Journal of Development Economics

Behavioral and Technological Strategies to Mitigate Effects of Air Pollution on Children: Empirical Evidence from an RCT in Delhi's Schools

--Manuscript Draft--

Manuscript Number:	DEVEC-D-24-00902R1
Article Type:	Registered Report Stage 1: Proposal
Section/Category:	Health, Education, gender, poverty
Keywords:	Environment and Development; Air Pollution; Mitigation Strategies; Human Capital
Corresponding Author:	J. Cristobal Ruiz-Tagle The University of Manchester London, London UNITED KINGDOM
First Author:	J. Cristobal Ruiz-Tagle
Order of Authors:	J. Cristobal Ruiz-Tagle
	Nikita Sangwan
	M. Marcela Jaime
	César Salazar
	Kanishka Kacker
	Pankaj Kumar
Abstract:	Air pollution is a serious problem in many regions of the developing world as it adversely affects the health, education, and human capital of the population, especially children. Mitigating strategies can potentially alleviate some of the most severe effects of high air pollution. By conducting an RCT in Delhi's KV schools, this study assesses the potential role of behavioral and technological strategies in mitigating the adverse effects of high air pollution on the health and educational outcomes of students. In particular, we evaluate the effectiveness of an educational campaign during the period of peak air pollution and air purifiers in classrooms. This work is important for building human capital in low- and middle-income countries faced with high pollution levels, which is essential for their human and economic development.
Response to Reviewers:	

Letter to the editor

Dear Professor Dean Yang, Co-Editor of Journal of Development Economics,

Thank you for the opportunity to revise and resubmit our manuscript for Registered Report Stage 1. We have considered all suggestions by referees. We have implemented some key changes in a revised version of our manuscript. Moreover, we have written a detailed response to referees (please see attached letter). In our response, we often reference specific sections and line numbers of the revised manuscript.

We have paid particular attention to issues you have flagged. Specifically:

(1) As pointed out by Ref 1, the outcome variable can be best understood as air pollution inside classrooms, rather than classroom pollution exposure. Accordingly, we have changed the language throughout the manuscript and we are responding to Ref 1's concern below.

(2) In our response to referees, we have added a section discussing cost-effectiveness. Moreover, we even expanded onto a sketch of cost-benefit analysis. This is a 'strawman' exercise – at this point – of what we would be able to write in the final version of the paper once we have our experimental results (i.e., 'Stage 2 Registered Report', if we are successful with this R&R).

(3) Contribution to existing and emerging literature and multiple treatment arms.

To make a clearly unique contribution to the literature we are bringing the Educational and Behavioral Strategies (EBS) treatment to the forefront of our experimental work. We have followed recommendations from both referees for having two treatment arms. In one treatment arm we assess the EBS treatment alone, and in the other treatment arm we assess an intervention of EBS and Purifiers treatment coupled together.

We argue that this work makes a unique contribution to the existing and emerging literature by focusing on the role of education and behavioral change on protecting children's health. Importantly, Information-based interventions are less costly than technological interventions and can be easily scaled up. Thus, assessing experimentally the effect of an educational and behavioral intervention can inform policymakers about the cost-effectiveness of this type of policy.

(4) Spillovers and sample size.

In our response to Ref 2, we have addressed many of the main issues regarding spillovers. While we cannot increase the sample size due to budgetary and administrative limitations, we discuss how we are trying to contain the spillovers in the paper and in our response to Ref 2 below.

We would like to also bring to your attention the next section in which we explain additional changes we have done to the project design and Registered Report Stage 1.

Thank you very much for considering our work for Register Report Stage 1. We are hopeful that the revised manuscript will result in a positive outcome of JDE's pre-results review.

Sincerely,

J. Cristobal Ruiz-Tagle

(On behalf of our research team)

Other changes to the Revised Registered Report Stage 1

Please note that we have made a few changes to our original Stage 1 manuscript.

First, we have changed our timeline slightly to better reflect the actual implementation of the fieldwork. We have pushed back the starting of the interventions and starting data collection at the baseline by about two to three weeks (we are facing delays getting started). However, we have managed to extend data collection into 2025. Thus, we will effectively be conducting the interventions during November, December 2024, and January 2025 – the three months of peak PM pollution in Delhi, as shown in Figure 1.

Second, we have added an additional survey wave. As a consequence, what used to be the ‘Endline’ survey (in the previous manuscript) is now labeled as a ‘Midline’ survey, scheduled for December 2024. And we have moved the ‘Endline’ survey to early February 2025. Please see the updated Timeline section.

