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

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Abstract

What are the political consequences of setting ambitious targets and then failing to meet them? This paper studies this question in the context of air pollution in India, which causes an estimated 1.3 million deaths annually. The National Clean Air Programme (NCAP) was launched by the government with an ambitious aim to reduce air pollution by 40% across 131 cities in seven years. If successful, NCAP would be one of the most important environmental policies in history. We evaluate the effect of NCAP using a difference-in-differences approach that compares NCAP cities to cities not covered by NCAP, and find a precisely estimated zero effect on air pollution. Using a survey experiment, we show that residents of NCAP cities are more satisfied with the government's actions when told about the ambitious targets. When we also provide the information that NCAP has had no effect, their satisfaction decrease compared those just told about the targets, but there is still a positive effect compared to the control group. These public opinion benefits can explain why the government sets targets that it then fails to meet.

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1 Introduction

Setting policy targets can be beneficial for politicians because they clearly define priorities and allow responsible parties to be held accountable. However, they can also be politically costly if they are not met (Born et al., 2018). Because of the electoral consequences of failing to meet policy goals, democratically-elected leaders are often risk averse and avoid policy innovation (Hood, 2010). Given these concerns, why do politicians adopt ambitious policies that they may fail to meet?

Air pollution policy in India provides a compelling setting to explore the political economy of target setting. Air pollution poses a serious threat to health (Chay and Greenstone, 2003; Currie and Walker, 2011; Deryugina et al., 2019) and productivity (Graff Zivin and Neidell, 2012; Chang et al., 2016; Adhvaryu et al., 2022). The situation is especially critical in South Asia where approximately 1.3 million deaths annually are attributed to air pollution (GBD, 2024). To address this problem, India's central government has designed the National Clean Air Programme (NCAP). NCAP, which started in 2019, identified 131 cities with high air pollution, and required these cities to create action plans to reduce air pollution. NCAP's target is for each city to reduce particulate air pollution to 40% of 2017 levels, and the policy provides both funding and incentives to achieve this goal by 2026. This is a very ambitious target: since satellite-derived estimates of particulate pollution began in 1998, annual particulate pollution in the NCAP cities has never been so low. 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).

If NCAP is successful in meeting its target, it is likely to be one of the most

important environmental policies in history. NCAP covers highly polluted cities with a combined population of 260 million people. We estimate that achieving a 40% decrease in air pollution across these cities would save approximately 70,000 lives per year.

We estimate the effect of NCAP on $PM_{2.5}$ — that is, fine inhalable particles, with diameters that are generally 2.5 micrometers and smaller — using two types of difference-in-difference strategies. To accomplish this, we assemble a new longitudinal dataset that matches satellite-derived estimates of $PM_{2.5}$ from 1998 until 2023 by van Donkelaar et al. (2021) to all 468 cities in India with a population above 100,000. 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. All approaches control for fixed differences across cities and across different periods of time.

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 level of our preferred estimate is a decrease of 0.02 % or 0.1 $\mu g/m^3$. We show that these results remain stable throughout a battery of robustness tests. For example, results are similar using ground measurements of air pollution from monitoring stations instead of satellite-derived data, using a range of bands around the eligibility cut-off, and using the synthetic difference-in-differences approach developed by Arkhangelsky

et al. (2021). The results are surprising for three reasons. First, NCAP is based on policies that have proven successful in reducing air pollution in other contexts 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% decrease in air pollution, an effect size which can be rejected based on the results of our analysis.

Why do governments and political leaders set ambitious targets that they fail to make progress towards meeting? To answer this question, we are conducting a survey experiment with 4,074 respondents across 16 Indian cities that are part of NCAP.[1] We randomize respondents into one of three arms. The first arm is a control group, which receives no information about NCAP. The second arm receives information about NCAP and its goals. The third arm receive information about NCAP and its goals, and also that the policy has thus far had no effect on air pollution.

We find that informing respondents about NCAP substantially increases their satisfaction with the central government's policies to reduce air pollution. While informing respondents about NCAP's failure to reduce air pollution reduces their satisfaction with the government's policies compared to the group that was only told about NCAP's ambitions, these respondents are not less satisfied than those not informed about NCAP at all.

These findings can explain why it is common for governments to set ambitious

[1]The survey is ongoing and the sample size will increase.

goals even when they are unable to meet them. This is particularly common in the realm of environmental policy where, for example, the Paris Climate Accords were celebrated for their ambition while most informed observers agreed that they would not be met in practice.[2] Our results suggest two reasons why a government might set such unrealistic goals. First, if the realization of failure occurs in the future, current governments will reap the public opinion benefits of target-setting without having to face the negative consequences of failure. Second, even if the government is still in power and accountable at the time that policy failure is realized, as is likely in the case of NCAP, there is still no public opinion backlash from setting the goal despite not being able to meet it.

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 on citizen engagement (Singh and Thachil, 2023; Buntaine et al., 2022). We contribute to this literature by providing insight on the public opinion effects of adopting ambitious environmental policy. We show that the Indian government's policy announcement to tackle air pollution improved public opinion, despite that the government is not following through with the implementation of the policy.

Second, we contribute to the literature on pledges and promises made by politicians.

[2]The Metaculus community prediction as of August 15, 2024 is that there is a 97% probability that the goal of the Paris Climate Accords will not be met and that global warming will exceed 2 degrees celsius by 2100. For more information, see www.metaculus.com/questions/585/2c-global-warming-by-2100.

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) shows that in an experimental setting "voters" punish promise-breaking politicians. Contrary to this finding, we find that in a highly consequential setting in a developing country, people do not only fail to punish politicians who do not meet their targets, but reward them for setting an ambitious target even though they fail to make any progress towards it.

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] The policy is similar to air pollution policies that have been effective in the US and China (Chay and Greenstone, 2005; Isen et al., 2017; Shapiro and Walker, 2018; Niu et al., 2023). Furthermore, earlier air pollution action plans in India have been found effective (Greenstone and Hanna, 2014; Harrison et al., 2015). In contrast, we show that the most comprehensive air pollution policy to date in India did not cause any reduction in pollution.

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

[3] 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. However, previous studies did not use a comparison group to establish the causal effect of NCAP.

empirical strategies for estimating the effect of NCAP on air pollution. Section 4 provides results of the effect of NCAP on air pollution. Section 5 describes our survey experiment and its results. Section 6 concludes.

2 Background

2.1 Air Pollution in India

India is now one of the most polluted countries in the world. 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 average annual levels of $PM_{2.5}$ across the country in 2018 and 2022. Pollution levels in most of the country were higher than the WHO guideline of $5\,\mu g/m^3$, as well as the Indian government's guideline of $40\,\mu g/m^3$. Pollution is also highly seasonal in India, with worse pollution in the winter months, partially because of meteorology, relative to summer and monsoon (see Appendix Figure A.5).

Air pollution policy in India has to a large extent focused on monitoring air quality, which is carried out by the Central Pollution Control Board (CPCB). 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. According to government documentation

of NCAP, cities were included in the program based on air quality measured at these stations. 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 measures of $PM_{2.5}$, among other pollutants, available online. We use data from this system to validate the satellite-based estimates of $PM_{2.5}$ that we use in our main analyses.

Although the CPCB is also tasked with controlling air pollution, political will has been lacking and enforcement mechanisms have been weak. Since 1985, the Supreme Court has repeatedly taken the lead in reforms to improve air quality. For example, in 1998, the Court ordered that all commercial vehicles in Delhi switch from diesel to compressed natural gas. More recently, in 2016, the Court temporarily ordered cars in Delhi to be permitted on city streets on alternate days depending on whether the license plate ended in even or odd numbers. In response to particularly poor air quality in Delhi in 2016, the Graded Response Action Plan was established to respond to air pollution emergencies in the city.

2.2 National Clean Air Programme

The National Clean Air Programme (NCAP) aimed to improve air quality in India's 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 a part of the program. 102 cities were initially identified based on these criteria. In 2018, the Ministry of Environment, Forests, 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. 22 more cities were subsequently added. In 2021, eight cities that had populations greater than eight million were also included in NCAP. Two cities subsequently merged, which brings 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 them affected by NCAP from 2019 onwards.

When the program was launched, the goal of NCAP was to bring about a 20% to 30% reduction in $PM_{2.5}$, relative to 2017 levels, by 2024. In September 2022, the government set a new target of a 40% reduction by 2025-26 relative to 2017 levels.

Plans were developed by state committees, and then were 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 others. A comprehensive review of the initial 102 action plans by Ganguly et al. (2020) identified that across all plans, 50% of the action points address transportation and road dust, and 2% of action points address domestic cooking and heating. From 2019 to 2026, INR 197 billion (USD 2.6 billion[4]) of funding has been earmarked for NCAP. Since 2021, a performance payment scheme has been put in place where approximately 40% of the

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

funding is contingent on the city having achieved certain air pollution reductions. We provide more information on NCAP financing in Appendix Section A.

2.3 NCAP's Potential Benefit and Predictions About its Effect

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 260 million people.[5] To generate a rough 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 67.6 per 100,000 population (GBD, 2024). This would mean that approximately 175,000 deaths in NCAP cities are attributable to air pollution. 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 70,000 deaths per year.

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. While decreases in air pollution of similar magnitudes have occurred in the US and China under similar programs, India's income level and state capacity are far below that of those countries. To anchor our expectations of the effects 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

[5]If these cities were a country, it would be the fifth most populous country in the world, similar to the combined populations of Germany, France, Spain, and the UK.

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. If we use the assumptions described above, an 8.5% decrease in air pollution would result in 15,000 deaths avoided per year.

3 Empirical Strategies and Data

3.1 Data

We obtain and process air pollution data compiled by two different methods — satellite-derived estimates of air pollution and air quality observations from monitors located in ground stations. Appendix D.1 shows that satellite and station data are highly correlated.

We use satellite-derived estimates for our main analyses because they span greater spatial and temporal bounds. The satellite data are available at 1×1km grid resolution for all of India from 1998 to 2023 (van Donkelaar et al., 2021). We geographically match the satellite data to urban agglomerations in the 2011 Census using SHRUG's shrid polygons.[6] We then aggregate pollution data among the shrids within each identified city. Because some NCAP cities have a population of less than 100,000 and some urban agglomerations have multiple NCAP cities within them, our final dataset has 104 NCAP cities and 364 non-NCAP cities. We provide more details on

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

the collection and processing of data on pollution (from satellite data and ground monitors), urban agglomerations, and shrid polygons in Appendix B.

In alternative analyses, we limit our analysis 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 data from additional sources to construct a measure of closeness to the NCAP eligibility cutoff. We provide more details on data collection and processing in Appendix B.

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 t, $Post_t$ is an indicator variable for whether the month is on or after January 2019, and $NCAP_c$ is an indicator variable for whether the city was part of NCAP. τ_t and δ_c are time period and city fixed effects, respectively.

