest shifts in pollution levels between different measuring stations than overall time trends in pollution levels.

2.3 Infant Mortality Rate Data

For the years 1987-1995 Greenstone and Hanna (2014) used infant mortality data from Vital Statistics of India to compile their city-level data set. For later years they used data from the different registrar's offices from all of Indias states. However, since not all births and deaths are registered, this data might not be that accurate. As it is most likely for the deaths to get even less registered than the births, the infant mortality rate is assumed to be somewhat downward biased. The authors also explain that the data from the Vital Statistics of India is only one-third as the one measured by state level surveys, however, the overall trend of the different infant mortality measurements is still highly correlated, making both of them sufficient to test for the impacts of policies. They also state that it is reasonable to assume the measurement error to not be correlated with the different pollution measurements.

Infant mortality was chosen as a measure for the impact of pollution on health, as infants are more likely to respond to short term changes in pollution levels. In addition to this, infants are extremly sensitive to environmental changes when compared to adults.

Figure 1 reveals a significant downward trend in infant mortality rates. Starting with a mean of 29.6 deaths per 1000 live births in 1987 to 1990, infant mortality fell by about 45% over the years of our analysis to a level of only 16.4 deaths per 1000 live births in 2001 to 2004. The 10th and the 90th percentile also reflect this trend. The 10th percentile fell from 4.9 deaths per 1000 live births to 2.1 deaths per 1000 live births and the 90th percentile reduced from 55.3 deaths per 1000 live births to 27.4 deaths per 1000 live births.

2.4 Newspaper Pollution Refrences

To get a measure for demand for clean air and water, Greenstone and Hanna (2014) used mentions of 'air pollution' and 'water pollution'in the Times of India, one of Indias biggest newspapers. They used the searchable library database of the University of Pennsylvania to get their data for years 1986 to 2003 and for later years made use of the Times of India's online searchable database.

3 Methodological Approach

In this section we will discuss the theoretical ideas behind the main part of our analysis. The core of the analysis done in this paper is a regression done in two stages to gain some insights on whether or not three of India's regulatory policies had any effect on air and water pollution levels. The first stage of our regression is an event-style equation of the following form:

$$Y_{ct} = \alpha + \sum_{\tau} \sigma_{\tau} D_{\tau,ct} + \mu_t + \gamma_c + \beta X_{ct} + \varepsilon_{ct}. \tag{1}$$

In this regression, Y_{ct} will either hold one of the six measures of pollution or the infant mortality rate in city c in year t. In Figure 1 we can observe an overall time trend in all of the seven measurements we are interested in. To keep this trend from distorting our regression result we control for it by including the year fixed effects μ_t into our equation. Similarly, we also include a control for the city fixed effects

γ_c. We also use urban literacy rates as X_{ct} from city c in year t to control for differential rates of growth across districts. The urban versions of these measurements are used here instead of the measurements from the whole district as data from rural areas is not always available.

The variable τ in the indices describes the year with respect to the first year the policy comes into force in city c. It is normalized such that it equals zero in the year the policy is first enacted and can range from -17 (for 17 years before the policy starts) to 12 (representing 12 years after the policy's adoption). For nonadopting cities we set all τ's to be equal to zero, so formally they are always in the first year of the policy's adoption.

The variable $D_{\tau,ct}$ indicates whether or not the policy we are currently examining is in force in city c in year t, i.e. if $\tau \geqslant 0$ in year t.

In this paper we are especially interested in the σ_τ's, which indicate the impact of a policy on annual pollution levels before and after the policy came into force. By including the variables μ_t and γ_c into our regression we are able to control for national pollution trends in our estimation. As not all cities implement the policies in the same year, using the τ's allows us to estimate the impact of the different policies over the years more accurately.

The resulting estimates for the different σ_τ's are visualized in Figures 2, 3 and 5 where they are plotted against the respective τ's.

For the estimation of Equation (1) not all cities were used. Cities adopting the policy were only included in the regression, if there was at least one observation from three or more years before the start of the policy (i.e. $\tau \leqslant 3$) and at least one measurement after the policy was already in place (i.e. $\tau \geqslant 0$). Cities that did not adopt the policy were only included in the regression if there were at least two pollution measurements included in the data set.