Relatedly, we have applied for additional research funding to extend data collection, past the updated Endline, and thus continue surveying these students well into 2025. This will allow us to better examine cumulative effects and mid-to-long term effects. [The outcome of this grant application is still to be known.]

Third, we have decided to change the way we assess students' lung capacity. Instead of using spirometry, we will be using Peak Expiratory Flow (PEF) meters. The reason for this change is the user-friendliness of the PEF meters over spirometers. Whereas conducting spirometry requires highly-trained professionals and lengthy explanations to the patients/students for properly conducting the tests (plus trial and error), PEF meters are much easier to use and are recommended by doctors for personal monitoring of respiratory conditions (such as asthma). Importantly, as with spirometry PEF meters allow for readily assessment and test of lung obstruction, and there is a direct relationship between PEF test scores and spirometry test scores. It is important to note that the main difference between spirometers and PEF meters is that the former allows for measuring lung restriction in addition to lung obstruction. However, for purposes of our project and for conducting power analysis of expected effects, lung obstruction is considered a good measure of lung capacity as this is more common in children (lung restriction is more common for those suffering from lung cancer, who have undergone lung surgery or other major issues that are very rare in children).

Fourth, to expedite lung capacity testing (due to the time it takes to conduct these tests), we have decided to test only on a subsample of 10 percent of students in each class (about 5 students per class). We have re-run the power calculations and have updated the Minimum Detectable Effect (shown in Table 2). This MDE increases from 3.4 to 4.8, which is still well below the expected effect of 12.32. Thereby, we are confident to be able to observe a statistically significant effect.

Other changes to the Revised Registered Report Stage 1

Please note that we have made a few changes to our original Stage 1 manuscript.

First, we have changed our timeline slightly to better reflect the actual implementation of the fieldwork. We have pushed back the starting of the interventions and starting data collection at the baseline by about two to three weeks (we are facing delays getting started). However, we have managed to extend data collection into 2025. Thus, we will effectively be conducting the interventions during November, December 2024, and January 2025 – the three months of peak PM pollution in Delhi, as shown in Figure 1.

Second, we have added an additional survey wave. As a consequence, what used to be the ‘Endline’ survey (in the previous manuscript) is now labeled as a ‘Midline’ survey, scheduled for December 2024. And we have moved the ‘Endline’ survey to early February 2025. Please see the updated Timeline section.

Relatedly, we have applied for additional research funding to extend data collection, past the updated Endline, and thus continue surveying these students well into 2025. This will allow us to better examine cumulative effects and mid-to-long term effects. [The outcome of this grant application is still to be known.]

Third, we have decided to change the way we assess students' lung capacity. Instead of using spirometry, we will be using Peak Expiratory Flow (PEF) meters. The reason for this change is the user-friendliness of the PEF meters over spirometers. Whereas conducting spirometry requires highly-trained professionals and lengthy explanations to the patients/students for properly conducting the tests (plus trial and error), PEF meters are much easier to use and are recommended by doctors for personal monitoring of respiratory conditions (such as asthma). Importantly, as with spirometry PEF meters allow for readily assessment and test of lung obstruction, and there is a direct relationship between PEF test scores and spirometry test scores. It is important to note that the main difference between spirometers and PEF meters is that the former allows for measuring lung restriction in addition to lung obstruction. However, for purposes of our project and for conducting power analysis of expected effects, lung obstruction is considered a good measure of lung capacity as this is more common in children (lung restriction is more common for those suffering from lung cancer, who have undergone lung surgery or other major issues that are very rare in children).

Fourth, to expedite lung capacity testing (due to the time it takes to conduct these tests), we have decided to test only on a subsample of 10 percent of students in each class (about 5 students per class). We have re-run the power calculations and have updated the Minimum Detectable Effect (shown in Table 2). This MDE increases from 3.4 to 4.8, which is still well below the expected effect of 12.32. Thereby, we are confident to be able to observe a statistically significant effect.

Response to referees

A. Response to Ref #1

Thank you for your insightful comments and suggestions. Below we provide point-by-point responses to your comments and detail the corresponding revisions we have made to the earlier draft of the Registered Report Stage 1.

General comments

1. Contributions

a. **“High” and “Very High Air pollution setting”.** Our contribution could be best understood in terms of mitigation strategies and their associated outcomes in school children in terms of *both* health and educational outcomes (the China study by Yang et al., (2021) does not assess educational outcomes).

