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

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Using the most comprehensive developing country dataset ever compiled on air and water pollution and environmental regulations, the paper assesses India's environmental regulations with a difference-in-differences design. The air pollution regulations are associated with substantial improvements in air quality. The most successful air regulation resulted in a modest but statistically insignificant decline in infant mortality. In contrast, the water regulations had no measurable benefits. The available evidence leads us to cautiously conclude that higher demand for air quality prompted the effective enforcement of air pollution regulations, indicating that strong public support allows environmental regulations to succeed in weak institutional settings. (*JEL* I12, J13, O13, Q53, Q58)

Weak institutions are a key impediment to advances in well-being in many developing countries. Indeed, an extensive literature has documented many instances of failed policy in these settings and has been unable to identify a consistent set of ingredients necessary for policy success (Banerjee, Duflo, and Glennerster 2008; Duflo et al. 2012; Banerjee, Hanna, and Mullainathan 2013). The specific question of how to design effective environmental regulations in developing countries with weak institutions is increasingly important for at least two reasons.[1] First, "local" pollutant concentrations are exceedingly high in many developing countries and in many instances are increasing (Alpert, Shvainshtein, and Kishcha 2012). Further, the high pollution concentrations impose substantial health costs, including shortened lives (Chen et al. 2013; Cropper 2010; Cropper et al. 2012), so understanding the most efficient ways to reduce local pollution could significantly improve well-being.

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[1] There is a large literature measuring the impact of environmental regulations on air quality, with most of the research focused on the United States. See, for example, Chay and Greenstone (2003, 2005), Greenstone (2003, 2004), Henderson (1996), and Hanna and Oliva (2010), etc. The institutional differences between the United States and many developing countries mean that the findings are unlikely to be valid for predicting the impacts of environmental regulations in developing countries.

Second, the Copenhagen Accord makes it clear that it is up to individual countries to devise and enforce the regulations necessary to achieve their national commitments to combat global warming by reducing greenhouse gas emissions (GHG). Since most of the growth in GHG emissions is projected to occur in developing countries, such as India and China, the planet's well-being rests on the ability of these countries to successfully enact and enforce environmental policies.

India provides a compelling setting to explore the efficacy of environmental regulations for several reasons. First, India's population of nearly 1.2 billion accounts for about 17 percent of the world's population. Second, it has been experiencing rapid economic growth of about 6.4 percent annually over the last two decades, placing significant pressure on the environment. For example, panel A of Figure 1 demonstrates that ambient particulate matter concentrations in India are five times the United States' level (while China's are seven times the US level) in the most recent years with comparable data, while panel B of Figure 1 shows that water pollution concentrations in India are also higher. Further, a recent study concluded that India currently has the worst air pollution out of the 132 countries analyzed (Environmental Performance Index 2013). Third, India is widely regarded as having suboptimal regulatory institutions; identifying which regulatory approaches succeed in this context would be of great practical value. More generally, since the air and water regulations were implemented and enforced in different manners, a comparison of their relative effectiveness can shed light on how to design policy successfully in weaker regulatory contexts. Fourth, India has a rich history of environmental regulations that dates back to the 1970s, providing a rare opportunity to answer these questions with extensive panel data.[2]

This paper presents a systematic evaluation of India's environmental regulations with a new city-level panel data file for the years 1986–2007 that we constructed from data on air pollution, water pollution, environmental regulations, and infant mortality. The air pollution data comprise about 140 cities, while the water pollution data cover 424 cities (162 rivers). Neither the government nor other researchers have assembled a city-level panel database of India's antipollution laws, and we are unaware of a comparable dataset in any other developing country.

We consider two key air pollution policies: the Supreme Court Action Plans and the Mandated Catalytic Converters, as well as India's primary water policy, the National River Conservation Plan, which focused on reducing industrial pollution in rivers and creating sewage treatment facilities.[3] These regulations resemble environmental legislation in the United States and Europe, thereby providing a comparison of the efficacy of similar regulations across very different institutional settings. We test for the effect of these programs using a difference-in-differences style design in order to account for potential differential selection into regulation. Importantly, we

[2] Previous papers have compiled datasets for a cross-section of cities or a panel for one or two cities, including Foster and Kumar (2008; 2009), which examines the effect of CNG policy in Delhi; Takeuchi, Cropper, and Bento (2007), which studies automobile policies in Mumbai; Davis (2008), which looks at driving restrictions in Mexico; and Hanna and Oliva (2011), which studies a refinery closure in Mexico City.

[3] We also documented other anti-pollution efforts (e.g., Problem Area Action Plans, and the sulfur requirements for fuel), but they had insufficient variation in their implementation across cities and/or time to allow for a credible evaluation.

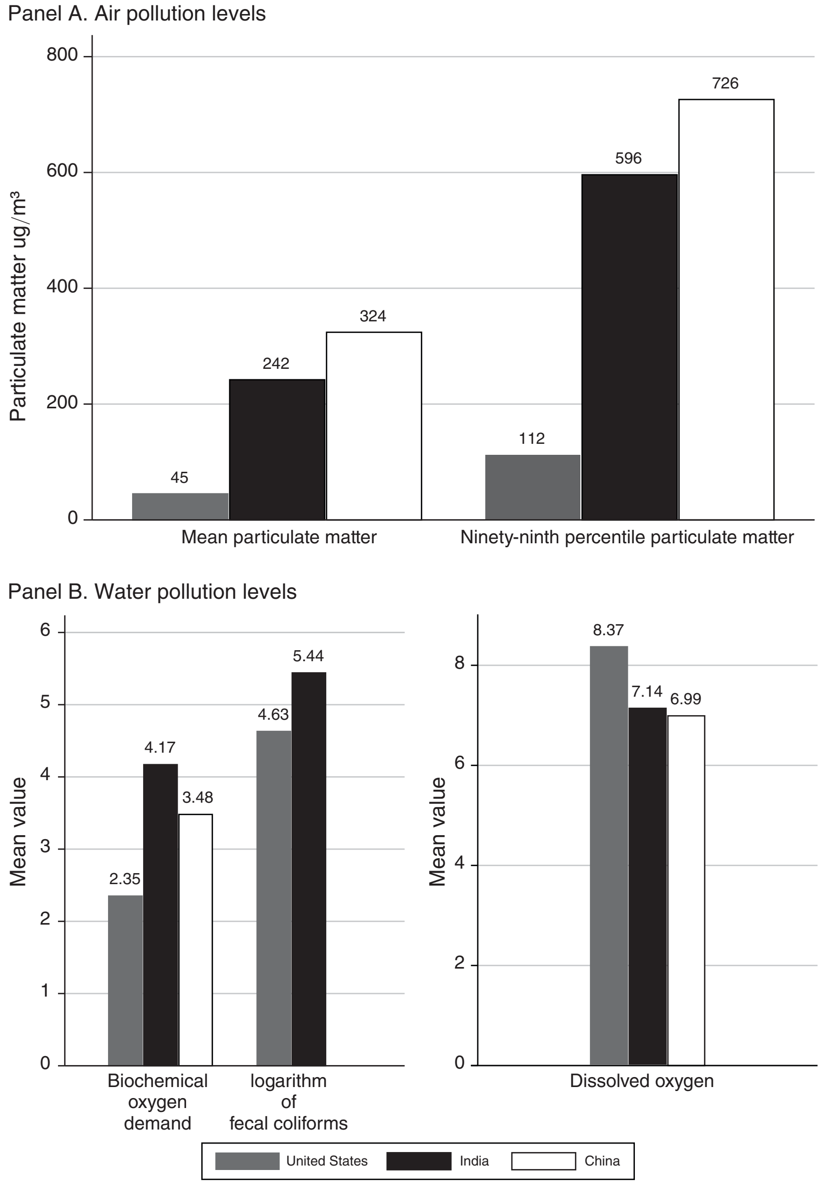

Figure 1. Comparison of Pollution Levels in India, China, and the United States

Notes: In panel A, the air pollution values are calculated from 1990–1995 data. For India, only cities with at least seven years of data are used. In panel B, water pollution values for India and the United States are calculated from 1998–2002 data. For India, only city-rivers with at least seven years of data are used. Pollution values for China are calculated across six major river systems for the year 1995 and are weighted by a number of monitoring sites within each river system. Fecal coliform data for China were unavailable. "Particulate matter" refers to all particles with diameter less than 100μm, except in the case of the United States, where particle size is limited to diameter less than 50μm. Units are mg/l for biochemical oxygen demand and dissolved oxygen. For logarithm of fecal coliforms, units are the most probable number of fecal coliform bacteria per 100 ml of water or MPN/100ml. An increase in biochemical oxygen demand or fecal coliforms signals higher levels of pollution, while an increase in dissolved oxygen signals lower levels of pollution. Indian pollution data (both air and water) were drawn from the Central Pollution Control Board's online and print sources. Data for the United States (both air and water pollution) were obtained from the United States Environmental Protection Agency. Air pollution data for China came from the World Bank and China's State Environmental Protection Agency. Doug Almond graciously provided these data. Chinese water pollution data come from the World Bank; Avi Ebenstein graciously provided them.

additionally control for potential, preexisting differential trends in pollution among those who have and have not adopted the policies.

The analysis indicates that environmental policies *can* be effective in settings with weak regulatory institutions. However, the effect is not uniform, as we find a large impact of the air pollution regulations, but no effect of the water pollution regulations. In the preferred econometric specification that controls for city fixed effects, year fixed effects, and differential preexisting trends among adopting cities, the requirement that new automobiles have catalytic converters is associated with large reductions in airborne particulate matter with diameter less than 100 micrometers (μm) (PM) and sulfur dioxide (SO_2) of 19 percent and 69 percent, respectively, five years after its implementation. Likewise, the supreme court-mandated action plans are associated with a decline in nitrogen dioxide (NO_2) concentrations; however, these policies are not associated with changes in SO_2 or PM. In contrast, the National River Conservation Plan—the cornerstone water policy—was not associated with improvements in the three available measures of water quality.

As a complement to these results, we adapt a Quandt likelihood ratio test (Quandt 1960) from the time-series econometrics literature to the difference-in-differences (DD) style setting to probe the validity of the findings. Specifically, we test for a structural break in the difference between adopting and nonadopting cities' pollution concentrations and assess whether the structural break occurs around the year of policy adoption. The analysis finds evidence of a structural break in adopting cities' PM and SO_2 concentrations around the year of adoption of the catalytic converter policy and no breaks in the time-series that correspond to cities' adoption of the National River Conservation Plan. In addition to these substantive findings, this demonstrates the value of this technique in DD-style settings.

A mix of qualitative and quantitative evidence leads us to cautiously conclude that the striking difference in the effectiveness of the air and water pollution regulations reflects a greater demand for improvements in air quality by India's citizens. Higher demand for cleaner air is to be expected given the international evidence that ambient air quality is responsible for an order of magnitude greater number of premature fatalities than water pollution. Moreover, the costs of self-protection against air pollution are substantially higher than against water pollution; household technologies to clean dirty water and using bottled water rather than tap water are effective and inexpensive ways to protect against waterborne disease, while comparable technologies for protection against air pollution simply do not exist. Additionally, higher demand for cleaner air is consistent with the greater public discourse on air quality; we find that the *Times of India*, the country's leading English-language newspaper, reports on air pollution three times as much as water pollution. Further, high levels of citizen engagement caused India's supreme court, widely considered the country's most effective public institution, to promptly promulgate many air pollution regulations and follow up on their enforcement. In contrast, the water regulations were characterized by jurisdictional opacity about implementation, enforcement that was delegated to agencies with poor track records, and a failure to identify a dedicated source of funds. These differences in promulgation and enforcement are especially striking because there are many similarities between the legislations that govern air and water pollution regulation.

Empirical evidence supports these qualitative findings. We assess whether the effectiveness of air pollution regulations differed with observed proxies for the demand for cleaner air. We find suggestive evidence that the catalytic converter policies were more effective in cities with higher literacy rates and greater newspaper attention to the problems of air pollution.