With the second step of the regression we want to test whether or not the policies are actually related to the reduction in emissions or not. To do this, we used three different approaches. We first looked for a linear relationship between the implementation of emission policies and the impact on pollution levels, using

$$\hat{\sigma}_\tau = \pi_0 + \pi_1 \mathbb{1}(\text{Policy})_\tau + \varepsilon_\tau \tag{2A}$$

as our regression equation. By $\mathbb{1}(\text{Policy})_\tau$ we denote an indicator variable that specifies whether or not the policy is in effect at that τ, that is, $\mathbb{1}(\text{Policy})_\tau = 1$ if $\tau \geqslant 0$. With π_1 we therefore test for a mean shift of the pollution levels after the policy came into force.

Looking at the results from the regression on Equation (1), we can see that even before the policies were implemented they had some impact on pollution levels that cannot be fully be explained by city or year fixed effects. To examine those we augment equation (2B) to also account for a linear time trend and get the following equation:

$$\hat{\sigma}_\tau = \pi_0 + \pi_1 \mathbb{1}(\text{Policy})_\tau + \pi_2 \tau + \varepsilon_\tau. \tag{2B}$$

Most of the policies also are not just a one year thing. The SCAP for example includes measures for polluters to take over multiple years to reduce their emission. So just controlling for a linear time trend might not be enough for all policies. We therefore again augment our regression Equation (2A) to not only include controls for a time trend but also for a policy trend evolving over time. In the end we thus get an equation of the following form:

$$\hat{\sigma}_\tau = \pi_0 + \pi_1 \mathbb{1}(\text{Policy})_\tau + \pi_2 \tau + \pi_2 (\mathbb{1}(\text{Policy})_\tau \cdot \tau) + \varepsilon_\tau \tag{2C}$$

While we are focusing on the two-step approach for our analysis here, we also do a one-stage approach of estimating Equation (2C). To get the regression equation of the one-stage approach that is equivalent to the two step approach, we simply combine Equations (1) and (2C) to get the final regression equation used in our analysis.

$$Y_{ct} = \alpha + \sum_\tau \big(\pi_0 + \pi_1 \mathbb{1}(\text{Policy})_\tau + \pi_2 \tau + \pi_2 (\mathbb{1}(\text{Policy})_\tau \cdot \tau) + \varepsilon_\tau\big) D_{\tau,ct} + \mu_t + \gamma_c + \beta X_{ct} + \varepsilon_{ct} \tag{3}$$

For all of our regression models we used an ordinary least squares approach to numerically compute the estimates.

4 Results

4.1 Effects of Policies on Air Pollution

In Figure 2 we visualize the results of the regression on the event study style Equation (1). The first column presents the estimated effects of the Supreme Court Action Plan (SCAP) on air pollution whereas the second column visualizes the estimated effects of the Catalytic Converter (CatConv) policy. We marked the year the policies came into force, $\tau = 0$, by a vertical dashed line in all figures. We also normalised all of the results such that the effect of the policy in the year prior to the starting year, $\tau = -1$, which we marked by a vertical dashed line in the figures. This was done to allow an easier visual analysis of the results, as change in emissions compared to $\tau = -1$ now can be depicted by positive or negative values.

We used the graphs of Figure 2 to get an idea of the patterns of the data and to identify which of the equations (2A), (2B) and (2C) will be best to explain the relationships of the policies and the impacts on pollution. We can easily see that the parallel trends assumption of the difference-in-differences model (Equation (2A)) is violated and we therefore need to amend the model to take into account different trends in adopting and non adopting cities. One particular case of this violation is the introduction of catalytic converters in Indian cities with worsening pollution levels.

Although we see different trends between adopting and non-adopting cities, there is no evidence for a mean reverting process in any of the three pollution measurements, as there is no symmetry noticeable around a mean pollution level.

All of the graphs suggest that Equations (2B) and (2C) will probably be better in explaining the different impacts of the policies on pollution levels. However, from the graphs it is not clear whether or not the policies are good in reducing the pollution concentrations. While the CatConv Policy seems to be effective in reducing the upwards trend in PM levels, our results suggest it to be ineffective with regards to SO_2 and NO_2 levels. On the other hand, the SCAP seems to be effective for to SO_2 levels but it is not clear whether it is effective regarding NO_2 levels and it does seem to be ineffective when it comes to PM levels.

In Table 3 we present the more formal findings of the second stage regression regarding the impacts of the policies on pollution levels. For each policy, the first column reports the estimated value of π_1 from Equation (2A). This value shows whether or not the average of σ_τ is lower after the policy is implemented. The second column provides the estimates for π_1 and π_2 from our regression using Equation (2B). In this equation, π_1 estimates the impact of a policy after we control for a trend in pollution levels, which is measured by π_2. In the third column we report the results from our regression of Equation (2C). This equation includes a mean shift (π_2) as well as a trend break after the policy came into force. We also report the five year effect ($\pi_1 + 5\pi_3$). In the fourth column of each policy we report the results of the one-step version of the regression on Eqiation (3).