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. The key identifying assumption is that in the absence

of NCAP, 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:

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

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 the NCAP eligibility cut-off

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 other cities would have trended differently even in the absence of NCAP. To minimize these concerns we restrict our sample to NCAP cities close to the eligibility cut-off. The benefit of this strategy is that we analyze the effect of NCAP among a set 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 measuring the distance to being included in NCAP.

We discuss in detail the criteria, data sources, and construction of the eligibility score in Appendix B.5.3. It is implausible that cities manipulated the variables determining eligibility for the purpose of being included or excluded. Empirically, Figure 4 also shows that there is no substantial increase in the density of cities just above or just below the cut-off.

In Figure 5 we show the cities that were actually included in NCAP among the cities that had eligibility scores between 70% to 130% of the NCAP eligibility cut-off.[7] 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.

Appendix Table A.2 shows summary statistics and differences in these statistics between the group of cities eligible for NCAP (100%-130% of the eligibility threshold) and cities not eligible for NCAP (70%-100% of the eligibility threshold). The cities are similar across the observable characteristics not related to NCAP, such as population, population density, literacy rate, and share of labor force in manufacturing.

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 directly determined by the eligibility score, while the actual NCAP status may have been influenced by other considerations.

[7] Appendix Figure A.6 provides the same information for the complete sample of cities.

4 Results

4.1 Difference-in-Differences

Figure 2 shows that there were no differential changes in air pollution in cities with and without NCAP over time, neither before nor after the start of the program. As expected, cities covered by NCAP were slightly more polluted than cities not covered by the program. It is also clear that the averages of the two groups of cities were on parallel trends for the decade before the start of NCAP. These patterns hold both when displaying the differences in levels (Sub-figure 2a) and when displaying the average of the natural logarithm of air pollution (Sub-figure 2b).

Table 2 confirms the finding that the NCAP program did not have an effect on 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 $ln(PM_{2.5})$. Column 1 and 3 include city and month-year fixed effects, as described in Equation 1, and Columns 2 and 4 additionally include city-year trends. Based on the results shown in Column 3, our preferred specification, pollution was actually 2.05 (95% CI: .76 to 3.35) higher in NCAP cities relative to cities not in NCAP, before versus after January 2019.

Figure 3 shows the dynamic effects of NCAP in log points, using the regression described in Equation 2. In the decade before the policy started taking effect, there was only one year in which there was a statistically significant differential between the cities with and without the program, compared to the 2018 differential. After the start of the program, the estimated effects are also close to zero with narrow confidence intervals, spanning 2 log points above and below the point estimates.

4.2 Difference-in-Differences for Cities Close to the NCAP Eligibility Cut-Off

Focusing on cities close to the NCAP eligibility cut-off, we find similar results: that NCAP has had no effect on air pollution. Figure 6 shows that when restricting the sample to cities within 30 percent of the NCAP eligibility cutoff, and comparing eligible cities with those not eligible, the two groups of cities have similar levels of pollution as well as similar time trends in pollution, both before and after the start of NCAP.

Table 3 presents the estimated effect of NCAP 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 find no evidence of NCAP's effect on cities around the eligibility cutoff.

Finally, Figure 7 shows the dynamic difference-in-differences results for cities within 30 percent of the NCAP eligibility cutoff. Again, the figure confirms that the trends between the two groups of cities were parallel prior to the start of NCAP and that NCAP did not affect air pollution levels.

4.3 Robustness Tests

We show that our main result is robust to a variety of alternative empirical strategies and specifications. First, we assess the robustness of our estimates to the selection of the starting year of our study period. The pre-period in our main specification starts in 2009, 10-years before NCAP took effect. Appendix Tables A.3 and A.4 present the results of analyses on an expanded study period starting from 2004, as well as a contracted study period starting from 2014, respectively. Both tables show effects close to zero. However, expanding the study period to start from 2004 results in positive and statistically significant coefficients when not controlling for linear time trends.[8]

Second, Appendix Table A.5 shows the standard errors for alternative levels of clustering the standard errors. Columns (1) and (4) use robust standard errors without any clustering, (2) and (5) cluster standard errors at the state or union territory level, and (3) and (6) use two-way clustered standard errors at both the city and time period levels. Except for the two-way clustered standard errors (where standard errors are lower than in our main specification), both the robust and state-level clustered standard error specifications are similar to those in our main results.

Third, we examine the effect of changes in the fixed effects used in the main specification in Appendix Table A.6. Beyond the routine fixed effects for city and month-year, columns (1) and (3) include state-by-month-year fixed effects. Columns (2) and (4) instead include quadratic city-year trends. The main results are robust

[8]These positive coefficients are driven by differential trends in the 2004-2009 period and we do not interpret them as evidence that NCAP led to increased air pollution.

to both of these inclusions.

Fourth, Appendix Table A.7 shows the results when excluding any comparison city closer than 30 km from an NCAP city. As air pollution moves geographically, there could be spillovers from the NCAP policy on nearby cities reducing the difference between NCAP and comparison cities. When dropping cities within a 30 km buffer zone around each NCAP city polygon, we continue to find a precisely estimated zero effect when using our main specification in Column (3). We find small but marginally statistically significant negative effects when including controls for city-wise linear trends.

Fifth, we assess the effect of excluding 17 cities that were included in the Indian Supreme Court's Action Plan as reported in Greenstone and Hanna (2014) and Harrison et al. (2015), as these cities may have already experienced some of the policy changes that NCAP is aiming to bring about. Appendix Table A.8 shows that excluding these 17 cities does not substantially change our results.

Sixth, we assess the robustness of our results to the use of ground station measurements of air pollution. This has two benefits compared to the satellite derived data. First, it measures a wider range of air pollutants and not just $PM_{2.5}$. Second, we have collected the ground station data until October 2024, adding an additional 10 months to our analysis. However, a drawback of the ground station data is that we have to limit our analysis to the 86 cities for which we have measurements from both before and after the start of NCAP. In Appendix Table A.9, we show that when using the $PM_{2.5}$ station data, our estimate of the effect of NCAP is close to zero, consistent with our main results. Furthermore, appendix tables A.9 to A.11 also show estimates

for the effects on PM_{10}, O_3, SO_2, CO, and NO_2. Most of these estimates are close to zero, except for the estimate for $\ln(NO_2)$ is large, negative, but not statistically significant. As we are using 12 different outcome variables, it is not surprising to find some outliers and overall the ground station data supports our the main conclusion that NCAP had no effect on air pollution.

Seventh, to make our results representative for individuals living in the cities, instead of the cities themselves, we weigh our data by the population of each city. Appendix Table A.12 shows the population-weighted results. Column (3) shows that our preferred specification yields a statistically insignificant estimate that is very close to zero. However, in Columns (2) and (4), when including linear time trends for each city, we find negative but small estimates for the effect of NCAP on air pollution, one of these estimates is statistically significantly different from zero.

Lastly, we apply the synthetic differences-in-differences method of Arkhangelsky et al. (2021). This technique constructs a weighted average of cities without NCAP to create a "synthetic" comparison group. Most cities without NCAP receive similar weights, meaning that in our case the results are very similar to our main results. Appendix Figure A.7 shows parallel trends between the NCAP cities and the synthetic differences-in-differences sample of cities that are not part of NCAP (Arkhangelsky et al., 2021). The average treatment effect estimated with synthetic differences-in-differences is 1.2%.[9]

[9]The 95% confidence interval ranges from 0.4% to 2.0%.

4.4 Discussion: Why did NCAP not affect air pollution?

There are several potential reasons for why NCAP had no effect on air pollution. One leading hypothesis is that most of the NCAP resources are spent on activities that don't directly decrease air pollution or that only addresses a small part of the overall air pollution problem. For example, Appendix Table A.13 uses our difference-in-differences specification to show that NCAP substantially increased the number of active ground measuring stations. While installing and maintaining ground measuring stations is an important part of air quality management, it does not directly reduce air pollution. It is possible that actions such as improving measurement of air pollution is crowding out actions that are both financially and politically more costly, such as enforcing environmental regulations on industries, vehicles, and individuals.

Another potential reason for the lack of an overall effect is that the resources aimed at actually reducing air pollution were spent on sources of air pollution that does not constitute a large share of overall pollution. For example, 50% of the action points address transportation and road dust which are only responsible for about a fifth of overall air pollution, while only 2% of the action points address air pollution from residential sources (e.g. cooking and heating), estimated to be responsible for a third of all air pollution (Ganguly et al., 2020).

5 Why do Governments Overpromise?

5.1 Survey Experiment Providing Information on NCAP

We have now shown that NCAP is nowhere close to meeting its target and that the program has thus far had no effect on air pollution. This leaves us with the puzzle of why such an ambitious target was set in the first place.

To address this question, we conducted a survey experiment in two languages (Hindi and Bengali) across 16 cities covered by NCAP. We selected the three most populous NCAP cities in the five most populous states in India.[10] To this list of 15 cities, we added the Delhi National Capital Region because of its large population and salience in the debate around air pollution policy. The survey experiment is pre-registered and a pre-analysis plan can be found at the AEA RCT Registry.[11] The surveys were carried out over phone calls from July 2024 until February 2025.[12]

The sampling frame consists of mobile numbers of individuals living in these 16 cities. The list was constructed by our survey company from sources such as network service providers. Appendix Table A.14 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. Respondents to our survey are substantially more likely to own a refrigerator, motorcycle/scooter, car, and computer, compared to urban adults in these districts. Respondents to our survey are also more educated, and a couple

[10] We excluded Maharashtra because of a lack of Marathi language expertise in the research team.

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

[12] The survey is ongoing and is predicted to be completed in March 2025.

of 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 of our sample. For more information about the sample, please see Appendix C.1.

Respondents were 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 described NCAP's design and it's goals. For participants randomized into the "No effect information," we provided the same information about NCAP as to the NCAP information treatment group, but we also informed the respondents that NCAP has had no effect on air pollution.[13] While we only provide a short paragraph of information about NCAP, we believe that this treatment is the most policy relevant treatment. If citizens hear about NCAP, the majority would have heard a similarly short description on the news or as part of a political campaign. See Appendix C.2 for a detailed description of the interventions.

Appendix Table A.15 shows summary statistics for the survey respondents and confirms that there is balance between the control and treatment groups among variables not affected by the information interventions.

After the randomized information provision described above, 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

[13]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.

policies and actions on air pollution. 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 C.3 for the exact phrasing of the questions.

5.2 Experiment Regression Specification

We used the following pre-specified regression to estimate the effect of the information provision 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, while 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 seven states in which respondents live.