   We didn’t intend to make the distinction between a “high” (say, China) and a “very high” (say, India) air pollution setting, although we acknowledge that our writing was not clear enough here (our fault). Nonetheless, now we note, in Footnote 9, that $PM_{2.5}$ concentrations for Delhi during the period of our intervention are about twice as large as that for the China study.

b. **Claim about contribution of information intervention.** We have toned down the reach of the contributions by not referring to cost-effectiveness at this point. Nonetheless, in addition to evaluating the effectiveness of the interventions we plan on also evaluating their cost-effectiveness (we explain this in further detail below).

2. Outcomes

   a. **Exposure.** Thank you very much for your suggestion. We have now changed the language from ‘*exposure* to air pollution inside classrooms’ to simply ‘air pollution inside classrooms' regarding the Purifier treatment and its associated hypothesis.

b. **Lung capacity at baseline.** We are indeed taking baseline measures of lung capacity as we acknowledge that this variable is indeed very student-specific. Moreover, we'll be analyzing the student-specific change in lung capacity – as compared to baseline levels – for both the treatment groups and the control group.

c. **Self-Reported Health.** Unfortunately, our budget does not allow for hiring health professionals or visiting absent students at home.

   However, please note that we are planning to ask very simple questions about self-reported health, so that we expect students to understand them. Examples of these questions are "Do you experience Coughing?", if so, "when?"[we give them options of the various timelines/events]; "Have you noticed any changes in your breathing?", If so, "when?". On the other hand, for questions about respiratory symptoms that are more technical and/or harder to remember, we expect that those students who have seen a healthcare professional recently, and/or have received treatment due to some respiratory disease, will be able to identify and remember experiencing specific respiratory symptoms.

   Moreover, as with lung capacity, we will be conducting these self-reported health questions both at baseline and at midline/endline (to look at student-specific change in the answers). So, if a student correctly understands and remembers symptoms at baseline, then we will expect that he/she will also do so at midline/endline.

   Students with illnesses may not report to school. If this is due to diseases linked to air pollution, and because of the time pattern of variation of air pollution in Delhi, this should be more likely to occur at the time of the midline/endline survey (when air pollution is and has been very high over the previous weeks) than at the time of baseline survey. Moreover, this selection should be less likely among those in the treatment groups than among those in the control groups. If this happens, it is more likely that we will be missing the observations for those sicker students in the control group. Thereby, this selection would bias our results towards the null of no effect.

d. **End-of-year exam grades.** These exams are standardized for students in KV schools. However, we cannot guarantee that the grading scale will not be 'graded to a curve' and, therefore, grading may change as a result of assignment to treatment.

   If this happens, however, we may be able to identify this effect by contrasting grades in end-of-year exams to results of cognitive tests in midline/endline surveys (whereby results of cognitive tests are not 'graded to a curve'). Unfortunately, we are afraid that we cannot prevent teachers from 'grading to a curve'.

e. **Assessment of adoption of personal mitigation strategies.** When laying out Hypothesis 1.2. we have added Footnote 20 explaining these behavioral strategies and a reference to the section (section 3.d.i.) where we further list the specific strategies being assessed.

> Footnote 20 reads: *"We are planning on teaching students ten personal exposure mitigation strategies. These include: avoidance behaviors of ambient and indoor air pollution, defensive behaviors for ambient and indoor air pollution, behavioral change to minimize emissions of indoor air pollution, and heightened awareness of own respiratory health. Section 3.d.i. below explains these personal behavioral strategies in further detail."*

   In addition, for the section that explains the power analysis for this outcome, we have added footnotes 26 and 27 that explain, respectively, how this outcome has been assessed in the existing literature (Araban et al., 2017) and how we are planning to assess it. In a nutshell, we will follow a similar index, as in Araban et al. (2017), based on rating answers to questions about adoption of the behavioral strategies listed in section 3.d.i.

3. A**ir purifiers alone as an intervention.** Thank you very much for your suggestion. Following this advice, and that of the other reviewer, we have revised the treatment arms. Now, there will be two treatment arms, one with EBS alone and another one with both EBS and Purifiers. This is now explained in Section 3.d (lines 315 to 322).

4. **Air purifiers compliance.** Thank you for pointing this out. Air purifiers will be running continuously throughout the period of our intervention.

Additionally,our research team will pay weekly visits to the schools over the weekends to ensure the purifiers and sensors are working correctly. And we have requested the point-of-contact person at each school to immediately inform us if they notice any functionality issues.

5. **Air Pollution Monitors.** Yes, the PM pollution monitors will be deployed in all classrooms (both treatments and control), including those assigned to the EBS-only treatment.