Finally, we tested whether the catalytic converter policy, which had significant effects on air pollution, was associated with changes in measures of infant health. To the best of our knowledge, this is the first paper to rigorously relate infant mortality rates to environmental regulations in a developing country context.[4] The data indicate that a city's adoption of the policy is associated with a decline in infant mortality, but this relationship is not statistically significant. As we discuss below, there are several reasons to interpret the infant mortality results cautiously.

The paper proceeds as follows. Section I provides a brief history of environmental regulation in India focusing on the policies that the paper analyzes. Section II describes the data sources and presents summary statistics on the city-level trends in pollution, infant mortality, and adoption of environmental policies in India. Section III outlines the econometric approach and Section IV reports and discusses the results. Section V presents evidence that the relative success of the air regulations reflected a greater demand for air quality improvements. Section VI concludes.

I. Background on India's Environmental Regulations

India has a relatively extensive set of regulations designed to improve both air and water quality. Its environmental policies have their roots in the Water Act of 1974 and Air Act of 1981. These acts created the Central Pollution Control Board (CPCB) and the State Pollution Control Boards (SPCBs), which are responsible for data collection and policy enforcement, and also developed detailed procedures for environmental compliance. Following the implementation of these acts, the CPCB and SPCBs quickly advanced a national environmental monitoring program (responsible for the rich data underlying our analysis). The Ministry of Environment and Forests (MoEF), created in its initial form in 1980, was established largely to set the overall policies that the CPCB and SPCBs were to enforce (Hadden 1987).

The Bhopal Disaster of 1984 represented a turning point in India's environmental policy. The government's treatment of victims of the Union Carbide plant explosion "led to a re-evaluation of the environmental protection system," with increased participation of activist groups, public interest lawyers, and the judiciary (Meagher 1990). In particular, there was a steep rise in public interest litigation, and the supreme court instigated a wide expansion of fundamental rights of citizens (Cha 2005). These developments led to some of India's first concrete environmental regulations, such as the closures of limestone quarries and tanneries in Uttar Pradesh in 1985 and 1987, respectively.[5] We discuss the supreme court's role in the promulgation and enforcement of air pollution regulations in greater detail in Section V.

[4] See Chay and Greenstone (2003) for the relationship between infant mortality and the Clean Air Act in the United States. Burgess et al. (2013) estimate the relationship between weather extremes and infant mortality rates using the same infant mortality data used in this paper. Other papers that have explored the relationship between infant mortality and pollution in developing countries include Borja-Aburto et al. (1998); Loomis et al. (1999); O'Neill et al. (2004); Borja-Aburto et al. (1997); Foster, Gutierrez, and Kumar (2009); and Tanaka (2012).

[5] See *Rural Litigation and Entitlement Kendra v. State of Uttar Pradesh* (Writ Petitions Nos. 8209 and 8821 of 1983); and *M.C. Mehta v. Union of India* (WP 3727/1985).

Throughout the 1980s and 1990s, India continued to adopt policies which were designed to counteract growing environmental damage. The paper's empirical focus is on two key air pollution policies: the Supreme Court Action Plans (SCAPs) and the catalytic converter requirements; and the National River Conservation Plan, the primary water pollution policy. These policies were at the forefront of India's environmental efforts. Importantly, there was substantial variation across cities in the timing of adoption, which provides the basis for the paper's research design.

The first policy we focus on is the SCAPs. The action plans are part of a broad, ongoing effort to stem the tide of rising pollution in cities identified by the Supreme Court of India as critically polluted. The SCAPs involve the implementation of a suite of policies that could include fuel regulations, building of new roads that bypass heavily populated areas, transitioning of buses to CNG, and restrictions on industrial pollution. Measured pollution concentrations are a key ingredient in the determination of these designations. In 1996, Delhi was the first city ordered to develop an action plan, while the most recent action plans were mandated in 2003.[6] To date, 17 cities have been given orders to develop action plans.

Although the exact form of the SCAPs varies across cities, they are typically aimed at reducing several types of air pollutants. At least one round of plans was directed at cities with unacceptable levels of respired suspended particulate matter (RSPM), which is a subset of PM characterized by the particles' especially small size. Given the heavy focus on vehicular pollution, it is reasonable to presume that the plans affected NO_2 levels. Finally, since SO_2 is frequently a co-pollutant, it may be reasonable to expect the action plans to affect its ambient concentrations. However, there has not been a systematic exploration of the SCAP's effectiveness across cities.[7]

The second policy we examine is the mandatory use of catalytic converters for specific categories of vehicles, which was a policy distinct from the SCAPs. The fitment of catalytic converters is a common means of reducing vehicular pollution across the world, due to the low cost of its end-of-the-pipe technology. In 1995, the supreme court required that all new petrol-fueled cars in the four major metros (i.e., Delhi, Mumbai, Kolkata, and Chennai) were to be fitted with converters. In 1998, the policy was extended to 45 other cities. It is plausible that this regulation could affect all three of our air quality indicators.

Just as with the SCAPs, there has not been a systematic evaluation of the catalytic converter policies. Qualitative evidence suggests that the catalytic converter policies were enforced stringently by tying vehicle registrations to installation of a catalytic converter.[8] However, it is not clear that this was indeed successful: Oliva (2011),

[6] As documented in the court orders, the supreme court ordered nine more action plans in critically polluted cities "as per CPCB data" after Delhi. A year later, the court chose four more cities based on their having pollution levels at least as high as Delhi's. Finally, a year later, nine more cities (some repeats) were identified based on respired suspended particulate matter (i.e., smaller diameter particulate matter) concentrations.

[7] Many believe that the overwhelming approval of Delhi's CNG bus program as part of its action plan provides indications of its success. Takeuchi, Cropper, and Bento (2007) show that the imposition of a similar conversion of buses to CNG would be the most effective policy for reducing passenger vehicle emissions in Mumbai.

[8] Narain and Bell (2005) write, "In 1995 the Delhi government announced that it would subsidize the installation of catalytic converters in all two- and three-wheel vehicles to the extent of 1,000 Rs. within the next three years (*Indian Express*, January 30, 1995). Furthermore, the Petroleum Ministry banned the registration of new four-wheel cars and vehicles without catalytic converters in Delhi, Mumbai, Chennai, and Calcutta effective April 1, 1995 (*Telegraph*, March 13, 1995). This directive was implemented, although it is alleged that some vehicle owners had the converters removed illegally (court order, February 14, 1996)."

Davis (2008), and Bertrand et al. (2007) all show that drivers often evade regulations. Moreover, in contrast to the SCAPs, public response to the catalytic converter policy was less favorable for several reasons: petrol's lower fuel share made the scope of the policy narrower than, for example, the mandate for low-sulfur in diesel fuel; unleaded fuel, which is necessary for effective functioning of catalytic converters was at best inconsistently available until 2000; and the implementation in only a subset of cities created opportunities for purchases of cars in the uncovered cities that would be driven in the covered cities.

Finally, we study the cornerstone of efforts to improve water quality, the National River Conservation Plan (NRCP). Begun in 1985 under the name Ganga Action Plan (Phase I), the water pollution control program expanded first to tributaries of the Ganga River, including the Yamuna, Damodar, and Gomti in 1993. It was later extended in 1995 to the other regulated rivers under the new name of NRCP. Today, 164 cities on 35 rivers are covered by the NRCP. The criteria for coverage by the NRCP are vague at best, but many documents on the plan cite the CPCB Official Water Quality Criteria, which include standards for BOD, DO, FColi, and pH measurements in surface water. Much of the focus has centered on domestic pollution control initiatives over the years (Asian Development Bank 2007). The centerpiece of the plan is the sewage treatment plant: the interception, diversion, and treatment of sewage through piping infrastructure and treatment plant construction has been coupled with installation of community toilets, crematoria, and public awareness campaigns to curtail domestic pollution. If the policy has been effective, it should affect several forms of water pollution; but the largest impacts would be expected to be on FColi levels, which are most directly related to domestic pollution.

The NRCP has been panned in the media for a variety of reasons, including poor cooperation among participating agencies, imbalanced and inadequate funding of sites, and an inability to keep pace with the growth of sewage output in India's cities (Suresh et al. 2007, p. 2). However, similar to the air pollution programs, there has never been a systematic evaluation or even a compilation of the data that would allow for one.

II. Data Sources and Summary Statistics

To conduct the analysis, we compiled the most comprehensive city-level panel data file ever assembled on air pollution concentrations, water pollution concentrations, and environmental policies in any developing country. We supplemented this data file with a city-level panel data file on infant mortality rates. This section describes each data source and presents some summary statistics, including an analysis of the trends in the key variables.

A. *Regulation Data*

India has implemented a series of environmental initiatives over the last two decades. Using multiple sources, we assembled a dataset that systematically documents these policy changes at the city-year level. We utilized print and web documents from the Indian government, including the CPCB, the Department of Road Transport and Highways, the Ministry of Environment and Forests, and several

Table 1—Prevalence of Air and Water Policies

	Air			Water	
Year	All cities (1A)	SCAP (1B)	Cat conv (1C)	All cities (2A)	NRCP (2B)
1986	—	—	—	104	0
1987	20	0	0	115	0
1988	25	0	0	191	0
1989	31	0	0	218	0
1990	44	0	0	271	0
1991	47	0	0	267	0
1992	58	0	0	287	0
1993	65	0	0	304	10
1994	57	0	0	316	10
1995	42	0	2	317	38
1996	68	0	4	316	39
1997	73	1	4	326	43
1998	65	1	22	325	43
1999	74	1	26	320	43
2000	66	1	24	303	39
2001	54	1	19	363	43
2002	63	1	22	376	41
2003	72	11	25	382	42
2004	78	15	24	395	41
2005	93	16	24	295	38
2006	112	16	24	—	—
2007	115	16	24	—	—

Notes: Columns 1A and 2A tabulate the total number of cities in each year, while columns 1B, 1C, and 2B tabulate the number of cities with the specified policy in place in each year. We subject the full sample to two restrictions before analysis, both of which are applied here. (i) If there is pollution data from a city after it has enacted a policy, then that city is only included if it has at least one data point three years or more before policy uptake and four years or more after policy uptake. (ii) If there is no post-policy pollution data in a city (or if that city never enacted the policy), then that city is only included if it has at least two pollution data points. In this table, a city is counted if it has any pollution data in that year. A city is only included in the subsequent regressions if it has pollution data for the specific dependent variable of that given regression. Thus, the above city counts must be interpreted as maximums in the regressions. Most city-years have available data for all pollutants studied here. The data were compiled by the authors from Central Pollution Control Board's online sources, print sources, and interviews.

Indian SPCBs. We then exploited information from secondary sources, including the World Bank, the Emission Controls Manufacturers Association, and Urbanrail.net. We believe that a comparable dataset does not exist for India.

Table 1 summarizes the prevalence of these policies in the data file of city-level air and water pollution concentrations by year. Columns 1A and 2A report the number of cities with air and water pollution readings, respectively. The remaining columns detail the number of these cities where each of the studied policies is in force. The subsequent analysis exploits the variation in the year of enactment of these policies across cities.[9]

B. *Pollution Data*

Air Pollution Data.—This paper takes advantage of an extensive and growing network of environmental monitoring stations across India. Starting in 1987, India's

[9] Online Appendix Table 1 replicates Table 1 for all cities in India.

Central Pollution Control Board (CPCB) began compiling readings of NO_2, SO_2, and PM. The data were collected as a part of the National Air Quality Monitoring Program, which was established by the CPCB to identify, assess, and prioritize the pollution control needs in different areas, as well as to aid in the identification and regulation of potential hazards and pollution sources.[10] Individual state pollution control boards (SPCBs) are responsible for collecting the pollution readings and providing them to the CPCB for checking, compilation, and analysis. The air quality data are collected from a combination of CPCB online and print materials for the years 1987–2007.[11]

The full dataset includes 572 air pollution monitors in 140 cities. Many of these monitors operate for just a subset of the sample, and for most cities data is not available for all years.[12] In the earliest year (1987), the functioning monitors cover 20 cities, while 125 cities are monitored by 2007 (see online Appendix Table 2 for annual summary statistics).[13] Figure 2 maps cities with air pollution data in at least one year.

