Why do Governments Overpromise and Underdeliver? Evidence from India's National Clean Air Programme*

Archana Dhinakar Bala
Columbia University

Martin Mattsson
National University of Singapore

Sangita Vyas
CUNY Hunter College

October 28, 2025

Abstract

What are the political consequences of setting ambitious policy targets, but then failing to meet them? We study this question in the context of India's National Clean Air Programme (NCAP), a flagship policy designed to cut air pollution by 40% in 131 cities and address a crisis that causes 1.2 million deaths annually. Using multiple difference-in-differences approaches, we demonstrate that the program had no effect on air pollution. In a survey experiment with residents of NCAP cities, we show that informing citizens about NCAP boosted their approval of the government's air pollution policy. Surprisingly, this effect persisted even when respondents were told the program had no impact — revealing a clear political benefit from the ambitious announcement, and minimal cost for the implementation failure. This incentive structure is consistent with the lack of political commitment to implementing NCAP, which we document, and is a likely explanation for the program's failure.

Keywords: Air Pollution, Government Policy, Policy Targets, Policy Implementation
JEL Codes: D78, K32, Q53, Q58

*Bala: ad4353@columbia.edu; Mattsson: martin.mattsson@nus.edu.sg; Vyas: sangita.vyas@hunter.cuny.edu. We thank Xinming Du, Navroz Dubash, Siddharth George, Sarath Guttikunda, Meera Mahadevan, Matthew Neidell, Rohini Pande, Dean Spears, Tariq Thachil, and Sumil Thakrar, as well as participants at seminars at ANU, BREAD, University of Melbourne, UNSW, and Uppsala University for helpful comments and suggestions. We thank Prayog Bhattarai and Maahir Garg for their excellent research assistance. A pre-analysis plan for the survey experiment is available at: www.socialscienceregistry.org/trials/13941. This project was approved by CUNY Hunter College and National University of Singapore IRBs. This project was supported financially by the National University of Singapore and CUNY Hunter College.

1 Introduction

Air pollution in India claims 1.2 million lives annually and is one of the most serious public health emergencies in the world (Health Effects Institute, 2024). In 2019, the Government of India announced an ambitious clean air policy, which required 131 of India's largest and most polluted cities to reduce pollution by 40%, relative to 2017 levels, by 2026. If the program is successful, it could save more than 100,000 lives annually and be one of the most important environmental programs in the world.[1] However, achieving this target is far from certain,[2] and as the program nears its end, its actual impact on air pollution remains an important yet unanswered question.

India's clean air policy is an example of a common practice in public policy: the setting of aspirational targets that are difficult to achieve. Leaders have pledged, for example, to cut greenhouse gas emissions, protect biodiversity, and achieve universal primary education, but actual progress on these goals has fallen short of promises (UN, 2015; SCBD, 2020; Li et al., 2024). Clear targets are a core element of good management practices and may motivate and coordinate government officials towards a common goal (Bloom et al., 2014). However, failing to meet a stated target can erode public trust and reduce politicians' credibility (Bytzek et al., 2024). What are the public opinion consequences of setting ambitious goals and then failing to meet them?

In this paper, we study the political consequences of ambitious policy goals in the context of the National Clean Air Programme (NCAP), the Indian government's flagship program to improve air quality. First, we estimate the effect of the program on air pollution, and find a precisely-estimated zero impact. Second, we implement a survey experiment to investigate the public opinion consequences of the policy and its failure. Our experiment reveals that political incentives for policy implementation in this context are weak: notifying respondents about

[1] Section 2.3 describes our strategy for developing this estimate.

[2] To put the target into context: it took about twelve years for the United States to achieve a similar decline after the Clean Air Act Amendment in 1970 (Chay and Greenstone, 2005). Moreover, since satellite-derived estimates of particulate pollution began in 1998, annual particulate pollution in NCAP cities has never been so low.

NCAP improved opinions of the government, even when respondents were told that the program failed to reduce air pollution. Our findings rationalize setting ambitious targets that go unmet: governments can reap the reputational benefits from announcing a policy without bearing any political costs for its failure.

We estimate the effect of NCAP on $PM_{2.5}$ — that is, fine inhalable particles that have a diameter of 2.5 micrometers or smaller — using two types of difference-in-differences strategies. To accomplish this, we assemble a new longitudinal dataset that matches satellite-derived estimates of $PM_{2.5}$ from van Donkelaar et al. (2021) to Indian cities. Our first difference-in-difference approach compares cities that were part of NCAP to all cities that were not covered by NCAP, before and after the start of the policy in 2019. For our second approach, we limit our analysis sample to cities that narrowly met and narrowly failed to meet the NCAP inclusion criteria. This strategy effectively combines a regression discontinuity design with a difference-in-differences design.

Using both research designs, we find a precisely estimated zero effect of NCAP on $PM_{2.5}$. In particular, the lower bound of the 95% confidence interval of our preferred estimate is a decline of -1.6%. The program is very far off track from meeting its stated objective of a 40% reduction by the 2025-2026 financial year. We show that these results are stable through a battery of robustness tests. For example, results are similar using air pollution measurements from government monitoring stations on the ground, excluding cities that may have experienced pollution reduction spillovers, and using the synthetic difference-in-differences approach developed by Arkhangelsky et al. (2021).

Our findings are surprising for three reasons. First, similar policy efforts have proven successful in reducing air pollution in other contexts, such as the US and China (Chay and Greenstone, 2005; Niu et al., 2023). Second, previous initiatives to reduce air pollution by the Indian central government have been described as successful in the academic literature (Greenstone and Hanna, 2014; Harrison et al., 2015; De Simone et al., 2024). Third, when 82 social scientists made predictions about the effect of NCAP, their median prediction was that it would bring about

an 8.5% decline in air pollution, an effect size which can be rejected based on the results of our analysis.

What are the public opinion consequences of setting such an ambitious goal and then failing to meet it? To answer this question, we conducted a survey experiment with 4,610 respondents across 16 NCAP cities. We randomized respondents into one of three arms. The control group received no information about NCAP. One of the treatment arms received information about NCAP and its goals. The other treatment arm received information about NCAP, its goals, and was also told that the policy had thus far had no effect on air pollution. We find that informing respondents about NCAP substantially improved their opinions of the central government's policies to reduce air pollution, even when they were also told that the program had no effect.

We also uncover evidence of a lack of political commitment to reducing air pollution. In an interview with one of the authors, a senior politician confirmed that the government is not prioritizing air pollution reduction. NCAP has also received little attention in the Prime Minister's public addresses: it has only been mentioned three times in his monthly radio broadcasts, while other programs have been mentioned ten times as often. Finally, an analysis of NCAP's budget reveals that funds allocated to emission-reduction activities that would provoke opposition from politically strong interest groups, such as industries, are lower than for other activities.

The findings from our survey experiment help to rationalize this lack of political will. When the public rewards the government for ambitious announcements alone, and the reputational costs of policy failure are minimal, the incentive to undertake the difficult work of effective implementation is weak. This incentive structure can explain the lack of political commitment to NCAP and its subsequent failure to achieve its target.

This paper contributes to three strands of literature. First, we contribute to the literature examining the political economy of environmental policy. Existing research in this area primarily focuses on the role of interest groups (Oates and

Portney, 2003), the strategic behavior of politicians and governments (List and Sturm, 2006; Kahn et al., 2015; Lipscomb and Mobarak, 2016; He et al., 2019; Dipoppa and Gulzar, 2024) and citizen engagement (Buntaine et al., 2022; Singh and Thachil, 2023). A study closer to our own examines the links between air pollution and public opinion in China, and finds that reducing air pollution increases support for the government in China (Alkon and Wang, 2018). We extend this literature by showing that public opinion can shape policymakers' incentives in ways that reward ambition over effectiveness, allowing political gains to persist even when implementation fails.

Second, we contribute to the literature on pledges and promises made by politicians. This literature has focused on pre-election pledges and subsequent behavior by the winner of the election. Theoretical models typically regard election pledges either as perfectly binding or as inconsequential cheap talk (Persson and Tabellini, 2000). The empirical literature has focused on high-income countries and shows that parties tend to keep most of their pre-election pledges, especially if they form a single-party government (Thomson et al., 2017; Naurin et al., 2019). Furthermore, Born et al. (2018) and Bytzek et al. (2024) show that in experimental settings, promise-breaking by politicians causes "voters" to lose trust in the government and punish politicians in the subsequent election. Contrary to this finding, we find that in a highly consequential setting in a developing country, residents do not only fail to punish politicians who fail to meet targets, but instead reward them for the simple act of adopting ambitious goals.

Third, we conduct the first comprehensive evaluation of the causal effect of NCAP, the largest policy initiative to reduce air pollution in South Asia.[3] Similar air pollution policies have been found to be effective in the US (Chay and Greenstone, 2005; Isen et al., 2017; Shapiro and Walker, 2018), China (Niu et al., 2023), and India (Greenstone and Hanna, 2014; Harrison et al., 2015). In contrast, we show

[3]Previous studies of NCAP do not use a comparison group to establish the causal effect. Guttikunda et al. (2024) shows that most types of pollution have increased in NCAP cities from 2019 to 2023. Xie et al. (2024) shows that the decreases in $PM_{2.5}$ in a subset of NCAP cities are partially driven by meteorological factors. Manojkumar and Muruganandam (2025) reports that very few NCAP cities have achieved their pollution reduction targets.

that the most comprehensive air pollution policy to date in India did not reduce air pollution. Furthermore, we provide suggestive evidence that one significant factor in this failure is a lack of political will to implement the policy, and that this lack of commitment could be optimal from the perspective of the government.

The remainder of the paper is organized as follows. Section 2 provides background information on air pollution in India and NCAP. Section 3 describes our data and empirical strategies for estimating the effect of NCAP on air pollution. Section 4 presents the results on the impact of NCAP on air pollution. Section 5 describes our survey experiment and its results. Section 6 discusses potential reasons why NCAP did not reduce air pollution, and Section 7 concludes.

2 Background

2.1 Air Pollution in India

India has some of the world's worst air pollution. Based on data from the World Health Organization's Ambient Air Quality database, 24 of the 30 most polluted cities in the world are in India (World Health Organization, 2024). Over the past two decades, air pollution in India has worsened as industry, car ownership, electricity-generation, burning of biomass for cooking and heating, and crop-burning have grown (Guttikunda and Nishadh, 2022). Figure 1 shows a map of average annual levels of $PM_{2.5}$ in India in 2018. Pollution levels in most of the country are higher than the WHO guideline of $5\,\mu g/m^3$, and in many parts of the country are higher than the Indian government's guideline of $40\,\mu g/m^3$. Panel (a) of Appendix Figure A.1 shows sources of air pollution in 43 NCAP cities.

In India, the Central Pollution Control Board (CPCB) is responsible for both air pollution data collection and enforcement of regulations. As part of its National Air Monitoring Programme, the CPCB has worked with other agencies to set up 931 manual air quality monitoring stations in 398 cities and towns to monitor air pollution twice per week. The CPCB also maintains the Continuous Ambient Air Quality Monitoring System, which is a real-time monitoring network. This network has 542 stations throughout India, and makes daily measurements of $PM_{2.5}$, among

other pollutants, available online.

Although the CPCB is also tasked with controlling air pollution, the Supreme Court has often taken the lead in reforms to improve air quality. In 1996, the Court began to order cities identified as critically polluted to develop Supreme Court Action Plans to reduce air pollution. The plans included activities such as fuel regulations, the construction of new roads bypassing highly populated areas, the transition of buses to compressed natural gas, and restrictions on industrial pollution. In total, the supreme court ordered 17 cities to develop action plans and the program has been found to be effective in reducing certain types of air pollution (Greenstone and Hanna, 2014).[4] The Supreme Court Action Plans are similar to NCAP, which we study here, in that cities developed and implemented their own strategies for reducing air pollution.

2.2 National Clean Air Programme

The National Clean Air Programme (NCAP) aims to improve air quality in India's 131 largest and most polluted cities. Cities that failed to meet India's ambient air quality standards for PM_{10}, $PM_{2.5}$, and NO_2 consecutively between 2011 and 2015, or were one of the top ten polluted cities in the WHO's 2018 Database, were designated as "non-attainment" cities and selected to be part of the program.[5] 102 cities were initially identified based on these criteria. In 2018, the Ministry of Environment, Forest, and Climate Change (MoEFCC) directed states and union territories with cities identified based on the criteria listed above to develop action plans to reduce air pollution in these cities, and in January 2019, the program was officially launched. After the program began, 22 more cities were added to NCAP based on newly available pollution data. In 2021, eight cities that had populations greater than one million were also included in NCAP. Subsequently, two cities merged, bringing the total number of NCAP cities to 131. In our main analyses, we do not treat the cities that were added later differently and consider

[4] In robustness checks, we show that our results are robust to dropping these 17 cities from our analysis (see Table 4).

[5] Since many Indian cities did not have monitoring stations during the 2011 to 2015 period, a large number of cities that most likely violated the air quality standards were not included in the program.

them affected by NCAP from 2019 onward. Dropping the cities that were added after January 2019 does not change the main results of the analysis (see Table 4).

When the program was launched, the goal of NCAP was to bring about a 20% to 30% reduction in $PM_{2.5}$ and PM_{10}, relative to 2017 levels, by 2024 (MoEFCC, 2019). In September 2022, the government set a new target of a 40% reduction in particulate matter concentrations by 2025-26, relative to 2017-18 levels.[6] In our main analyses, we study NCAP's impact on $PM_{2.5}$, though we also show that results are similar for PM_{10} and other pollutants.

Plans were developed by state committees and then reviewed and approved by a central committee consisting of academic experts and CPCB officials. Examples of action items in the plans include: expansion of air quality monitoring, assessment of pollution sources, transitioning to electric vehicles for public transport, changing brick kilns to cleaner technology, building waste and construction debris management facilities, and using mechanical street sweepers, among other strategies for reducing air pollution. Panel (b) of Appendix Figure A.1 shows that all major sources of pollution were targeted by the action plans.

From the 2019-2020 fiscal year until 2025-2026, INR 197 billion (USD 2.6 billion[7]) of funding has been earmarked for NCAP. This is a large amount of funding compared to other environmental projects in India. Even though only one third of NCAP funding comes directly from the MoEFCC, NCAP accounted for more than a fifth of MoEFCC spending in the 2023-2024 fiscal year (MoEFCC, 2025). Since 2021, a performance payment scheme has been implemented, in which approximately 40% of the funding is contingent on the city having achieved certain air pollution reductions.[8] We provide more information on NCAP financing in Appendix Section A.

[6]The new target was initially communicated via media in September 2022 (e.g. The Hindu, 2022). A government press release in March 2023 specified that the new target was to achieve a 40% reduction or to meet the National Ambient Air Quality Standards for PM_{10} by the 2025-26 financial year.

[7]Throughout the paper we use a USD/INR exchange rate of 75.96, the average exchange rate from 2019 to 2023.

[8]NCAP was not directly funded by international donors such as the World Bank or UN agencies. Therefore, it is unlikely that the ambitious goals were set to satisfy donors or other outside actors.

2.3 NCAP's Potential Benefits

If successful, NCAP has the potential to be one of the most impactful environmental policies in history. It covers 131 highly polluted cities with a combined population of 350 million people.[9] If NCAP reaches its target of a 40% reduction in pollution, we estimate that about 118,000 deaths could be avoided annually.[10]

NCAP set a very ambitious target of reducing air pollution by 40%, but it is not clear that this should be our expectation of the program. Although decreases in air pollution of similar magnitudes have occurred in the US and China under similar programs,[11] India's income level and state capacity are far below that of those countries. To anchor our expectations of the effect of NCAP in an impartial and transparent way, we solicited predictions of the effect of NCAP on air pollution from social scientists and forecasters using the Social Science Prediction Platform. The results are presented in Appendix Table A.1. We received 82 predictions. 83% of those who made a prediction hold a PhD or are enrolled in a PhD Program. The median prediction was that air pollution would decrease by 12% between 2017 and 2026 in NCAP cities and that the causal effect of NCAP would be an 8.5% decrease. Using the assumptions described above for our back-of-the-envelope estimate of potential lives saved, an 8.5% decrease in air pollution could result in 15,000 fewer deaths per year.

[9]We estimate the cities' current population by taking their 2011 census population (260 million) and increasing it proportionally to the growth of the urban Indian population between 2011 and 2024, estimated by the World Bank (2025). If these cities were a country, it would be the third most populous country in the world.

[10]To generate a back-of-the-envelope estimate of NCAP's potential benefits, we make the conservative assumption that these cities have a mortality attributable to air pollution that is equal to the Indian average of 84 deaths per 100,000 population for ambient particulate matter pollution and ozone (Health Effects Institute, 2024). This would mean that approximately 295,000 deaths in NCAP cities are attributable to ambient air pollution annually. If we further assume that deaths decline linearly with pollution levels, this would mean that NCAP reaching its target of a 40% reduction would avoid 118,000 deaths per year.

[11]In the US, total suspended particle pollution fell by approximately 40% within 12 years of the 1970 Clean Air Act Amendments (Chay and Greenstone, 2005). In China, $PM_{2.5}$ levels decreased by more than 40% in the five years after the government declared "war on pollution" in 2014 (Greenstone et al., 2021).