5.3 Experiment Results

Table 4 shows the results of the survey experiment. Column (1) shows that being informed about NCAP increases perceptions of how much the government is doing to reduce air pollution, relative to how much the respondent thinks should be done, by 0.06 standard deviations, but the effect is not statistically significant. When the respondents are also informed about NCAP's lack of an effect, there is no

substantial change in the reported perceptions of the governments actions. Column (2) shows that being informed about NCAP increases perceptions of the government's dedication to reducing air pollution by 0.11 standard deviations. This effect decreases to 0.09 when we provide information about NCAP's lack of an effect, but the differences in the two effects is not statistically significant. Column (3) shows that the overall satisfaction with the government's air pollution policy increases by 0.07 standard deviations when respondents are informed about NCAP. This effect decreases to just 0.02 standard deviations for those who are also told that NCAP had no effect but the effect is still not negative indicating that respondents do not "punish" the government for not meeting its targets.

In Column (4) we aggregate the three opinions into an index and we find that providing citizen with information about NCAP generally improve their perception of the governments air pollution policy making. Informing citizens both about the NCAP policy and the policy's failure to reduce air pollution has a smaller effect than just informing them about NCAP but it still has a positive effect compared to the control group. However, the effect of informing citizens both about the positive effect of NCAP and about its lack of an effect is only statistically significantly different from zero at the 90% level and is not statistically significantly different from the effect of just informing citizens about the effect of NCAP.

5.4 Heterogeneity in Survey Experiment Effects

Figure 8 and Appendix Table A.16 shows the heterogeneity in the effect of the survey experiment's information interventions on the government policy opinion

index summarizing the three outcome variables. The heterogeneity is measured along five pre-specified dimensions: if the respondent has more than 12 years of education (38.56% of respondents), if the respondent voted in the 2024 general election (81.49% of respondents), if the respondent is satisfied with the current air quality (57.98% of respondents), the respondent expectation about NCAP's effect (89.21% of respondents believe it would have at least some effect, while 30.79% believed NCAP would meet its goal), and if the respondent supports a party in the alliance forming the central government (34.41% of respondents).[14] We also analyze the effect by levels of PM2.5 air pollution in the city, which was not pre-specificed.

The general pattern observed in Figure 8 and Appendix Table A.16 is that information about NCAP increased satisfaction with the government's air quality policy for almost all sub-groups, except for those with less than 12 years of education, those who expects that NCAP would meet its goals, and those who supports the parties forming the central government.[15] However, the effect is only statistically significant for some sub-groups. Similarly, for most groups being told about NCAP having no effect reduces their opinions of the governments policies, but the point estimate for the overall effect of the information is still positive for all sub-groups.

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

[15]Appendix Figure A.16 shows that the treatment effects are not statistically significantly different between respondents who are inside vs. outside the sub-group for almost any of the comparisons.

6 Conclusion

We have shown that NCAP has not generated any decrease in air pollution. This is despite it being based on policies such as the Clean Air Act that have proven successful in other settings and despite the median prediction among social scientists that it would reduce air pollution by 8.5%. Furthermore, we have shown that as individuals become aware of NCAP their satisfaction with the central government's handling of air pollution increases. Surprisingly, this is true even after informing individuals about the failure of NCAP to actually reduce air pollution.

Given these results, it is not surprising that governments tend to announce goals that are more ambitious than what is realistic for them to achieve. Announcing a policy target has very few real costs but generates a substantial benefit in terms of improved public opinion. Furthermore, as the government does not have to fear being punished for not meeting its targets it is clear that announcing these targets is beneficial to them, regardless of if they intend to pursue them or not.

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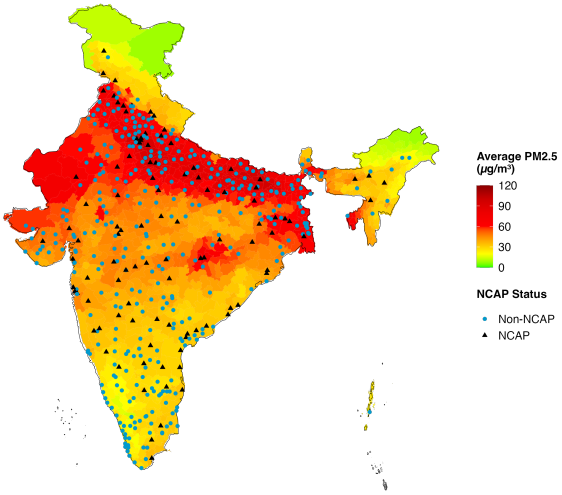
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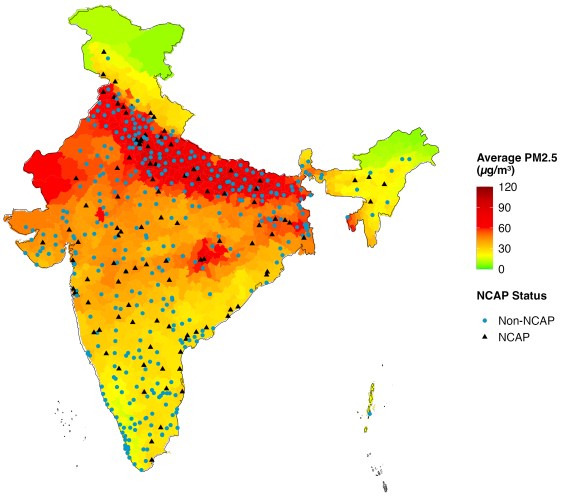
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Figure 1: Map of air pollution and NCAP cities

(a) 2018

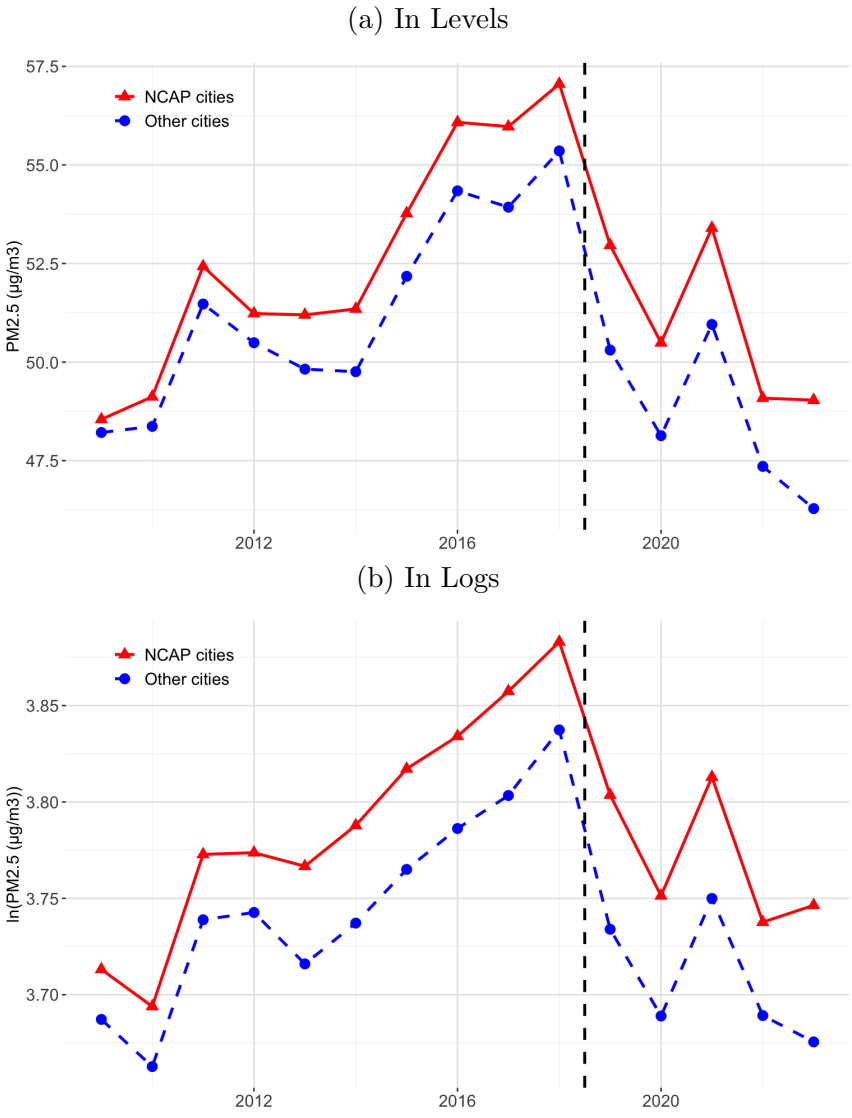


(b) 2022



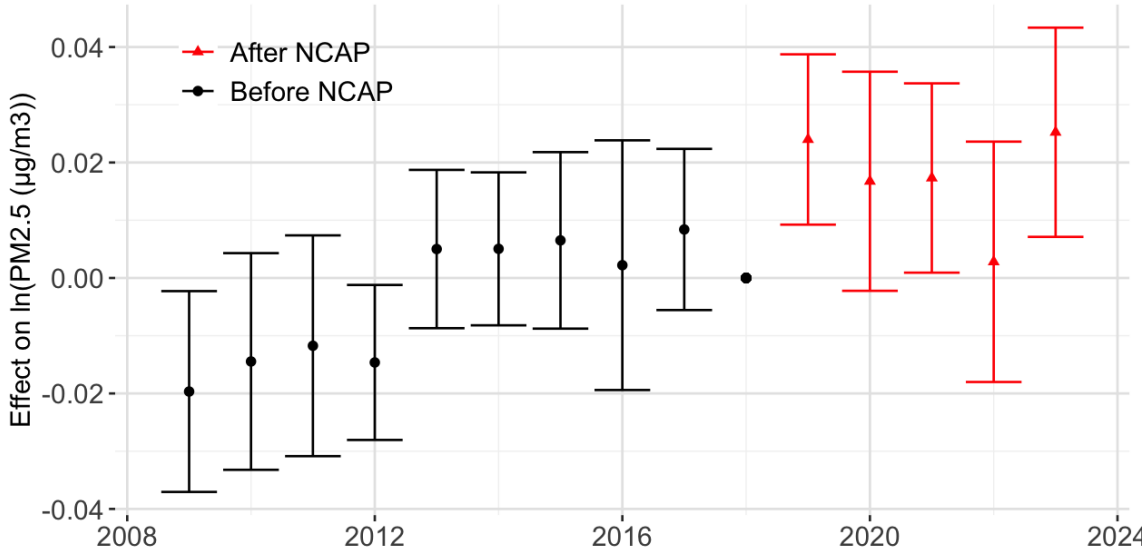
Note: The figure presents district-level $PM_{2.5}$ concentration in India in 2018 and 2022. First, we retrieved annual data on $PM_{2.5}$ concentration from van Donkelaar et al. (2021) for 2018 and 2022. Then, we calculated average $PM_{2.5}$ concentrations at the district-level using a district-level map of India. Finally, we overlaid indicators for NCAP and other urban agglomerations on the $PM_{2.5}$ concentration maps. See discussion in Section 2.1.