The monitored pollutants can be attributed to a variety of sources. PM is regarded by the CPCB as a general indicator of pollution, receiving key contributions from "fossil fuel burning, industrial processes and vehicular exhaust." SO_2 emissions, on the other hand, are predominantly a by-product of thermal power generation; globally, 80 percent of sulfur emissions in 1990 were attributable to fossil fuel use (Smith, Pitcher, and Wigley 2001). NO_2 is viewed by the CPCB as an indicator of vehicular pollution, though it is produced in almost all combustion reactions.

Water Pollution Data.—The CPCB also administers water quality monitoring, in cooperation with SPCBs. As of 2008, 1,019 monitoring stations are maintained under the National Water Monitoring Programme (NWMP), covering rivers and creeks, lakes and ponds, drains and canals, and groundwater sources. We focus on rivers due to the consistent availability of river quality data, the seriousness of pollution problems along the rivers, and, most significantly, the attention that rivers have received from public policy. We have obtained from the CPCB, in electronic format, observations from 489 monitors in 424 cities along 162 rivers between the years 1986 and 2005 (see online Appendix Table 2).[14] Figure 3 maps the locations of these monitors along India's major rivers.

The CPCB collects either monthly or quarterly river data on 28 measures of water quality, of which nine are classified as "core parameters." We focus on three core

[10] For a more detailed description of the data, see http://www.cpcb.nic.in/air.php (accessed on June 25, 2011).

[11] From the CPCB, we obtained monthly pollution readings per city from 1987–2004, and yearly pollution readings from 2005–2007. The monthly data were averaged to get annual measures. The station composition used to generate these averages is fairly stable over this time period. For all of the years in which a city is present in our dataset, an included water station is present, on average, about 99 percent of time. This estimate is lower for air pollution, but still high (56 percent). Moreover, the number of times that an air pollution station is present is uncorrelated with air pollution levels across the three pollutants, and the average frequency of estimates is similar for those with and without the catalytic converter policies.

[12] The CPCB requires that 24-hour samplings be collected biweekly from each monitor for a total of 104 observations per monitor per year. As this goal is not always achieved, 16 or more successful hours of monitoring are considered representative of a given day's air quality, and 50 days of monitoring in a year are viewed as sufficient for data analysis. Some cities, such as Delhi, conduct more frequent readings, but we do not include these.

[13] Each monitor is classified as belonging to one of three types of areas: residential (71 percent), industrial (26 percent), or sensitive (2 percent). The rationale for specific locations of monitors is, unfortunately, not known to us at this time so all monitors with sufficient readings are included in the analysis.

[14] From 1986 to 2004, monthly data is available. For 2005, the data is only available yearly.

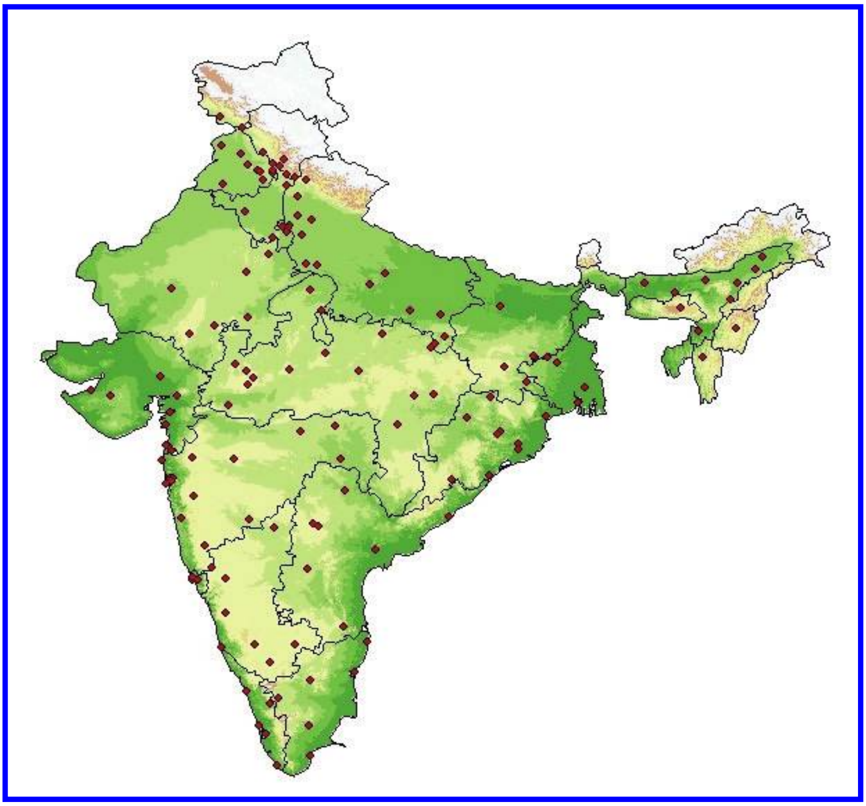

Figure 2. Air Quality Monitors across India

Notes: Dots denote cities with monitoring stations under India's National Ambient Air Quality Monitoring Programme (NAAQMP). Geographical data are drawn from MIT's Geodata Repository. Monitoring locations are determined from CPCB and SPCB online sources and Google Maps.

parameters: biochemical oxygen demand (BOD), dissolved oxygen (DO), and fecal coliforms (FColi). We chose them because of their presence in CPCB official water quality criteria, their continual citation in planning and commentary, and the consistency of their reporting.[15]

These indicators can be summarized as follows. BOD is a commonly used broad indicator of water quality that measures the quantity of oxygen required by the decomposition of organic waste in water. High values are indicative of heavy pollution; however, since waterborne pollutants can be inorganic as well, BOD is not considered a comprehensive measure of water purity. DO is similar to BOD except that it is inversely proportional to pollution; that is, lower quantities of dissolved oxygen in water suggest greater pollution because waterborne waste hinders mixing of water with the surrounding air, as well as hampering oxygen production from aquatic plant photosynthesis.

Finally, FColi, is a count of the most probable number of coliform bacteria per 100 milliliters (ml) of water. While not directly harmful, these organisms are

[15] See *Water Quality: Criteria and Goals* (February 2002); *Status of Water Quality in India* (April 2006); and the official CPCB website, http://www.cpcb.nic.in/Water_Quality_Criteria.php.

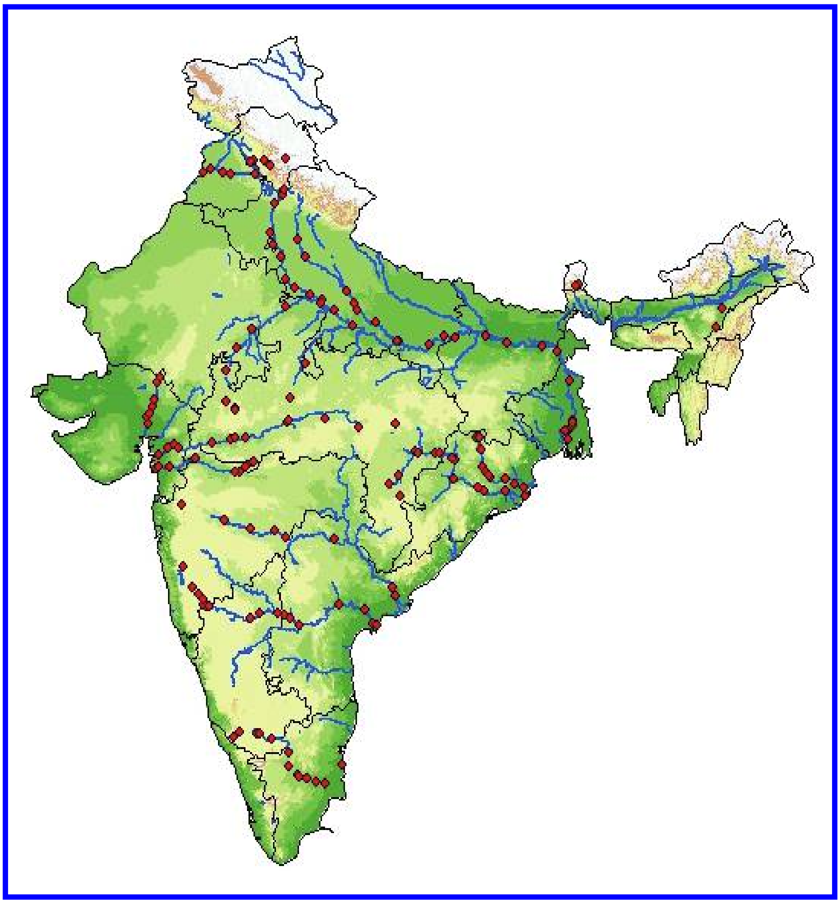

Figure 3. Water Quality Monitors on India's Major Rivers

Notes: Dots denote cities with monitoring stations under India's National Water Monitoring Programme (NWMP). Only cities with monitors on major rivers are included, as geospacial data for smaller rivers is unavailable. Geographical data are drawn from MIT's Geodata Repository. Monitoring locations are determined from CPCB and SPCB online sources and Google Maps.

associated with animal and human waste and are correlated with the presence of harmful pathogens. FColi is thus an indicator of domestic pollution. Since its distribution is approximately ln normal, FColi is reported as ln(number of bacteria per 100 ml) throughout the paper.

Trends in Pollution Concentrations.—Figure 4 graphs national air and water quality trends. Panel A plots the average air quality measured across cities, by pollutant, from 1987 to 2007, while panel B graphs water quality measured across city-rivers, by pollutant, from 1986 to 2005. Table 2 reports corresponding sample statistics, providing the average pollution levels for the full sample, as well as values at the start and end of the sample.

Air pollution levels have fallen. Ambient PM concentrations fell quite steadily from 252.1 micrograms per cubic meter ($\mu g/m^3$) in 1987–1990 to 209.4 $\mu g/m^3$ in 2004–2007. This represents about a 17 percent reduction in PM. The SO_2 trend line is flat until the late 1990s, and then declines sharply. Comparing the 1987–1990 to

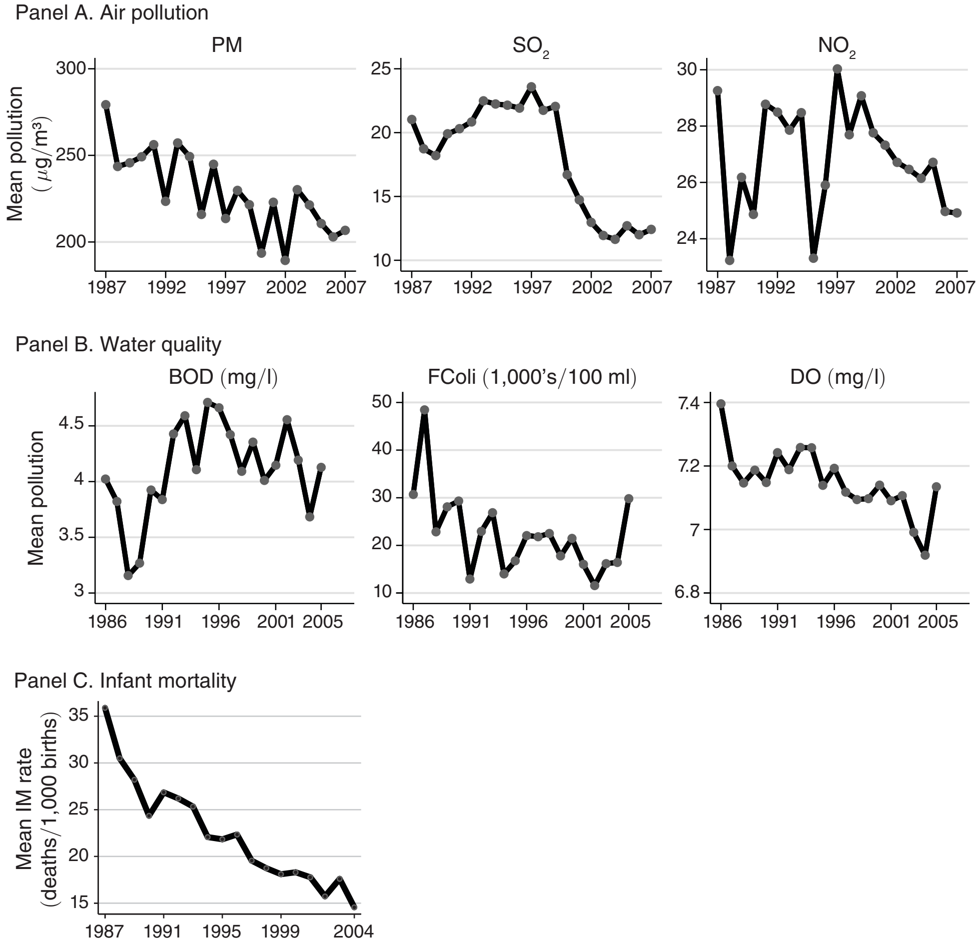

Figure 4. Trends in Air and Water Quality

Notes: 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. Infant mortality data are restricted to those cities which have at least one air or water pollution measurement in the full sample. Pollution data were drawn from Central Pollution Control Board's online and print sources. Infant mortality data were taken from the book, *Vital Statistics of India*, as well as various state registrar's offices.