3 Data and Empirical Strategies

3.1 Data

We obtain and process air pollution data compiled from two different sources — satellite-derived estimates of air pollution from van Donkelaar et al. (2021) and measurements of air quality from monitors in measurement stations on the ground.

We rely on satellite-derived air pollution estimates for our primary analyses because they offer broader spatial and temporal coverage. The satellite data are available at $0.01° \times 0.01°$ grid resolution for all of India for every month between 1998 to 2023.[12] We geographically match the satellite data to urban agglomerations in the 2011 Census using SHRUG's shrid polygons (Asher et al., 2021).[13] We then aggregate pollution data for the shrids in each identified city. We include cities with populations above 100,000 so that NCAP cities are more comparable — in terms of population and population density — to the cities that did not have NCAP in our sample. This population criterion excludes from our analysis 21 NCAP cities with a population of less than 100,000. Furthermore, 6 NCAP cities are in the same urban agglomeration as another NCAP city and are therefore not uniquely identifiable in our data. This means that our final dataset has 104 uniquely identified NCAP cities and 364 comparison cities. Table 1 shows summary statistics for NCAP and comparison cities in our sample. The table shows that NCAP cities are more populated and have a higher population density than comparison cities, but are otherwise similar. We provide more details on the collection and processing of data on pollution (from satellite data and ground monitors), urban agglomerations, and shrid polygons in Appendix Section B. Appendix Section C discusses data quality and analyses showing the strong correlation between satellite and station data.

In alternative analyses, we limit our sample to cities that narrowly met and narrowly failed to meet the NCAP inclusion criteria. We use government documentation to identify the criteria used to determine NCAP status, and construct a measure of closeness to the NCAP eligibility cutoff. We describe

[12] At India's centroid point, $0.01° \times 0.01° = 1.1 \times 1.0$km.

[13] Census 2011 urban agglomerations are matched to SHRUG's shrids by name.

this strategy in greater detail in Section 3.2.2.

3.2 Empirical Strategies

3.2.1 Difference-in-Differences

For our main specification, we use a difference-in-differences approach that compares the 104 cities included in NCAP to all 364 other Indian cities. We estimate the effect of NCAP using the following two-way fixed effects regression:

$$Pollution_{ct} = \beta \times Post_t \times NCAP_c + \tau_t + \delta_c + \epsilon_{ct} \tag{1}$$

where $Pollution_{ct}$ is the pollution level in city c in month-year t, $Post_t$ is an indicator variable for whether the month is January 2019 or after, and $NCAP_c$ is an indicator variable for whether the city was part of NCAP. τ_t and δ_c are time (month-year) and city fixed effects, respectively. In some specifications, we also control for city-specific time trends.

β, the coefficient of interest, estimates the average effect of treatment on the treated (ATT). It measures the average effect of NCAP on air pollution in cities that were part of the program. Our identification strategy is not dependent on cities being randomly or exogenously assigned to NCAP. Instead, the key identifying assumption is that in the absence of NCAP, pollution in the cities that did and did not become part of the program would have trended in parallel.

To test if the parallel trends assumption holds in the period before NCAP started, as well as to estimate the dynamic effects of NCAP over time, we use the following dynamic difference-in-differences regression:

$$y_{ic} = \sum_{y=2009}^{2017} \gamma_y \times NCAP_i + \sum_{y=2019}^{2023} \beta_y \times NCAP_i + \tau_t + \delta_c + \epsilon_{ic} \tag{2}$$

where γ_y coefficients test the parallel trends assumption by comparing all the pre-period coefficients to 2018, the year before NCAP started. The β_y coefficients estimate the effect of NCAP, individually for each of the years after NCAP started.

3.2.2 Difference-in-Differences for Cities Close to Eligibility Cutoff

The cities included in NCAP are different from cities not included in NCAP, as shown in Table 1. It is possible that pollution levels in NCAP versus comparison cities would have trended differently even in the absence of NCAP. To minimize these concerns, in an alternative specification, we restrict our sample to NCAP cities close to the eligibility cutoff. The benefit of this strategy is that we analyze the effect of NCAP among a subset of cities that are more similar in terms of observable characteristics.

Eligibility for NCAP was determined based on three main criteria: historical air pollution based on ground station measurements, rank in the WHO Ambient Air Quality Database, and population size. We collected data on each criterion and created an NCAP eligibility score reflecting how close a city was to being eligible for the program. We provide more details on the criteria, data sources, and construction of the eligibility score in Appendix Section B.5.3.

Figure 2 shows the distribution of eligibility scores across all cities and around the cutoff. It is implausible that cities manipulated the variables determining eligibility for the purpose of being included or excluded because the eligibility criteria was set after the data for each underlying variable were collected and made public. Empirically, Sub-Figure 2a shows a similar density of cities just above and just below the cutoff.

In Sub-Figure 2b, we show the cities that were included in NCAP among the cities that had eligibility scores between 70% to 130% of the NCAP eligibility cutoff.[14] In this sample, none of the 27 cities that were not eligible for NCAP were included in the program. Among the 27 cities eligible for NCAP, 21 cities (77.78%) received the program.

Table 1 shows summary statistics separately for the group of cities just-eligible for NCAP (100%-130% of the eligibility threshold) and just-ineligible for NCAP (70%-100% of the eligibility threshold). In this sample of cities that are near the eligibility cutoff for NCAP, the two types of cities are similar on characteristics for

[14]Appendix Figure A.2 provides the same information for the complete sample of cities.

which we have data.

After restricting the sample to cities close to the NCAP eligibility cutoff, we run the regressions described in Equations 1 and 2. In these analyses, the treatment variable is an indicator variable that the city was *eligible* for NCAP. This is determined by the eligibility score. Actual NCAP status may have been influenced by other considerations.

4 Results: The Effect of NCAP on Air Pollution

4.1 Difference-in-Differences

Figure 3 shows that there were only small differences in air pollution between NCAP cities and comparison cities, both before and after the start of the program. Cities covered by NCAP were slightly more polluted than cities not covered by the program, and there was only a slight decrease in air pollution across all cities in the five years after NCAP was launched.[15]

The two groups of cities in Sub-Figure 3a were on almost parallel trends for the decade before the start of NCAP, but air pollution in cities that became part of NCAP increased slightly more before 2018 compared to cities that did not get included in NCAP. The trends are more evident in Sub-Figure 3b, where we use the dynamic difference-in-difference specification from Equation 2. Here, the coefficients increase across years. In the analysis below, we account for these differences over time by controlling for city-specific linear time trends and by restricting the sample to cities close to the eligibility cutoff.

Table 2 confirms the finding that NCAP did not reduce air pollution. Columns (1) and (2) show estimates from regressions on levels of $PM_{2.5}$, and columns (3) and (4) show estimates from regressions on $ln(PM_{2.5})$. Columns (1) and (3) include city and month-year fixed effects, as described in Equation 1, and Columns (2) and (4) additionally include city-time trends. In all specifications, the coefficients are

[15]This is consistent with Manojkumar and Muruganandam (2025), who use government data to show that after six years of NCAP implementation, only 20 cities met their NCAP goals, while 29 cities had seen an increase in air pollution relative to 2017. They do not, however, measure the causal effect of NCAP.

small, relative to overall levels of pollution. When not controlling for city-specific time trends, the coefficients are positive, implying that pollution increased in NCAP cities compared to comparison cities after 2019. However, when we control for city-specific time trends, the estimates are close to zero, suggesting that the positive coefficients are driven by underlying differential trends unrelated to NCAP. Our preferred results are shown in Column (4). Based on this specification, the effect of NCAP on air pollution is precisely zero. The lower bound of the 95% confidence interval of our preferred estimate is a decrease of -1.6%.

4.2 Difference-in-Differences: Cities Close to Eligibility Cutoff

To improve our identification strategy and compare cities that are more similar in terms of both levels and trends in air pollution, we restrict our sample to cities close to the NCAP eligibility cutoff. Our results using this restricted sample are very similar to our main estimates from Table 2: NCAP has had no effect on air pollution.

Figure 4 shows that when restricting the sample to cities within 30% percent of the NCAP eligibility cutoff and comparing eligible and ineligible cities, the two groups of cities have similar pollution levels and trends, both before and after the start of NCAP. Sub-Figure 4a shows average pollution levels over time for the two groups of cities separately, and Sub-Figure 4b shows estimates from the dynamic difference-in-differences regression using the eligibility sample. Both confirm parallel trends prior to NCAP's start. Both also show that NCAP did not have an effect on air pollution in eligible cities.

Table 3 presents the estimated effect of NCAP eligibility among cities close to the NCAP eligibility threshold. We use the specification described in Section 3.2.2, with $ln(\text{PM}_{2.5})$ as our dependent variable and NCAP eligibility as the treatment variable. Column 1 limits the sample to cities within 50 percent of the eligibility cutoff, and columns 2, 3, 4, and 5 limit the sample to cities within 40, 30, 20, and 10 points from the eligibility cutoff, respectively. Across all specifications, we consistently estimate that NCAP had no effect on air pollution.

These results are robust to linearly controlling for the eligibility score on either side of the cutoff separately, as shown in Appendix Table A.2. This strategy is similar to how one typically controls for the running variable and the running variable interacted with the treatment variable in a regression discontinuity design. The estimated effects in this table are statistically indistinguishable from zero across all specifications.

4.3 Robustness Tests

Table 4 shows that our main results are robust to using a variety of alternative samples and specifications. In ten distinct tests, we consistently estimate that NCAP did not reduce air pollution in program cities. The only specification in which we find a statistically significant (at the 10% level) reduction in air pollution is the model in which we weight estimates using the city's population size. In this specification, we estimate a 3.0% reduction in air pollution, which is small and not economically meaningful.

Row (1) of Table 4 replicates our preferred estimate from Column (4) of Table 2. We then show that our results are robust to accounting for potential air pollution or policy spillovers from NCAP to comparison cities in two ways. First, because air pollution can spread across city boundaries, it is possible that a reduction in emissions in NCAP cities could have led to a reduction in air pollution in nearby comparison cities. This type of spillover would reduce our estimated effect of the policy. Row (2) addresses this concern by excluding comparison cities closer than 30 km from an NCAP city. We continue to find a precisely estimated zero effect of NCAP.[16] Second, we address potential policy spillovers, such as the possibility that comparison cities may have taken inspiration from NCAP cities, or that states budgeted additional funds for comparison cities to supplement the funding

[16] Goodkind et al. (2019) finds that in the US, averaging across all locations, sources, and stack heights, 50% of all damages of air pollution (primary and secondary $PM_{2.5}$) occur within 32 km of the emission source. By comparison, only about 20% of damages occur in the area 32 to 128 km from the pollution source, despite this area being 15 times larger. Hence, the damages per square kilometer for the area within 32 km is almost 40 times higher than those in the 32 to 128 km area. We conclude that, even if air pollution can travel to areas further away, on average, the air pollution per square kilometer (the outcome in our analysis) is negligible for areas more than 30 km away from the emission source.

provided for NCAP cities. In row (3), we compare NCAP cities to all 188 cities with populations above 100,000 in the neighboring countries of Bangladesh, Nepal, Pakistan, and Sri Lanka. It is unlikely that cities in other countries would have received policy spillovers.[17] In this specification, the coefficient is negative but not statistically significant or economically meaningful, suggesting that NCAP cities did not experience a substantially larger decrease in air pollution relative to other cities in South Asia.

Next, we show that our results are robust to excluding the 17 cities that may have already experienced reductions in air pollution as part of the Supreme Court Action Plans. These cities may have already experienced some of the policy changes that NCAP aims to bring about (Greenstone and Hanna, 2014; Harrison et al., 2015). Row (4) of Table 4 shows that excluding these cities does not meaningfully change our results. Row (5) additionally shows that our results are robust to excluding the 13 cities in which NCAP started after the initial roll-out in 2019.

Rows (6) and (7) show that our results are robust to varying the length of the pre-period in our sample. The pre-period in our main specification starts in 2009, 10-years before NCAP took effect. Row (6) expands the pre-period so that it begins in 2004, and row (7) abbreviates the pre-period so that it begins in 2014. Results from both of these analyses are very similar to the preferred specification.

The robustness tests thus far have addressed alternative samples. In our remaining robustness tests, we vary the specification. Row (8) shows that our results are robust to including state-by-month-year fixed effects, in addition to the city and month-year fixed effects in our preferred specification. Row (9) shows that our results are robust to adding quadratic, rather than linear, city trends. Row (10) shows the results of an alternative approach to accounting for linear trends. Our preferred specification controls for city-time trends by estimating linear trends

[17]We created this sample by taking the smallest administrative units for which a digitized map was available. A unit was classified as a city if it contained a city with a population of more than 100,000. We then estimated the average monthly $PM_{2.5}$ using the van Donkelaar et al. (2021) data for the map polygon in which the city is located. As the NCAP cities and comparison cities are no longer in the same geographical areas, we cluster the standard errors at the state level for India and at the country level for the other South Asian countries and use the `boottest` Stata command to estimate bootstrapped standard errors.

using the full period before and after NCAP. However, it is possible that city trends in NCAP cities are different after NCAP and that the city-time trends may be absorbing some of the effects of NCAP. In this robustness test, we correct for this by estimating linear city trends using data before NCAP began only.[18] Our main result holds.

In row (11), we vary our specification to include population weights, so that results are representative of individuals living in cities, rather than cities. This is the only specification in which we find a negative and marginally significant (at the 10% level), although not economically significant, effect. This finding differs from our preferred specification, possibly because cities with larger populations have reduced air pollution by more than cities with smaller populations. It is also possible that this finding has come about by chance alone in the process of testing multiple samples and specifications.

We also test robustness using the synthetic differences-in-differences method of Arkhangelsky et al. (2021). This technique constructs a weighted average of comparison cities to create a "synthetic" comparison group. Appendix Figure A.3 shows the results of the synthetic differences-in-differences analysis. The average treatment effect estimated using this method is 1.2%.

Finally, in Appendix Table A.3, we show that our findings are robust to clustering our standard errors at the state-level, and to two-way clustering by city and month-year.

4.4 Estimating the Effect of NCAP Using Data from Monitors

For our main analysis, we use satellite-derived air pollution estimates. However, in this section, we use direct measures of air pollution from continuous air quality monitors managed by the CPCB. There are two benefits to using data from monitors: they contain a wider range of air pollutants in addition to $PM_{2.5}$, and they include an additional ten months of data, until October 2024. However, a

[18] We implement this method by first regressing log of $PM_{2.5}$ on city fixed effects, month-year fixed effects, and city-time trends, using pre-NCAP data from 2009 to 2018 only. We then use the parameters from this regression to calculate air pollution residuals for the full time period, before and after NCAP. Finally, we regress these residuals on $Post_t \times NCAP_c$, and month-year and city fixed effects. We bootstrap our standard errors, clustering by city.

drawback of the ground station data is that it limits our analysis to the 63 cities for which we have measurements from both before and after the start of NCAP. Consistent with our main analysis, Column (1) of Table **??** shows that NCAP did not reduce $PM_{2.5}$ in the station data.[19] The estimates for PM_{10} in Column (2) are also worth noting because NCAP goals were subsequently changed to address reductions in PM_{10}. Even using this measure of particulate matter, we find that NCAP did not reduce air pollution: the point estimate is small, positive, and not statistically significant. Furthermore, Columns (3)-(6) shows estimates for O_3, SO_2, CO, and NO_2. The general pattern of these analyses is that NCAP has not reduced air pollution. The only statistically-significant estimate is a positive effect on CO.

5 Why do Governments Overpromise?

We have shown that NCAP is very far from meeting its target and that the program has had no effect on air pollution thus far. What are the political consequences of overpromising yet underdelivering on air pollution policy? To address this question, we conducted a survey experiment with residents of NCAP cities to understand opinions about the government's work on air pollution. In this section, we describe the survey experiment and discuss the results.

5.1 Survey Experiment Sample

The survey was carried out in 16 cities covered by NCAP. We selected the three most populous NCAP cities in five of the most populous states in India.[20] To this list of 15 cities, we added the Delhi National Capital Region because of its large population and salience in debates around air pollution policy. The survey experiment is pre-registered and a pre-analysis plan can be found at the AEA RCT

[19]For most cities, we only have station data available for a short period before NCAP began. Therefore, we do not control for city-specific linear trends. This can at least partially explain the larger, positive, point estimates in analyses of station compared to satellite data.

[20]The states we selected are within the top seven most populous states, and include Uttar Pradesh, Bihar, West Bengal, Madhya Pradesh, and Rajasthan. We excluded Maharashtra, which is the second most populous state, because of a lack of Marathi language expertise in the research team. We excluded Tamil Nadu, which is the sixth most populous state, because of a high refusal rate. The survey was conducted in Hindi and Bengali.

Registry.[21] The surveys were carried out over the phone from July 2024 to May 2025.

Table 6 shows summary statistics for the survey respondents and confirms that there is balance between the control and treatment groups for variables collected before the interventions. The table also shows sample statistics on other variables that describe the context. 28% of respondents had heard of NCAP before our survey. Despite the fact that all survey respondents lived in areas with dangerously high pollution, 59% of survey respondents said that they believed the air in their neighborhood was clean. This statistic can be compared to the 74% of respondents who believed that their drinking water was clean, and the 51% of respondents who believed that their neighborhood's public spaces were clean. 81% of respondents voted in the last election. More information about the experiment sample can be found in Appendix Section D.1.