Figure 2: Parallel Trends for Cities With and Without NCAP



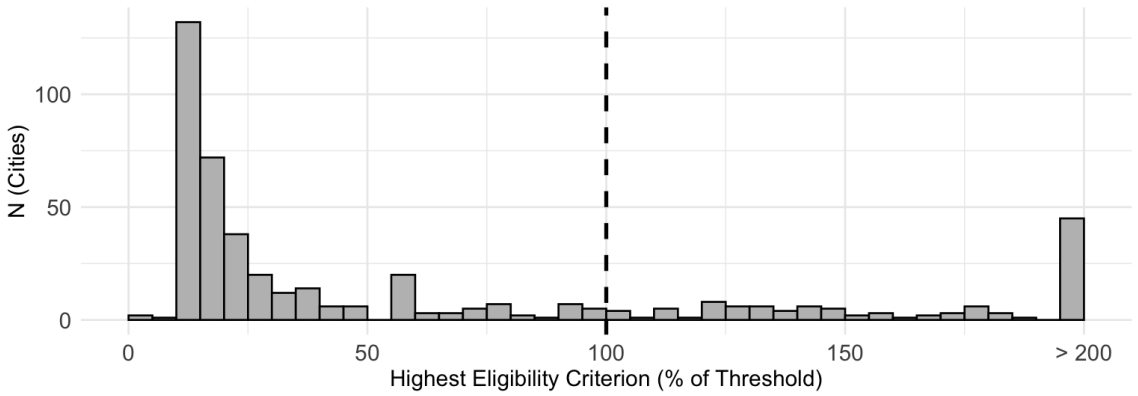
Notes: This figure shows annual air pollution averages in cities with and without NCAP from 2009 until 2023. The vertical dashed line represents the start of NCAP. Sub-Figure (a) presents data in levels while Sub-Figure (b) presents data as the average of the natural logarithm of each observation. See discussion in 4.1.

Figure 3: Effects of NCAP Over Time



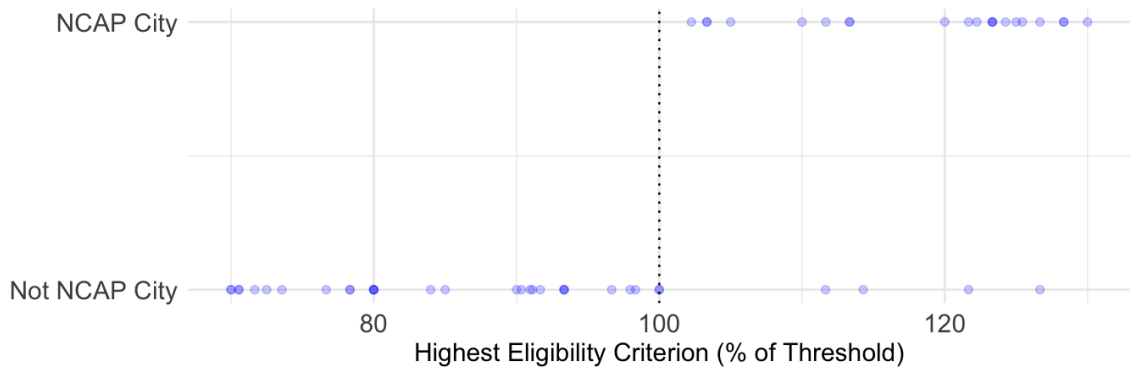
Notes: This figure displays the coefficients from the regression described in Equation 2. 95% confidence intervals are constructed using standard errors clustered at the city level. See discussion in Section 4.2. See Table 2 for overall difference-in-differences estimate.

Figure 4: Histogram of NCAP Eligibility Criteria



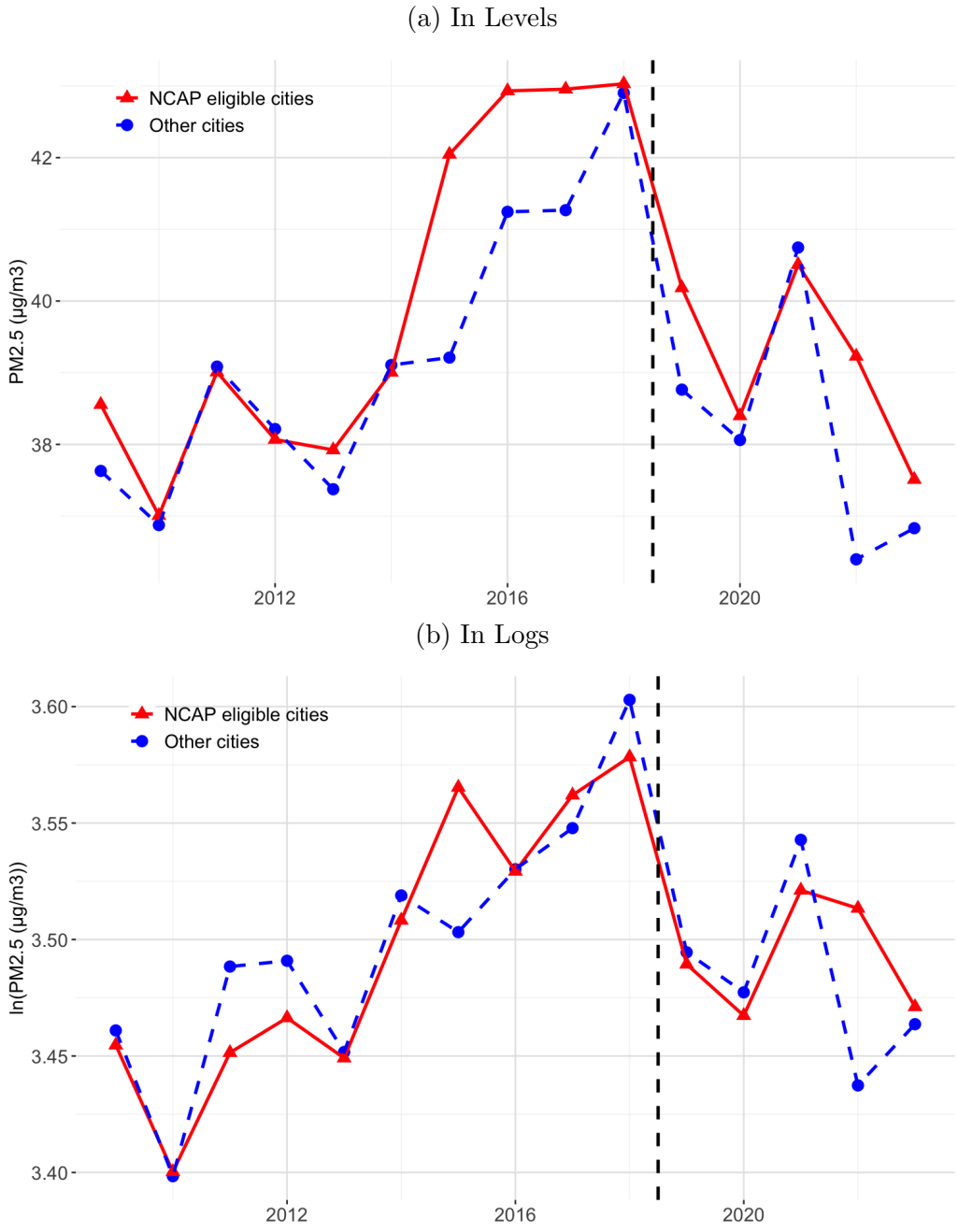
Notes: This figure shows the density of cities above and below the cutoff for inclusion into NCAP. The x-axis is the highest of the three eligibility criteria as a percentage of the NCAP threshold. See discussion in Section 3.2.2.

Figure 5: Inclusion into NCAP: Sample ±30% around Eligibility Cut-Off



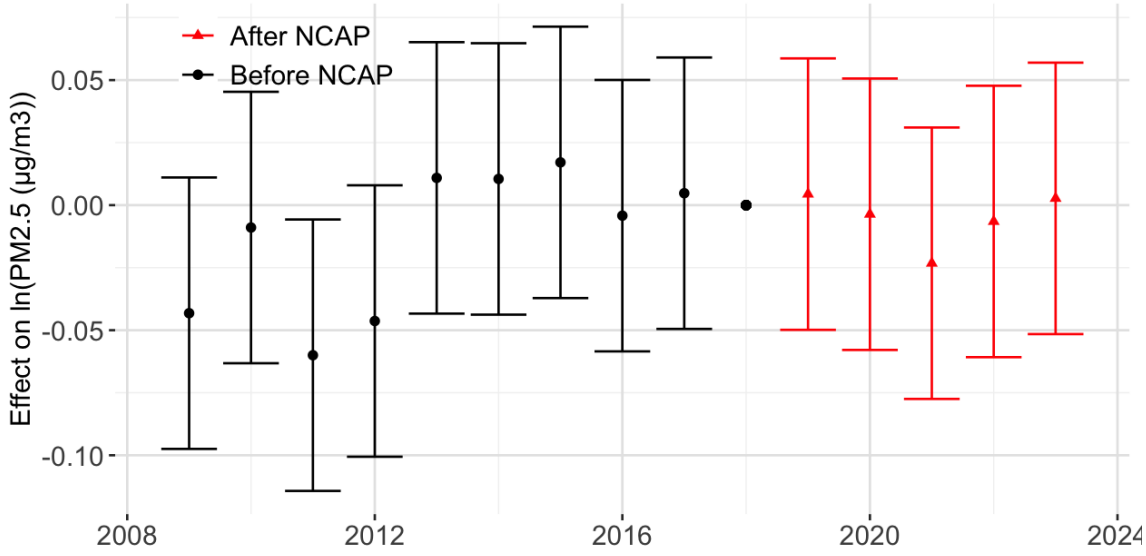
Notes: This figure shows the relationship between the NCAP eligibility criteria and inclusion into NCAP, for the 54 cities in the range between 70% to 130% of the eligibility cut-off. The x-axis is the highest of the three eligibility criteria as a percentage of the NCAP threshold. The y-axis is an indicator of whether the city was included in NCAP or not. Appendix Figure A.6 provides the same visualization for the complete sample of cities. See discussion in Section 3.2.2.