2004–2007 time periods, mean SO_2 decreased from 19.4 to 12.2 $\mu g/m^3$ (or 37 percent). In contrast, NO_2 appears more volatile at the start of the sample period, but then falls after its peak in 1997.

Is there spatial variation in these trends? Online Appendix Figure 1A provides kernel density estimates of air pollutant distributions across Indian cities for the periods 1987–1990 and 2004–2007. The figure shows that not only have the means of PM and SO_2 decreased, but their entire distributions have shifted to the left over the last two decades. As Table 2 reports, the tenth percentiles of PM and SO_2 pollution both declined by about 10 percent from 1987–1990 to 2004–2007. Particularly striking, however, is the drop in the ninetieth percentile of ambient SO_2 concentration: 38.2 to 23.0 $\mu g/m^3$, or about 40 percent. In contrast, the NO_2 distribution appears to have worsened, with increases in the mean and tenth and ninetieth percentiles.

Table 2—Summary Statistics

	Air pollution			Water quality			Infant mortality
Period	PM (1)	SO_2 (2)	NO_2 (3)	BOD (4)	ln(FColi) (5)	DO (6)	IM rate (7)
Full Period							
Mean	223.2	17.3	26.8	4.2	5.4	7.1	23.5
Standard deviation	[114.0]	[15.2]	[18.0]	[8.0]	[2.7]	[1.3]	[22.1]
Observations	1,370	1,344	1,382	5,948	4,985	5,919	1,247
Tenth percentile	90.5	4.0	10.0	0.8	1.9	5.7	3.4
Ninetieth percentile	378.4	35.4	48.7	7.0	9.0	8.5	46.2
1987–1990							
Mean	252.1	19.4	25.5	3.5	6.4	7.2	29.6
Standard deviation	[126.4]	[13.3]	[21.5]	[6.9]	[2.3]	[1.2]	[31.4]
Observations	120	116	117	644	529	648	358
Tenth percentile	101.6	4.4	8.5	0.9	3.6	6.0	4.8
Ninetieth percentile	384.3	38.2	42.6	5.8	9.7	8.5	56.2
2004–2007							
Mean	209.4	12.2	25.6	4.1	5.3	7.0	16.7
Standard deviation	[97.1]	[8.1]	[14.0]	[7.9]	[2.9]	[1.5]	[14.1]
Observations	420	381	417	1,509	1,339	1,487	216
Tenth percentile	92.0	4.0	10.4	0.9	1.8	5.5	2.7
Ninetieth percentile	366.6	23.0	47.0	7.9	9.1	8.4	36.1

Notes: This table provides summary statistics on air and water quality. Infant mortality data are restricted to those cities which have at least one air or water pollution measurement in the full sample. Pollution data were drawn from Central Pollution Control Board's online and print sources. Infant mortality data were taken from the book, *Vital Statistics of India*, as well as various state registrar's offices.

The overall trends in water quality are more mixed. Panel B of Figure 4 demonstrates that BOD steadily worsens throughout the late 1980s and early 1990s and then begins to improve around 1997. The improvement, though, did not make up for early losses, as mean BOD increased by about 19 percent over the sample period. FColi drops precipitously in the 1990s, but rises somewhat in the 2000s. The general decrease in FColi is notable, suggesting that domestic water pollution may be abating despite the alarmingly fast-paced growth in sewage generation (Suresh et al. 2007). DO declines fairly steadily over time (a fall in DO indicates worsening water quality) from 7.21 to 7.03 mg/l.

The distributions of the water pollutants across cities and their changes are presented in online Appendix Figure 1B, which comes from kernel density estimation. The distribution of BOD has widened over the last 20 years, with many higher readings in the later time period.[16] While the tenth percentile of BOD has dropped slightly, the ninetieth percentile has increased from 5.78 to 7.87 mg/l between the earlier and more recent periods. In contrast, the FColi distribution has largely shifted

[16] The right tail of the 2002–2005 period extends to 100 mg/l, but the figure has been truncated at 20 mg/l to give a more detailed picture of the distribution.

to the left. The relatively clean cities show tremendous drops in FColi levels, with the tenth percentile value falling from 3.61 to 1.79, while dirtier cities show more modest declines. Lastly, the DO distribution does not appear to have changed noticeably, with very little difference between the distributions from the earlier and later periods.

Figure 4, Table 2, and online Appendix Figures 1A and 1B report on trends from the full sample, which raises the possibility that the observed trends might reflect changes in the composition of monitored locations, rather than changes in pollution within locations. We believe that this is not a major concern in this setting. For example over the roughly two decades covered by Figure 4, the average number of years that a city is in the air pollution data is 15.4 and 17.2 for the water pollution data. Further, we redid these figures but dropped cities that were included for fewer than ten years; the qualitative conclusions are unchanged by this sample restriction.

C. *Infant Mortality Rate Data*

We obtained annual city-level infant mortality data from annual issues of *Vital Statistics of India* for the years prior to 1996.[17] In subsequent years, the city-level data were no longer complied centrally; therefore, we visited the registrar's office for each of India's larger states and collected the data directly.[18] Many births and deaths are not registered in India and the available evidence suggests that this problem is greater for deaths, so the infant mortality rate is likely downward-biased. Although the infant mortality rate from the *Vital Statistics* data is about one-third of the rate measured from state-level survey measures of infant mortality rates (i.e., the Sample Registration System), trends in the *Vital Statistics* and survey data are highly correlated. While these data are likely to be noisy, there is no reason to expect that the measurement error is correlated with the pollution measures.[19]

Infant mortality rates are an appealing measure of the effectiveness of environmental regulations for at least two reasons. First, relative to measures of adult health, infant health is likely to be more responsive to short and medium changes in pollution. Second, the first year of life is an especially vulnerable one, and so losses of life expectancy may be large.

Since 1987, infant mortality has fallen sharply in urban India (panel C of Figure 4). As Table 2 shows, the infant mortality rate fell from 29.6 per 1,000 live births in 1987–1990 to 16.7 in 2001–2004. The kernel density graphs of infant mortality from the earlier and later periods further confirm the reduction in mortality rates (online Appendix Figure 1C).

[17] We digitized the city-level data from the books. All data were double entered and checked for consistency.

[18] Specifically, we attempted to obtain data in all states except the Northeastern states (which have travel restrictions) and Jammu-Kashmir. We were able to obtain data from Andhra Pradesh, Chandigarh, Delhi, Goa, Gujarat, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, and West Bengal.

[19] Burgess et al. (2013) show that these mortality data are correlated with inter-annual temperature variation, providing further evidence that there is signal in these data.

D. *Demographics Characteristics, Corruption, and Newspaper Pollution References*

We additionally collected data on sociodemographic characteristics, corruption, and social activism at the city-level. Sociodemographic data come from two sources.[20] First, we obtained district-level data on population and literacy rates from the 1981, 1991, and 2001 Censuses of India. For noncensus years, we linearly interpolated these variables. Second, we collected district-level expenditure per capita data, which is a proxy for income. The data come from the survey of household consumer expenditure carried out by India's National Sample Survey Organization in the years 1987, 1993, and 1999 and are imputed in the missing years.

We used a variety of novel resources to develop measures of demand for clean air and water and the degree of local corruption or institutional quality. First, we collected mentions on "air pollution" and "water pollution" from the *Times of India*, the largest newspaper in India, by state-year. Data prior to 2003 were obtained from the University of Pennsylvania's searchable library database, while data afterward were obtained from the *Times of India*'s online public searchable database. We interpret the pollution mentions as indicators for the demand for clean air and water but, as we discuss below, note that these measures may also be subject to other reasonable interpretation. Systematic data on the degree of corruption across cities, as well as measures of social activism, are notoriously difficult to obtain, particularly for developing countries (Banerjee, Hanna, and Mullainathan 2013). We found and compiled data from two sources. We conducted analogous newspaper searches from the *Times of India*, but in this case searched for "corruption," "graft," and "embezzlement," all of which are intended to provide a proxy for institutional quality. Second, we collected data from Transparency International on public perceptions of corruption by state for 2005.

III. Econometric Approach

This section describes a two-step econometric approach for assessing whether India's regulatory policies impacted air and water pollution concentrations. The first step is an event study-style equation:

$$Y_{ct} = \alpha + \sum_{\tau} \sigma_{\tau} \mathbf{D}_{\tau,ct} + \boldsymbol{\mu}_t + \boldsymbol{\gamma}_c + \boldsymbol{\beta}\mathbf{X}_{ct} + \epsilon_{ct}, \tag{1}$$

where Y_{ct} is one of the six measures of pollution in city c in year t. The city fixed effects, $\boldsymbol{\gamma}_c$, control for all permanent unobserved determinants of pollution across cities, while the inclusion of the year fixed effects, $\boldsymbol{\mu}_t$, nonparametrically adjust for national trends in pollution, which is important in light of the time patterns observed in Figure 2. The equation also includes controls for per capita consumption and literacy rates ($\mathbf{X}_{ct}$) in order to adjust for differential rates of growth across districts.

[20] Consistent city-level data in India is notoriously difficult to obtain. We instead acquired district-level data, and matched cities to their respective districts.

To account for differences in precision due to city size, the estimating equation is weighted by the district-urban population.[21]

The vector $\mathbf{D}_{\tau,ct}$ is composed of a separate indicator variable for each of the years before and after a policy is in force. τ is normalized so that it is equal to zero in the year the relevant policy is enacted; it ranges from -17 (for 17 years before a policy's adoption in a city) to 12 (for 12 years after its adoption). All τs are set equal to zero for nonadopting cities; these observations aid in the identification of the year effects and the βs. In the air pollution regressions, there are separate $\mathbf{D}_{\tau,ct}$ vectors for the SCAP and catalytic converter policies, so each policy's impact is conditioned on the other policy's impact.[22]

The parameters of interest are the σ_τs, which measure the average annual pollution concentration in the years before and after a policy's implementation. These estimates are purged of any permanent differences in pollution concentrations across cities and of national trends due to the inclusion of the city and year fixed effects. The variation in the timing of the adoption of the individual policies across cities allows for the separate identification of the σ_τs and the year fixed effects.

In Figures 5 and 6, the estimated σ_τs are plotted against the τs. These event study graphs provide an opportunity to visually assess whether the policies are associated with changes in pollution concentrations. Additionally, they allow for an examination of whether pollution concentrations in adopting cities were on differential trends. These examinations lend insights into whether the data are consistent with cities adopting the policies in response to changing pollution concentrations and whether mean reversion may confound the policies' impacts. Put simply, these figures will inform the choice of the preferred second-step model.

The sample for equation (1) is based on the availability of data for a particular pollutant in a city. For adopting cities, a city is included in the sample if it has at least one observation three or more years before the policy's enactment and at least one observation four or more years afterward (including the year of enactment). If a city did not enact the relevant policy, then that city is required to have at least two observations for inclusion in the sample.