5.2 Experimental Intervention

Figure 5 provides a visual overview of how the experiment was carried out.[22] The phone call started by obtaining consent and asking a few introductory questions. Respondents were then randomly assigned to one of three arms: "No information" (control), "NCAP information," or "No effect information." For participants randomized into the "NCAP information" treatment, we describe NCAP's design and its goals.[23] For participants randomized into the "No effect information," we describe NCAP's design and its goals, and also inform the respondents that

[21] https://www.socialscienceregistry.org/trials/13941

[22] The questionnaire is available here: https://github.com/sangitavyas/public/blob/main/ncap-survey-questionnaire.pdf.

[23] Respondents in this group are told the following: "Breathing polluted air contributes to heart and lung disease and can even lead to death. Because air pollution is bad for health, the National Clean Air Programme (NCAP) was started by the central government in January 2019 to reduce air pollution. The goal of the program is to reduce air pollution by 40% from 2017 levels by 2026. 131 cities are covered by the program. Your city is covered by the program. Cities have come up with their own plans for reducing air pollution, including things like expanding air quality monitoring, switching to electric buses, and reducing industrial emissions. The central government has set aside more than 9,000 crore for this program since 2019."

NCAP has had no effect on air pollution.[24] Respondents in the control group were informed about NCAP and the lack of an effect on air pollution *after* data on the outcome variables was collected. The short NCAP description is policy relevant because the majority of citizens who would have heard of NCAP would have heard a similarly short description in the news or as part of a political campaign. See Appendix Section D.2 for more information about the interventions.

After the randomized information provision, we collected data on our three main outcome variables: opinion about government actions on air pollution, perception of government dedication to reduce air pollution, and satisfaction with policies and actions on air pollution.[25] Response options were in a three-point Likert-scale. We rescaled responses to each question into standard deviations from the control group mean. See Appendix Section D.3 for more information about the outcomes.

5.3 Experiment Regression Specification

We use the following pre-specified regression to estimate the effect of the information treatment on our main outcome variables:

$$Response_i = \alpha + \beta_1 \times NCAPInfo_i + \beta_2 \times NoEffectInfo_i + StateFE_i + \varepsilon_i \quad (3)$$

where the coefficients β_1 and β_2 are the parameters of interest. β_1 is the effect of "NCAP information" on respondents' opinions, and β_2 is the effect of "No effect information," that is, the effect of NCAP information *as well as* being told that NCAP has had no effect on air pollution. $StateFE_i$ is a vector of fixed effects for the states in which respondents live.[26]

[24] In addition to the description of NCAP and its goals, respondents in this group were also told the following: "Since the policy started, there has been no effect on air pollution. The cities covered by NCAP have not seen any decline in air pollution compared to the cities not covered by NCAP."

[25] Opinions about government actions are measured using the question: "What do you think of what the government is doing to reduce air pollution? Do you think they are doing too much, they are taking all the required actions, or they are not taking enough actions?" We ask about perceptions of government dedication in the question: "How dedicated do you think the Indian national government is to reducing air pollution. Are they dedicated, slightly dedicated, or not dedicated?" Satisfaction is measured using the question: "How satisfied are you with the Indian national government's policies and actions on air pollution? Are you satisfied, slightly satisfied, or not satisfied?"

[26] Appendix Table A.4 shows that the results are robust to excluding state fixed effects.

5.4 Experiment Results

Table 7 shows the results of the survey experiment. Column (1) shows that respondents who were informed about NCAP believed that the government was doing more to reduce air pollution, relative to how much they thought should be done, by 0.07 standard deviations. Interestingly, the effect was similar among respondents who were also informed that NCAP has not had an effect on air pollution. Column (2) shows that respondents who were informed about NCAP believed that the government was more dedicated to reducing air pollution by 0.11 standard deviations. Again, the results are similar among respondents who were also informed that the program has had no effect. Column (3) shows that overall satisfaction with the government's air pollution policy increased by 0.07 standard deviations when respondents were informed about NCAP. The effect was smaller — although not statistically significantly so — at 0.02 standard deviations, for those who were also told that NCAP has had no effect.

In Column (4), we aggregate the three opinion measures into an index constructed by first summing the responses to the prior questions and then rescaling it into an index of standard deviations away from the control group mean. Findings here are similar to prior columns. Across outcomes, providing respondents with information about NCAP improved their opinions of air pollution policy, even when they were also informed about the program's ineffectiveness. Interestingly, respondents did not punish the government for not meeting its targets. Instead, respondents credited the government for their intention to reduce air pollution, even though they have not been successful.

5.5 Heterogeneity in Survey Experiment Effects

Figure 6 and Appendix Table A.5 show heterogeneity in the effect of the survey experiment's information interventions on the opinion index summarizing the three outcome variables. Heterogeneity is measured along five pre-specified dimensions: if the respondent had more than 12 years of education (45% of respondents), if the respondent voted in the 2024 general election (81% of respondents), if the

respondent believed their neighborhood's air was clean (59% of respondents), the respondent's expectation about NCAP's effect (89% of respondents believed it would have at least some effect, while 30% believed it would meet its goal), and if the respondent supported a party in the alliance forming the central government (32% of respondents).[27] We also analyzed the effect by levels of $PM_{2.5}$ air pollution in the city, which was not pre-specificed.

The general pattern observed in Figure 6 and Appendix Table A.5 is that information about NCAP, and even its failure to reduce air pollution, improved opinions of the government's work on air pollution for almost all sub-groups. The results also show that there were no substantial differences in effects across most sub-groups. Appendix Table A.5 shows the p-values of each of the tests of equality of the effects between sub-groups. We find that only 2 out of 12 of the effects are statistically significantly different between sub-groups, which is only slightly more than we would expect to find by random chance.[28]

The heterogeneous results by the political party the respondent supports are worth noting. Even without the treatment, respondents who stated that they supported a political party in the alliance forming the central government were substantially more favorable of the government's air pollution policies, relative to those who supported parties that were not in the alliance or preferred not to answer the question on political party support.[29] Providing these respondents with information on NCAP, and the failure of NCAP to reduce air pollution, slightly — but not statistically significantly — improved their opinions of the government's policies, likely because their opinions were already very positive. Interestingly, for

[27]The question about which political party the respondent supports was added to the survey after the data collection started. Therefore, this heterogeneity analysis has fewer observations. We added this heterogeneity analysis to the pre-analysis plan before we collected any data on what political party the respondents support.

[28]We find statistically significantly smaller effects among respondents who believed that the air is clean and among respondents who expected NCAP to meet its goal, relative to their respective counterparts. Smaller effects among respondents can most likely be explained by the fact that they already have very positive opinions of the national government's air pollution policies, as can be seen from the coefficients on the sub-group variable in Appendix Table A.5.

[29]16.9% of respondents responded that they supported the ruling party alliance, 4.1% of respondents responded that they supported another party, and 31.6% of respondents refused to answer the question.

respondents who supported a political party that was not in the alliance forming the central government or refused to answer the question on political party support, information about NCAP, and even that NCAP has not had an effect, significantly improved their opinions of the government's air pollution policy.

6 Why Did NCAP Not Deliver?

There are several potential reasons why NCAP has been ineffective in reducing air pollution. In this section, we explore multiple explanations and find evidence consistent with a lack of political commitment being an important constraint. We also rule out several alternative explanations.

6.1 Lack of Political Commitment

Political commitment is an important component of effective policy implementation, particularly in contexts with low state capacity. For example, for environmental regulations to be effective, politicians must be willing to decline local businesses' requests to be exempted.[30] In addition, to ensure the successful implementation of a policy, direct monitoring or oversight by senior leaders may be required (Dodge et al., 2025).

The results of our survey suggest that political incentives to implement NCAP are low. Most respondents, who lived in NCAP cities, were not aware of NCAP and were satisfied with the air quality. Moreover, knowledge of the NCAP program, and even that it has thus far failed, only improved perceptions towards the government. In this context, the political benefits associated with expending the effort and capital to implement NCAP are minimal.

In a conversation with one of the authors about air pollution policy, a prominent politician and member of the upper house of India's parliament stated: "Until air pollution starts mattering at the ballot box, politicians will not take it seriously. You can have all kinds of programs, but if the people in charge don't take the problem seriously, and the bureaucrats know that it is not a political priority,

[30] See e.g., Duflo et al. (2018); Greenstone et al. (2025); Gechter and Kala (2025) for estimates of costs of environmental regulations to firms in India.

not much will actually happen on the ground." This qualitative evidence points towards a lack of political commitment, which may be optimal from an electoral perspective, as a substantial barrier to NCAP effectiveness.[31]

Quantitative evidence also points towards a lack of political commitment to NCAP. Figure 7 plots how often NCAP or air pollution was mentioned by the Prime Minister in his monthly radio broadcasts to the nation, *Mann Ki Baat*. We compare mentions of NCAP to mentions of national campaigns on sanitation (*Swacch Bharat Mission*), financial inclusion (*Jan Dhan Yojana*), and manufacturing (Make in India). NCAP or air pollution was mentioned in only three broadcasts, compared to 41 mentions of the *Swacch Bharat Mission*, 28 mentions of Make in India, and nine mentions of the *Jan Dhan Yojana*.[32] The minimal attention given to NCAP in these speeches signals that the program is not a policy priority for the national government.

Further evidence of a lack of political commitment is the fact that few action points and little NCAP funding have been dedicated to reducing industrial emissions, where political resistance is likely. Appendix Figure A.1 compares the share of pollution from different sources to the share of NCAP actions and spending on these pollution sources.[33] Action items and funding have been allocated across all sources of pollution. Yet, industrial pollution is receiving a smaller allocation of funds relative to its pollution contribution, while dust control, transportation, monitoring, and awareness are receiving the majority of funding.[34] Common spending items for managing dust, transportation, monitoring, and awareness

[31]Interestingly, and consistent with our explanation, Alkon and Wang (2018) show that reducing air pollution increases support for the government in China. This could explain why China reduced air pollution so rapidly during it's "war on pollution."

[32]Consistent with our hypothesis that programs receiving high levels of political attention are more likely to succeed, the *Swacch Bharat Mission* achieved constructing more than a hundred million toilets, and substantially increased latrine ownership among rural households (Gupta et al., 2020). Curtis (2019) argues that "high-level political support" and "an ambitious goal" were key factors in this success.

[33]Source apportionment studies, action plans, and information on amounts budgeted are not available for every NCAP city. Each sub-figure is based on all cities with available data, which means that each analysis is based on a different sample of cities. Furthermore, budget allocations are only available for some action points. See Appendix Section B.6 for more information.

[34]Minutes from Government meetings show that as much as two-thirds of utilized NCAP funding was spent on reducing road dust (MoEFCC, 2024).

include the procurement of mechanical street sweepers, sprinklers, electric vehicles for public transportation, and monitoring stations, activities that may receive less political resistance.

6.2 Alternative Explanations

One potential explanation for the muted effect of NCAP is that the program simply did not do anything, and that the budgeted funding was not spent. We find two types of evidence against this explanation. First, for the 118 cities for which data are available, the average share of funds released that have been used is 76 percent. This means that the majority of the funding is actually being spent. Second, Appendix Table A.6 uses our difference-in-differences specification to show that NCAP substantially increased the number of monitoring stations on the ground, implying that NCAP spending has at least led to improved monitoring of air pollution.

Another possible reason for NCAP's failure to reduce air pollution is misalignment of incentives between different levels of government.[35] Appendix Table A.7 shows the effect of NCAP in BJP-aligned states — which are governed by the same party as the central government, or a party in the ruling coalition — and states controlled by other parties separately. In three of the four specifications in the table, the effect of NCAP in BJP-aligned states is different compared to other states, meaning that there is some evidence that the effect of NCAP is slightly greater in BJP-aligned states compared to states controlled by other parties. However, in both types of places, the effect sizes are small and economically insignificant. Moreover, when using our preferred specification in Column (4), the effect of NCAP in the two types of states is not statistically different. Although there is evidence that governments in BJP-aligned states have invested slightly greater effort to reduce pollution, the results are consistent with limited political commitment, even or especially by the BJP in the central government, explaining the overall ineffectiveness of NCAP in all states.

[35]Prior research has shown that such misalignment can affect the implementation of road construction programs, social welfare schemes, and even overall economic growth (Asher and Novosad, 2017; Thomas, 2021; Halder and Mehra, 2025).

7 Conclusion

We have shown that NCAP has not reduced air pollution. This is despite similar policies having been effective in other settings, and despite the prediction among social scientists that it would reduce air pollution. Even though NCAP has not been effective, our survey results suggest that the political consequences of its failure have been minimal. In fact, in our experiment, knowledge of NCAP only improved opinions towards the government's policies even when respondents were told that NCAP has not been effective.

Our findings reveal a political landscape in which ambitious policy announcements are rewarded, and subsequent failures incur minimal reputational cost. This incentive structure explains why a government would launch a lofty program like NCAP, regardless of its ability or commitment to achieve the stated goals. The Indian government's inaction is consistent with these political realities, and their lack of commitment, for which we provide evidence, is the most likely reason for the program's failure.

References

M. Alkon and E. H. Wang. Pollution lowers support for china's regime: Quasi-experimental evidence from beijing. *The Journal of Politics*, 80(1):327–331, 2018.

D. Arkhangelsky, S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager. Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118, 2021.

S. Asher and P. Novosad. Politics and local economic growth: Evidence from india. *American Economic Journal: Applied Economics*, 9(1):229–273, 2017.

S. Asher, T. Lunt, R. Matsuura, and P. Novosad. Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in india using the shrug open data platform. *The World Bank Economic Review*, 35(4): 845–871, 2021.

N. Bloom, R. Lemos, R. Sadun, D. Scur, and J. Van Reenen. Jeea-fbbva lecture 2013: The new empirical economics of management. *Journal of the European Economic Association*, 12(4):835–876, 2014.

A. Born, P. Van Eck, and M. Johannesson. An experimental investigation of election promises. *Political Psychology*, 39(3):685–705, 2018.

M. Buntaine, M. Greenstone, G. He, M. Liu, S. Wang, and B. Zhang. The squeaky wheel gets more grease? citizen participation, social media, and environmental governance in China. Working paper, 2022.

E. Bytzek, J. C. Dupont, M. C. Steffens, N. Knab, and F. M. Schneider. Do election pledges matter? the effects of broken and kept election pledges on citizens' trust in government. *Politische Vierteljahresschrift*, pages 1–20, 2024.

Central Pollution Control Board. Guidelines for release and utilisation of funds under the national clean air program, August 2022a. URL https://prana.cpcb.gov.in/ncapDashboard/download_public_portal_file/OM_and_Funding_Guidelines.pdf. Accessed: 2024-10-28.

Central Pollution Control Board. Revised guidelines for swachh vayu survekshan, 2022b. URL https://prana.cpcb.gov.in/ncapDashboard/download_public_portal_file/Revised_Guidelines_-_Swachh_Vayu_Survekshan.pdf. Accessed: 2024-10-28.

M. o. S. Central Statistics Organisation and G. o. I. Programme Implementation. Economic census of India, 2013. http://microdata.gov.in/nada43/index.php/catalog/ECO.

K. Y. Chay and M. Greenstone. Does air quality matter? evidence from the housing market. *Journal of political Economy*, 113(2):376–424, 2005.

D. Clarke, D. Pailañir, S. Athey, and G. Imbens. On synthetic difference-in-differences and related estimation methods in stata. *The Stata Journal*, 24(4):557–598, 2024. doi: 10.1177/1536867X241297914.

V. Curtis. Explaining the outcomes of the'clean india'campaign: institutional behaviour and sanitation transformation in india. *BMJ global health*, 4(5), 2019.

R. De Simone, S. L. Naaraayanan, and K. Sachdeva. Opening the brown box: Production responses to environmental regulation. *Available at SSRN*, 2024.

G. Dipoppa and S. Gulzar. Bureaucrat incentives reduce crop burning and child mortality in south asia. Technical report, Working Paper, 2024.

E. Dodge, Y. Neggers, R. Pande, and C. M. T. Moore. From delay to payday: Easing bureaucrat access to implementation information strengthens social protection delivery. Technical report, National Bureau of Economic Research, 2025.

E. Duflo, M. Greenstone, R. Pande, and N. Ryan. The value of regulatory discretion: Estimates from environmental inspections in India. *Econometrica*, 86 (6):2123–2160, 2018.

T. Ganguly, K. L. Selvaraj, and S. K. Guttikunda. National clean air programme (NCAP) for Indian cities: Review and outlook of clean air action plans. *Atmospheric Environment: X*, 8:100096, 2020.

M. Gechter and N. Kala. Firm presence, pollution, and agglomeration: Evidence from a randomized environmental place-based policy. Technical report, National Bureau of Economic Research, 2025.

A. L. Goodkind, C. W. Tessum, J. S. Coggins, J. D. Hill, and J. D. Marshall. Fine-scale damage estimates of particulate matter air pollution reveal opportunities for location-specific mitigation of emissions. *Proceedings of the National Academy of Sciences*, 116(18):8775–8780, 2019.

M. Greenstone and R. Hanna. Environmental regulations, air and water pollution, and infant mortality in India. *American Economic Review*, 104(10):3038–3072, 2014.

M. Greenstone, G. He, S. Li, and E. Y. Zou. China's war on pollution: Evidence from the first 5 years. *Review of Environmental Economics and Policy*, 15(2): 281–299, 2021.