6. **Spillovers (a & b).** Thank you for pointing this out. We have now corrected this and relabeled that discussion in a section titled ‘possible indirect effects’ (Section 3.d.ii, lines 409 to 444), and (as suggested) we are still planning to collect the necessary data to analyze these effects.

7. **Timeline.** We are now planning for the air purifiers to continue running into January and February (both months of very high air pollution, as shown in Figure 1). Moreover, we have recently submitted a bid for an additional research grant to obtain the necessary funding to extend data collection from May to September 2025. We are now waiting for the outcome of this grant proposal.

   On the other hand, after the end of the Indian academic year, the purifiers will be collected and made available for future research projects.

8. **Cost Effectiveness.** We are indeed collecting information on the costs of the interventions. The main pecuniary costs are those of the air purifiers, while the main non-pecuniary costs are those of the small curriculum change to allow for the EBS treatment.

   In addition, at the end of this response, we present a discussion that outlines how we will conduct a ‘back of the envelope’ cost-benefit analysis and cost-effectiveness analysis.

Specific comments – These are all suggestive.

1. **Opening in the Introduction section**. Thank you for your suggestion. The objective of this work is to focus on both health and educational effects of mitigating air pollution for

school children. We believe that the effects of air pollution on health, through increased morbidity, could impact school absenteeism and broader educational outcomes. Nonetheless, this may not be the only channel, as you mentioned. Air pollution may also impact students' cognition (even if these students do not miss schooldays) in a way that is reflected in lower scores in cognitive tests and lower grades in exams. Therefore, we would like to keep the focus on health effects at the beginning of the introduction.

2. **Data in Background section.** Thank you for pointing this out. We have now updated it to the latest available data, from 2023.

3. **Change in language for air pollution instead of air quality.** Thank you for pointing this out. We have changed this as per your suggestion.

4. **Claim about reach of interventions.** Thank you for your comment. In the revised intervention design, as discussed in response to your comment 3, we now have a "Behavioral Strategies"-only treatment arm. This allows us to test the cost-effectiveness of this potentially scalable intervention. Kindly refer to the discussion below for a more detailed discussion of cost-effectiveness and cost-benefit analysis.

5. **Wording of 'tangible benefits'.** Thank you for pointing this out. We have changed this, as suggested.

Cost-Effectiveness and Cost-Benefit Analysis

The benefits of reduced air pollution in schools can additionally be assessed in terms of potential improvements in educational and learning outcomes. To that end here we also sketch a cost-effectiveness analysis of improving students' performance in cognitive tests, and contrast this with alternative policy interventions. The Purifiers treatment (the most expensive treatment) costs about $ 328 annually, and the expected improvements in a cognitive assessment test is .365 standard deviations (SD), averaging for boys and girls. Then, for an average classroom size of 50 students, the annual costs of 0.1 SD improvement in cognitive tests is $1.80 per student. This figure contrasts with Banerjee et al. (2007), who evaluate a remedial education program in India that costs $ 2.25 (that is, $ 3.50 in 2024 dollars) per 0.1 SD of a cognitive assessment test. This figure can also be contrasted with Kremer et al. (2004), who calculate costs per standard deviation of cognitive test for a range of educational programs in India. Kremer et al. (2004) find that the most cost-effective program costs between $ 1.77 and $ 3.53 per 0.1 SD (that is, between $ 3 and $ 6 in 2024 dollars). Thus, demonstrating that this intervention can also be cost-effective for improving outcomes in cognitive tests.

Additionally, in this section we sketch how we can conduct a back-of-the-envelope calculation for Cost-Benefit Analysis (CBA) of the effects of our interventions by weighing the direct costs of the interventions against their expected benefits. As benefits we will first consider the reduction in morbidity costs associated with treating illnesses exacerbated by particle air pollution, particularly for children. These morbidity costs should be deemed as a lower bound of the total human costs of air pollution in children.