Figure 6: Parallel Trends for Cities +-30% of Eligibility Cutoff



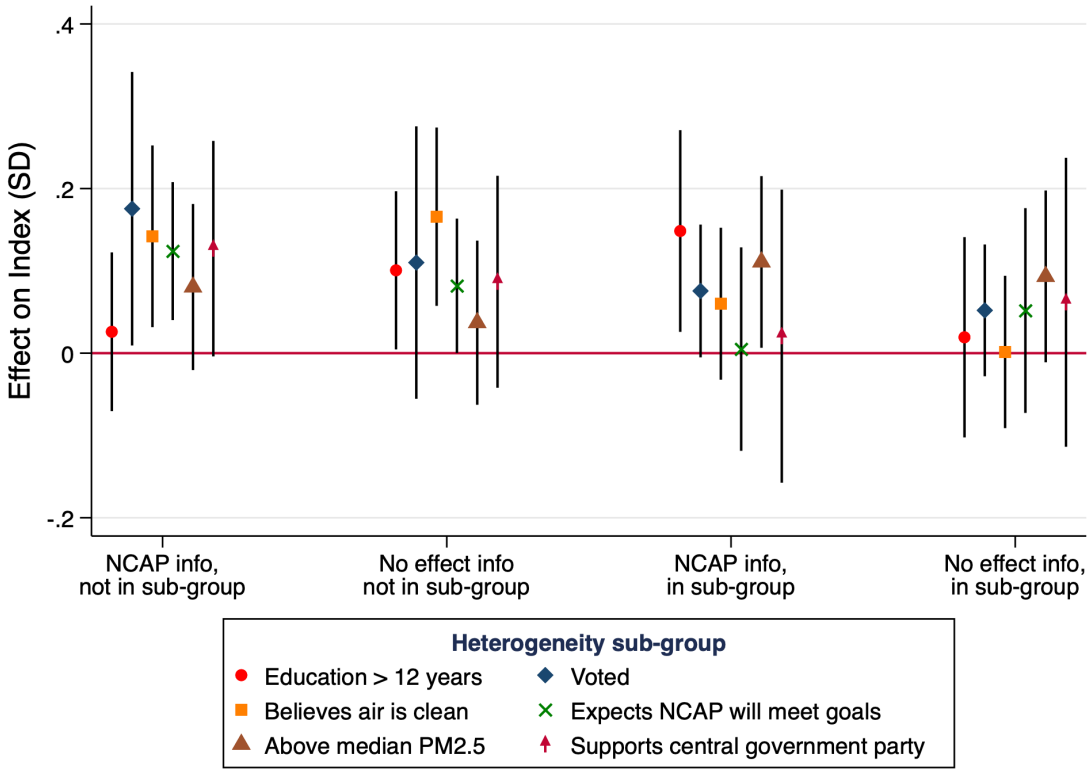
Notes: This figure shows annual air pollution averages in cities with and without NCAP, for cities within 30% of the NCAP eligibility criteria. The vertical dashed line represents the start of NCAP. Sub-Figure (a) presents data in levels while Sub-Figure (b) presents data as the average of the natural logarithm of each observation. See discussion in Section 4.2.

Figure 7: Effects of NCAP Over Time: Cities ±30% around Eligibility Cut-Off



Notes: This figure displays the coefficients from the regression described in Equation 2. The sample is limited to the 54 cities with an eligibility score between 70% and 130%. 95% confidence intervals are constructed using standard errors clustered at the city level. See discussion in Section 4.2. See Table 3 for the overall difference-in-difference estimate using the restricted sample.

Figure 8: Heterogeneity in Survey Experiment Effects: Effect on Satisfaction



Notes: This figure presents the estimated coefficients from six regression specifications, each showing the effects of the two information interventions (i.e. informing respondents about NCAP (T1) and informing them that NCAP had no effect on pollution (T2)) on the index of respondents' opinion on the central government's air pollution policy. The first two clusters of coefficients from the left represent the estimated effects for participants who are not in the heterogeneity sub-group, while the latter two clusters on the right reflect the effects for those who are in the heterogeneity sub-group being considered. Coefficients are expressed in terms of changes in standard deviations from the control group mean, with 95% confidence intervals. Appendix Table A.16 shows the results in the format of a regression table. See discussion in Section 5.4.

Table 1: Summary Statistics: NCAP and Other Cities

Variable	NCAP Status		
	NCAP	Other	Difference
	Mean (S.D.)	Mean (S.D.)	Coef. (S.E.)
Eligiblity score	242.981 (280.675)	32.629 (36.280)	210.352*** (15.098)
NCAP Eligibility	0.913 (0.283)	0.052 (0.223)	0.861*** (0.026)
Population (100k)	16.510 (29.974)	2.429 (2.588)	14.081*** (1.589)
Population density (per sq. km)	7,784.161 (4,698.222)	6,657.722 (4,588.684)	1,126.439* (548.869)
Literacy rate	0.751 (0.053)	0.737 (0.072)	0.014 (0.008)
Manufacturing labor share	0.239 (0.120)	0.214 (0.115)	0.025 (0.013)
Service labor share	0.756 (0.119)	0.779 (0.115)	-0.023 (0.013)
Scheduled Caste	0.129 (0.052)	0.126 (0.066)	0.003 (0.007)
Scheduled Tribe	0.027 (0.049)	0.028 (0.071)	-0.001 (0.007)
Observations	104	364	468

Notes: This table shows summary statistics for all 466 cities by their NCAP status. Data on the eligibility score is calculated as is described in Section B.5.3. Data on manufacturing and labor share are retrieved from the Economic Census of India (Central Statistics Organisation and Programme Implementation, 2013). Data on population, population density, literacy rates, Scheduled Caste population share, and Scheduled Tribe population share are from the Indian Population Census 2011 Abstract (Office of the Registrar General and Census Commissioner of India, 2011). See discussion in Section 3.2.2.

Table 2: Main result: No effect of NCAP on $PM_{2.5}$

	PM2.5		ln(PM2.5)	
	(1)	(2)	(3)	(4)
NCAP×post	1.106**	0.005	0.021***	0.002
	(0.496)	(0.683)	(0.007)	(0.007)
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
Non-NCAP 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. 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. See Figure 3 for the dynamic difference-in-differences estimates.

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
Non-NCAP 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. See Equation 1 for regression equation. *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. 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: Survey experiment results: Awareness of NCAP improves satisfaction with government policies, even among those informed of policy's failure to reduce air pollution

	Govt Actions	Govt Dedication	Satisfaction	Index
	(1)	(2)	(3)	(4)
NCAP info	0.057	0.117***	0.077**	0.098***
	(0.037)	(0.037)	(0.038)	(0.037)
No effect info	0.063*	0.093**	0.016	0.067*
	(0.037)	(0.037)	(0.038)	(0.037)
State FEs	Yes	Yes	Yes	Yes
Observations	4061	4061	4061	4061
P-value: Equal Effects	.878	.523	.102	.398

Notes: The table shows results from a survey experiment in 16 NCAP cities. Interviews were conducted over the phone. Larger numbers signify more action, more dedication, and more satisfaction. Outcome variables have been standardized based on the mean and standard deviation of responses among respondents in the control group, who received no information about NCAP. "Govt Actions" refers to responses to the question: "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?" "Govt Dedication" refers to responses to the question: "Now I want you to think about the financial and political costs the government is willing to pay to achieve the objective of reducing air pollution. 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?" See discussion in Section 5.3.

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 Ministry of Environment and Forests and Climate Change (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 PM10 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 2026. 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 in 2021-22

In 2021-22, the performance based funding was determined by the preparation of the city action plan based on CPCB guidelines and successful execution of air pollution monitoring, source apportionment studies, and progress on action plan items. [16]

A.1.2 Release of funds in 2022-23 onwards

From 2022-23, cities would be assigned annual PM10 reduction targets, and would be evaluated solely based on improvements in air quality over the period of 1st April to 31st March (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

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

funding allocated to them. It is possible that some cities may achieve PM10 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.2 Ranking of cities under *Swachh Vayu Survekshan*

In 20The MOEFCC launched a new initiative to rank cities based on air quality and their implementation of their action plans. The CPCB split cities into three categories based on 2011 Census population, and provides holistic assessment criteria for each category. The top three ranking cities in each category will be rewarded with cash prizes, a trophy, and will be designated a "National Clean Air City" by the MOEFCC. The central government has allocated INR 210 million in rewards from 2022-23 to 2025-26 (Central Pollution Control Board, 2022b).

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 migrograms 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 B.3. We validate the satellite-derived data against ground-based measurements in Appendix D.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 [17].

[17] 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

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 Central Pollution Control Board's website.[18] 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.

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

First, we downloaded the station data available from the CPCB CAAQMS data repository.[19] 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)*.[20]

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 Ministry of Environment, Forest & Climate Change published a report on NCAP in 2019 (Ministry of Environment, Forest and Climate Change, 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

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

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

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 PM10, SO2, and NO2, based on data

from the National Air Quality Monitoring Programme from 2011 to 2015. The annual standards set are 60ug/m3 for PM10, 50ug/m3 for SO2, and 40ug/m3 for NO2[21]. 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[22]. 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.[23] 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.

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

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 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 112 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.

C Additional Information About Survey Experiment

C.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 number 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.14 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 6.7 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.

C.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.

C.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.

D Additional Empirical Analyses

D.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 Central Pollution Control Board.[24]

Figure A.1 shows the correlation between month-shrid level satellite and station $PM_{2.5}$ measurements, subsetting to station observations in 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 Fig A.2, 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 Fig A.3 we plot the same correlation as Fig A.1 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.

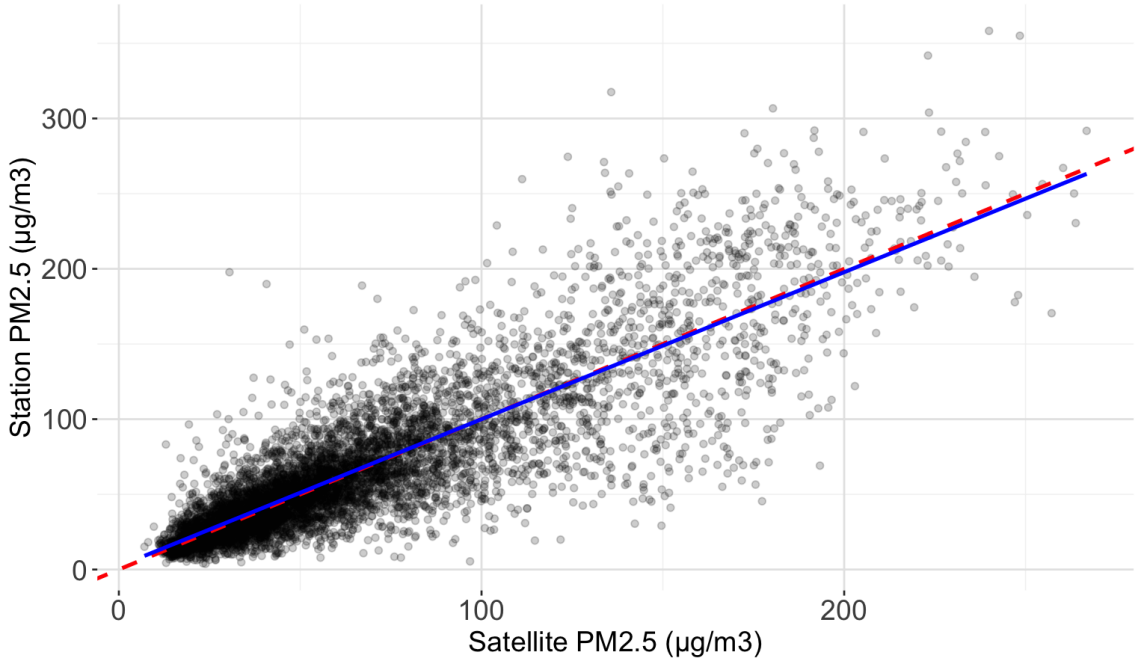
[24]The spreadsheet with locations was provided to us via email in October 2023.