M. Greenstone, R. Pande, N. Ryan, and A. Sudarshan. Can pollution markets work in developing countries? experimental evidence from india. *The Quarterly Journal of Economics*, 140(2):1003–1060, 2025.

A. Gupta, N. Khalid, D. Deshpande, P. Hathi, A. Kapur, N. Srivastav, S. Vyas, D. Spears, and D. Coffey. Revisiting open defecation: evidence from a panel survey in rural north india, 2014–18. *Economic and political weekly*, 55(21):55, 2020.

S. Guttikunda and K. Nishadh. Evolution of India's pm 2.5 pollution between 1998 and 2020 using global reanalysis fields coupled with satellite observations and fuel consumption patterns. *Environmental Science: Atmospheres*, 2(6): 1502–1515, 2022.

S. K. Guttikunda, K. A. Nishadh, and P. Jawahar. Air pollution knowledge assessments (apna) for 20 indian cities. *Urban Climate*, 27:124–141, 2019.

S. K. Guttikunda, S. K. Dammalapati, and G. Pradhan. Assessing air quality during India's National Clean Air Programme (NCAP): 2019-2023. *Atmospheric*

Environment, page 120974, 2024.

I. I. Halder and M. K. Mehra. Aligned or sidelined? political motives in welfare funding. 2025.

A. Harrison, B. Hyman, L. Martin, and S. Nataraj. When do firms go green? comparing command and control regulations with price incentives in India. Technical report, National Bureau of Economic Research, 2015.

J. He, H. Liu, and A. Salvo. Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics*, 11(1):173–201, 2019.

Health Effects Institute. State of global air 2024, 2024.

A. Isen, M. Rossin-Slater, and W. R. Walker. Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy*, 125(3):848–902, 2017.

M. E. Kahn, P. Li, and D. Zhao. Water pollution progress at borders: the role of changes in China's political promotion incentives. *American Economic Journal: Economic Policy*, 7(4):223–242, 2015.

S. Li, J. Meng, K. Hubacek, S. M. Eskander, Y. Li, P. Chen, and D. Guan. Revisiting copenhagen climate mitigation targets. *Nature Climate Change*, 14 (5):468–475, 2024.

M. Lipscomb and A. M. Mobarak. Decentralization and pollution spillovers: evidence from the re-drawing of county borders in brazil. *The Review of Economic Studies*, 84(1):464–502, 2016.

J. A. List and D. M. Sturm. How elections matter: Theory and evidence from environmental policy. *The Quarterly Journal of Economics*, 121(4):1249–1281, 2006.

N. Manojkumar and N. Muruganandam. Tracing the hazy air 2025: Progress report on national clean air programme (ncap). Policy report, Centre for Research on Energy and Clean Air, 2025.

Ministry of Environment, Forest and Climate Change. *National Clean Air Program*. 2019. URL https://moef.gov.in/wp-content/uploads/2019/05/NCAP_Report.pdf.

Ministry of Environment, Forest, and Climate Change. Minutes of 4th meeting of national apex committee under national clean air programme (ncap). Meeting

minutes, Government of India, 2024.

Ministry of Environment, Forest, and Climate Change. Notes on demands for grants, no. 28. Notes on demands for grants, Government of India, 2025.

E. Naurin, T. J. Royed, and R. Thomson. *Party mandates and democracy: Making, breaking, and keeping election pledges in twelve countries*. New Comparative Politics, 2019.

S. Niu, Y. Chen, R. Zhang, and Y. Feng. How does the air pollution prevention and control action plan affect sulfur dioxide intensity in China? *Frontiers in Public Health*, 11:1119710, 2023.

W. E. Oates and P. R. Portney. The political economy of environmental policy. In *Handbook of environmental economics*, volume 1, pages 325–354. Elsevier, 2003.

Office of the Registrar General and Census Commissioner of India. Census of India, 2011. https://censusindia.gov.in/census.website/data/census-tables.

T. Persson and G. Tabellini. *Political economics: explaining economic policy*. MIT press, 2000.

Secretariat of the Convention on Biological Diversity. Global biodiversity outlook 5. Policy report, 2020.

J. S. Shapiro and R. Walker. Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade. *American Economic Review*, 108(12):3814–3854, 2018.

S. Singh and T. Thachil. Why citizens don't hold politicians accountable forair pollution. Working paper, 2023.

The Hindu. National clean air programme: Centre aims at 40% reduction in particulate matter by 2026. Newspaper article, 2022. URL https://www.thehindu.com/news/national/national-clean-air-programme-centre-aims-at-40-reduction-in-particulate-matter-b article65941247.ece.

A. Thomas. Development or rent seeking? how political influence shapes public works provision in india. *British Journal of Political Science*, 51(1):253–274, 2021.

R. Thomson, T. Royed, E. Naurin, J. Artés, R. Costello, L. Ennser-Jedenastik, M. Ferguson, P. Kostadinova, C. Moury, F. Pétry, et al. The fulfillment of parties' election pledges: A comparative study on the impact of power sharing.

American Journal of Political Science, 61(3):527–542, 2017.

United Nations. The millennium development goals report. Policy report, 2015.

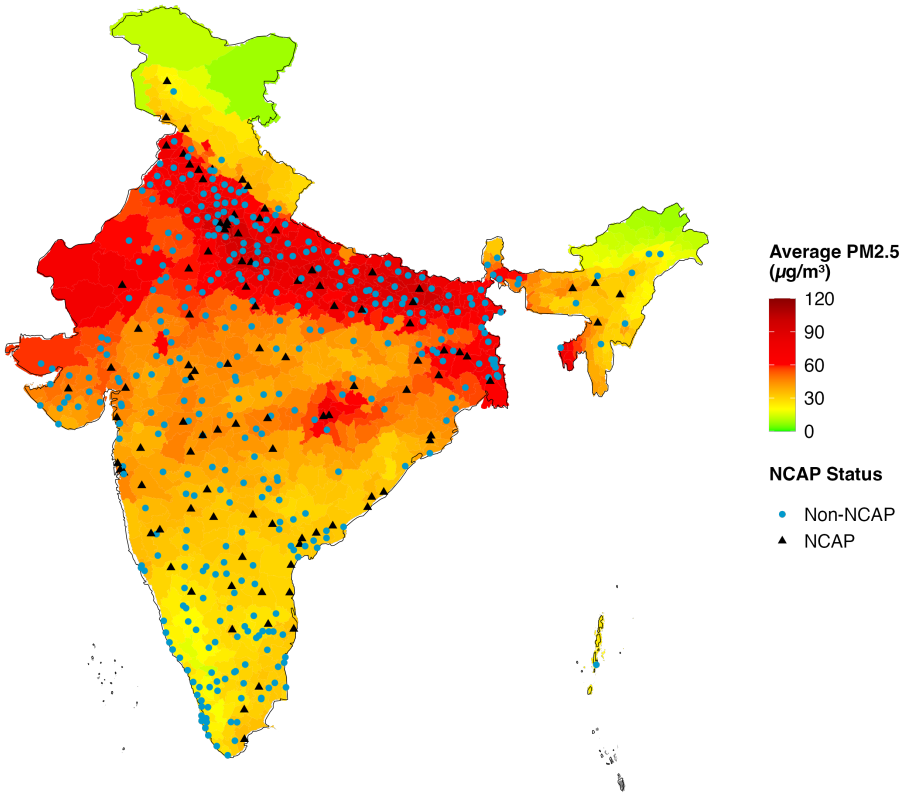
A. van Donkelaar, M. S. Hammer, L. Bindle, M. Brauer, J. R. Brook, M. J. Garay, N. C. Hsu, O. V. Kalashnikova, R. A. Kahn, C. Lee, et al. Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology*, 55(22):15287–15300, 2021.

World Bank. World bank open data. Database, 2025. https://data.worldbank.org/.

World Health Organization. Who ambient air quality database (update jan 2024), 2024. URL https://www.who.int/publications/m/item/who-ambient-air-quality-database-(update-jan-2024). [Online; accessed 24-July-2024].

Y. Xie, M. Zhou, K. M. Hunt, and D. L. Mauzerall. Recent pm2. 5 air quality improvements in India benefited from meteorological variation. *Nature Sustainability*, pages 1–11, 2024.

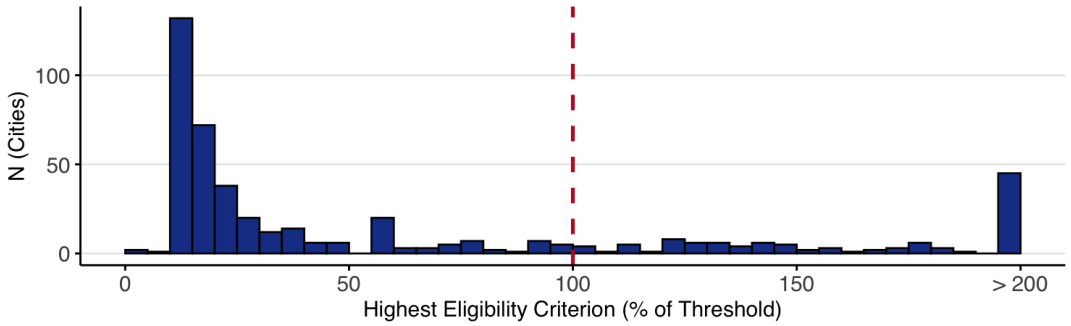
Figure 1: Map of Air Pollution and Cities by NCAP Status



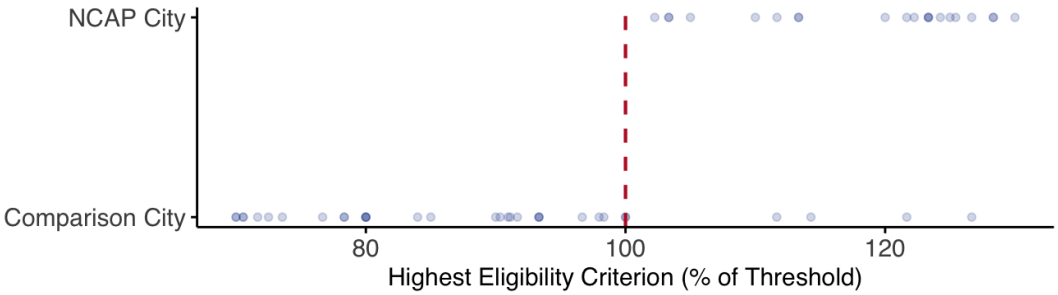
Note: The figure shows district-level average $PM_{2.5}$ concentrations (in $\mu g/m^3$) in 2018 using the satellite-derived van Donkelaar et al. (2021) data, as well as the cities in our sample. Urban agglomerations with populations above 100,000 are included in our sample. NCAP cities are marked with a black triangle, and comparison cities are marked with a blue circle. See discussion in Section 2.1.

Figure 2: NCAP Eligibility and Inclusion into NCAP

(a) Histogram of Eligibility



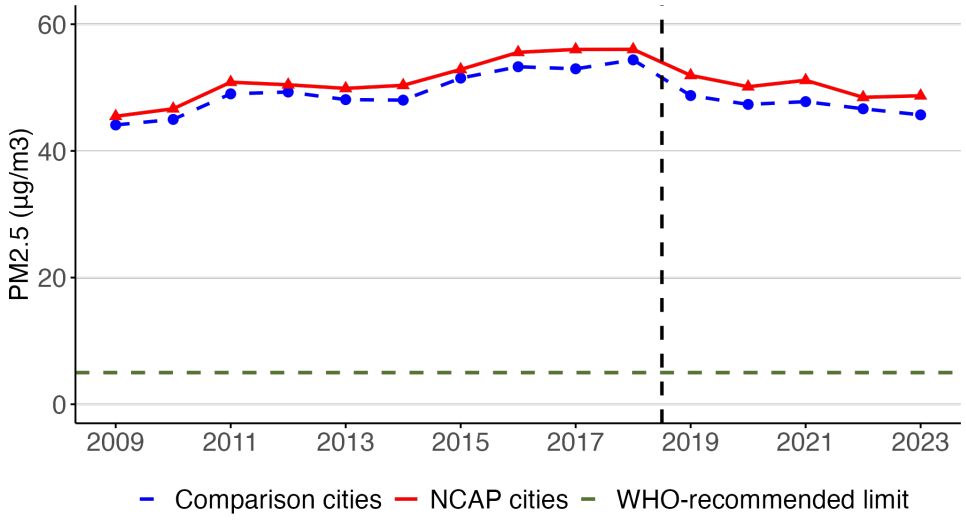
(b) Inclusion into NCAP Around Cutoff



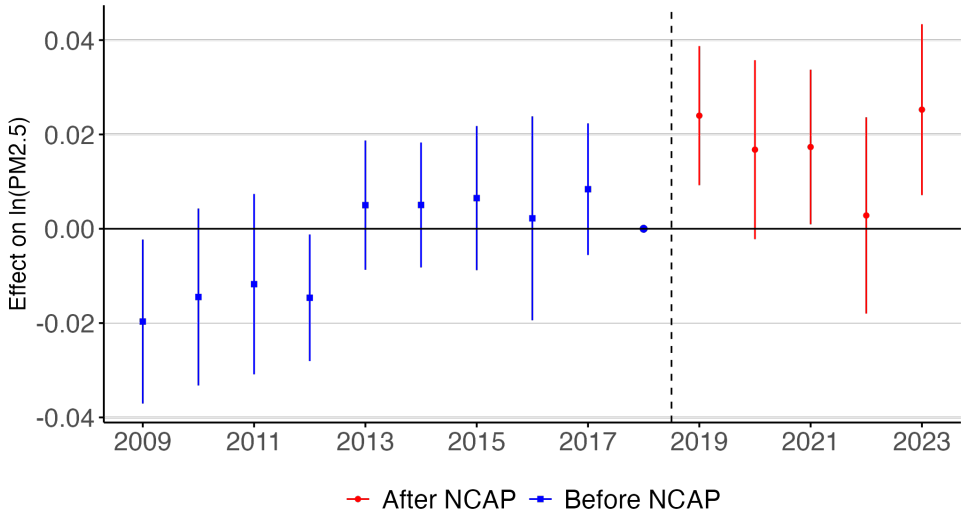
Note: Panel (a) shows the density of cities above and below the cutoff for inclusion into NCAP based on the eligibility criteria. The x-axis is the highest of the three eligibility criteria as a percentage of the NCAP threshold. Panel (b) shows NCAP inclusion based on NCAP eligibility, for the 54 cities in the range between 70% to 130% of the eligibility cutoff. Appendix Figure A.2 provides the same visualization for the complete sample. Data on the eligibility score are constructed as described in Appendix Section B.5.3. See discussion in Section 3.2.2.

Figure 3: NCAP Does Not Reduce Air Pollution

(a) Air Pollution in Indian Cities by NCAP Status



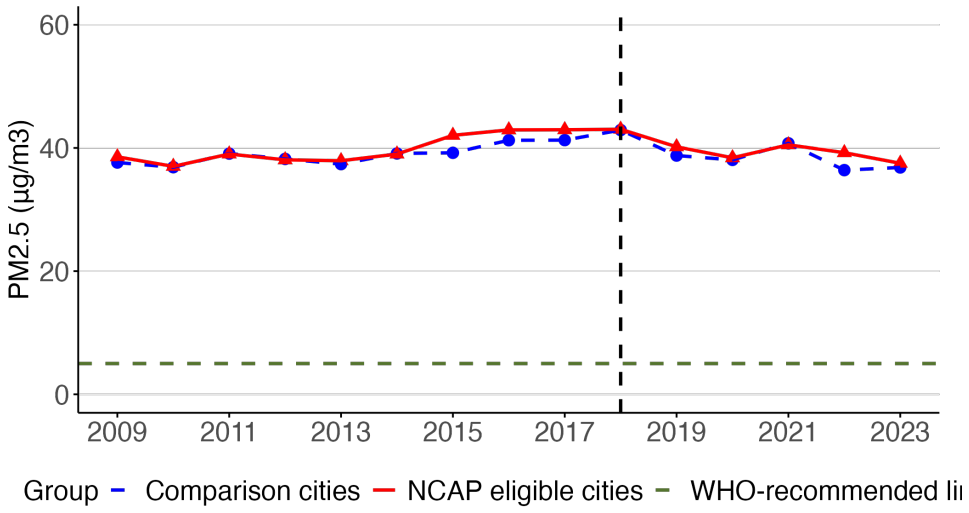
(b) Effects of NCAP Over Time



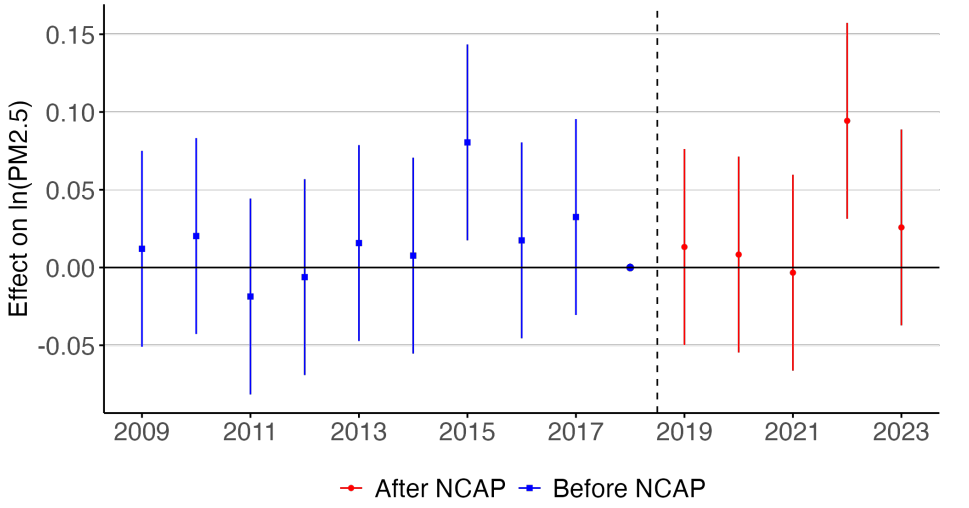
Notes: This figure shows air pollution trends in NCAP cities compared to other Indian cities from 2009 until 2023. The vertical dashed line represents the start of NCAP. Sub-Figure (a) presents annual averages for the two groups of cities. Sub-Figure (b) displays the coefficients from the dynamic difference-in-differences regression described in Equation 2. See Table 2 for the overall difference-in-difference estimate. 95% confidence intervals are constructed using standard errors clustered by city. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.1.