Particle air pollution is causally linked to asthma (Jans et al., 2018)[1] – both a chronic and an acute respiratory disease – that is more prevalent in children than in adults. For Delhi, Salvi et al. (2021) conduct spirometry tests to empirically examine the prevalence of asthma among 12- to 14-year-old students, Based on results from these tests and an widely used index of obstructive lung capacity[2] Salvi et al. (2021) estimate that 29.31 percent of children in Delhi are found to have obstructed lungs consistent with asthma.[3] However, most children that are found to suffer from asthma in Salvi et al. (2021)'s sample do not receive treatment. In fact, Salvi et al. (2021) reports that only 12 percent out of those found to have obstructed lungs consistent with asthma in Delhi

---

[1] See Paulin et al. (2016) for a review of the literature showing statistical associations between exposure to particle air pollution and asthma as well as other indicators of lung capacity,

[2] Spirometry tests yield both measures of Full Expiratory Volume in 1 second (FEV1) and Forced Vital Capacity (FVC). The index of obstructive lung capacity considers the ratio FEV1/FVC. A test result ratio that is between 50 and 59 percent indicates moderately severe lung obstruction, a test result ratio less than 50 percent indicates severe lung obstruction and a test result ratio less than 35 percent indicates very severe lung obstruction.

[3] In diagnosing asthma disease, after a lung capacity test that yields results indicative of obstructed lungs, doctors give the patient a puff of a bronchodilator (such as albuterol or salbutamol). A new spirometry test is conducted approximately 20 minutes after the application of the bronchodilator. If the index of lung capacity, FEV1/FVC, improves by more than 10 percentage points, then doctors usually diagnose the patient as suffering from asthma. Importantly, as we lack the capacity to medically diagnose asthma, in this work we will not provide a bronchodilator to students.

are actually diagnosed with asthma. That is, only 3.52 percent of children in Delhi are effectively diagnosed and receive some sort of treatment. In addition, Aneeshkumar and Singh (2018) estimates the mean annual direct cost for treating asthma in India at $223 (i.e., ₹18,737 /year). Therefore, to estimate the potential monetized health benefits of our interventions we will focus on the expected effects on reducing the prevalence of asthma in children and its associated cost.

To measure changes in severe lung obstruction associated with asthma we will conduct respiratory tests of obstructive lung capacity on students in our sample, both at baseline and at midline/endline surveys. As in Salvi et al. (2021) we will link changes in lung obstruction to changes in asthma, while also factoring in that only about 12 percent of those with asthma actually receive a diagnosis and treatment. Finally, we will employ Aneeshkumar and Singh (2018)'s cost estimates for treatment of asthma to monetize the health benefits of our interventions in terms of the expected reductions in cost of treating asthma.

We illustrate this exercise by conducting a prospective CBA of the *expected* effect of our intervention on students' respiratory health associated with the Purifiers treatment (the most expensive of our treatments). The expected reduction in average indoor $PM_{2.5}$ pollution under the Purifiers treatment – a 12.04 μg/m3 reduction in average indoor $PM_{2.5}$ pollution over a 2-month period – is expected to result in an improvement of 12.32 points in the lung capacity index (see subsection 3.d.iii. and Table 2 above).[4] Using the cutoff for severe lung obstruction employed by Salvi et al. (2021) (i.e., lung capacity index FEV1/FVC < 60 %), this improvement in $PM_{2.5}$ pollution would result in a reduction in the rate of students with asthma of 24.15 percentual points. That is, down to 5.16 percent of students with asthma. As in Salvi et al., 2021 we assume that only 12 percent of those fewer asthma cases would actually be corroborated by a medical diagnosis. Thus, the Purifiers treatment would bring diagnosed asthma cases, from an average of 3.52 percent, down by 2.9 percentual points. The benefits of these fewer diagnosed cases of asthma can be monetized using Aneeshkumar and Singh (2018)'s costing estimates for treating those children diagnosed with asthma. Therefore, this reduction in confirmed asthma cases should result in an average annual savings of $ 6.46 per student, or $ 323 per 50 students (~ per number of students in an average sized classroom). On the other hand, the direct costs of the purifiers equipment is $240 and their associated monthly operational costs are approximately $ 8.14.[5] Thereby, the cost of procuring and running this equipment for a 9-month academic year is $ 313.25. To this, we should add the costs of producing the material for the educational information, which should amount to about $ 20 or $ 30 per classroom. Together, these costs are on par with the monetized health benefits from reduced expenditure for treating asthma – arguably a lower bound for the overall health benefits of reducing air pollution in children.

REFERENCES

---

[4] The bundling of this treatment with EBS treatment should result in even a larger improvement of lung capacity.

[5] These purifiers consume 90 W per hour, and they would be running inside classrooms for about 5 hours a day. Moreover, for residential consumers, the average price of 1 kWh in India is $0.074 (₹6.09). This yields an average monthly consumption of $8.14.