The first four columns of table (1) show that the SCAP does not have significant efffects on air pollution. Our analysis only resulted in rather unclear impacts of the SCAP on PM levels and found no significance of the impact of the SCAP on SO_2 levels, eventhough the regression fit was rather good, especially for SO_2 levels . However, our results might imply some effect on NO_2 pollution. Our regression found an estimated reduction of NO_2 levels of $8.51\mu g/m^3$. These results are not that significant though. Greenstone and Hanna (2014) found much more concrete effects with their analysis. This indicates that their model might be better suited for this analysis as they also controlled for the effects of the CatConv policy while regressing on the SCAP policy. We did not manage to include this additional control in our analysis.

The last four columns of Table 1 imply the reverse for the catalytic converter policy. As discussed before we expect Equations (2B) and (2C) to be the best at explaining the relationship of the policy to the reduction emission. As the policy is dependent of a change in the stock of vehicles it is reasonable to assume (2C) will be best in explaining the relationship as it takes this time trend into account. We find significant impacts of the policy on PM and SO_2 pollution, wheras the results for NO_2 are not significant. We estimate the CatConv policy to reduce PM concentrations by $67.63\mu g/m^3$ over a 5 year period, or about 27% compared to mean pollution levels from 1987 to 1990. Our model also estimates the 5 year effect of the CatConv policy on SO_2 levels to be a reduction of $10.32\mu g/m^3$ or 40% compared