Figure 4: NCAP Does Not Reduce Air Pollution among Cities Close to the Eligibility Cutoff

(a) Air Pollution in Indian Cities ±30% of Eligibility Cutoff

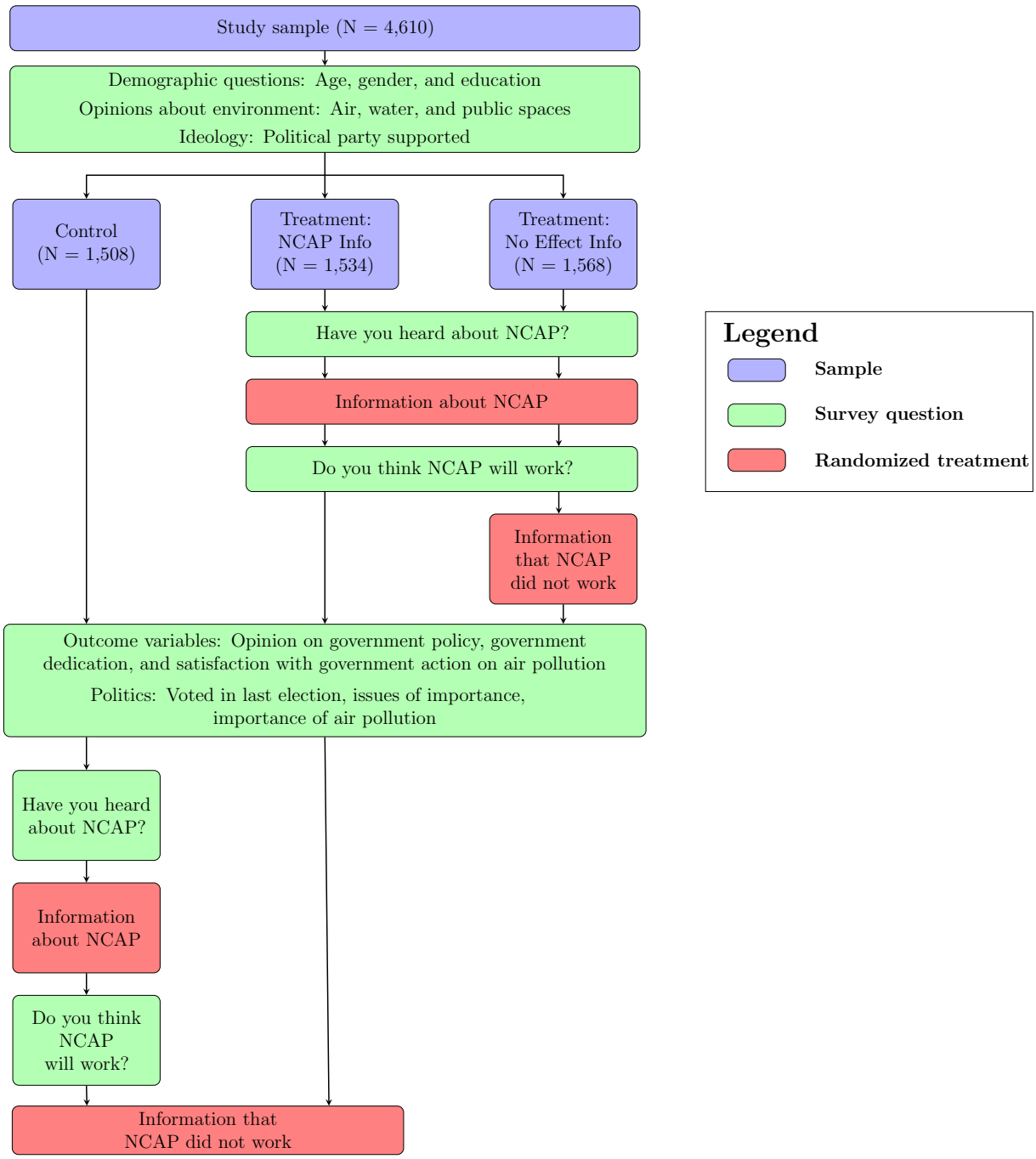


(b) Effects of NCAP Over Time in Cities ±30% of Eligibility Cutoff



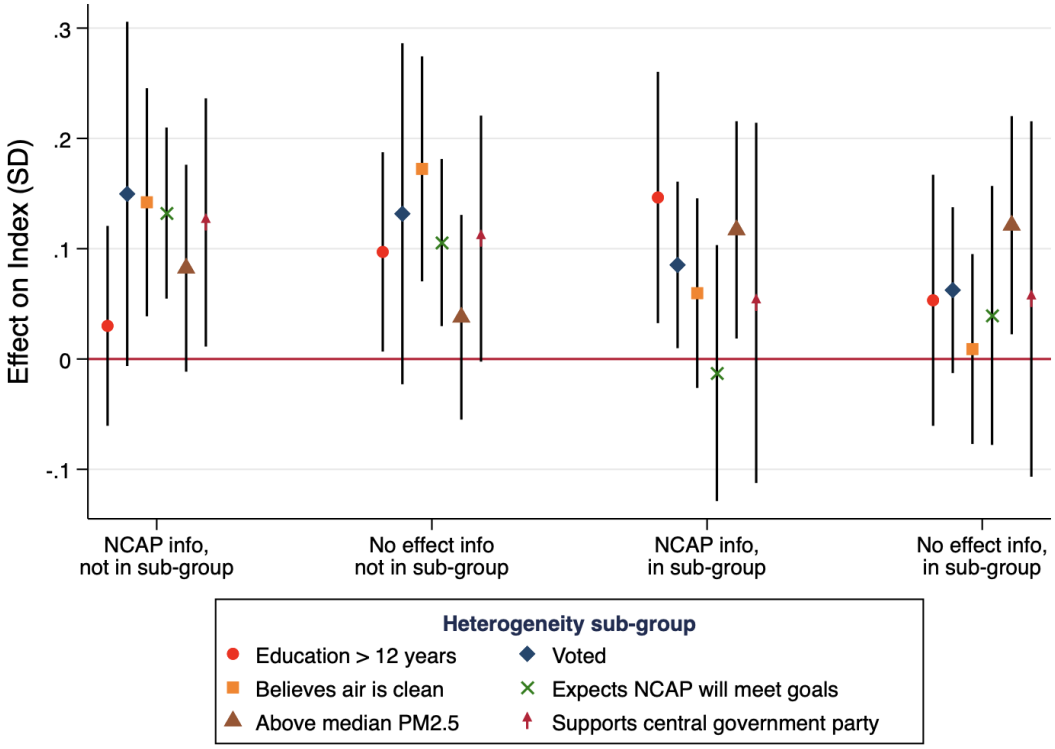
Notes: This figure shows air pollution trends in cities within 30% of the NCAP eligibility criteria. Here, cities are grouped based on *eligibility* for NCAP, rather than NCAP status. The vertical dashed line represents the start of NCAP. Sub-Figure (a) presents annual averages for the two groups of cities. Sub-Figure (b) displays the coefficients from the dynamic difference-in-differences regression described in Equation 2 using *eligibility* for NCAP instead of treatment. See Table 3 for the overall difference-in-difference estimate using the restricted sample. 95% confidence intervals are constructed using standard errors clustered by city. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.2.

Figure 5: Survey Experiment Flow



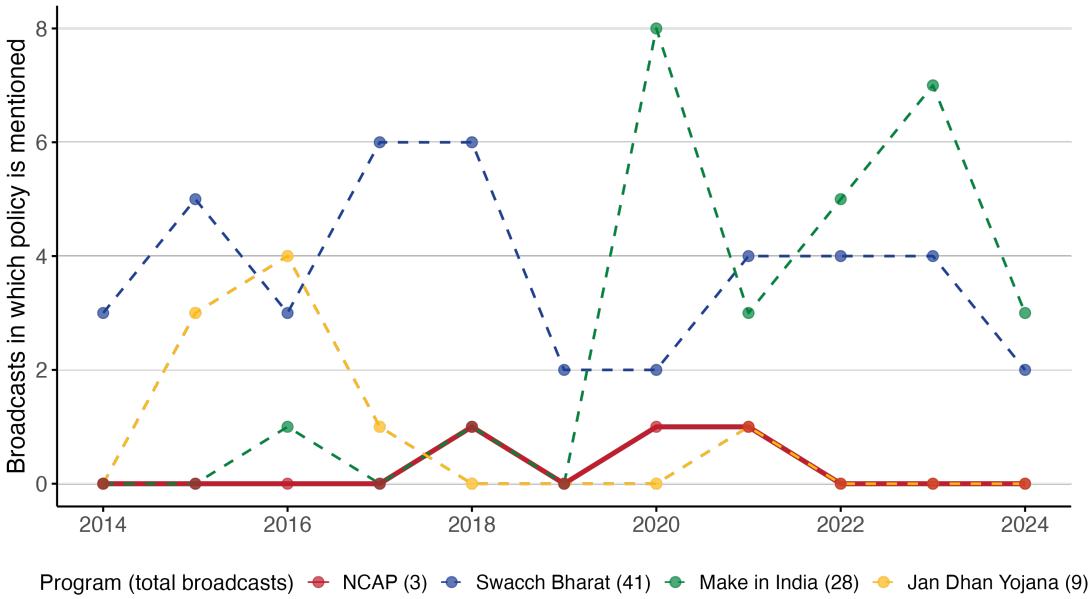
Note: This flowchart shows the order of questions and randomized information treatments for each treatment arm in the survey. See discussion in Section 5.2. The survey questionnaire is available here: https://github.com/sangitavyas/public/blob/main/ncap-survey-questionnaire.pdf.

Figure 6: Heterogeneity Analysis: Similar Effects of Information among Different Sub-groups in Experiment



Notes: The figure shows heterogeneity analyses from our survey experiment. The outcome variable is an index of respondents' opinions of the central government's air pollution policies, which has been normalized based on the control group mean and standard deviation. Larger numbers signify better opinions. The two left-most groups of coefficients show the estimated effects for participants who are not in the heterogeneity sub-group, and the two right-most groups show effects for those who are in the heterogeneity sub-group considered. We interact treatments with the respondent's education, whether the respondent voted in the national election in 2024, whether the respondent believes the air in her neighborhood is clean, whether the respondent believes that NCAP will meet its goal, whether the respondent lives in an above-median pollution city, and whether the respondent supports the BJP, or a party in alliance with the BJP. "NCAP info" represents the effect of receiving information on NCAP. "No effect info" represents the effect of receiving information on NCAP and that it failed to reduce air pollution. 95% confidence intervals are constructed with heteroskedasticity robust standard errors. Appendix Table A.5 shows the results in the format of a regression table. See discussion in Section 5.5.

Figure 7: NCAP Received Little Attention Relative to Other Programs in the Prime Minister's Monthly Broadcasts



Notes: This figure shows the number of monthly radio broadcasts of the Prime Minister's *Mann Ki Baat* show in which different programs, including NCAP, have been mentioned. We looked for direct mentions of each program, as well as terms related to each program. See discussion in Section 6 and Appendix Section B.7.

Table 1: Summary Statistics

	NCAP Status: All Cities			NCAP Eligibility: Cities ±30% of Threshold		
	NCAP	Comparison	Difference	Eligible	Ineligible	Difference
	Mean (S.D.)	Mean (S.D.)	Coef. (S.E.)	Mean (S.D.)	Mean (S.D.)	Coef. (S.E.)
NCAP Status	1.00 (0.00)	0.00 (0.00)	1.00 (0.00)	0.78 (0.42)	0.00 (0.00)	-0.78*** (0.08)
NCAP Eligibility	0.91 (0.28)	0.05 (0.22)	0.86*** (0.03)	1.00 (0.00)	0.00 (0.00)	-1.00 (0.00)
Eligiblity score	242.98 (280.67)	32.63 (36.28)	210.35*** (15.10)	116.98 (9.72)	83.27 (9.55)	-33.71*** (2.62)
Population (100k)	16.51 (29.97)	2.43 (2.59)	14.08*** (1.59)	5.86 (3.70)	4.31 (3.13)	-1.54 (0.94)
Population density (per sq. km)	7,784.16 (4,698.22)	6,657.72 (4,588.68)	1,126.44* (548.87)	6,160.57 (4,003.48)	7,484.12 (6,216.72)	1,323.56 (1,541.82)
Literacy rate	0.75 (0.05)	0.74 (0.07)	0.01 (0.01)	0.76 (0.05)	0.76 (0.07)	0.00 (0.02)
Manufacturing labor share	0.24 (0.12)	0.21 (0.12)	0.03 (0.01)	0.23 (0.12)	0.20 (0.09)	-0.03 (0.03)
Service labor share	0.76 (0.12)	0.78 (0.12)	-0.02 (0.01)	0.76 (0.12)	0.79 (0.09)	0.03 (0.03)
Scheduled Caste	0.13 (0.05)	0.13 (0.07)	0.00 (0.01)	0.12 (0.05)	0.11 (0.07)	-0.01 (0.02)
Scheduled Tribe	0.03 (0.05)	0.03 (0.07)	-0.00 (0.01)	0.02 (0.03)	0.08 (0.22)	0.06 (0.04)
Observations	104	364	468	27	27	54

Notes: This table presents summary statistics by NCAP status for the full sample, and by NCAP eligibility for the sample of cities between 70% and 130% of the eligibility cutoff. Data on the eligibility score are constructed as described in Appendix Section B.5.3. Data on manufacturing and labor share are from the Economic Census of India (Central Statistics Organisation and Programme Implementation, 2013), while data on population, population density, literacy rates, and Scheduled Caste and Scheduled Tribe population shares are from the 2011 Indian Population Census Abstract (Office of the Registrar General and Census Commissioner of India, 2011). Standard errors for differences are clustered by city. * for p-value<0.10, ** for p-value<0.05, and *** for p-value<0.01. See discussion in Section 3.2.2.

Table 2: Main Result: No Negative Effect of NCAP on $PM_{2.5}$

	PM2.5		ln(PM2.5)	
	(1)	(2)	(3)	(4)
NCAP×post	1.107**	-0.222	0.021***	-0.003
	(0.496)	(0.815)	(0.007)	(0.008)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-time trends	No	Yes	No	Yes
Observations	84,240	84,240	84,240	84,240
Cities	468	468	468	468
Comparison city mean	50.46	50.46	3.73	3.73

Notes: This table presents the main result: the effect of NCAP on $PM_{2.5}$ using a difference-in-differences estimation strategy. See Equation 1 for regression equation. *NCAP* is an indicator for an NCAP city, and *Post* is an indicator for periods including and after January 2019. Columns (1) and (2) show results using levels of $PM_{2.5}$, and columns (3) and (4) show results using $ln(PM_{2.5})$. Columns (1) and (3) include fixed effects for city and month-year, and columns (2) and (4) add in city-year trends. See Figure 3b for the dynamic difference-in-differences estimates. Standard errors are clustered by city. * for p-value<0.10, ** for p-value<0.05, and *** for p-value<0.01. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.1.

Table 3: No Effect of NCAP Among Cities Close to the NCAP Eligibility Cutoff

	ln(PM2.5)				
	(1)	(2)	(3)	(4)	(5)
Above cutoff × post	0.007	0.009	-0.002	-0.015	-0.027
	(0.012)	(0.012)	(0.015)	(0.020)	(0.026)
City FEs	Yes	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes	Yes
Observations	17,820	14,940	9,720	5,400	3,240
Cities	99	83	54	30	18
Comparison city mean	3.53	3.53	3.48	3.51	3.43
Distance $\leq$	50	40	30	20	10

Notes: This table shows that results are robust to limiting the sample to cities that are close to the NCAP eligibility cutoff. The dependent variable is $ln(\text{PM}_{2.5})$ in all models. *Above cutoff* is an indicator for the city being above the NCAP eligibility cutoff, and *post* is an indicator for periods including and after January 2019. Data on the eligibility score are constructed as described in Appendix Section B.5.3. Column (1) limits the sample to cities that are within ±50% of the eligibility cutoff, Column (2) to cities within ±40%, Column (3) to cities within ±30%, column (4) to cities within ±20%, and column (5) to cities within ±10%. Standard errors are clustered by city. * for p-value<0.10, ** for p-value<0.05, and *** for p-value<0.01. Satellite estimates of $\text{PM}_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.2.