D.2 Validation of the Station Derived $PM_{2.5}$ Data

Manipulation of air pollution data or "gaming" of official targets has been documented in several settings (e.g. Ghanem and Zhang, 2014; Zou, 2021). Therefore, we test the air monitoring station data for patterns of manipulation. One of the simplest ways of manipulating air pollution data is to turn off the monitoring station or refuse to make the data public on days when air pollution is especially high. Figure A.4 shows the correlation between the average satellite $PM_{2.5}$ measurement in a month, and the percentage of valid observations recorded and made public from the ground station in the same location in that month. We find no evidence of manipulation – monitoring stations do not appear to record fewer measurements when air pollution is higher.

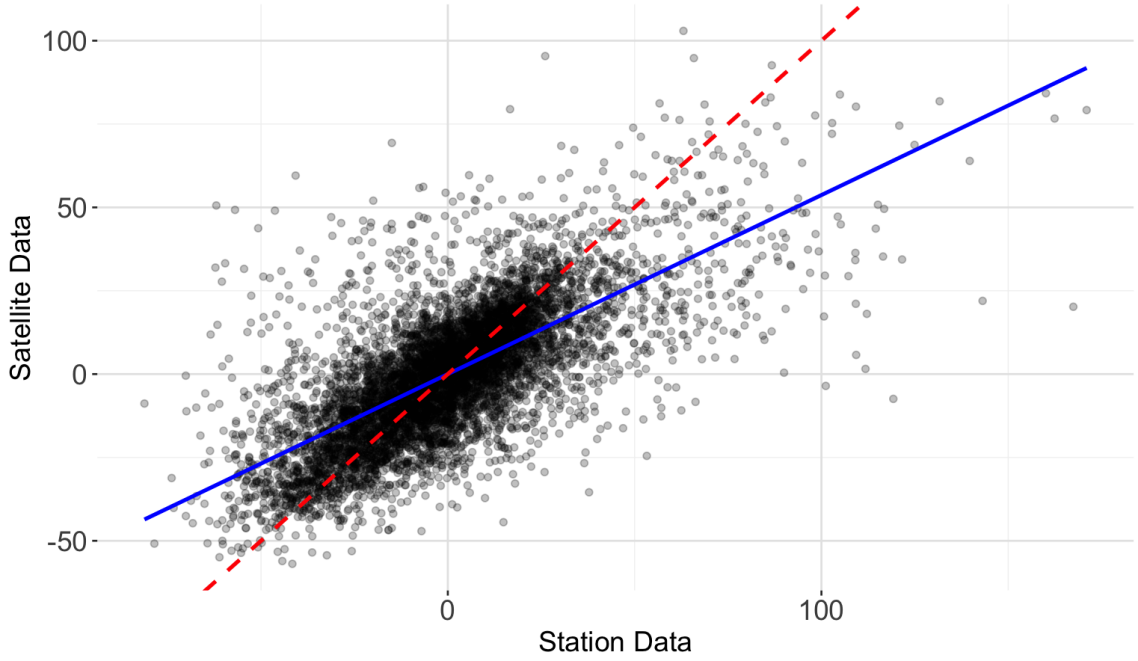
E Additional Tables and Figures

Figure A.1: Correlation between satellite and monitoring station $PM_{2.5}$ measurements



Notes: This figure shows the correlation between estimates of $PM_{2.5}$ air pollution derived from satellite data and ground station measures of $PM_{2.5}$. Each observation is a month by measuring station. Each measuring station is matched with the satellite derived measurement that is geographically closest to the measuring station. The red dashed line represents the 45 degree line, while the blue solid line represents the actual relationship fitted using OLS. Only measuring station months with measurements for at least 90% of the days are included. The number of observations are 7,224. See discussion in Appendix Section D.1.

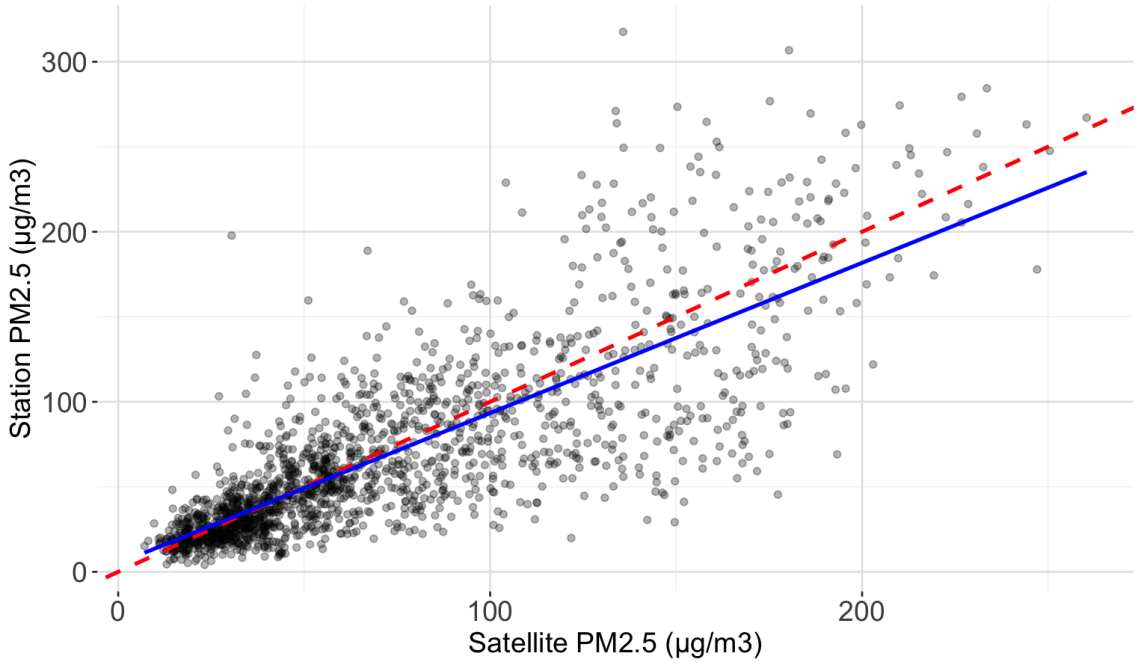
Figure A.2: Correlation between residualized satellite and monitoring station $PM_{2.5}$ measurements



Notes: This figure shows the correlation between the satellite-derived data and the ground monitoring station data after residualizing the variables by parsing out both time (month-year) and city fixed effects. Each observation is a month by measuring station. Each measuring station is matched with the satellite derived measurement that is geographically closest to the measuring station. The red dashed line represents the 45 degree line, while the blue solid line represents the actual relationship fitted using OLS. Only measuring station months with measurements for at least 90% of the days are included. The number of observations are 7,224. See discussion in Appendix Section D.1.

Figure A.3: Correlation between satellite and monitoring station $PM_{2.5}$ measurements, excluding stations used for calibration of satellite data

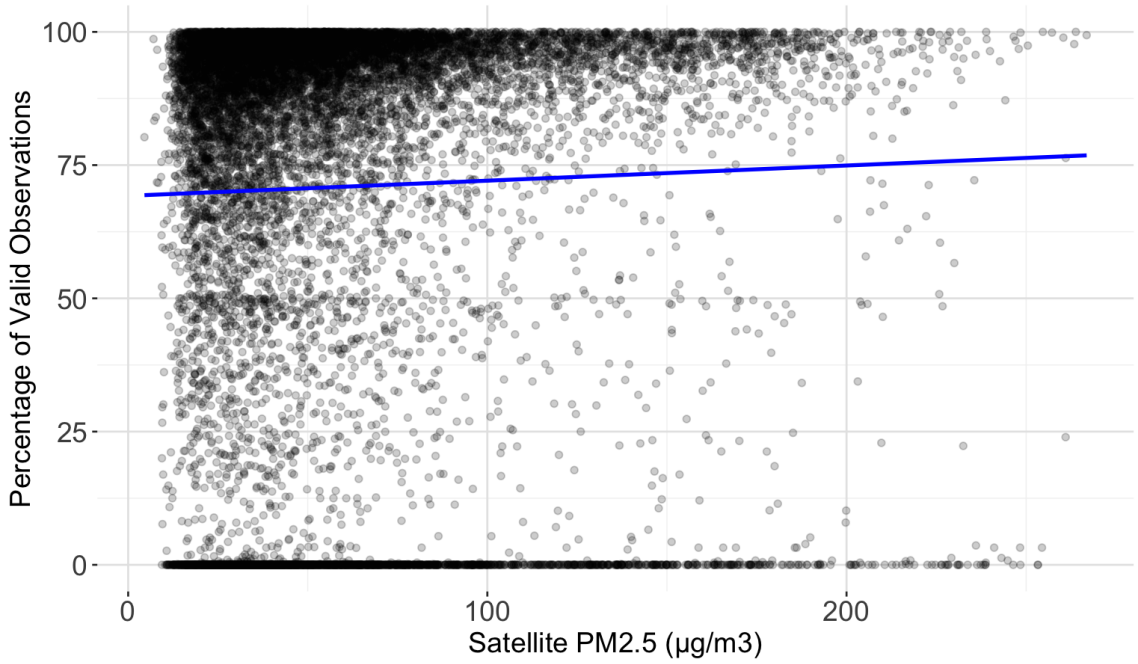
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Notes: This figure shows the correlation between estimates of $PM_{2.5}$ air pollution derived from satellite data and ground station measures of $PM_{2.5}$, excluding data from stations that were used in the calibration of the satellite derived data. Each observation is a month by measuring station. Each measuring station is matched with the satellite derived measurement that is geographically closest to the measuring station. The red dashed line represents the 45 degree line, while the blue solid line represents the actual relationship fitted using OLS. 206 out of the 517 stations were used for calibration. The number of observation included in this figure is 1,753. Compared to Appendix Figure A.1, the drop in the number of observations is larger than the drop in the number of stations because the sites used for the calibration had been in use for a longer time. See discussion in Appendix Section D.1.