The second step of the econometric approach formally tests whether the policies are associated with pollution reductions with three alternative specifications. We first estimate:

$$\text{(2A)} \qquad \hat{\sigma}_\tau = \pi_0 + \pi_1 1(Policy)_\tau + \epsilon_\tau,$$

where $1(\text{Policy})_\tau$ is an indicator variable for whether the policy is in force (i.e., $\tau \geq 1$). Thus, π_1 tests for a mean shift in pollution concentrations after the policy's implementation.

[21] City-level population figures are not systematically available, so we use population in the urban part of the district in which the city is located to proxy for city-level population.

[22] The results are qualitatively similar in terms of sign, magnitude, and significance from models that evaluate each policy separately.

In several cases, the event study figures reveal trends in pollution concentrations that predate the policy's implementation (even after adjustment for the city and year fixed effects). Therefore, we also fit the following equation:

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

This specification includes a control for a linear time trend in event time, τ, to adjust for differential preexisting trends in adopting cities.

Equations (2A) and (2B) test for a mean shift in pollution concentrations after the policy's implementation. A mean shift may be appropriate for some of the policies that we evaluate. On the other hand, the full impact of some of the policies may emerge over time as the government builds the necessary institutions to enforce a policy and as firms and individuals take the steps necessary to comply. For example, an evolving policy impact seems probable for the SCAPs since they specify actions that polluters must take over several years.

To allow for a policy's impact to evolve over time, we also report the results from fitting:

$$\hat{\sigma}_{\tau} = \pi_0 + \pi_1 1(Policy)_{\tau} + \pi_2 \tau + \pi_3 (1(Policy)_{\tau} \times \tau) + \epsilon_{\tau}. \tag{2C}$$

From this specification, we report the impact of a policy five years after it has been in force as $\pi_1 + 5\pi_3$.

There are three remaining estimation issues about equations (2A)–(2C) that bear noting. First, the sample is chosen so that there is sufficient precision to compare the pre- and postadoption periods. Specifically, for two of the policies it is restricted to values of τ for which there are at least 20 city-by-year observations to identify the σ_{τ}s. For the catalytic converter regressions, the sample therefore covers $\tau = -7$ through $\tau = 9$ and for the National River Conservation Plan regressions it includes $\tau = -7$ through $\tau = 10$ (see online Appendix Table 4). In the case of the SCAP policies which were implemented more narrowly, the sample is restricted to values of τ for which there are a minimum of 15 observations for each σ_{τ}, and this leads to a sample that includes $\tau = -7$ through $\tau = 3$. We demonstrate below that the qualitative results are unchanged by other reasonable choices for the sample. Second, the standard errors for these second-step equations are heteroskedastic consistent. Third, the equation is weighted by the inverse of the standard error associated with the relevant σ_{τ} to account for differences in precision in the estimation of these parameters.

The two-step approach laid out in this section is used less frequently than the analogous one-step approach. We emphasize the two-step approach, because it provides a convenient solution to the problem of intragroup correlation in unobserved determinants of pollution concentrations. In this setting, groups are defined by each of the years before and after a policy is in force and are denoted by the $\mathbf{D}_{\tau}$s above. The difficulty with the one-step procedure is that efficient estimation requires knowledge or efficient estimation of the variance-covariance matrix to implement GLS or FGLS, respectively. The two-step procedure is numerically identical to the GLS and FGLS approaches, but it avoids the difficulties with implementing them by collapsing the data to the group-level (Donald and Lang 2007). Nevertheless, we complement the presentation of the two-step results from the estimation of the preferred equation (2C) with results from the analogous one-step approach in the below results section. To match what is frequently done in difference-in-differences applications, the standard errors from the one-step approach are clustered at the city-level. The online Appendix describes further details on how we implemented the one-step approach.

IV. Results

A. *Air Pollution*

Figure 5 presents the event study graphs of the impact of the policies on PM (panel A), SO_2 (panel B), and NO_2 (panel C). Each graph plots the estimated σ_τs from equation (1). The year of the policy's adoption, $\tau = 0$, is demarcated by a vertical dashed line in all figures. Additionally, pollution concentrations are normalized so that they are equal to zero in $\tau = -1$, and this is noted with the dashed horizontal line.

These figures visually report on the patterns in the data and help to identify which version of equation (2) is most likely to be valid. It is evident that accounting for differential trends in adopting cities is crucial, because the parallel trends assumption of the simple difference-in-differences or mean shift model (i.e., equation (2A)) is violated in many cases. This is particularly true in the case of the catalytic converter policies that were implemented in cities where pollution concentrations were worsening. Note, however, that although the trends differ in the cities adopting the catalytic converter policy, the figures fail to reveal symmetry around a mean pollution concentration that would indicate that any of the three measured pollutants follow a mean reverting process. The upward pretrend in pollution concentrations is also apparent in the case of the SCAPs and NO_2.[23] In all of these instances with differential trends, equations (2B) and (2C) are more likely to produce valid estimates of the policies' impacts. With respect to inferring the impact of the policies, the figures suggest that the catalytic converter policy was effective at reversing the upward trend in pollution concentrations, while the SCAPs appear ineffective, with the possible exception of NO_2.

Table 3 provides more formal tests by reporting the key coefficient estimates from fitting equations (2A)–(2C). For each pollutant-policy pair, the first column reports the estimate of π_1 from equation (2A), which tests whether σ_τ is on average lower after the implementation of the policy. The second column reports the estimate of π_1 and π_2 from the fitting of equation (2B) in the second column for each pollutant. Here, π_1 tests for a policy impact after adjustment for the trend in pollution levels (π_2). The third column reports the results from equation (2C) that allow for a mean shift and trend break after the policy's implementation. It also reports the estimated effect of the policy five years after their implementation, which is equal to $\pi_1 + 5\pi_3$. The fourth column reports the results from the one-step version of equation (2C).

[23] Interestingly, the differential trends in SO_2 concentrations between cities that were and were not subject to Supreme Court Action Plans bear some resemblance to a mean reverting process. There is little evidence in Figure 5 that the SCAP affected SO_2 concentrations.

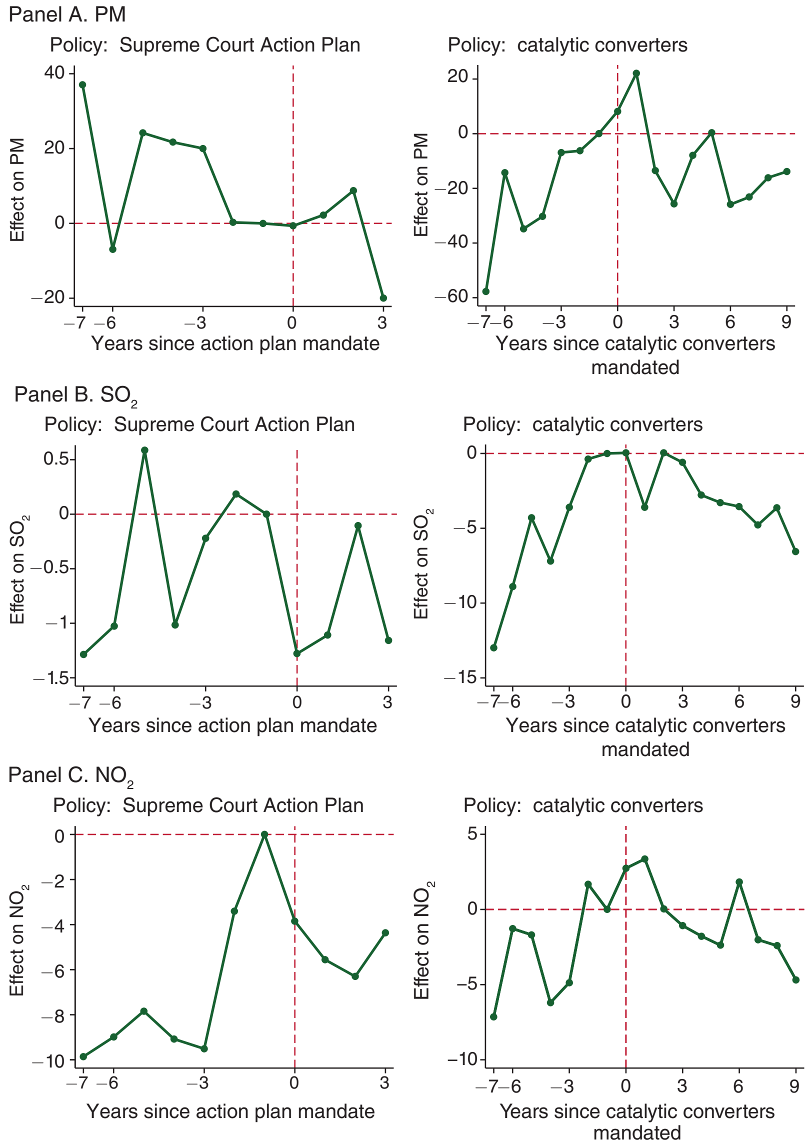

Figure 5. Event Study of Air Pollution Policies

Notes: The figures provide a graphic analysis of the effect of the SCAPs and mandated catalytic converter policies on air pollution. The figures plot the estimated σ_τs against the τs from the estimation of equation (1). Each pair of graphs within a panel are based on the same regression. See the text for further details.

From columns 1–4 of Table 3, it is evident that the SCAPs have a mixed record of success.[24] There is little evidence of an impact on PM or SO_2 concentrations. The available evidence for an impact comes from the NO_2 regressions that control for preexisting trends. In column 10 the estimated impact would not be judged

[24] Note that for the SCAPs, the analysis lags the policies by one year. The dates we have correspond to court orders, which mandated submission of action plans. However, a special committee frequently reviewed the SCAPs and only afterwards declared/implemented them.

Table 3—Trend Break Estimates of the Effect of Policy on Air Pollution

	Supreme Court Action Plans				Catalytic converters			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. PM								
π_2: time trend		−3.8	−3.6	−2.9		−0.3	7.8***	7.8**
		(2.4)	(2.8)	(4.3)		(1.8)	(2.5)	(3.3)
π_1: 1(*Policy*)	−16.2	4.9	7.5	0.3	11.9	14.7	5.6	7.6
	(9.4)	(15.8)	(20.6)	(21.5)	(8.8)	(17.4)	(12.8)	(12.3)
π_3: 1(*Policy*) × time trend			−1.5	0.1			−10.8***	−11.2**
			(7.1)	(6.0)			(2.9)	(4.6)
5-year effect $= \pi_1 + 5\pi_3$			−0.2	0.9			−48.6**	−48.4*
p-value			0.99	0.98			0.04	0.06
Observations	11	11	11	1,165	17	17	17	1,165
Panel B. SO_2								
π_2: time trend		0.2	0.2	0.1		0.1	2.0***	1.9***
		(0.1)	(0.1)	(0.6)		(0.3)	(0.3)	(0.7)
π_1: 1(*Policy*)	−0.5	−1.5*	−1.4	−1.3	2.5	1.5	−0.5	−0.8
	(0.4)	(0.7)	(0.9)	(2.1)	(1.7)	(3.3)	(1.5)	(2.6)
π_3: 1(*Policy*) × time trend			−0.1	0.1			−2.6***	−2.4**
			(0.3)	(1.0)			(0.3)	(1.0)
5-year effect $= \pi_1 + 5\pi_3$			−1.7	−0.8			−13.5***	−12.7**
p-value			0.21	0.87			0.00	0.02
Observations	11	11	11	1,158	17	17	17	1,158
Panel C. NO_2								
π_2: time trend		1.2**	1.4**	1.6*		−0.3	0.9*	0.7
		(0.4)	(0.4)	(0.9)		(0.3)	(0.4)	(0.8)
π_1: 1(*Policy*)	1.9	−4.4	−1.7	−2.6	2.2	4.5	3.2	3.7
	(2.0)	(2.7)	(3.1)	(4.4)	(1.4)	(2.8)	(2.2)	(4.0)
π_3: 1(*Policy*) × time trend			−1.6	−1.7			−1.5***	−1.4
			(1.1)	(2.1)			(0.5)	(1.2)
5-year effect $= \pi_1 + 5\pi_3$			−9.8*	−11.3			−4.4	−3.3
p-value			0.06	0.22			0.25	0.62
Observations	11	11	11	1,177	17	17	17	1,177
Equation (2A)	Yes	No	No	No	Yes	No	No	No
Equation (2B)	No	Yes	No	No	No	Yes	No	No
Equation (2C)	No	No	Yes	No	No	No	Yes	No
One-stage version of (2C)	No	No	No	Yes	No	No	No	Yes

Notes: This table reports results from the estimation of the second-step equations (2A), (2B), and (2C) for PM, SO_2, and NO_2, in panels A, B, and C respectively. Columns 4 and 8 complement the second-step results from the estimation of equation (2C) by reporting results from the analogous one-step approach for the SCAPs and the catalytic converter policy respectively. Rows denoted "5-year effect" report $\pi_1 + 5\pi_3$, which is an estimate of the effect of the relevant policy 5 years after implementation from equation (2C) and the analogous one-step approach. The *p*-value of a hypothesis test for the significance of this linear combination is reported immediately below the five-year estimates. See the text for further details.