Aneeshkumar, Surendran and Singh, Raj B. “Economic burden of asthma among patients visiting a private hospital in South India”. Lung India. 2018 Jul-Aug; 35(4): 312–315. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6034364/

Jans, J., Johansson, P., & Nilsson, J. P. (2018). Economic status, air quality, and child health: Evidence from inversion episodes. Journal of health economics, 61, 220-232.

Paulin, L., & Hansel, N. (2016). Particulate air pollution and impaired lung function. F1000Research, 5.

Salvi, S. S., Kumar, A., Puri, H., Bishnoi, S., Asaf, B. B., Ghorpade, D., ... & Kumar, A. (2021). Association between air pollution, body mass index, respiratory symptoms, and asthma among adolescent school children living in Delhi, India. *Lung India*, *38*(5), 408-415.

B. Response to Ref #2

Thank you very much for acknowledging the potential for contribution of our paper. Below we provide point-by-point responses to your insightful comments and suggestions and detail the corresponding revisions we have made to the earlier draft of the Registered Report Stage 1.

1.) RCT Design for explicitly distinguishing contribution of this paper.

Thank you very much for noting the potential for a massive impact of this study and contribution coming from our paper.

We are aware that emerging literature (i.e., currently ongoing RCTs) may provide experimental evidence of the effect of technology-based mitigation strategies (air purifiers) in reducing classroom air pollution exposure and affecting educational outcomes. However, our experimental design also advances the literature by focusing on the role of an educational campaign and behavioral change in reducing air pollution exposure among school children. Our project assesses the effect of this sort of campaign and its associated effects on respiratory health and educational outcomes. Information-based interventions are less costly and, therefore, can be easily scaled up. Therefore, we believe that it is important to explore the effect of this type of intervention for informing policymakers about the cost-effectiveness of these policies.

2.)

a.) **Sample size and spillovers.** Thank you for your comment. We have taken various measures to minimize spillovers and have added a discussion in the paper. To minimize possible spillovers of the information and education treatment we are taking additional provisions. For instance, we will no longer produce and display posters inside classrooms in the treatment group. Instead, we will display a video in the classroom, and this video will not be shareable with anyone else (in particular, it won't be shareable with students not in the treatment group). As explained in the revised Registered Report (lines 389 to 394), this video explains the problem of air pollution and teaches students about personal strategies to mitigate the effects of air pollution on their own health. A working version of this video can be found at this link https://bityl.co/SFpU. In addition, at the time of the showing of the video, we will hand a digital leaflet explaining these strategies (with figures and text similar to the ones shown in Appendix C of the Registered Report). After the showing of the video, the students will go over this leaflet and answer a few follow-up questions on their understanding of the video. We have also included a follow-up question of whether they have siblings in our treatment classrooms, to be able to account for any intra-household spillovers..

Moreover, if information spillovers remain after taking these provisions, we will be able to measure them by means of contrasting outcomes in control classrooms to those in 'pure control' schools (whereby, in these 'pure control schools' there will be no class assigned to the information and education treatment, nor to the purifiers treatment). Thus, we will be able to account for this possible spillover in our analytical framework if they exist.

Therefore, to the extent that these provisions allow us to effectively minimize information spillovers, and by properly accounting for them in our analytical framework, we expect that our experimental design will yield effective variation of outcomes at the class level (for both indoor air pollution and rate of absenteeism) and at the individual level (for all other health and educational outcomes).

Finally, both our budget and our agreement with the head of KV schools in Delhi, unfortunately, does not allow us to expand our sample of schools beyond the 10 schools for this project. Notably, we have a total of 126 classrooms across 10 schools in Delhi's KV schools. Of these classrooms, 54 have two shifts of classes a day (morning and afternoon), making for a total of 180 classes under this study. We are confident that, with this number of observations, our power analysis for the Minimum Detectable Effect (MDE) is sensible. Here again, the spillover will further be limited across the morning and evening sessions.

b.) **Multiple treatment arms and cross-randomization.** Thank you for your valuable feedback. Sincere apologies if it was not clear enough, we had initially intended for two treatments – (1) Purifiers and (2) Information & Behavior treatments – in two treatment arms, with one treatment in each treatment arm. However, as per your and the other referee's suggestions we have revised it, as follows.

> **Section 3.d (lines 315 to 322)** now states that we will randomly assign the classrooms into one of three groups: "*(Group 1) those assigned to treatment Educational & Behavioral Strategies (EBS), (Group 2) those assigned to both treatment EBS and treatment Purifiers, jointly, and (Group 3) a Control group*".

Additionally, we discuss the cost-effectiveness considerations in the response to the other referee above.