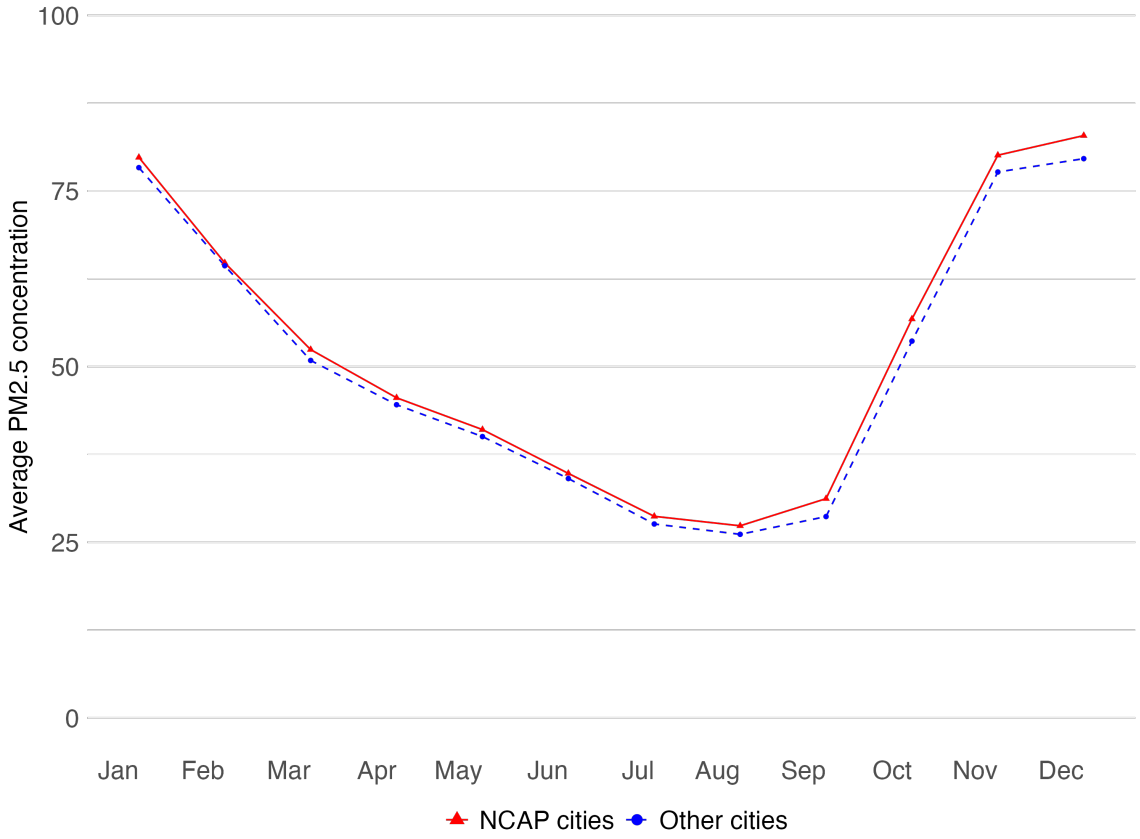
Figure A.4: Relationship between satellite $PM_{2.5}$ and percentage of available ground station measurements

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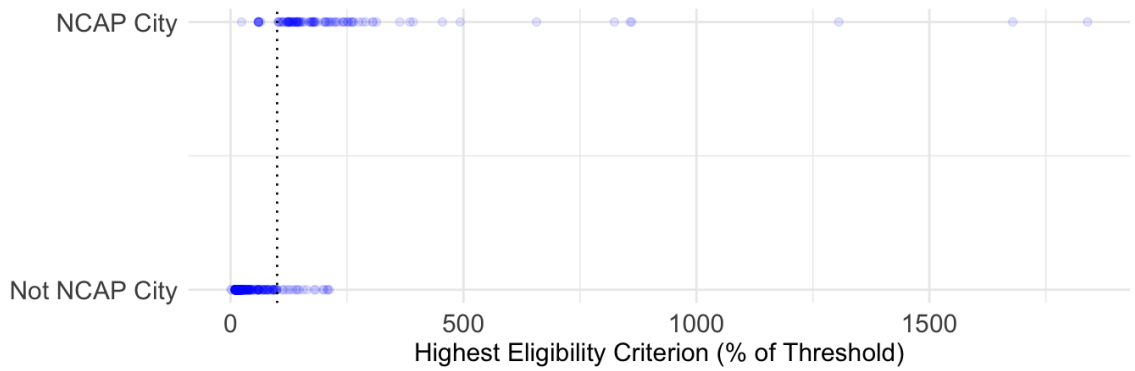
Notes: This figure shows the correlation between the satellite derived air pollution data and the share of a month's observations that are reported in the official statistics. Stations with no data for a whole month are coded as zero. See discussion in Appendix Section D.2.

Figure A.5: Seasonality of air pollution in India



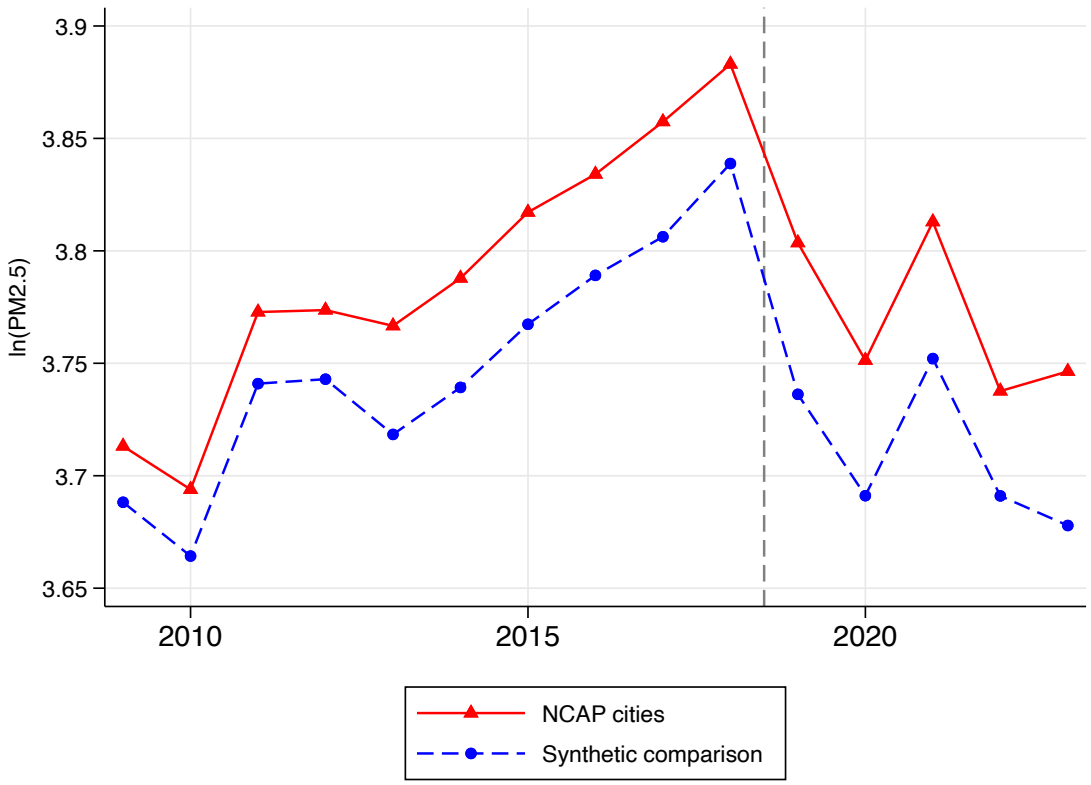
Note: This figure shows the seasonality of air pollution in India, as measured by $PM_{2.5}$ concentration by month from 2009 to 2023 for both NCAP cities and other cities. The vertical axis represents average $PM_{2.5}$ concentration in $\mu g/m^3$. Data from van Donkelaar et al. (2021). See discussion in Section 2.1.

Figure A.6: Eligibility and inclusion into NCAP



Notes: This figure shows the relationship between the eligibility criteria that a city scored the highest in and their inclusion into NCAP, for all 468 cities. The x-axis is the highest eligibility criterion as a percentage of the NCAP threshold. The y-axis is an indicator of whether the city was included in NCAP or not. Figure 5 provides the same visualization for the cities ±30% around eligibility cut-off. See discussion in Section 3.2.2.

Figure A.7: Parallel trends between NCAP and other cities in synthetic differences-in-differences sample



Notes: This figure shows parallel trends between the NCAP cities and the synthetic differences-in-differences sample of cities that are not part of NCAP (Arkhangelsky et al., 2021). This technique constructs a weighted average of cities without NCAP to create a "synthetic" comparison group. See discussion in Section 4.3.

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: Summary statistics: Eligible and ineligible cities near NCAP eligibility cutoff

Variable	NCAP Eligibility		
	Eligible	**Ineligible**	**Difference**
	Mean (S.D.)	Mean (S.D.)	Coef. (S.E.)
Eligiblity score	116.980 (9.716)	83.267 (9.551)	-33.712*** (2.622)
NCAP Status	0.778 (0.424)	0.000 (0.000)	-0.778*** (0.082)
Population (100k)	5.858 (3.701)	4.314 (3.130)	-1.544 (0.943)
Population density (per sq. km)	6,160.566 (4,003.479)	7,484.125 (6,216.722)	1,323.559 (1,541.815)
Literacy rate	0.762 (0.050)	0.762 (0.065)	0.000 (0.016)
Manufacturing labor share	0.229 (0.119)	0.196 (0.093)	-0.033 (0.029)
Service labor share	0.759 (0.115)	0.792 (0.093)	0.032 (0.029)
Scheduled Caste	0.124 (0.047)	0.115 (0.072)	-0.010 (0.017)
Scheduled Tribe	0.024 (0.030)	0.082 (0.217)	0.058 (0.042)
Observations	27	27	54

Notes: This table shows summary statistics for cities with NCAP eligibility scores between 70% and 130% of the eligibility threshold by their NCAP eligibility. Data on the eligibility score is calculated as is described in Section B.5.3. Data on manufacturing and labor share are retrieved from the Economic Census of India (Central Statistics Organisation and Programme Implementation, 2013). Data on population, population density, literacy rates, Scheduled Caste population share, and Scheduled Tribe population share are from the Indian Population Census 2011 Abstract (Office of the Registrar General and Census Commissioner of India, 2011). See discussion in Section 3.2.2.