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

statistically significant, while in columns 11 and 12 of Table 3 it is of a larger magnitude and is marginally significant in 11.

In contrast, the regressions confirm the visual impression that the catalytic converter policies were strongly associated with air pollution reductions. In light of the differential pretrends in pollution in adopting cities and that the policy's impact will only emerge as the stock of cars changes, the richest specification (equation (2C)) is likely to be the most reliable. These results indicate that five years after the policy was in force, PM, SO_2, and NO_2 declined by 48.6 $\mu g/m^3$, 13.5 $\mu g/m^3$, and 4.4 $\mu g/m^3$, respectively. The PM and SO_2 declines are statistically significant when judged by conventional criteria, while the NO_2 decline is not. These declines are 19 percent, 69 percent, and 17 percent of the 1987–1990 nationwide mean concentrations, respectively. All of these declines are large, reflecting the rapid rates at which ambient pollution concentrations were increasing before the policy's implementation in adopting cities—put another way, if the pretrends had continued then pollution concentrations would have reached levels much higher than those recorded in the 1987–1990 period. The one-step results are qualitatively similar.

Online Appendix Table 4 demonstrates that the findings are largely unchanged by reasonable alternative sample selection rules that determine the number of event years included in the analysis.[25] Specifically, we fit equation (2C) on a wider range of τs (i.e., from $\tau = -9$ through $\tau = 9$ for the catalytic converters and $\tau = -14$ through $\tau = 4$ for the SCAPs) and a narrower range τs (i.e., from $\tau = -5$ through $\tau = 5$ for the catalytic converters and $\tau = -4$ through $\tau = 4$ for the SCAPs). The pattern of the coefficients for the catalytic converters policy is similar to that of Table 3 for both the wider and narrower event year samples. The SCAP is associated with a large and significant decline in NO_2 with the narrower range. With the wider range, the SCAP continues to be associated with a decline in NO_2 but it no longer would be judged to be statistically significant; however, it is associated with a statistically significant decline in PM.

B. *Effects of Policies on Water Quality*

Panels A–C of Figure 6 present event study analyses of the impact of the National River Conservation Plan (NRCP) on BOD, ln(FColi), and DO, respectively. As in Figure 5, the figures plot the results from the estimation of equation (1). From the figures, there is little evidence that the NRCP was effective at reducing pollution concentrations. However, this visual evidence suggests that all three pollutants are improving in the years preceding adoption of the NRCP in adopting cities, relative to nonadopting ones (recall higher DO levels means higher pollution concentrations). With respect to obtaining an unbiased estimate of the effect of the NRCP, the figures indicate that conditioning on pretrends is important and for that reason we

[25] There is a trade-off to including a greater or smaller number of event years or τs in the second-stage analysis. The inclusion of a wider range of τs provides a larger sample size and allows for more precise estimation of pre- and post-adoption trends. But at the same time, it moves further away from the event in question so that other unobserved factors may confound the estimation of the policy effects. Further, it exacerbates the problems associated with estimating the τs from an unbalanced panel data file of cities. In contrast, the inclusion of fewer τs results in a smaller sample size (and number of cities) to estimate pre- and post-trends, but the analysis is more narrowly focused around the policy event. Online Appendix Table 3 reports on the number of city-by-year observations that identify the σ_τs associated with each event year.

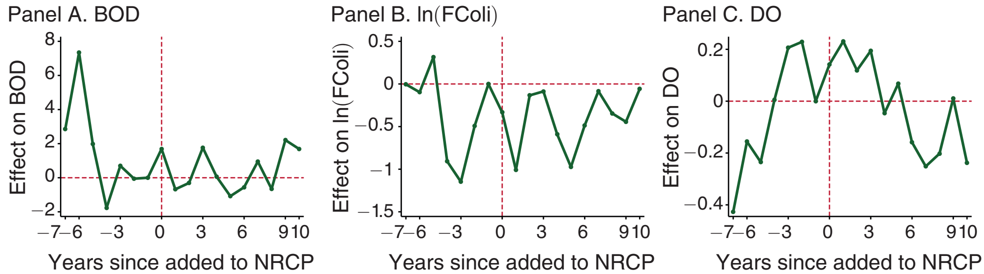

FIGURE 6. EVENT STUDY OF WATER POLLUTION POLICY

Notes: The figures provide a graphical analysis of the effect of the NRCP policy on water pollution. The figures plot the estimated σ_τs against the τs from the estimation of equation (1). See the text for further details.

emphasize the results from the equation (2B) and (2C) specifications that account for these differences in trends between adopting and nonadopting cities.

Table 4 provides the corresponding regression analysis and is structured similarly to Table 3. The evidence in favor of a policy impact is weak. Indeed, the richest statistical models suggest that BOD concentrations are higher after the NRCP's implementation. While the NRCP targets domestic pollution, the data fail to reveal a statistically significant change in FColi concentrations, which is the best measure of domestic sourced water pollution. The DO results from the fitting of equation (2C) are reported in columns 11 and 12 and confirm the perverse visual impression that the NRCP is associated with a worsening in DO concentrations.[26] Finally we note that in some instances it can take a couple of years to plan and construct a sewage treatment plant, so the regulations might not immediately reduce water pollution concentrations. Returning to Figure 6, there is little evidence that water pollution declined in the latter half of the postadoption decade.

C. *Assessing Robustness with a Structural Break Test*

The previous subsection presented results from a difference-in-differences (DD) approach that can accommodate differential trends across cities that did and did not adopt the environmental regulations. This subsection adapts a structural break test from time-series econometrics and demonstrates that these tests can be used to shed light on the validity of a DD-style design. Structural break tests have generally been limited to settings where this is a single time-series and a control group is unavailable. However as equation (1) and the event-study figures highlight, it is straightforward to collapse a DD framework into a single time-series, even when the policy date varies across units (i.e., cities in our setting) that have been adjusted for unit and time fixed effects. We are unaware of previous efforts to apply structural

[26] Online Appendix Table 4 demonstrates that the qualitative result that the NRCP had little impact on the available measures of water pollution is unchanged by reasonable alternative selection rules for the number of event years to include in the analysis. The table reports on specifications that increase and decrease the number of event years or τs (i.e., changing the event years to include $[-9, 12]$ or to include $[-5, 5]$) in the second-stage analysis.

Table 4—Trend Break Estimates of the Effect of the NRCP on Water Pollution

Time trend	(1)	(2)	(3)	(4)
Panel A. BOD				
π_2: time trend		−0.12	−0.88**	−0.92
		(0.18)	(0.34)	(0.86)
π_1: 1(*policy*)	−1.11	−0.06	1.07	0.87
	(0.99)	(1.88)	(1.67)	(2.07)
π_3: 1(*policy*) $\times$ time trend			0.96**	1.03
			(0.38)	(0.79)
5-year effect $= \pi_1 + 5\pi_3$			5.85*	6.03
p-value			0.06	0.28
Observations	18	18	18	5,576
Panel B. ln(Fcoli)				
π_2: time trend		0.01	−0.08	−0.06
		(0.04)	(0.08)	(0.11)
π_1: 1(policy)	−0.08	−0.14	−0.01	−0.07
	(0.20)	(0.39)	(0.40)	(0.46)
π_3: 1(policy) $\times$ time trend			0.11	0.10
			(0.09)	(0.17)
5-year effect $= \pi_1 + 5\pi_3$			0.53	0.42
p-value			0.45	0.66
Observations	18	18	18	4,640
Panel C. DO				
π_2: time trend		−0.02	0.09***	0.07
		(0.02)	(0.02)	(0.08)
π_1: 1(*policy*)	0.04	0.19	0.03	0.08
	(0.10)	(0.18)	(0.12)	(0.29)
π_3: 1(*policy*) $\times$ time trend			−0.13***	−0.12
			(0.03)	(0.09)
5-year effect $= \pi_1 + 5\pi_3$			−0.63***	−0.51
p-value			0.01	0.40
Observations	18	18	18	5,553
Equation (2A)	Yes	No	No	No
Equation (2B)	No	Yes	No	No
Equation (2C)	No	Yes	Yes	No
One-stage version of (2C)	No	No	No	Yes

Notes: This table reports results from the estimation of the second-step equations (2A), (2B), and (2C) for the impact of the NRCP on BOD, ln(Fcoli), and DO in panels A, B, and C respectively. Column 4 complements the second-step results from the estimation of equation (2C) by reporting results from the analogous one-step approach. The row denoted "5-year effect" reports $\pi_1 + 5\pi_3$, which is an estimate of the effect of the policy five years after implementation from equation (2C) and the analogous one-step approach. The *p*-value of a hypothesis test for the significance of this linear combination is reported immediately below the five-year estimates. See the text for further details.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

break tools to a DD setting and believe that these tests can and should be used more broadly with DD designs.[27]

Inspired by Piehl et al. (2003), we adapt the Quandt likelihood ratio (QLR) statistic to determine if there is a structural break in a time-series. Specifically, we take the estimated σ_τs from the estimation of equation (1) and the most robust second-step specification (i.e., (2C)) that assumes that the regulations cause a mean shift and trend break in pollution concentrations. Note that the test for whether a policy has any effect in equation (2C) is tantamount to calculating the *F*-statistic associated with the null hypothesis that $\pi_1 = 0$ and $\pi_3 = 0$. In time-series, this is often referred to as a Chow-test for parameter constancy, but it essentially boils down to a joint *F*-test.

The idea is to assess whether there is a structural break in the policy parameters (i.e., π_1 and π_3) near the true date of the policy's adoption. The test does two things: It identifies the date at which there is the largest change in the parameters (defined as the date associated with the largest change in the *F*-statistic) and produces *p*-values for whether the change in those parameters is different than zero (i.e., whether there is a break). A failure to find a break or a finding of a break significantly before the measured date of policy implementation would suggest that the policies were ineffective and undermine any findings to the contrary from the DD approach. In contrast, a finding of a policy effect in the years around $\tau = 0$, especially the years after $\tau = 0$, would support the findings of a policy effect from the DD results.

This test is implemented in two steps. First, equation (2C) is re-estimated redefining a new "policy implementation" date each time and the *F*-statistic associated with the null hypothesis that $\pi_1 = 0$ and $\pi_3 = 0$ is calculated. We test for break dates within a window of the middle 50 percent of the event years in each time-series. There needs to be a sufficient amount of data outside the window, so, for example, the possible break dates are limited to $\tau = -3$ through $\tau = 6$ (out of the total available years that range from $\tau = -7$ through $\tau = 9$) for the effect of the catalytic converter policy on PM.

Second, the QLR test selects the maximum of the *F*-statistics to test for a break at an unknown date. The maximum of a number of *F*-statistics does not converge to any known distribution. Andrews (1993) provides critical values that are asymptotically correct, but we instead run a Monte Carlo simulation to compute the critical values due to our small sample. Specifically, to compute the small-sample critical values, we first generated data with the variance set equal to the variance of the actual data, but without a break in the data. We then compute the QLR test over the simulated data to obtain the maximum *F*-statistics. We replicate this 100,000 times to obtain the distribution of the QLR statistics under a null of hypothesis of no break.