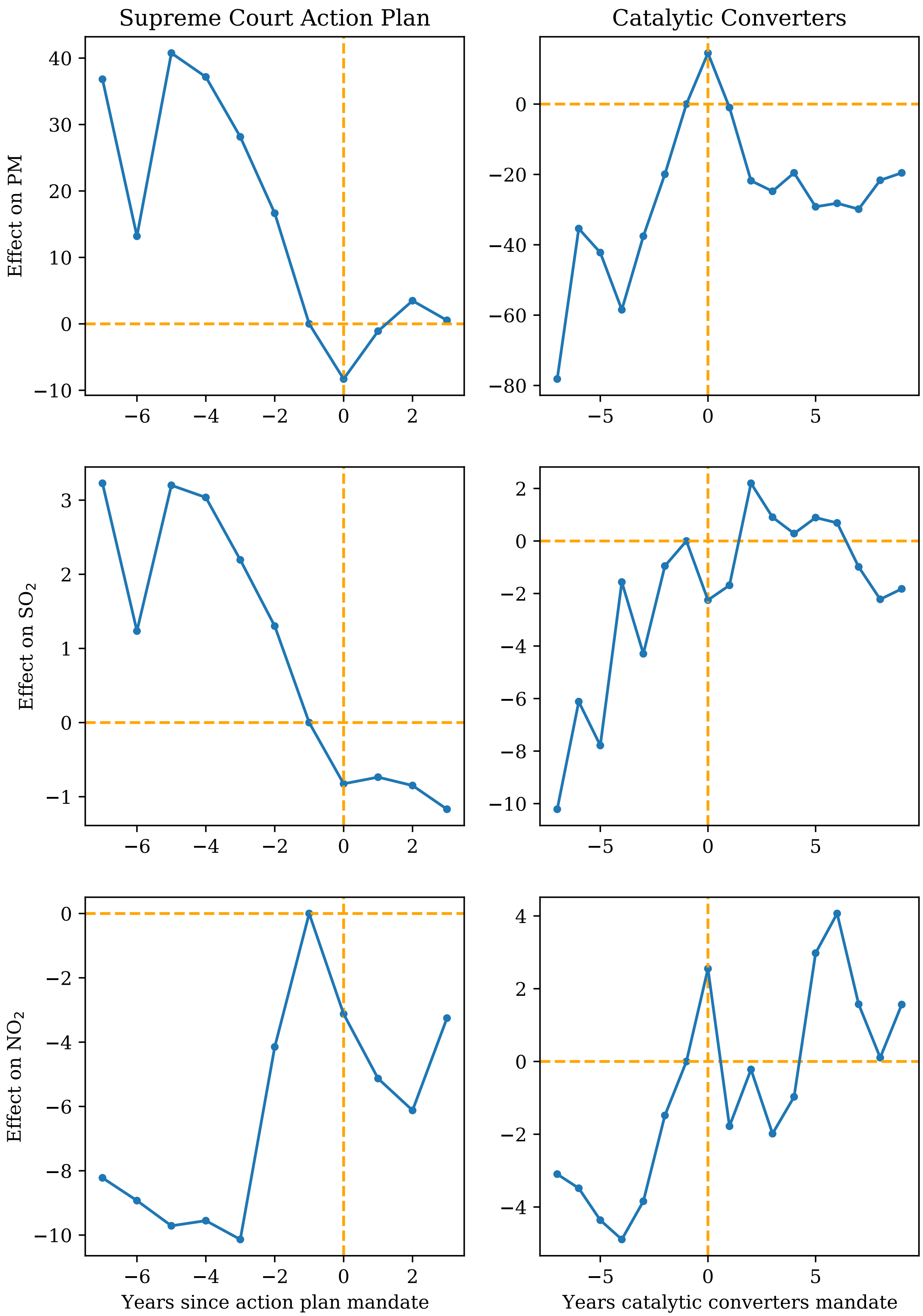

Figure 2: Sigmas of the air regression

Table 3: These are the results from the regression on the different air pollution measurements.

	Supreme Court Action Plans				Catalytic Converters			
	(2A)	(2B)	(2C)	(3)	(2A)	(2B)	(2C)	(3)
PM								
π_1: $\mathbb{1}$(Policy)	-26.02	-9.25	-14.09	5.92	20.72	19.62	-3.91	-29.34
	7.97	13.71	13.67	20.50	9.54	18.96	13.45	15.30
π_2: τ		-3.05	-4.15	-5.83		0.13	9.64	9.60
		2.09	2.17	3.22		1.91	2.47	2.91
π_3: $\mathbb{1}$(Policy)$\times\tau$			7.26	6.34			-12.74	-11.17
			5.58	11.92			2.86	3.59
5-year effect			22.18	37.62			-67.63	-85.18
p-Value			0.45	0.50			0.01	0.00
R^2	0.54	0.64	0.71	0.72	0.24	0.24	0.70	0.73
Observations	11.00	11.00	11.00	1241.00	17.00	17.00	17.00	1258.00
SO_2								
π_1: $\mathbb{1}$(Policy)	-2.92	-1.07	-1.24	-0.09	4.02	1.21	-1.90	0.40
	0.63	0.95	1.02	3.51	1.33	2.50	1.78	2.52
π_2: τ		-0.34	-0.38	-0.50		0.33	1.59	0.94
		0.14	0.16	0.55		0.25	0.33	0.49
π_3: $\mathbb{1}$(Policy)$\times\tau$			0.26	0.26			-1.68	-1.22
			0.42	2.05			0.38	0.60
5-year effect			0.07	1.20			-10.32	-5.69
p-Value			0.97	0.90			0.00	0.21
R^2	0.70	0.82	0.83	0.58	0.38	0.45	0.78	0.58
Observations	11.00	11.00	11.00	1219.00	17.00	17.00	17.00	1244.00
NO_2								
π_1: $\mathbb{1}$(Policy)	2.83	-2.68	-1.79	-5.20	3.81	1.39	0.87	-3.60
	2.00	3.10	3.22	4.01	0.96	1.74	1.93	2.93
π_2: τ		1.00	1.21	1.47		0.29	0.49	1.12
		0.47	0.51	0.63		0.18	0.35	0.56
π_3: $\mathbb{1}$(Policy)$\times\tau$			-1.34	-0.51			-0.28	-0.66
			1.31	2.34			0.41	0.69
5-year effect			-8.51	-7.77			-0.52	-6.92
p-Value			0.23	0.47			0.88	0.18
R^2	0.18	0.48	0.55	0.61	0.51	0.59	0.61	0.60
Observations	11.00	11.00	11.00	1256.00	17.00	17.00	17.00	1274.00

to levels in the starting period of our analysis. The results from the equivalent one-stage results are similar to the two-stage results from our analysis. However, the estimated 5 year effect of the CatConv policy on NO_2 concentrations is not significant. Our findings are generally in line with the results of Greenstone and Hanna (2014), with minor differences that can be explained by our slightly different regression model as well as possible differences in the numerical computation of the regression.