Table A.3: Main results robust to expanding dataset to 2004

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	1.383***	0.142	0.027***	0.001
	(0.401)	(0.794)	(0.007)	(0.007)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	112,320	112,320	112,320	112,320
Cities	468	468	468	468
Other city mean	49	49	4	4

Notes: This table shows the robustness of our main results to expanding our pre-period to start from 2004, instead of 2009. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) include city and month-year fixed effects, while Columns (2) and (4) also include city-specific linear time trends. Standard errors are clustered at the city level. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.4: Main results robust to restricting the dataset to 2014

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	0.655	0.600	0.013**	0.018**
	(0.539)	(0.684)	(0.006)	(0.009)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	56,160	56,160	56,160	56,160
Cities	468	468	468	468
Other city mean	51	51	4	4

Notes: This table shows the robustness of our main results to restricting our pre-period to start from 2014, instead of 2009. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) include city and month-year fixed effects, while Columns (2) and (4) also include city-specific linear time trends. Standard errors are clustered at the city level. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.5: Main results robust to alternative clustering of standard errors

	$PM_{2.5}$			$\ln(PM_{2.5})$		
	(1)	(2)	(3)	(4)	(5)	(6)
NCAP×post	1.106***	1.106**	1.106	0.021***	0.021***	0.021***
	(0.305)	(0.410)	(.)	(0.004)	(0.006)	(0.007)
Cluster level	None	State	City & time	None	State	City & time
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,240	84,240	84,240	84,240	84,240	84,240
Number of Clusters	-	31	462 & 168	-	31	462 & 168
Other city mean	50	50	50	4	4	4

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

Table A.6: Main results robust to inclusion of state-year and quadratic time-city trends

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	0.270	0.032	0.006	0.003
	(0.355)	(0.792)	(0.005)	(0.010)
City FE	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes
State x month-year FE	Yes	No	Yes	No
Linear time-city trend	No	Yes	No	Yes
Quadratic time-city trend	No	Yes	No	Yes
Observations	82,260	84,240	82,260	84,240
Number of Clusters	457	468	457	468
Other city mean	50	50	4	4

Notes: This table shows the robustness of our main results to the inclusion of state-year and quadratic time-city trends. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) includes city, time, and state-year fixed effects. Columns (2) and (4) also include quadratic time-city trends. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.7: Robustness of main results to exclusion of non-NCAP cities that are within a 30 km buffer of an NCAP city

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	0.860*	-0.480	0.018***	-0.001
	(0.501)	(0.689)	(0.007)	(0.008)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	71,280	71,280	71,280	71,280
Cities	396	396	396	396
Other city mean	49	49	4	4

Notes: This table presents a robustness check where we exclude non-NCAP cities that are within a 30km buffer of an NCAP city. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) includes city, time, and state-year fixed effects. Columns (2) and (4) also include quadratic time-city trends. Satellite estimates of $PM_{2.5}$ from van Donkelaar et al. (2021). * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.8: Main results robust to exclusion of cities in Supreme Court Action Plan

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	1.179**	0.125	0.021***	0.004
	(0.492)	(0.676)	(0.007)	(0.007)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	83,880	83,880	83,880	83,880
Cities	466	466	466	466
Other city mean	50	50	4	4

Notes: This table shows the robustness of our main results to the exclusion of 17 cities that were included in the Supreme Court's Action Plan. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) include city and month-year fixed effects. Columns (2) and (4) include city, month-year, and city-year fixed effects. See discussion in Section 4.3.

Table A.9: Main results robust to use of station $PM_{2.5}$ and PM_{10} data

	$PM_{2.5}$	$ln(PM_{2.5})$	PM_{10}	$ln(PM_{10})$
	(1)	(2)	(3)	(4)
NCAP×post	2.422	-0.012	14.135	0.067
	(6.573)	(0.063)	(9.194)	(0.051)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
Observations	5,373	5,373	4,887	4,887
Cities	63	63	62	62
Other city mean	59.76	3.87	129.09	4.67

Notes: This table shows the robustness of our main results to the use of station $PM_{2.5}$ PM_{10} data. Column (1) has $PM_{2.5}$ levels as the dependent variable. Column (2) has the log of $PM_{2.5}$ levels as the dependent variable. Column (3) has PM_{10} levels as the dependent variable. Column (4) has the log of PM_{10} levels as the dependent variable. All columns include city and month-year fixed effects. Standard errors are clustered at the city level. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.10: Effect of NCAP on ozone and sulfur dioxide

	O_3	$\ln(O_3)$	SO_2	$\ln(SO_2)$
	(1)	(2)	(3)	(4)
NCAP×post	-0.818	0.015	-2.064	-0.008
	(3.063)	(0.090)	(2.195)	(0.123)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
Observations	5,110	5,110	5,313	5,313
Cities	60	60	63	63
Other city mean	34.28	3.45	14.32	2.51

Notes: This table shows the robustness of the station data results with the pre-period starting from 2010 up to October 2024. Column (1) has Ozone (O_3) levels as the dependent variable, and column (2) has the log of O_3 levels as the dependent variable. Column (3) has Sulfur Dioxide (SO_2) levels as the dependent variable, and column (4) has the log of SO_2 levels as the dependent variable. All columns include city and month-year fixed effects. Standard errors are clustered at the city level. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.11: Effect of NCAP on carbon monoxide and nitrogen dioxide

	CO	ln(CO)	NO_2	ln(NO_2)
	(1)	(2)	(3)	(4)
NCAP×post	-0.011	-0.011	-5.691	-0.165
	(0.097)	(0.041)	(4.471)	(0.132)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
Observations	5,248	5,248	5,322	5,322
Cities	62	62	63	63
Other city mean	0.85	0.58	26.45	3.12

Notes: This table shows the robustness of the station data results with the pre-period starting from 2010 up to October 2024. Column (1) has Carbon Monoxide (CO) levels as the dependent variable, and column (2) has the log of CO levels as the dependent variable. Column (3) has Nitrogen Dioxide (NO_2) levels as the dependent variable, and column (4) has the log of NO_2 levels as the dependent variable. All columns include city and month-year fixed effects. Standard errors are clustered at the city level. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.3.

Table A.12: Main results weighted by the population of each city

	$PM_{2.5}$		$\ln(PM_{2.5})$	
	(1)	(2)	(3)	(4)
NCAP×post	-0.269	-2.591*	0.003	-0.022
	(0.974)	(1.457)	(0.011)	(0.015)
City FEs	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes
City-year trends	No	Yes	No	Yes
Observations	84,060	84,060	84,060	84,060
Cities	467	467	467	467
Non-NCAP city mean	47.00	47.00	3.65	3.65

Notes: This table shows the robustness of our main results to the use of population weights. Columns (1) and (2) have $PM_{2.5}$ levels as the dependent variable, and columns (3) and (4) have the log of $PM_{2.5}$ levels as the dependent variable. Columns (1) and (3) include city and month-year fixed effects, while Columns (2) and (4) also include city-specific linear time trends. Standard errors are clustered at the city 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.13: Effect of NCAP on the number of active ground measuring stations

	$PM_{2.5}$	PM_{10}	SO_2	Ozone	CO	NO_2
	(1)	(2)	(3)	(4)	(5)	(6)
NCAP×post	1.685***	1.698***	1.662***	1.717***	1.739***	1.735***
	(0.371)	(0.381)	(0.351)	(0.387)	(0.390)	(0.387)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	82,236	82,236	82,236	82,236	82,236	82,236
Cities	462	462	462	462	462	462
Other city mean	0.26	0.26	0.26	0.25	0.26	0.26

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. "Other city mean" is the average number of active measuring stations in cities that are not part of NCAP in the period from 2019 onwards. Standard errors are clustered at the city level. * p<0.10, ** p<0.05, and *** p<0.01. See discussion in Section 4.4.

Table A.14: Comparison of summary statistics between survey sample and NFHS sample

	(1) Survey	(2) NFHS
Age	36.5	40.3
Is Female	0.46	0.49
Years of schooling	11.4	4.7
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	4,061	50,800

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. The representative survey is the National Family and Health Survey (NFHS). Ownership of a car, computer, motorcycle, and refrigerator are shown as a share of the respondents. We used the weights provided in the NFHS data when calculating the means. See discussion in Section 5.1.

Table A.15: Balance of randomization in survey data

	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	0.474	0.452	0.468	-0.022	-0.006
	(0.499)	(0.498)	(0.499)	(0.019)	(0.019)
Age	36.031	36.033	36.505	0.003	0.474
	(12.753)	(12.532)	(12.789)	(0.489)	(0.490)
Years of schooling	11.355	11.382	11.420	0.027	0.064
	(3.783)	(3.850)	(3.790)	(0.156)	(0.153)
Satisfaction with water quality	0.829	0.828	0.839	-0.001	0.010
	(0.304)	(0.304)	(0.286)	(0.012)	(0.011)
Satisfaction with sewage quality	0.657	0.646	0.637	-0.011	-0.020
	(0.387)	(0.390)	(0.393)	(0.015)	(0.015)
Satisfaction with air quality	0.723	0.715	0.698	-0.007	-0.025
	(0.365)	(0.375)	(0.381)	(0.014)	(0.014)
Voted in the last election	0.794	0.824	0.826	0.030*	0.032*
	(0.405)	(0.381)	(0.379)	(0.015)	(0.015)
Heard of NCAP	0.320	0.304	0.296	-0.016	-0.024
	(0.467)	(0.460)	(0.457)	(0.018)	(0.018)
Observations	1332	1344	1385	2676	2717

Notes: This table shows summary statistics for the variables in the survey experiment measured before the information intervention. Satisfaction with water quality, sewage quality, and air quality are measured on a three-point Likert scale ranging from 0 to 1. The "Hear 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 A.16: Survey experiment results: Heterogeneity in effects of NCAP information on satisfaction with government policies

	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	0.148**	0.076*	0.060	0.005	0.111**	0.021
	(0.063)	(0.041)	(0.047)	(0.063)	(0.053)	(0.091)
No effect info × sub-group	0.019	0.052	0.001	0.052	0.093*	0.062
	(0.062)	(0.041)	(0.047)	(0.063)	(0.053)	(0.090)
NCAP info × not in sub-group	0.026	0.175**	0.142**	0.124***	0.080	0.127*
	(0.049)	(0.085)	(0.056)	(0.043)	(0.051)	(0.067)
No effect info × not in sub-group	0.101**	0.110	0.166***	0.082**	0.037	0.087
	(0.049)	(0.084)	(0.055)	(0.042)	(0.051)	(0.066)
Sub-group	-0.205***	0.178***	0.534***	0.723***	0.160**	0.508***
	(0.057)	(0.065)	(0.053)	(0.054)	(0.067)	(0.079)
Subgroup share	0.39	0.81	0.58	0.31	0.48	0.35
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,652.00	4,061.00	4,061.00	4,011.00	4,061.00	1,876.00
NCAP info:						
P-value in vs. not in sub-group	0.12	0.29	0.26	0.12	0.68	0.35
No effect info:						
P-value in vs. not in sub-group	0.30	0.54	0.02	0.69	0.44	0.82
Not in sub-group:						
P-value NCAP info vs. no effect info	0.13	0.45	0.67	0.32	0.39	0.54
In sub-group:						
P-value NCAP info vs. no effect info	0.03	0.56	0.21	0.46	0.74	0.65

Notes: The table shows heterogeneity analyses from a survey experiment in 16 NCAP cities. Interviews were conducted over the phone. The outcome variable in all regressions is satisfaction with government policies on air pollution. Larger numbers signify more satisfaction. The outcome variable has been standardized based on the mean and standard deviation of responses among respondents in the control group, who received no information about NCAP. The first column interacts treatment with the respondent's education, the second column with whether the respondent voted in the national election in 2024, the third with whether the respondent believes the air in her neighborhood is clean, and the fourth with whether the respondent believes that NCAP will have some effect. See Figure 8 for a visualization of the results. See discussion in Section 5.3.