Table 4: The Main Effect is Robust to Alternative Samples and Specifications

		Coefficient (S.E.)
(1)	Preferred specification	-0.003
		(0.008)
	Alternative samples	
(2)	Excluding comparison cities within 30km of NCAP city	-0.009
		(0.009)
(3)	South Asian cities outside India as comparison cities	-0.036
		(0.048)
(4)	Excluding Supreme Court Action Plan cities	0.004
		(0.009)
(5)	Excluding cities in which NCAP started after 2019	-0.004
		(0.009)
(6)	Pre-period start year = 2004	-0.002
		(0.008)
(7)	Pre-period start year = 2014	0.005
		(0.011)
	Alternative specifications	
(8)	State-by-month-year FEs	0.009*
		(0.005)
(9)	Quadratic time trends	0.003
		(0.010)
(10)	Pollution residualized based on pre-2019 city-time trends	-0.005
		(0.008)
(11)	Population weighted	-0.030*
		(0.016)

Notes: This table summarizes results from a series of robustness tests. Row (1) shows the estimated effect from our preferred specification, which corresponds to Column (4) of Table 2. Rows (2) - (7) show the results of robustness tests that use alternative samples. Rows (8) - (11) show results that use alternative specifications. For all rows except (3), the standard errors are clustered at the city-level. For row (3), standard errors are clustered at the country/Indian-state level. For rows (3) and (10), we use bootstrapped standard errors. * $p<0.10$, ** $p<0.05$, and *** $p<0.01$. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.3.

Table 5: Results are Robust to Use of Station Data

	PM2.5	PM10	O3	SO2	CO	NO2
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Levels						
NCAP × Post	7.362	3.876	-0.733	0.687	0.204***	2.107
	(6.064)	(8.493)	(2.625)	(2.029)	(0.076)	(3.146)
Comparison city mean	58.89	117.78	33.66	13.61	0.88	27.59
Panel B: Logs						
NCAP × Post	0.098	0.032	-0.028	0.027	0.095**	0.106
	(0.068)	(0.057)	(0.100)	(0.128)	(0.039)	(0.096)
Comparison city mean	3.87	4.60	3.42	2.48	0.60	3.17
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
City-time trends	No	No	No	No	No	No
Observations	5,373	4,887	5,110	5,313	5,248	5,322
Cities	63	62	60	63	62	63

Notes: This table shows the effect of NCAP on $PM_{2.5}$, PM_{10}, Ozone (O_3), Sulfur Dioxide (SO_2), Carbon Monoxide (CO), and Nitrogen Dioxide (NO_2). In Panel A, the outcome variables are in absolute levels of each pollutant. In Panel B, the outcome variables are the natural logarithmic transformation of each pollutant. Standard errors are clustered by city. * p<0.10, ** p<0.05, and *** p<0.01. Data are from CAAQMS. See discussion in Section 4.4.

Table 6: Balance Table: Treatment Arms are Balanced on Observable Characteristics

	Groups			Differences	
	(1)	(2)	(3)	(4)	(5)
	C: Control	T1: NCAP Information	T2: No Effect Information	T1 - C	T2 - C
	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Coef. (S.E.)	Coef. (S.E.)
Female	0.46	0.44	0.46	-0.02	-0.01
	(0.499)	(0.497)	(0.498)	(0.018)	(0.018)
Age	36.03	36.09	36.37	0.06	0.35
	(12.761)	(12.496)	(12.706)	(0.458)	(0.459)
$>$ 12 years of education	0.45	0.45	0.45	-0.00	0.00
	(0.498)	(0.498)	(0.498)	(0.018)	(0.018)
Believes air is clean	0.59	0.60	0.58	0.01	-0.01
	(0.493)	(0.491)	(0.494)	(0.018)	(0.018)
Believes water is clean	0.74	0.74	0.74	0.00	0.01
	(0.441)	(0.441)	(0.437)	(0.016)	(0.016)
Believes public spaces are clean	0.52	0.51	0.50	-0.01	-0.02
	(0.500)	(0.500)	(0.500)	(0.018)	(0.018)
Average PM2.5	65.13	64.29	63.03	-0.84	-2.10
	(17.585)	(17.922)	(16.803)	(0.644)	(0.620)
Voted in the last election	0.80	0.82	0.82	0.03	0.02
	(0.403)	(0.382)	(0.384)	(0.014)	(0.014)
Supports BJP	0.33	0.32	0.32	-0.01	-0.01
	(0.470)	(0.465)	(0.467)	(0.023)	(0.023)
Heard of NCAP	0.30	0.28	0.27	-0.02	-0.02
	(0.457)	(0.449)	(0.447)	(0.016)	(0.016)
Believes NCAP will meet goal	0.30	0.32	0.29	0.02	-0.01
	(0.459)	(0.466)	(0.453)	(0.017)	(0.016)
Observations	1,508	1,534	1,568	2,992	3,076

Notes: This table shows summary statistics for the variables in the survey experiment measured before the information intervention. The "Heard of NCAP" variable is measured for all three groups right before they are informed about NCAP. For the control group, this is after they have been asked about the outcome variables. In columns (4) and (5) heteroskedasticity robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 5.1.

Table 7: Knowledge of NCAP Improves Perceptions of the Government's Work on Air Pollution, Even When Combined with Information That NCAP has had No Effect

	Govt Actions	Govt Dedication	Satisfaction	Index
	(1)	(2)	(3)	(4)
NCAP info	0.072**	0.113***	0.074**	0.101***
	(0.035)	(0.035)	(0.035)	(0.035)
No effect info	0.077**	0.099***	0.025	0.078**
	(0.035)	(0.035)	(0.035)	(0.035)
State FEs	Yes	Yes	Yes	Yes
Observations	4,610	4,610	4,610	4,610
P-value: Equal Effects	0.893	0.695	0.163	0.510

Notes: The table shows results from the survey experiment, carried out across 16 NCAP cities. Interviews were conducted over the phone. Outcome variables have been normalized based on the control group mean and standard deviation. "Govt Actions" refers to responses to the question: "What do you think of what the government is doing to reduce air pollution? Do you think they are doing too much, they are taking all the required actions, or they are not taking enough actions?" "Govt Dedication" refers to responses to the question: "How dedicated do you think the Indian national government is to reducing air pollution. Are they dedicated, slightly dedicated, or not dedicated?" "Satisfaction" refers to responses to the question: "How satisfied are you with the Indian national government's policies and actions on air pollution? Are you satisfied, slightly satisfied, or not satisfied?" Larger numbers signify perceptions of more action, more dedication, and more satisfaction. The index in column (4) is constructed by summing the responses to the prior questions and then rescaling the sum into an index of standard deviations away from the control group mean. "NCAP info" is an indicator variable for whether the respondent was randomly assigned to the group that received information on NCAP. "No effect info" is an indicator variable for whether the respondent was randomly assigned to the group that received information on NCAP *and* that NCAP had no effect on air pollution. Heteroskedasticity robust standard errors. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 5.4.

Supplemental Appendix

A Further Details About NCAP

A.1 NCAP Financing and Performance-linked Funding

From FY2019-20 to FY2025-26, INR 197 billion has been earmarked for NCAP cities. This funding comes from two major funding sources. The MoEFCC has allocated INR 31.7 billion to 82 non-attainment cities with a population of less than one million, and the 15th Finance Commission has allocated the remaining INR 165.3 billion under the Million-Plus Cities Challenge Fund to urban local bodies in 49 cities with populations exceeding one million.

60% of NCAP funding allocations are determined by the ratio of the city's population and its 2019-20 PM_{10} concentration (Central Pollution Control Board, 2022a). The remaining 40% is allocated using a performance-linked funding mechanism. Cities need to demonstrate ongoing improvements in air quality and compliance with air pollution monitoring requirements, source apportionment studies, and progress on action plan items.

For the cities with NCAP funding from the MoEFCC, the CPCB gives annual targets in terms of reductions of the PM_{10} concentrations, with the aim of reaching an overall reduction of 40% by the 2025/26 financial year. The cities with NCAP funding from the 15th Finance Commission's air quality grant are assigned an annual target to reduce PM_{10} concentrations by 15%. Additionally, these cities must also show an increase in the number of 'good air days' (defined as days with Air Quality Index scores below 200). For all cities, meeting or exceeding their targets allows them to access performance-based supplemental grants for funding of activities approved under the city action plans. The exact funding allocation mechanism and criteria have evolved since NCAP was launched.

A.1.1 Release of Funds Before 2022

In 2021-22, the performance-based funding was determined by the preparation of the city action plan based on CPCB guidelines and the successful execution of air

pollution monitoring, source apportionment studies, and progress on action plan items.[36]

A.1.2 Release of Funds From 2022 and onwards

From the 2022-23 financial year and onwards, cities would be assigned annual PM_{10} reduction targets, and would be evaluated solely based on improvements in air quality (Central Pollution Control Board, 2022a). Based on a city's actual annual reduction in air pollution and its targeted reduction, a city received a performance index:

$$P = \frac{R(A)}{R(T)} \times 100$$

If a city meets its targeted annual reduction ($R(A) = R(T)$), their performance index would be 100, and they would be entitled to 100% of the performance-linked funding allocated to them. It is possible that some cities may achieve PM_{10} reductions larger than they originally targeted. In such cases, they would be entitled to incentive funding that comes from leftover funds from cities that did not meet their targets and were not given the full funding they were allocated.

A.1.3 Ranking of Cities and Cash Prizes Under *Swachh Vayu Survekshan*

In 2022, the MoEFCC launched a new initiative to rank NCAP cities based on air quality and their implementation of their action plans. The CPCB split cities into three categories based on population and provides holistic assessment criteria for each group of cities. The top three ranking cities in each group is then rewarded with a cash prize, a trophy, and will be designated a "National Clean Air City" by the MoEFCC. The central government has allocated INR 210 million to these rewards from 2022-23 to 2025-26 (Central Pollution Control Board, 2022b).

[36] For details on the performance evaluation criteria, please see the guidelines on release and utilisation of funds under NCAP (Central Pollution Control Board, 2022a).

B Data Processing

B.1 Satellite $PM_{2.5}$ Data Collection and Processing

To obtain a measure of air pollution that is consistent over time as well as across all Indian cities, we use satellite-derived high-resolution $PM_{2.5}$ data sourced from the Atmospheric Composition Analysis Group (van Donkelaar et al., 2021). This dataset offers monthly mean $PM_{2.5}$ concentrations, measured in micrograms per meter cubed ($\mu g/m^3$) at a granular $0.01^\circ \times 0.01^\circ$ resolution from 1998 to 2023. We extracted $PM_{2.5}$ data for areas corresponding to city boundaries and calculated average concentrations for each city by averaging the $PM_{2.5}$ levels of all grid points within those boundaries. We describe how we construct city boundaries in Appendix Section B.3. We validate the satellite-derived data against ground-based measurements in Appendix Section C.1.

B.2 Geography Data from SHRUG

The shapefile used in this study is part of the SHRUG open-source dataset provided by the Development Data Lab (Asher et al., 2021). SHRUG provides maps at different levels of granularity; we use the 'shrid'-level map which represents the town and village boundaries from the 2011 Population Census. The smallest geographical unit in the SHRUG is a shrid, which in the majority of cases is a town or village identifier; in most instances, no aggregation was required and a single shrid can be matched to a single town or village. The maps are constructed using multiple open-source maps from sources like SEDAC and Bharatmaps.

The SHRUG shapefile provides a near-complete match with the official 2011 Population Census localities, making it a reliable source for geographic boundaries in India. For more detailed information on the construction and validation of the shapefile – including aggregation methods, limitations, and data quality measures – please refer to the SHRUG documentation.[37]

[37] https://docs.devdatalab.org/SHRUG-Construction-Details/shrug-open-source-polygons/

B.3 Defining Cities by NCAP Status

In our study, we define cities based on the urban agglomerations identified in the 2011 Census of India. The Census lists 468 Urban Agglomerations each with a population exceeding 100,000, and comprising a total of 5,697 towns. Throughout the paper, we refer to these urban agglomerations as "cities".

To spatially locate these cities, we matched the names of towns within each urban agglomeration with the town names corresponding to shrids in the SHRUG dataset. This matching process involved the following steps:

1. Data Extraction: We extracted the list of urban agglomerations and their corresponding towns from the 2011 Census (Office of the Registrar General and Census Commissioner of India, 2011), which can be downloaded from the SHRUG website.

2. Name Matching: We compared the names of towns within each Urban Agglomeration with town names corresponding to shrids in the SHRUG dataset. For exact matches, we used string matching. For non-exact matches, we performed manual matching.

3. Geographic aggregation: For each urban agglomeration, we aggregated the corresponding shrids to create a comprehensive spatial representation

4. For 5 urban agglomerations there were no, or incomplete, shrid shapefiles. We used QGIS to manually create shapefiles for these urban agglomerations, resulting in a complete catelogue of shapefiles for all urban agglomerations with populations above 100,000

We identified 464 of the 468 urban agglomerations using this process. Because the SHRUG spatial data had gaps for four UAs, we added three UAs by using geoprocessing tools and plugins in QGIS. The last UA required us to manually create the UA boundary in QGIS based on the city's approximate boundary in Google Maps.

To classify each urban agglomeration as being included in NCAP or not, we obtained the list of NCAP cities from the official document available on the CPCB's website.[38] To integrate this information into our data, we matched the names of NCAP cities with those of urban agglomerations. This matching process allowed us to identify which urban agglomerations are NCAP cities and which are not.

While there are 131 NCAP cities listed in the official documentation, we identify 104 urban agglomerations as having NCAP status. The reasons some NCAP cities are not uniquely identified in our data are as follows:

1. 21 NCAP cities have populations of less than 100,000 and are therefore not in the Census's list of urban agglomerations. We exclude these from our analysis

2. 6 NCAP cities are part of the same urban agglomeration as another NCAP city, resulting in them being aggregated into the same urban agglomeration as another NCAP city

B.4 Ground Monitoring Station Data

There are over 500 government-operated ground-level continuous air pollution monitoring stations in India. The network of stations is referred to as Continuous Ambient Air Quality Monitoring Stations (CAAQMS). While a handful have been operating since as early as 2010, most stations have begun recording pollution from 2017 onwards. We collected data recorded by CAAQMS from two sources.

First, we downloaded the station data available from the CPCB CAAQMS data repository.[39] This data starts in 2017 and we obtained data for all available stations, and all pollutants, from January 2017 to October 2024. For cities where pollutant data was available before 2017, we added historical air quality data from 2010 to 2017 from the dataset *Time Series Air Quality Data of India (2010 - 2023)*.[40]

[38] https://cpcb.nic.in/uploads/Non-Attainment_Cities.pdf

[39] https://airquality.cpcb.gov.in/ccr/#/caaqm-dashboard-all/caaqm-landing/caaqm-data-repository

[40] https://www.kaggle.com/datasets/abhisheksjha/time-series-air-quality-data-of-india-2010-2023

We then matched the station data with cities and NCAP status based on the names of the cities in which the station is located. To obtain city-month-year-level station data, measurements from multiple stations within the same city within the same month were aggregated by first taking the average across all stations in that city and then taking the average across all days in the month. Only city-months with at least one monitor reading for more than 70% of days were included in the data.

B.5 Constructing the NCAP Eligibility Variable

B.5.1 NCAP's Inclusion Criteria

We use multiple sources to understand the criteria for which cities were included in NCAP. The MoEFCC published a report on NCAP in 2019 (MoEFCC, 2019). This lists three criteria on which non-attainment cities were to be identified and included. The first non-attainment criterion is to include cities that consistently exceeded the National Ambient Air Quality Standards from 2011 to 2015. The second non-attainment criterion is to include cities in the top 10 cities of the WHO's Fourth Ambient Air Quality Database. The third non-attainment criterion is to include cities that from 2015 onwards *consistently* exceeded the guidelines set by the National Ambient Air Quality Standards for $PM_{2.5}$, based on pollution data from the National Air Quality Monitoring Programme. These cities are called "non-attainment" cities. In addition to including non-attainment cities, the government also included all cities with a population of more than a million regardless of their pollution levels.

B.5.2 Data Used to Construct the Eligibility Variable

We use the first two non-attainment criteria as well as the population criterion to construct an eligibility measure that quantifies how close each city was to being included in NCAP. In our construction of the NCAP eligibility variable, we exclude the third non-attainment criterion, as we were unable to find detailed documentation of how the criterion was implemented by the government. Below we describe our interpretation of each criterion and the data we used to construct

the eligibility variable.

Non-Attainment Criterion 1: National Air Quality Monitoring Programme Data

A city was included if it consistently exceeded the guidelines set by the National Ambient Air Quality Standards (2019) for PM_{10}, SO_2, and NO2, based on data from the National Air Quality Monitoring Programme from 2011 to 2015. The annual standards set are 60μg/m3 for PM_{10}, 50μg/m3 for SO_2, and 40μg/m3 for NO_2[41]. We interpreted this to mean that, to be included in NCAP, a city was required to exceed the national guideline in each year for which data is available, on at least one of the pollutants.

We used annual data from the National Air Quality Monitoring Programme from the CPCB website[42]. This dataset provides annual air quality data from every operational monitoring station from 2011 to 2015. The data is available in PDF format, from which we extracted the relevant information.