Figure 7 and panel A of Table 5 report on the results of the QLR test for the catalytic converter policy, which the previous section found to be the most effective policy. For PM, panel A of Figure 7 plots the *F*-statistics associated with the test of a break for each of the event years. It is evident that this test selects $\tau = 2$ as the event year with the most substantive break. Table 5 reports that the null hypothesis of no break at $\tau = 2$ can be rejected at the 1 percent level. This break corresponds to the reversal of the upward trend in PM observed at $\tau = 2$ in Figure 5.

[27] Based on our investigation, the closest use of a structural break test in a non-time series setting is Ludwig and Miller's (2007) application within a regression discontinuity framework as a robustness check for the existence and timing of a discontinuity.

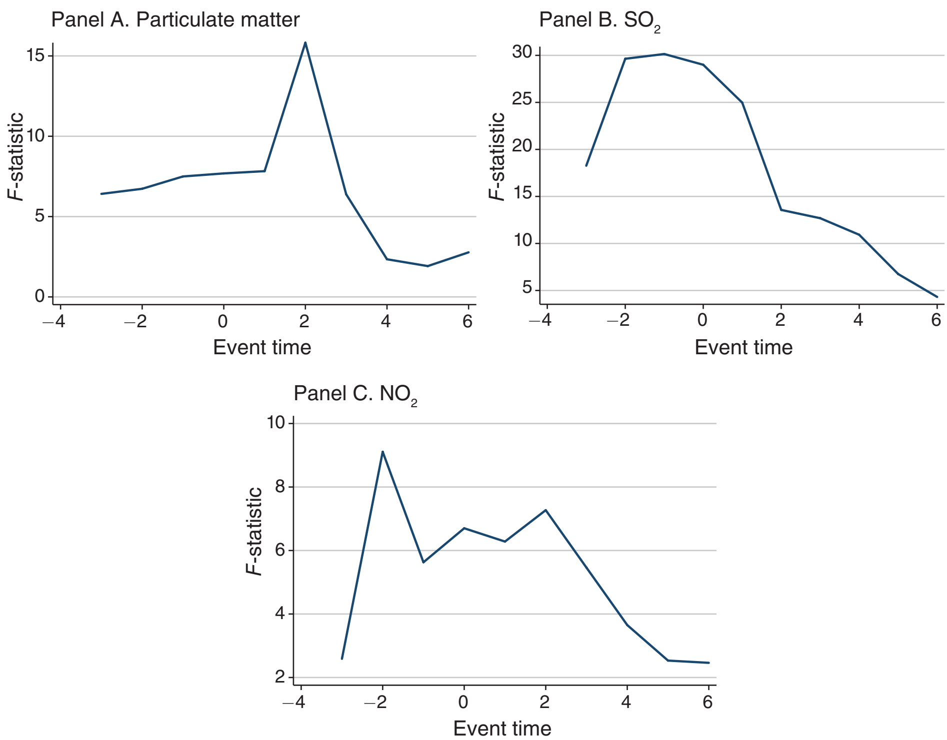

FIGURE 7. *F*-STATISTICS FROM QLR TEST FOR CATALYTIC CONVERTER POLICIES

TABLE 5—STRUCTURAL BREAK ANALYSIS

	Year of maximum *F* (1)	QLR test statistic (2)
Panel A. Catalytic converter policy		
PM	2	15.8
SO_2	−1	30.1
NO_2	−2	9.1
Panel B. National River Conservation Plan		
BOD	−3	4.9
ln(Fcoli)	−2	3.5
DO	−3	18.7

Notes: This table provides the QLR test statistic, as well as the corresponding year of the break in the data, for equation (2C). Asymptotic critical values are invalid due to the small sample sizes. Instead, we conducted a Monte Carlo analysis to generate the appropriate small sample critical values. The critical value corresponding to a 99 percent confidence level is 13.98.

The results from the other two structural break tests are also broadly supportive of the previous subsection's findings. With respect to SO_2, panel B of Figure 7 reveals that the largest *F*-statistics are concentrated in the period $\tau = -2$ through $\tau = 1$. The QLR statistic (i.e., the biggest *F*-statistic) occurs at $\tau = -1$ and is easily statistically significant at the 1 percent level (Table 5). A comparison of this figure and Figure 5 reveal that the QLR test, which is only designed to test for a single break, picks the arrest of the upward trend in SO_2 as a more important change than the downward trend that is first evident in $\tau = 1$. Overall, the test suggests that the case for the catalytic converter policy reducing SO_2 concentrations is not as strong as the case for a relationship between the policy and reduced PM concentrations. Finally, panel C of Figure 7 and Table 5 fail to provide evidence of a structural break in NO_2 concentrations, which is consistent with Table 3 where the null of zero effect cannot be rejected.

For comparison, panel B of Table 5 provides the QLR test statistics for the National River Conservation Policy. The null of no structural break cannot be rejected for the BOD or ln(FColi) time series, which is consistent with the results in Table 4. There is a significant break in DO, but it occurs three years prior to the event; this is consistent with the observed *worsening* of DO that, according to the event study analysis in Figure 6, begins about three years prior to the program implementation. Finally, we note that we could not conduct the QLR test for the SCAPs due to the limited number of event years for these policies.

As is always the case with a non-experimental design, there is a form of unobserved heterogeneity that can explain the findings without a causal explanation. For example, the catalytic converter policies may have been assigned based on an unobserved factor that also determined future air pollution reductions. Although we cannot rule out this possibility, this subsection's results at least fail to directly contradict the existence of a causal relationship between the catalytic converter policy and air pollution reductions.

D. *Effects of Catalytic Converter Policy on Infant Mortality*

The catalytic converter policy is the most strongly related to improvements in air pollution. This subsection explores whether the catalytic converter policy is associated with changes in human health, as measured by infant mortality rates.

Specifically, we fit equation (1) and equations (2A)–(2C), where the infant mortality rate is the outcome of interest. Several estimation details are noteworthy. First, despite a large data collection exercise (including going to each state to obtain additional registry data), there are fewer cities in the sample.[28] Second, the dependent variable is constructed as the ratio of infant deaths to births, and equation (1) is weighted by the number of births in the city-year. Third, it is natural to consider using the catalytic converter-induced variation to estimate the separate impacts of each of the three forms of air pollution on infant mortality in a two-stage least squares setting. However, such an approach is invalid in this setting because, even when the exclusion restriction is otherwise valid, there is a single instrument for three endogenous variables.

Figure 8 and Table 6 report the results. In light of the differential preexisting trend, the column 3 (of Table 6) specification is likely to be the most reliable. It suggests that the catalytic converter policy is associated with a reduction in the infant mortality rate of 0.64 per 1,000 live births. However, this estimate is imprecise and is not statistically significant.

[28] When the air pollution sample is restricted to the sample used to estimate the infant mortality equations, the catalytic converter policy is associated with substantial reductions in PM and SO_2 but not of NO_2 concentrations. For the analysis, the sample includes $\tau = -10$ through $\tau = 5$.

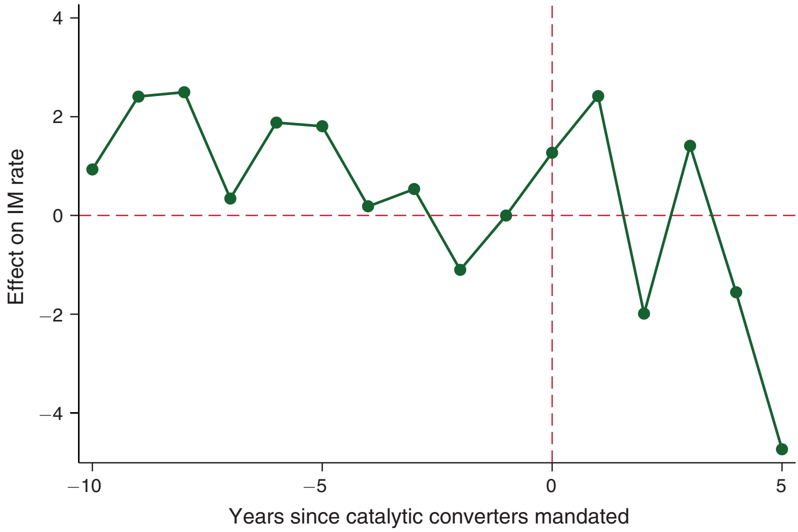

Figure 8. Event Study of Catalytic Converters and Infant Mortality

Notes: The figure provides a graphical analysis of the effect of the catalytic converter policy on the infant mortality rate. The figure plots the estimated σ_τs against the τs from the estimation of equation (1). See the text for further details.

V. Why Were the Air Pollution Policies More Effective than the Water Pollution Policies?

The previous section's analysis indicates that India's air pollution policies were more successful than the water pollution ones. The question that naturally arises is why? India has an extensive history of both types of policies, and, in fact, the National Water Act—giving the government the rights and official structure in which to regulate water pollution—was passed seven years *before* the Air Act. In the absence of precise measures of willingness to pay for improvements in air and water quality and the costs of supplying them, this section presents qualitative and quantitative evidence that suggests that the difference reflects a greater demand for air quality improvements.

A. *Qualitative Evidence*

There are several reasons why the demand for better air quality may exceed that for water. First, the costs of air pollution may be higher: the Global Burden of Disease study (Lim et al. 2012) suggests that outdoor PM and ozone air pollution are responsible for about 3.4 million premature fatalities annually. In contrast, the estimated number of annual premature fatalities due to unimproved water and sanitation (i.e., about 340,000) is an order of magnitude smaller. Further, recent evidence indicates that the mortality impacts of poor air quality at the high concentrations observed in many Indian cities may be worse than previously recognized (Chen et al. 2013).

TABLE 6—TREND BREAK ESTIMATES OF THE EFFECT OF THE CATALYTIC CONVERTER POLICY ON INFANT MORTALITY

	(1)	(2)	(3)
π_2: time trend		−0.4**	−0.3
		(0.2)	(0.2)
π_1: 1(*policy*)	−1.5	1.8	3.6
	(1.0)	(1.5)	(1.5)
π_3: 1(*policy*) $\times$ time trend			−0.84**
			(0.4)
5-year effect $= \pi_1 + 5\pi_3$			−0.6
p-value			0.7
Observations	16	16	16
Equation (2A)	Yes	No	No
Equation (2B)	No	Yes	No
Equation (2C)	No	No	Yes

Notes: This table reports estimates of the impact of the catalytic converter policy on infant mortality rates from the fitting of equations (2A), (2B), and (2C). The row denoted "5-year effect" reports $\pi_1 + 5\pi_3$, which is an estimate of the effect of the relevant policy five years after implementation from equation (2C). The *p*-value of a hypothesis test for the significance of this linear combination is reported immediately below the five-year estimates.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

The second, and related, reason may be a difference in avoidance costs. The argument starts with the observation that middle- and upper-income groups are the most likely to engage in public activism on environmental issues, and these groups may find it relatively easy to avoid water pollution through the purchase of clean, bottled water. In fact, the revenue generated from bottled water sales in India in 2010 exceeded \$250 million and was "expected to grow at a 30 percent rate in the next 7 years."[29] Further, it is common for middle-class households to use boiling and other techniques for cleaning water. In contrast, it is nearly impossible to completely protect oneself against air pollution because people spend time outdoors for leisure, travel to work, etc., and air pollution can penetrate buildings and affect indoor air quality.

Third, air pollution appears to have been a greater source of concern in public discourse, suggesting relatively greater demand for air quality. We collected data from the *Times of India*, which is the most widely read English-language newspaper in India (and the world), on the number of mentions of air and water pollution. Figure 9 demonstrates that air pollution was mentioned about three times as frequently as water pollution between 1986 and 2007.[30] While this finding is consistent with higher demand for air quality, it is possible that the greater mentions reflect differences in water or air pollution concentrations or some other factor.

Fourth, the implementation and enforcement of the water pollution regulations, compared to the air pollution regulations, suggest a relatively lower demand for water quality improvements. For starters, the lines of authority under the NRCP for

[29] http://www.researchandmarkets.com/research/f9deab/indian_bottled_wat (accessed on August 14, 2012).