4.2 Effects of Policies on Water Pollution

In Figure 3 we visualize the results from the regression of Equation (1) of the National River Conservation Plan (NRCP) on BOD, ln(FColi) and DO. The different graphs are formatted as before, with the results being normalised such that the change of pollution concentrations equal zero at $\tau = -1$. The different graphs imply a general lack of success of the NRCP in reducing pollution concentrations. While there is evidence for the water pollution levels to reduce in the years prior to the policy, there is no evidence for a reduction in emission levels after the policy was enacted.

As before with air pollution levels we see that the parallel trends assumption of the simple difference-in-differences model is violated, thus indicating Equations (2B) and (2C) to be better suited for the analysis of the impact of the NRCP on pollution concentrations.

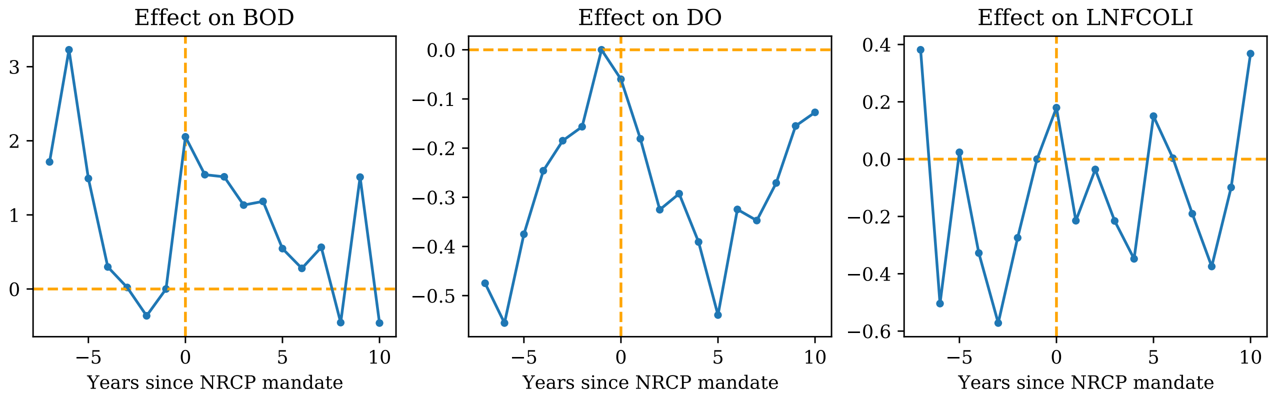

Figure 3: Sigmas of the water regression

Table 2 reports the results of our analysis of the effect of the NRCP on emissions level. We found no significant impact of the policy on the concentration of FColi bacteria, but there were significant effects of the concentrations of BOD and DO. However, these significant impacts all were negative with for the environment. We found a rise in BOD levels of $4.38 mg/l$ over 5 years correlated with the implementation of the NRCP. We also estimated the NRCP to be directly connected to a 5 year decrease of $0.77 mg/l$ in DO concentrations. (Note that a decrease in DO levels has negative effects on the environment.) While these results seem to be significant, it is likely for our regression process to be flawed. As it takes a lot of time to construct new sewage systems to combat water pollution, the policy probably did not have an effect on pollution levels right after it came into force. In addition to this, there could have been a natural upwards trend in pollution levels caused by other factors, such as urbanization and industrialization (Halder and Islam, 2015; Sahoo and Sethi, 2020).

4.3 Structural Break Test

In the previous sections we presented the results from our difference-in-differences style approach to assess the impacts of the different environmental regulations on pollution levels. We now want to test the data for structural breaks to complement our DiD approach. The Chow test we decided on for this tests whether or not there is a point in time, where it is possible to split the regression model into two differet models with significantly different estimation results for the coefficients.

We again used Equation (2C) for this structural break test, as this equation had the best fit on our model. The first step of this test is again the regression of Equation (1). We then use these estimation results and Equation (2C) to check for each τ whether or not there is significant evidence for the results

Table 4: Results from the water pollution regressions.