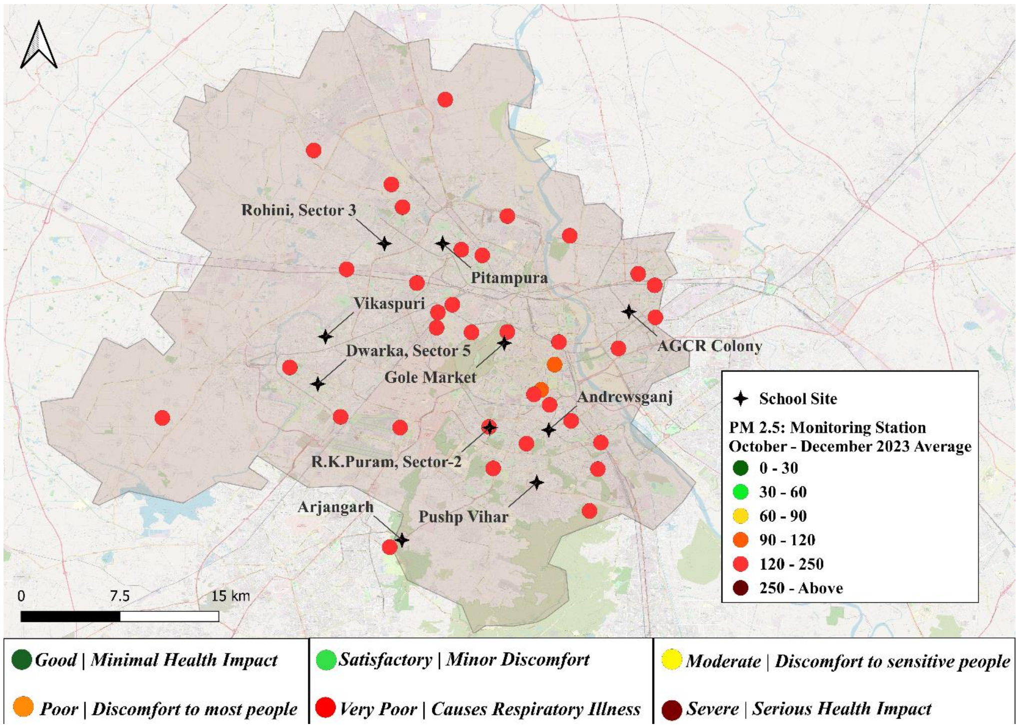
c.) **Measuring actual usage.** Thank you for your comment. Both the indoor PM pollution sensors and the Air Purifiers will be running continuously during this period. This has been discussed and agreed upon with the school principals. Regarding concerns about electricity expenses, it’s important to note that electricity for KV schools is heavily subsidized in India. Both air purifiers and PM pollution sensors are low-energy consumption devices and, therefore, should not substantially increase electricity costs. Additionally, our research team will run regular data quality checks and also have weekly visits to the schools over the weekends to ensure the purifiers and sensors are functioning correctly.

d.) **Future potential for scaling up.** Thank you for your feedback and noting the massive potential of scaling up given the countrywide presence of KV school. That, deed, was one of the underlying reasons for the choice of this collaboration.

As suggested by you and the first referee, we revised the design to have two treatment arms, as explained above in response to your comment 2b.

Moreover, when we conduct the randomisation we will check for the balance on ambient air pollution around each school. However, data on PM pollution from previous years suggests that this may not be a significant concern for Delhi. The map below marks the location of the KV Schools in our sample and plots average $PM_{2.5}$ pollution, from Delhi’s air quality monitoring stations, for the period October to December 2023.[6] As shown below, the schools in our sample are all exposed to average ambient $PM_{2.5}$ in the ‘Very Poor’ category (range 120 to 250 m/g^3), with little spatial heterogeneity.

[6] There are 40 Continuous Ambient Air Quality Monitoring Stations (CAAQMS) spread across Delhi. The Central Pollution Control Board (CPCB) and Delhi Pollution Control Committee (DPCC) provide real-time recorded data from all the functioning CAAQMS on multiple air quality variables (CCR ; DPCC). There are 9 CAAQMS which are located near the 10 school sites and provide daily data on $PM_{2.5}$ and PM_{10}. There are 8 sites with monitoring stations located within a radius of 1.5 km and the rest of the 2 sites have monitoring stations located within a radius of 6.5 km.