[30] Interestingly, this finding still holds even when reports from Delhi, which had especially poor air quality, are dropped.

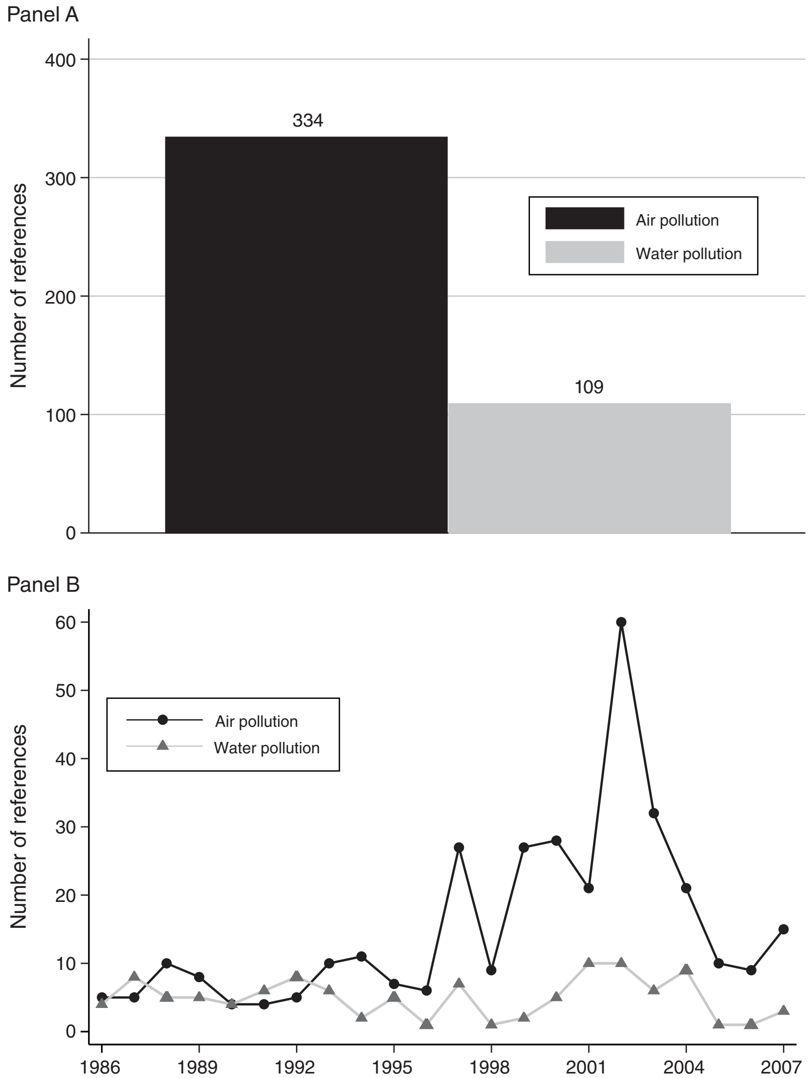

Figure 9. Total Nationwide References to Air and Water Pollution in *Times of India*, 1986–2007

Source: Author compilation from the *Times of India*.

the designation of water quality standards and their enforcement were muddled and unclear. No single organization was accountable for ensuring success. Although the NRCP was originally developed and launched by the MoEF, implementation and enforcement were split among a wide variety of institutions that frequently lack the power necessary for successful enforcement, including the CPCB, the State Pollution Control Boards, and local departments for public health, development, water, and sewage (Ministry of Environment and Forests 2006). Additionally, the recommended solutions to high water pollution concentrations involve the construction of sewage treatment plants and other expensive capital investments, but the legislation did not provide a dedicated source of revenues and funding responsibility jumped around across levels of government during this period.[31] Further, state and local bodies have been accused of financial mismanagement, including diversion, underutilization, and incorrect reporting of funds (Ministry of Environment and Forests 2006). The weak institutional support for the NRCP was evident in the failure to achieve basic "process" goals, such as construction of necessary sewage treatment plants.[32]

In principle, air pollution laws had many of the same jurisdictional and enforcement issues, but the key difference is that they often had the forceful support of India's supreme court. This difference is a critical one because the supreme court has the role of determining when there have been serious infringements of fundamental and human rights. The avenue for such determinations is India's public interest litigation that can compel the supreme court to deliver economic and social rights that are protected by the constitution but are otherwise unenforceable. Notably, a public interest litigation suit can be introduced by an aggrieved party, a third party (e.g., a nongovernmental organization), or even the supreme court itself. In many instances, the supreme court's rulings have been motivated by executive inaction.

India's supreme court became heavily involved in environmental affairs with its order that Delhi develop an action plan to address pollution in 1996.[33] The court followed that order with a directive to create an authority "to advise the court on pollution and monitor implementation of its order." Following the success of the Delhi efforts, new initiatives to address pollution were pushed forward by nongovernmental organizations, public sentiment, prominent Indian citizens, and the supreme court. These efforts ultimately led to further action by the supreme court, including requirements for city-level SCAPs, the mandatory installation of catalytic converters for designated cities, and other regulatory and enforcement efforts.

In summary, the air pollution regulations had the powerful supreme court's backing and this brought substantial bureaucratic effort to bear on the problem.[34] In contrast, the implementation and enforcement of the water pollution regulations appeared to lack widespread public support and was left to a mix of central and state government institutions without the tools, accountability, and resources that are generally critical for effective governance. Our read of the history is that the supreme court's decision to focus on air pollution, and largely ignore water pollution, was

[31] Under the first river action plan in 1985, the central government was responsible for 100 percent of policy funding. In 1990, it was decided that the cost would be split between central and state administrations. This division was revoked in 1997, returning the full cost to the Union government. One final change was made in 2001, allocating 30 percent of the financial burden to states, a third of which was levied on local bodies themselves (Suresh et al. 2007, p. 3).

[32] For example as of March 2009, 152 out of 165 towns officially covered under NRCP have been *approved* for sewage treatment plant capacity building, but construction has been initiated in only 82. Additionally, as of March 2009, there has not been any spending of federal or state monies on the NRCP in 15 NRCP towns (National River Conservation Directorate 2009). Furthermore, the Centre for Science and Environment (CSE) calculates that the 2006 treatment capacity was only 18.5 percent of the full sewage burden (Suresh et al. 2007, p. 11).

[33] It has been suggested that the mandate for an action plan to address pollution in Delhi was partially due to Justice Kuldeep Singh reading a book published by the influential NGO Centre for Science and Environment, entitled *Slow Murder: The Deadly Story of Vehicular Pollution in India* (Narain and Bell 2005, p. 10).

[34] A former CPCB chairman summed up the need for supreme court intervention: "When it comes to doing things, it is not up to the CPCB, even in the area of air pollution." (Sharma and Roychowdhury 1996, p. 128).

Table 7—Difference in Catalytic Converter Five-year Treatment Effect between Cities above and below the Median in Proxies for Demand for Clean Air

	Proxies for demand for clean air	
	Urban literacy (1)	Air pollution mentions (2)
Panel A. PM		
Difference in 5-year effect, above − below median = $\pi_3 + 5\pi_7$	21.34	−21.9
p-value	0.66	0.62
Observations	34	33
Panel B. SO_2		
Difference in 5-year effect, above − below median = $\pi_3 + 5\pi_7$	−3.81	−31.65***
p-value	0.51	0.00
Observations	33	34
Panel C. NO_2		
Difference in 5-year effect, above − below median = $\pi_3 + 5\pi_7$	−3.76	−3.71
p-value	0.65	0.55
Observations	33	33

Notes: This table explores the heterogeneity of the treatment effect for the catalytic converter policy. It reports estimates of whether the catalytic converter policy's effect five years after implementation differs in cities with above (relative to below) the median measures of demand for clean air. This test is implemented by allowing for separate σ_Ts for the above and below median cities of the relevant proxy (noted in the column headings) in equation (1), stacking the two sets of σ_Ts for the estimation of equation (2C), and then formally testing whether $\pi_1+5\pi_3$ is equal in the two sets of catalytic converter adopting cities from a fully interacted version of equation (2C). As in the main analysis, all regressions are estimated by OLS and include indicators for the SCAPs in the first stage, and have robust standard errors in the second stage. The number of cities adopting the catalytic converter policy who are above (below) the median for urban literacy are 13 (13) and air pollution mentions 14 (10).

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

due to the higher demand for government provision of improved air quality that manifested itself as public activism and citizen suits.[35]

B. *Quantitative Evidence*

This subsection quantitatively assesses the hypothesis developed in the previous subsection that the greater success of air pollution policies was due to higher demand for improvements in air quality. This exercise is conducted by dividing the sample of cities into those with above and below the median value of variables that can be interpreted as demand shifters for air quality.

Table 7 reports estimates of whether the catalytic converter policy's effect five years after implementation differs in cities with above (relative to below) the median

[35] As just one prominent example, see the court order from April 5, 2002, Supreme Court of India. Writ Petition (Civil) No. 13029 of 1985. *M.C. Mehta versus Union of India and Others*.

measures of proxies for demand for clean air. This test is implemented by allowing for separate σ_τs for the above and below median cities of the relevant proxy (noted in the column headings) in equation (1), stacking the two sets of σ_τs for the estimation of equation (2C), and then formally testing whether $\pi_1 + 5\pi_3$ is equal in the two sets of catalytic converter adopting cities from a fully interacted version of equation (2C).[36] In column 1 of Table 7, the sample is divided into cities above and below the median urban literacy rate; we assume that literacy is a proxy for higher demand for air quality because it provides knowledge on the health effects of air quality and/or higher income. In column 2, cities are divided by the number of mentions of air pollution (measured at the state-level) in the *Times of India*. We interpret the newspaper mentions as a proxy for demand for clean air, although it would be inappropriate to definitively rule out that the mentions reflect other factors that cannot be classified as demand shifters (e.g., they may provide new information that in turn increase demand for air quality).

In columns 1–2 of Table 7, five of the six estimates are negative, which indicates that the catalytic converter policy was associated with larger declines in air pollution in cities with above the median values of the proxies for high demand for air quality. However, only one of these estimates would be judged to be statistically significant by conventional criteria. Overall, we conclude that directionally the empirical exercise is supportive of the demand for air quality explanation but the imprecision of the estimates, along with the observational design, makes definitive conclusions unwarranted.[37]

VI. Conclusion

Using the most comprehensive data file ever compiled on air pollution, water pollution, environmental regulations, and infant mortality for a developing country, this paper tests for the impacts of key air and water pollution regulations in India. We find that air regulations were in part responsible for observed improvements in air quality over the last two decades. The most successful air regulation resulted in a modest but statistically insignificant decline in infant mortality. In contrast to the air findings, the results indicate that the NRCP—the cornerstone of India's water policies—failed to lead to improvements in any of the three available measures of water pollution.

India, like many developing countries, is widely considered to have weak regulatory institutions, so the success of the air policies is noteworthy. A range of qualitative and quantitative evidence suggests that citizens' higher relative demand for air quality improvements, especially those with the means to file public interest litigation suits, were critical to the air regulations' success. This demand and activism prompted the supreme court, which is widely considered the country's most efficacious institution, to become active in the implementation and enforcement of the air regulations.

[36] As in the main analysis, all regressions are estimated by OLS and include indicators for the SCAPs in the first stage, and have robust standard errors in the second stage.

[37] Table 7's results are unchanged qualitatively if cities are divided by the per capita *Times of India* mentions of air pollution, rather than the raw number of mentions.

There are several broader implications. First, the results demonstrate that environmental regulations and presumably other government interventions can succeed, even in weak institutional settings, when demand and/or public support is strong enough. Second, the results suggest that no matter what climate deals are worked out internationally, India may be unlikely to significantly reduce greenhouse gas emissions until climate change becomes an urgent issue domestically. This would pose challenges for addressing climate change because India is projected to be a major contributor to the growth in greenhouse gas emissions in the coming decades. Third, the paper has left unanswered the fundamental questions of the magnitudes of the marginal benefits and costs of regulation-induced emissions reductions and whether the benefits exceed the costs. Currently, there is very limited information on the costs and benefits of environmental regulations in developing countries and this is a rich area for future research.

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