Non-Attainment Criterion 2: WHO Ambient Air Quality Data

A city was included if it was in the top 10 cities of the WHO's fourth Ambient Air Quality Database on the basis of $PM_{2.5}$. We interpret this to refer to the 10 Indian cities with the highest average annual $PM_{2.5}$ across all the years recorded by the WHO database.

We use data from the World Health Organization's (WHO) Fourth Air Quality Database.[43] From this database, we took the all-time average $PM_{2.5}$ concentrations and identified the top 10 cities with the highest $PM_{2.5}$ levels.

Population Criterion: Population Data

A city was included if it had a population of over 1 million residents (i.e., it was a "million-plus" city). Since cities are identified by collections of shrids, we utilized shrid-level population data from the 2011 Census (Office of the Registrar General and Census Commissioner of India, 2011) aggregated to the urban agglomeration

[41] https://cpcb.nic.in/upload/NAAQS_2019.pdf
[42] https://cpcb.nic.in/namp-data/
[43] https://www.who.int/data/gho/data/themes/air-pollution/who-air-quality-database/2018

level.

B.5.3 Constructing and Validating the Eligibility Variable

Using the three criteria described above, we constructed an eligibility measure that quantifies how close each city was to being included in NCAP. This measure is the maximum of distance to being included based on each individual criterion, as it is sufficient for a city to meet one of the criteria to be included in NCAP.

To measure the distance to being included based on National Air Quality Monitoring Programme Data, we first calculated for each pollutant (PM_{10}, SO_2, NO_2) the maximum of (a) the percentage of years that the city exceeded the national guideline level and (b) in the year when the city recorded the lowest level of that pollutant, the percentage of that pollutant relative to the national guideline. We then take the maximum of this value across all three pollutants. This creates a variable indicating how close, as a percentage of the eligibility threshold, the city was to being included in NCAP based on the National Air Quality Monitoring Programme Data.

To measure the distance to being included based on WHO, for each city we calculated its all-time annual average $PM_{2.5}$ as a percentage of the all-time annual average $PM_{2.5}$ value of the tenth city among the 10 included in NCAP. As the tenth city is the least polluted city included in NCAP based on this criterion, the pollution level of the tenth city is effectively the threshold for inclusion into NCAP. Thus, this variable indicates how close each city was to being included in NCAP based on the WHO air pollution data.

To measure the distance to being included based on population, we simply calculated the population of each city as a percentage of 1 million.

We then took the maximum across these three measures of distance to get the distance to being included in NCAP, as a percentage of the eligibility threshold that the city was the closest to meet. If this was ≥ 100, we considered the city to be NCAP-eligible based on our replication of the government's calculations, while if it was < 100 the city was considered to be ineligible.

Of the 468 cities in our data, we find that 113 should have been included in

NCAP based on our recreation of these criteria, but only 104 of these cities were actually included in NCAP. We also find that 9 cities that are not NCAP-eligible are included in NCAP.

We use this data in Section 4.2 of our analysis, and in some of the robustness tests in Section 4.3.

B.6 Source Contributions, NCAP Action Points, and Funding Allocations Data

Appendix Figure A.1 uses data on source contributions, NCAP action points, and NCAP funding allocations data. This section describes the data sources and how the data was processed.

B.6.1 Pollution Source Contributions

The data presented in the first panel of Appendix Figure A.1 originates from the Air Pollution knowledge assessments (APnA) program (Guttikunda et al., 2019), which developed comprehensive emissions inventories for 50 Indian cities to plug the information gap regarding air pollution in Tier 1 and Tier 2 cities. The APnA program built emissions inventories at 1-km resolution covering multiple pollution sources, including transport, power generation, industries, dust, residential activities, waste burning, and natural sources for nine pollutants (PM_{10}, $PM_{2.5}$, black carbon, organic carbon, SO_2, NO_X, NMVOCs, and CO_2). The data was compiled from several government agencies as well as satellite data, meteorological models, and Google traffic data. The resulting inventory includes the following sectors: transportation, residential (domestic cooking and heating), industrial (industry, brick kilns, and generators), dust (generated by on-road re-suspension and construction), open waste burning, and sources outside the city (including sea salt). Because agricultural residue burning typically takes place outside the city's bounds, it is classified under "Sources outside the city" instead of open waste burning (Guttikunda et al., 2019). For the purpose of our visualization in Figure Appendix Figure A.1, we merge diesel generator sets and brick kilns into the industrial sector, and merged sea salt with sources outside the city. Of the 50

cities that had emission inventories under the ApNA program, 43 cities were under NCAP. We restrict our data to those 43 cities in our visualization.

B.6.2 Data on Action Points by Sector

Data on action points by pollution source comes from (Ganguly et al., 2020). The authors reviewed approved action plans for the 102 cities under NCAP at that time. They compiled counts of action points for transportation, industrial, waste burning, construction, residential, and dust emissions at the state level. We merge construction with industrial for our visualization. For a given Indian state, we calculate the share of action points in each category. We then average those shares across cities. We use this cross-city average in the second panel of Figure A.1.

B.6.3 NCAP Funding Allocation Information

We searched 132 approved action plans that are available in the CPCB's website[44] for information on financial allocation across action points. After filtering out action plans where financial allocations were unavailable, we reviewed 55 action plans and categorized available financial allocations across transportation, residential, industrial, dust emissions, open waste burning, and "monitoring and awareness", which captures investments in air quality monitoring stations and school-level awareness campaigns. If there was no specific monetary amount mentioned for the action point, we did not enter it into the data. After categorizing these budgeted amounts, we calculate the share of financial allocation taken up by each category in a city's action plan, and then average those shares across cities. We report across-city average of shares in the visualization in the third panel of Figure A.1.

B.7 Analysis of Mann ki Baat Transcripts

Figure 7 describes the frequency with which different government programs are mentioned in the Prime Minister's monthly radio broadcast. In this section, we provide further details on how the data was collected and processed.

Data Collection: Mann Ki Baat transcripts were collected using a custom Python-based web scraper.

[44]The website is https://cpcb.nic.in/approved-city-action-plans/.

Data Analysis: Mentions of key government programs were identified using keyword-based string matching. We also count mentions of keywords that describe the problem or the solution, without naming the specific government program. This is because these words are typically used when the Prime Minister discusses the government programs, even if the program is not explicitly named.

The keyword lists, including alternative spellings and synonymous phrases, are:

- **NCAP (National Clean Air Programme):** NCAP, National Clean Air Program, National Clean Air Programme, air pollution, polluted air, air quality, clean air, swachch vayu, swachh vayu, swacch vayu, swachch vaayu, swachh vaayu, swacch vaayu
- **Swachh Bharat:** Swachh Bharat, Swachch Bharat, Swacch Bharat, SwachhBharat, Swachh Abhiyan, Swachhta Abhiyan, toilet
- **Jan Dhan Yojana:** Jan Dhan, JDY, JanDhan, financial inclusion
- **Make in India:** Make in India, vocal for local

For each episode and program, the analysis records whether the program was mentioned at least once. Counts are then aggregated to the yearly level, producing the total number of broadcasts in which it was mentioned in each year.

C Additional Empirical Analyses

C.1 Validation of the Satellite Derived $PM_{2.5}$ Data

We validate the satellite-derived $PM_{2.5}$ data provided by van Donkelaar et al. (2021) by comparing it with data obtained by ground-level air pollution monitors. We match monitor stations to shrids based on the locations of the monitors which were provided to us by the CPCB.[45]

Appendix Sub-Figure A.4a shows the correlation between month-shrid level satellite and station $PM_{2.5}$ measurements, subsetting to station observations in

[45]The spreadsheet with locations was provided to us via email in October 2023.

which more than 90% of the month's observations are valid. We can see a high correlation between satellite and station $PM_{2.5}$ measurements.

In Appendix Sub-Figure A.4b, we show the correlation between residuals from station and satellite data, where residuals are extracted after controlling for month-year and city fixed effects. Even after controlling for month-year and city fixed effects, we observe a high correlation between station and satellite data.

In Appendix Sub-Figure A.4c we plot the same correlation as Appendix Sub-Figure A.4a but after dropping stations that were used for calibration of the satellite data. As expected, the correlation weakens a little, but remains high.

These exercises suggest that the satellite data, which is our main data source, is reliable and unbiased.

D Additional Information About Survey Experiment

D.1 Sample

The sampling frame for the survey consisted of mobile numbers of individuals living in 16 pre-selected cities that our survey company had put together from various sources. Phone numbers were aggregated from network service provider companies, educations portals, business directories, job portals, automobile portals, and yellow pages. From those the survey company identified residents of the 16 cities based on the name of the city or the area code.

Appendix Table A.8 compares our respondents to adults living in the urban parts of the districts in which the 16 cities are located. The comparison data is from India's National Family Health Survey 2019-21, a large nationally-representative survey. Compared to urban adults in these districts, respondents to our survey are 16 p.p. more likely to own a refrigerator, 15 p.p. more likely to own a motorcycle/scooter, 7 p.p. more likely to own a car, and 14 p.p. more likely to own a computer. Respondents to our survey are 0.2 years more educated, and 3.8 years younger than the average urban adult in these districts. Differences between our sample and urban residents of these districts do not threaten the internal validity of our survey results. However, the fact that our respondents are wealthier and

more educated than the average urban resident in these districts should be kept in mind when considering representativeness.

D.2 Experimental Intervention

In the survey experiment respondents were randomly assigned to one of three arms: "No information" (control), "NCAP information", or "No effect information"

1. **NCAP information.** For participants randomized into the NCAP information treatment, we first ask participants if they have heard about NCAP, and then we provide them with the following information:

   > "Breathing polluted air contributes to heart and lung disease and can even lead to death. Because air pollution is bad for health, the National Clean Air Programme (NCAP) was started by the central government in January 2019 to reduce air pollution. The goal of the program is to reduce air pollution by 40% from 2017 levels by 2026. 131 cities are covered by the program. Your city is covered by the program. Cities have come up with their own plans for reducing air pollution, including things like expanding air quality monitoring, switching to electric buses, and reducing industrial emissions. The central government set aside more than 9,000 crore for this program since 2019."

   These participants are then asked for their prediction of what effect this policy will have on air pollution.

2. **No effect information.** In addition to the information and questions detailed in the "NCAP information" treatment, participants in this arm will also be informed that NCAP has not had an effect on air pollution with the following text:

   > "Since the policy started, there has been no effect on air pollution. The cities covered by NCAP have not seen any decline in air pollution compared to the cities not covered by NCAP."

3. **No information.** Respondents who were not part of the information treatments described above are provided with the information about NCAP *after* data on the outcome variables and other information has been collected. They are then asked for their prediction of the effect the program on air pollution.

D.3 Main Outcome Variables

After the randomized information provision, we collect data on our three main outcome variables by asking the following questions:

1. **Opinion About Government Actions:** Now I want to learn about your opinion about the Indian national government's policies and actions to reduce air pollution. What do you think of what the government is doing to reduce air pollution? Do you think they are doing too much, they are taking all the required actions, or they are not taking enough actions?

2. **Perception of Government Dedication:** How dedicated do you think the Indian national government is to reducing air pollution. In other words, what financial and political costs is the government willing to pay to achieve the objective of reducing air pollution. Are they dedicated, slightly dedicated, or not dedicated?

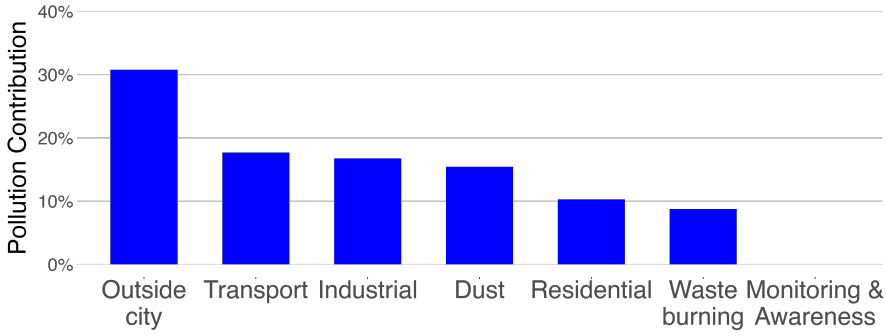
3. **Satisfaction with Government Policies:** How satisfied are you with the Indian national government's policies and actions on air pollution? Are you satisfied, slightly satisfied, or not satisfied?

We rescale responses to each question into standard deviations from the control group (no information) mean.

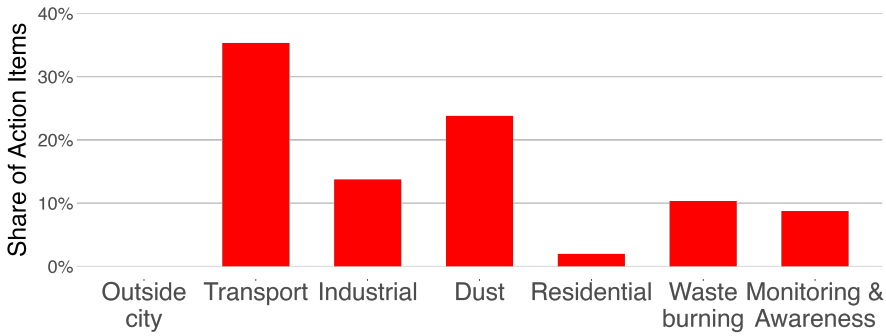
E Additional Tables and Figures

Figure A.1: Pollution Contribution, NCAP Action Items, and NCAP Funding by Pollution Source

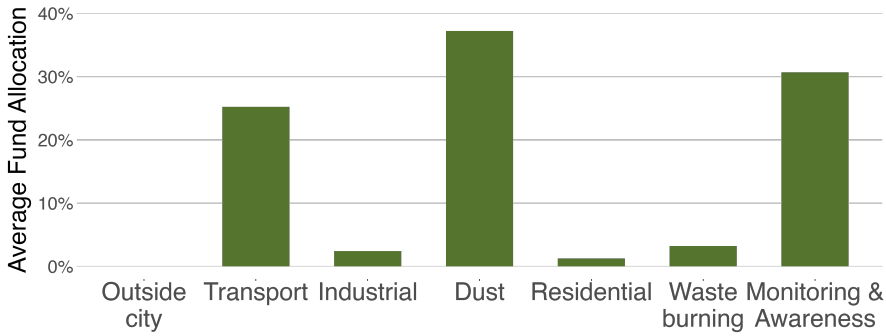
(a) Pollution Contribution



(b) Share of NCAP Action Plans' Items

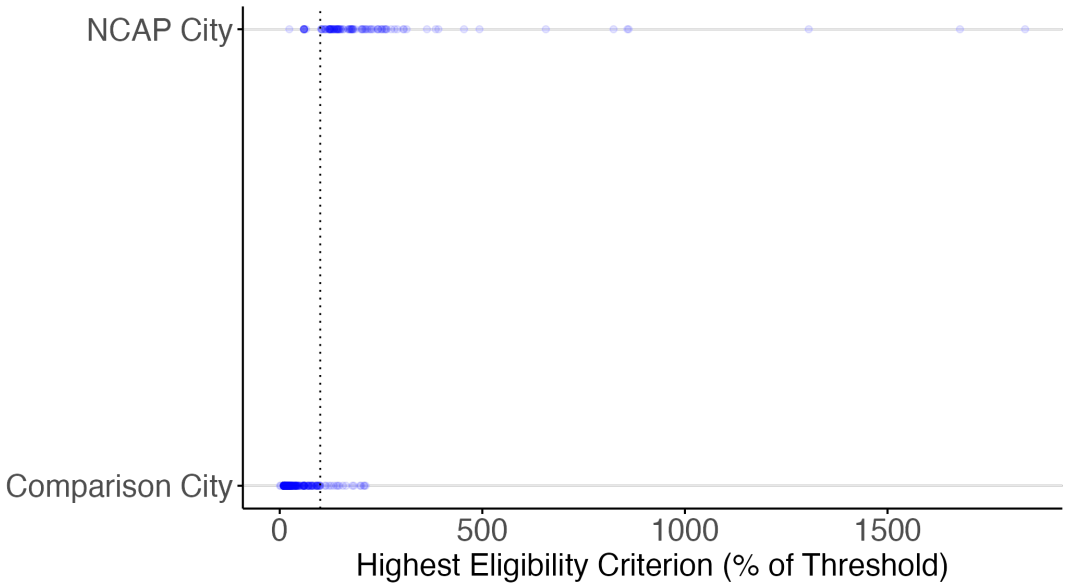


(c) Share of NCAP Action Plans' Funding Allocation



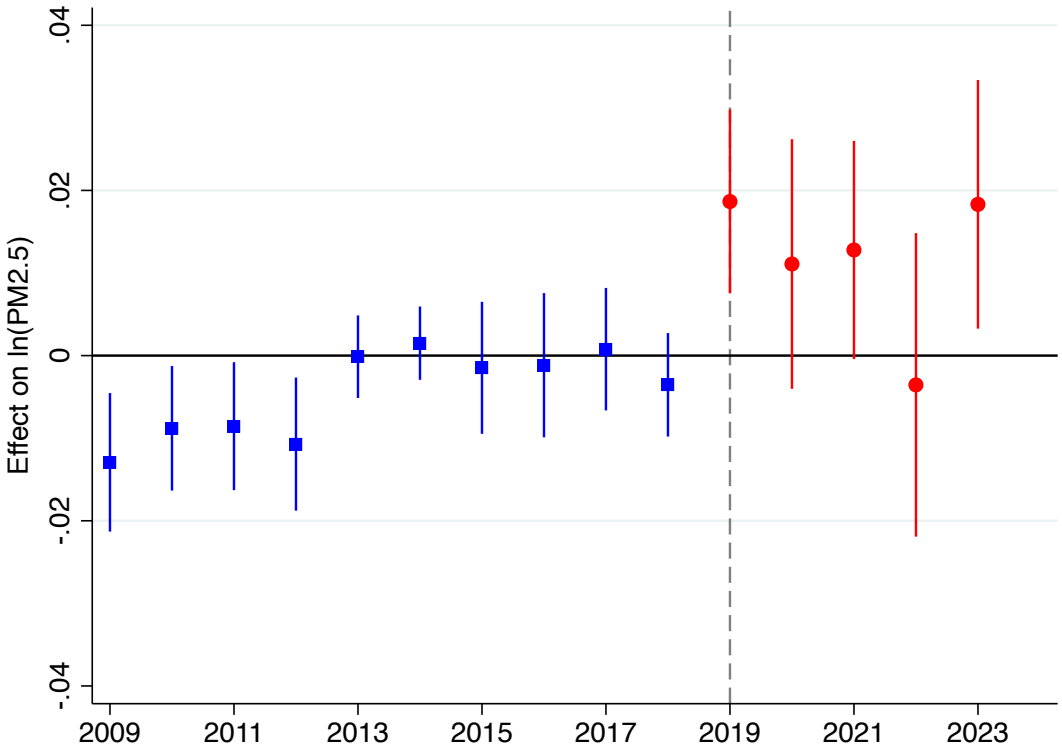
Notes: This figure shows the contribution of different pollution sources to overall air pollution, and the share of NCAP action points and funding allocated to addressing each source. Sub-Figure (a) shows pollution contribution by source, which is averaged across the 43 NCAP cities for which source apportionment studies have been made by APnA (Guttikunda et al., 2019). In Sub-Figure (b), we show the average share of action items in the 102 NCAP action plans analyzed by Ganguly et al. (2020). Action points are averaged across states after computing shares within each state. Sub-Figure (c) shows financial allocations across sources for the 55 NCAP cities for which financial allocations were disclosed in the action plans. Funding shares are calculated by first computing the within-city share of funding allocated to each source, and then averaging shares across cities. See Appendix Section B.6 for a detailed description of how the data was processed. See discussion in Sections 2 and 6.2.