	NRCP			
	(2A)	(2B)	(2C)	(3)
BOD				
π_1: $\mathbb{1}$(Policy)	-0.06	2.19	2.85	1.26
	0.50	0.67	0.68	0.78
π_2: τ		-0.25	-0.49	-0.18
		0.06	0.13	0.15
π_3: $\mathbb{1}$(Policy)$\times\tau$			0.31	0.02
			0.14	0.18
5-year effect			4.38	1.37
p-Value			0.00	0.33
R^2	0.00	0.51	0.63	0.76
Observations	18.00	18.00	18.00	5852.00
DO				
π_1: $\mathbb{1}$(Policy)	0.01	-0.14	-0.33	-0.43
	0.08	0.14	0.12	0.15
π_2: τ		0.02	0.09	0.08
		0.01	0.02	0.03
π_3: $\mathbb{1}$(Policy)$\times\tau$			-0.09	-0.07
			0.03	0.03
5-year effect			-0.77	-0.77
p-Value			0.00	0.00
R^2	0.00	0.09	0.51	0.68
Observations	18.00	18.00	18.00	5832.00
ln(FColi)				
π_1: $\mathbb{1}$(Policy)	0.11	0.14	0.26	-0.33
	0.13	0.26	0.29	0.31
π_2: τ		-0.00	-0.05	0.08
		0.02	0.05	0.06
π_3: $\mathbb{1}$(Policy)$\times\tau$			0.05	-0.06
			0.06	0.07
5-year effect			0.52	-0.61
p-Value			0.32	0.28
R^2	0.04	0.04	0.09	0.71
Observations	18.00	18.00	18.00	4929.00

of the different models to be different. We specified in our analysis for each of the periods to have at least two observations.

We visualized our findings of the CatConv policy in figure 4. In contrast to the findings of Greenstone and Hanna (2014) we did not find sufficient evidence for structural breaks in the data. While there is some evidence that might suggest a structural break right around the time the CatConv policy was implemented, these results are not significant. This different in results might be caused by Greenstone and Hanna (2014) having a better fit of Equation (1) in their regression, due to more controls.

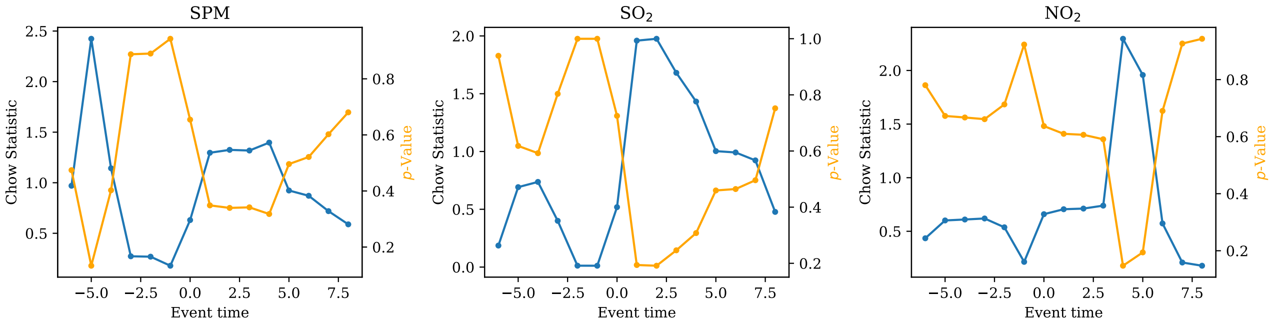

Figure 4: Chow Statistics and corresponding p Values

4.4 Effects of Policies on Infant Mortality

We found the CatConv Policy to have the most impact on air pollution levels. We will now take a closer look into whether or not the policy has a significant effect on infant mortality as well, thereby measuring its effect on human health.

To do this we again first fit Equations (1) with the IM rate as the outcome and then Equations (2A), (2B), (2C). We also fit Equation (3) to get a comparison of the two stage approach two the equivalent one stage version of (2C). There are several things to note here. Despite the data set containing the infant mortality rates being rather large, only a fraction of the measurements can be used here, as the data set for the pollution measurements is not as extensive.

Figure 5 and Table 5 depict the results from the regression. From the graph in Figure 5 we see that the CatConv policy is able to decrease the im rate in the years after it was implemented. We can also see such an decrease happening before the policy came into force. However, Table 5 disputes these results. Our regression yields a significant negative impact on IM rates, which probably indicates a flaw in our regression. The results from Greenstone and Hanna (2014) solidify this assumption. While their results were not statistically significant, they still found the CatConv policy to lower the IM rate.

5 Why Were the Air Pollution Policies More Effective than the Water Pollution Policies?

As discussed above, our analysis finds the air pollution policies to be much more effective than the water pollution regulations. We now want to try and explain why that might be. This section argues that the different successes of the different policies come from a greater public demand for air pollution regulations than for water pollution regulations.