Figure A.2: Eligibility and Inclusion into NCAP



Notes: This figure shows NCAP inclusion based on NCAP eligibility for the full sample of cities. Data on the eligibility score are constructed as described in Appendix Section B.5.3. Figure 2b provides the same visualization for the cities ±30% around the eligibility cutoff. See discussion in Section 3.2.2.

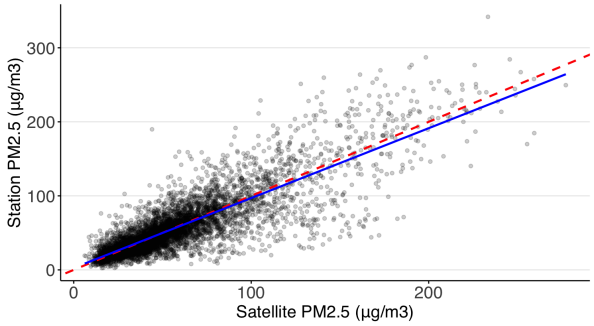
Figure A.3: Effect of NCAP Over Time Estimated with Synthetic Differences-in-Differences



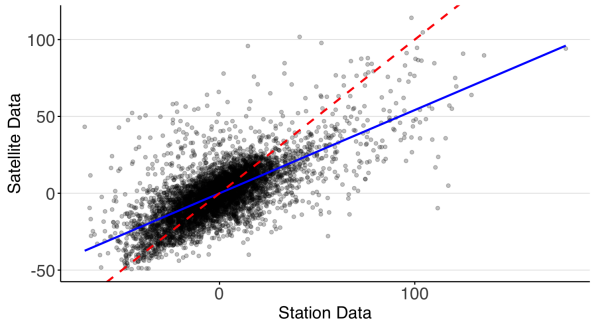
Notes: This figure shows synthetic differences-in-differences estimates of the effect of NCAP over time (Arkhangelsky et al., 2021). The analysis uses a dataset on annual pollution levels in cities, constructed by taking mean pollution levels across months for each year and for each city. The implementation of an event study graph based on synthetic difference-in-differences estimates was adapted from Clarke et al. (2024). This technique constructs a weighted average of cities without NCAP to create a "synthetic" comparison group. The confidence intervals are obtained using bootstrap resampling. See discussion in Section 4.3.

Figure A.4: Validation of Satellite-Derived $PM_{2.5}$ Data

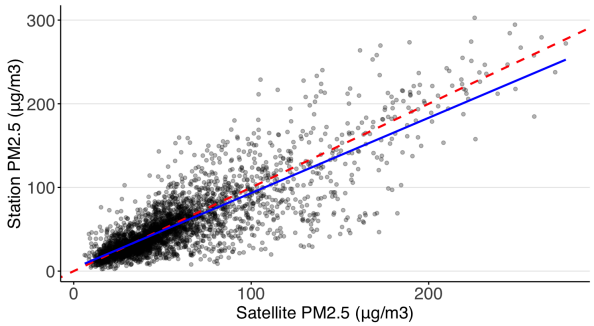
(a) Correlation Between Satellite and Monitoring Station $PM_{2.5}$



(b) Correlation Between Residualized Satellite and Monitoring Station $PM_{2.5}$



(c) Correlation Excluding Stations Used for Calibration



Notes: This figure shows scatter plots of satellite-derived $PM_{2.5}$ data and observations from measuring stations. Each observation is a month by measuring station, matched with the geographically closest satellite measurement. The red dashed line represents the 45-degree line, while the blue solid line represents the relationship fitted using OLS. Panel (a) shows the scatterplot using raw data. Panel (b) shows the scatterplot using residuals from satellite-derived data and ground monitoring station data, after controlling for time (month-year) and city fixed effects. Panel (c) shows the scatterplot excluding data from stations used in the calibration of the satellite-derived data. Only measuring station months with measurements for at least 90% of the days are included. The number of observations are 6,040 (panel a), 6,040 (panel b), and 1,263 (panel c). See discussion in Appendix Section C.1.

Table A.1: Social Science Prediction Platform Responses

Outcome	Median (%)	Mean (%)	Standard Deviation (%)
	(1)	(2)	(3)
Pollution Reduction 2017 - 2026	-11.68	-10.28	19.31
NCAP Causal Effect	-8.51	-7.16	15.53
Observations	82		

Notes: This table presents the prediction responses from the Social Sciences Prediction Platform for the estimated changes in air pollution from 2017 to 2026 and the causal effect of NCAP on air pollution. Columns (1) and (2) show the median and mean responses to the questions, respectively. Column (3) shows the standard deviations of the responses. Predictions were collected from November 2023 to January 2024, before any results from this paper were shared. See discussion in Section 2.3.

Table A.2: Results are Robust to Controlling for Eligibility Score in Analysis of Cities Close to the Eligibility Cutoff

	PM2.5		ln(PM2.5)	
	(1)	(2)	(3)	(4)
Eligible × Post	-0.427	0.924	-0.022	0.021
	(1.235)	(5.214)	(0.023)	(0.089)
Eligibility (% of Cutoff) × Post	0.011	0.018	0.001	0.001
	(0.025)	(0.030)	(0.000)	(0.001)
Eligible × Eligibility × Post		-0.014		-0.000
		(0.049)		(0.001)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-time trends	No	Yes	No	Yes
Observations	17,820	17,820	17,820	17,820
Cities	99	99	99	99
Comparison city mean	40.72	40.72	3.53	3.53

Notes: This table shows that our results are robust to limiting the sample to cities that are within ±50% of the NCAP eligibility cutoff and controlling for the continuous eligibility variable. *Eligible* is an indicator for the city being above the NCAP eligibility cutoff, *Eligibility* is a continuous variable that measures a city's eligibility score (as a percentage of the threshold) for NCAP, and *Post* is an indicator for periods including and after January 2019. Data on the eligibility score are constructed as described in Appendix Section B.5.3. Columns (1) and (2) show results using levels of $PM_{2.5}$, and columns (3) and (4) show results using $ln(PM_{2.5})$. Columns (1) and (3) include fixed effects for city and month-year, and columns (2) and (4) add in city-year trends. Standard errors are clustered by city. * for p-value<0.10, ** for p-value<0.05, and *** for p-value<0.01. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.2.

Table A.3: Results are Robust to Alternative Clustering of Standard Errors

	PM2.5				ln(PM2.5)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NCAP× Post	-0.222	-0.222	-0.222	-0.222	-0.003	-0.003	-0.003	-0.003
	(0.574)	(0.840)	(0.887)	(0.687)	(0.007)	(0.009)	(0.009)	(0.011)
Cluster level	None	State	State	City & time	None	State	State	City & time
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bootstrapped SE	No	No	Yes	No	No	No	Yes	No
Number of clusters	-	31	31	468 & 180	-	31	31	468 & 180
Comparison city mean	50.5	50.5	50.5	50.5	3.7	3.7	3.7	3.7

Notes: This table shows the robustness of our standard errors to alternative levels of clustering. Columns (1)-(4) show results using levels of $PM_{2.5}$, and columns (5)-(8) show results using $ln(PM_{2.5})$. Columns (1) and (5) use robust standard errors without any clustering. Columns (2) and (6) cluster the standard errors at the level of the state or union territory. Columns (3) and (7) cluster standard errors at the state or union territory level, but use bootstrapped standard errors instead. Columns (4) and (8) use two-way clustering at the city and time (month-year) level. * p<0.10, ** p<0.05, and *** p<0.01. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 4.3.

Table A.4: Survey Experiment Results are Robust to Excluding State Fixed Effects

	Govt Actions	Govt Dedication	Satisfaction	Index
	(1)	(2)	(3)	(4)
NCAP info	0.069*	0.116***	0.069*	0.099***
	(0.035)	(0.035)	(0.036)	(0.035)
No effect info	0.070**	0.111***	0.017	0.077**
	(0.035)	(0.035)	(0.036)	(0.035)
State FEs	No	No	No	No
Observations	4,610	4,610	4,610	4,610
P-value: Equal Effects	0.967	0.890	0.149	0.539

Notes: The table shows the robustness of the results from Table 7 to excluding state fixed effects. Outcome variables have been normalized based on the control group mean and standard deviation. "Govt Actions" refers to responses to the question: "What do you think of what the government is doing to reduce air pollution? Do you think they are doing too much, they are taking all the required actions, or they are not taking enough actions?" "Govt Dedication" refers to responses to the question: "How dedicated do you think the Indian national government is to reducing air pollution. Are they dedicated, slightly dedicated, or not dedicated?" "Satisfaction" refers to responses to the question: "How satisfied are you with the Indian national government's policies and actions on air pollution? Are you satisfied, slightly satisfied, or not satisfied?" Larger numbers signify perceptions of more action, more dedication, and more satisfaction. The index in column (4) is constructed by summing the responses to the prior questions and then rescaling the sum into an index of standard deviations away from the control group mean. "NCAP info" is an indicator variable for whether the respondent was randomly assigned to the group that received information on NCAP. "No effect info" is an indicator variable for whether the respondent was randomly assigned to the group that received information on NCAP *and* that NCAP had no effect on air pollution. Heteroskedasticity robust standard errors. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 5.4.

Table A.5: Heterogeneity Analysis: Similar Effects of Information among Different Sub-groups in Experiment

	Sub-group heterogeneity:					
	Education more than 12 years	Voted in 2024	Air is clean	Expects NCAP will meet goal	Above median $PM_{2.5}$	Ruling party aligned
	Outcome variable: Government policy opinion index					
	(1)	(2)	(3)	(4)	(5)	(6)
NCAP info × sub-group	0.186***	0.085**	0.060	-0.013	0.117**	0.051
	(0.051)	(0.039)	(0.044)	(0.059)	(0.050)	(0.083)
No effect info × sub-group	0.057	0.062	0.009	0.039	0.121**	0.054
	(0.051)	(0.038)	(0.044)	(0.060)	(0.050)	(0.082)
NCAP info × not in sub-group	0.030	0.150*	0.142***	0.132***	0.082*	0.124**
	(0.046)	(0.080)	(0.053)	(0.040)	(0.048)	(0.057)
No effect info × not in sub-group	0.097**	0.132*	0.172***	0.106***	0.038	0.109*
	(0.046)	(0.079)	(0.052)	(0.039)	(0.047)	(0.057)
Sub-group	-0.259***	0.177***	0.569***	0.786***	0.144**	0.494***
	(0.049)	(0.061)	(0.049)	(0.051)	(0.063)	(0.072)
Subgroup share	0.45	0.81	0.59	0.30	0.47	0.32
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,610	4,610	4,610	4,560	4,610	2,425
NCAP info:						
P-value in vs. not in sub-group	0.02	0.47	0.23	0.04	0.62	0.47
No effect info:						
P-value in vs. not in sub-group	0.56	0.43	0.02	0.35	0.23	0.58
Not in sub-group:						
P-value NCAP info vs. no effect info	0.15	0.82	0.56	0.49	0.34	0.80
In sub-group:						
P-value NCAP info vs. no effect info	0.01	0.55	0.24	0.38	0.93	0.97

Notes: The table shows heterogeneity analyses from our survey experiment. The outcome variable is an index of respondents' opinions of the central government's air pollution policies, which has been normalized based on the control group mean and standard deviation. Larger numbers signify better opinions. The first column interacts treatment with the respondent's education, the second column with whether the respondent voted in the 2024 national election, the third with whether the respondent believes the air in her neighborhood is clean, the fourth with whether the respondent believes that NCAP will meet its goal, the fifth with whether the respondent lives in an above- or below-median pollution city, and the sixth with whether the respondents supports the BJP or a party in alliance with the BJP. "NCAP info" is a dummy variable indicating that the respondent was randomly-assigned to the group that received information on NCAP. "No effect info" is a dummy variable indicating that the respondent was randomly-assigned to the group that received information on NCAP and that it failed. Heteroskedasticity robust standard errors. * p<0.10, ** p<0.05, and *** p<0.01. See Figure 6 for a visualization of the results. See discussion in Section 5.4.

Table A.6: NCAP Increased the Number of Active Measurement Stations on the Ground

	$PM_{2.5}$	PM_{10}	SO_2	Ozone	CO	NO_2
	(1)	(2)	(3)	(4)	(5)	(6)
NCAP×post	0.620***	0.662***	0.627***	0.662***	0.637***	0.638***
	(0.189)	(0.204)	(0.192)	(0.209)	(0.212)	(0.200)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
City-time trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,420	84,420	84,420	84,420	84,420	84,420
Cities	468	468	468	468	468	468
Comparison city mean	0.19	0.19	0.19	0.18	0.19	0.19

Notes: This table shows the effect of NCAP on the number of active monitoring stations in a city for each of the main pollutants. A station is classified as "active" in a month if it recorded measurements for at least 70% of the days. Each column header corresponds to the pollutant being considered. "Comparison city mean" is the average number of active stations in cities that are not part of NCAP in the period from 2019 onwards. Standard errors are clustered by city. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 6.2.

Table A.7: Heterogeneity Analysis: NCAP Was Neither Effective in BJP-aligned States Nor in States Ruled by Other Parties

	Levels		**Logs**	
	(1)	(2)	(3)	(4)
NCAP × Not BJP-aligned × Post	2.591***	1.683**	0.039***	0.005
	(0.471)	(0.688)	(0.008)	(0.008)
NCAP × BJP-aligned × Post	-0.917	-2.819*	-0.004	-0.014
	(0.814)	(1.482)	(0.009)	(0.014)
p-value: BJP-aligned vs. not BJP-aligned	0.000	0.004	0.000	0.227
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	84,240	84,240	84,240	84,240
Cities	468	468	468	468
Comparison city mean	50	50	4	4

Notes: This table shows heterogeneity in the effect of NCAP on pollution levels based on the party in power at the state level. "BJP-aligned" is a dummy variable indicating that the party in power in the state is the BJP, which is the same party in power in the central government, or a party in the BJP coalition. We treat the union territories as non-BJP-aligned states. Standard errors are clustered by city. * for p-value<0.10, ** for p-value<0.05, and *** for p-value<0.01. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). See discussion in Section 6.2.

Table A.8: Comparison of Summary Statistics Between Survey Sample and NFHS Sample

	(1) Survey	(2) NFHS
Age	36.5	40.3
Is Female	0.45	0.49
> 12 years of schooling	0.45	0.29
Owns a car	0.24	0.17
Owns a computer	0.37	0.23
Owns a motorcycle	0.83	0.68
Owns a refrigerator	0.84	0.68
N	4,610	50,850

Notes: This table compares means for selected variables in our survey sample with that of a representative sample of adults living in the urban parts of the districts in which the 16 surveyed cities are located, from the National Family Health Survey - 5 (NFHS), India's Demographic and Health Survey. Ownership of a car, computer, motorcycle, and refrigerator are shown as a share of respondents. Estimates from each source (from our survey and NFHS) are constructed using sample weights that equally weight each city. See discussion in Section 5.1.