The most obvious cause for a higher demand for good air quality are higher costs connected with high levels of air pollution. As stated in the beginning, air pollution can have major negative health impacts (Lin et al., 2013; Greenstone et al., 2015; Brook et al., 2004). Air pollution was found to be the cause of 3.1 million deaths in 2010, whereas unimproved water pollution levels only accounted for 300.000 deaths in the same year worldwide (Lim et al., 2012). While water pollution still poses a significant threat to health (Wu et al., 1999), the problem of air pollution is much more pressing.

Another reaso similar to the first one might be lower avoidance costs for water pollution. Especially middle and upper classes can have an impact on the environment as they are able to make higher

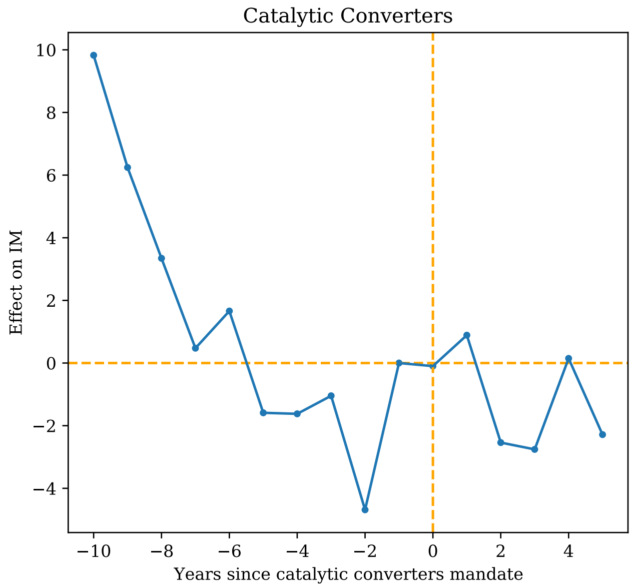

Figure 5: Sigmas of the CAT regression on IM rate

Table 5: Trend Break Estimates of the Effect of the Catalytic Converter Policy on Infant Mortality

	(2A)	(2B)	(2C)	(3)
π_1: $\mathbb{1}$(Policy)	-2.37	6.02	5.14	2.67
	1.82	2.12	2.14	2.47
π_2: τ		-1.05	-1.19	-0.67
		0.22	0.24	0.27
π_3: $\mathbb{1}$(Policy)$\times\tau$			0.81	0.31
			0.56	0.82
5-year effect			9.18	4.22
p-Value			0.01	0.28
R^2	0.11	0.67	0.72	0.71
Observations	16.00	16.00	16.00	1207.00

demands due to their higher consumption (Buch, 1993). For these classes it is much easier to avoid contaminated water. For example, bottled water consumption in India has tripled in the years 1999 to 2004 (Arnold and Larsen, 2006). However, air pollution is not as easily avoided. Studies show that driving in polluted areas can have a negative impact on ones health (Geng et al., 2021) and it is not surprising that simply being outside in polluted areas has severe negative effects on health, since the exposure to air pollution is much greater. Even staying inside is not save, as air pollution is also noticeable in houses as found by Lawrence and Fatima (2014).

In addition to all of this, air pollution is becoming more and more visible. With an increase in smog coverage in India and worse visibility (Jaswal et al., 2013; Shabbir, Junaid and Zahid, 2019), the decrease in air quality in India is all apparent.

Air pollution seems to be much more in the public eye as water pollution. As Figure 6 shows, there is a large difference in media coverage of air and water pollution. In fact, the coverage of air pollution in the Times of India in years 1986 to 2007 is about three times as high as the coverage for water pollution. Especially after 1995 the coverage on air pollution increased dramatically, whereas the water pollution mentions stayed more or less constant over the whole 30 year period. We assume these mentions to be roughly in line with the demand for better air quality in India. However, while this assumption is reasonable it is not clear whether or not there are other factors correlated with the media coverage of these different pollutions.

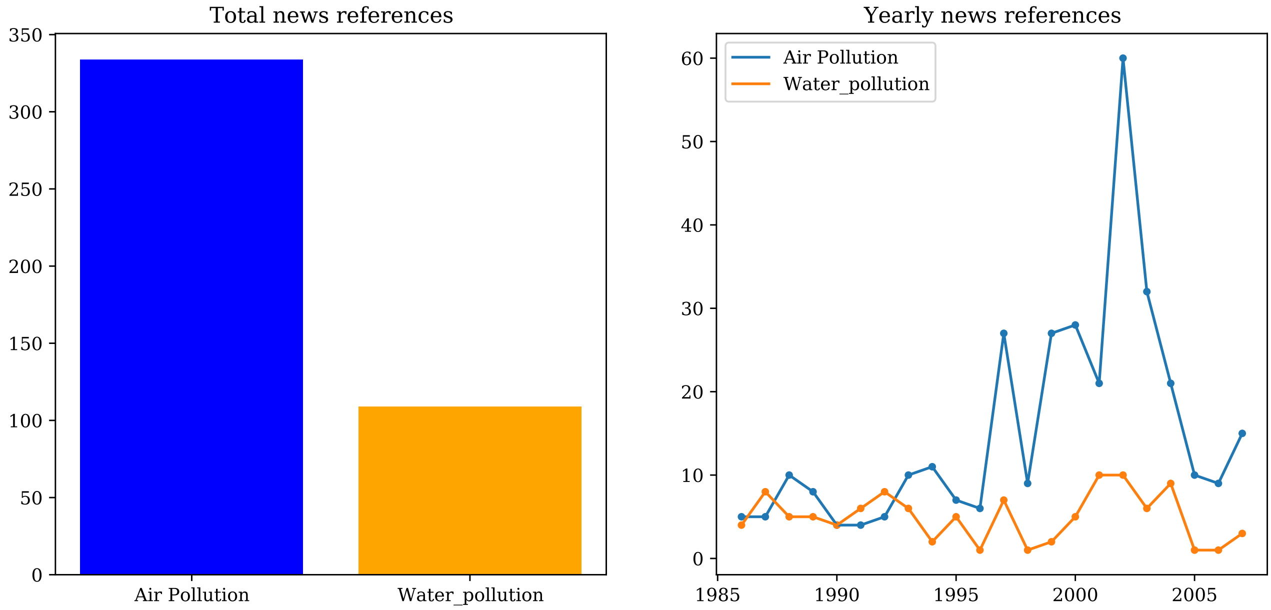

Figure 6: News references to air and water pollution in India.

Lastly, there are severe differences in the implementation of the air and water regulations. First, from the beginning there was no clear approach to implementing the NRCP, as no orgaisation alone was responsible for the implementation, but this responsibility was spread across multiple different institutions (Ministry of Environment and Forests, 2006). In addition to this, the planned actions for decreasing water pollution, such as building new sewage systems, were costly but no institution felt responsible for funding these constructions and there was the allegation of financial mismanagement and incorrect reporting (Ministry of Environment and Forests, 2006).

The air pollution regulations generally had similar problems as the NRCP. However, they were largely backed by Indias supreme court. This is an enormous difference and a significant advantage for the air pollution policies, as the supreme court determines when there have been major human rights violations. These determinations can then be used to compel institutions and organisations to comply with the policies, which otherwise would not be possible. Many of the supreme court's decisions have been motivated by inaction from the government or the respective institutions tasked with the implementation of the different policies.

In 1996 the supreme court ruled for Delhi to decide on an action plan to reduce pollution levels in the city. Following that order, it was decided to create an institution to help the supreme court to keep an eye on the implementation of the decided environmental regulations. After this order was successful in Delhi, other initiatives followed to further reduce pollution levels. All of this in the end led to the introduction of regional supreme court action plans and the mandate for catalytic converters in vehicles as well as other regulations.

In conclusion we find that the actions of the supreme court, motivated by a large public demand, had a significant impact on the success of the different air pollution policies. In contrast, the water pollution regulations were not backed by jurisdictions as much and therefore were not able to succeed as planned.

6 Conclusion

Using the data set compiled by Greenstone and Hanna (2014) we largely followed their analysis by investigating the effects of three policies on air and water pollution as well as infant mortality, and thus human health, in India. We found a significant connection between air pollution policies and improvements in air quality. However, our analysis did not suggest that the air pollution policy with the biggest impact on air pollution levels also had an impact on infant mortality rates. On the other hand, we did not find the NRCP to have had a significant positive impact on water pollution levels.

Generally, we found that even in countries with weak institutions it is possible for regulations to seucceed. However, this is dependent on the respective population. It is to be assumed that without a large media coverage and a large initiative for the public to exert pressure on the governmental institutions, most policies will fail. Thus, it is reasonable to assume that India and many other developing countries will only act successfully on stopping climate change, when the related global problems become local ones as well. As long as the respective population does not pay attention to these kinds of problems, it is to be expected for policies regarding these issues to fail. This in turn would imply a general obstacle in the fight against climate change, as many countries would not be able to act early enough to stop larger catastrophies from happening. Lastly, we did not manage to presentsignificant results on whether or not the implemented policies in India were successful in positively impacting the health of the population.

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