Rohini, Sector 3
Pitampura
Vikaspuri
Dwarka, Sector 5
Gole Market
AGCR Colony
Andrewsganj
R.K.Puram, Sector-2
Arjangarh
Pushp Vihar
0
7.5
15 km
School Site
PM 2.5: Monitoring Station
October - December 2023 Average
0 - 30
30 - 60
60 - 90
90 - 120
120 - 250
250 - Above
Good | Minimal Health Impact
Satisfactory | Minor Discomfort
Moderate | Discomfort to sensitive people
Poor | Discomfort to most people
Very Poor | Causes Respiratory Illness
Severe | Serious Health Impact

Journal of Development Economics
Registered Report Stage 1: Proposal

Technological and Behavioral Strategies to Mitigate Effects of Air Pollution on Children: Empirical Evidence from an RCT in Delhi's Schools

J. Cristóbal Ruiz-Tagle
London School of Economics
United Kingdom

Nikita Sangwan
Queen's University Belfast
United Kingdom

M. Marcela Jaime
Universidad de Concepción
Chile

César Salazar
Universidad del Bio Bio
Chile

Kanishka Kacker
Indian Statistical Institute Delhi
India

Pankaj Kumar
Indian Statistical Institute Delhi,
India

Date of latest draft: June 5th, 2024

Abstract

Air pollution is a serious problem in many regions of the developing world as it adversely affects the health, education and human capital of the population, especially children. Mitigating strategies can potentially alleviate some of the most severe effects of high air pollution. By conducting an RCT in Delhi's KV schools, this study assesses the potential role of technological and behavioral strategies in mitigating the adverse effects of high air pollution exposure on the health and educational outcomes of students. In particular, we evaluate the effectiveness of air purifiers in classrooms and an educational campaign during the period of peak air pollution. This work is important for building human capital in low- and middle-income countries faced with high pollution levels, which is essential for their human and economic development.

Keywords: Environment and Development, Air Pollution, Mitigation Strategies, Human Capital.

JEL codes: Q56, O13, O15, I15, I25.

Study pre-registration: We will register this study in the AEA RCT Registry before starting the field work.

Proposed timeline: This project plans to collect baseline data starting in October 2024. The two interventions will begin in the same month and will end in December (possibly extending into February 2025, depending on availability of funding). A follow-up will be completed in April 2025.

1. Introduction

Air pollution is linked to millions of deaths in the developing world and a myriad of other health problems (WHO 2016, HEI 2020). South Asia, and India in particular, suffers from some of the highest concentrations of air pollution, where Delhi consistently ranks at the very top of the most polluted cities in the world (IQAir, 2024). Air pollution is linked to 5.3 fewer years of life expectancy for India and to 11.9 fewer years of life expectancy for Delhi (AQLI 2023). In this work we experimentally assess technological and behavioral strategies to mitigate the adverse effects of air pollution on children in Delhi schools.

Air pollution also negatively impacts education and human capital accumulation, thus hampering human and economic development (Aguilar-Gomez et al., 2022). Avoiding exposure to air pollutants is especially important for children (Nhung et al., 2017; Goldizen et al., 2016; Schwartz, 2014) and for those suffering from chronic pulmonary diseases, such as asthma which is more prevalent in children (Laumbach et al., 2015).[1] Air pollution exposure is causally linked to adverse effects on children's health (Currie and Neidell, 2005), school absenteeism (Currie et al., 2009; Chen et al., 2018), standardized test scores (Bharadwaj et al., 2017; Carneiro et al., 2021; Heissel at al., 2022; Heyes and Saberian, 2024) as well as test-takers' future wages (Ebenstein et al., 2016). For India, exposure to fine particulate matter (i.e., particulates of size of 2.5 microns or smaller, $PM_{2.5}$) is causally linked to increased school absenteeism (Singh,2022) and reduced academic performance of children in rural (Balakrishnan and Tsaneva, 2021) and urban areas (Singh et al., 2022). Moreover, exposure to high levels of air pollution in childhood can carry long-lasting negative consequences well into adulthood (Isen and Walker, 2017).

Control of air pollution has proven very challenging for developing countries. Air pollution is a multifaceted problem involving many actors, many economic sectors and even varying geographies as the source of air pollutants. Moreover, developing countries often seek to raise living standards through added manufacturing activity of highly

[1] Children are more sensitive than adults to air pollution because they have a faster breathing rate, a relatively immature respiratory system and overall lower immunity. Moreover, due to their young ages, children are more likely to suffer from cumulative cognitive impacts from air pollution exposure (Ke at al., 2022).

polluting industries, a view in which air pollution control is not seen as a priority. The problem is made worse by weak regulatory capacity. Recent policies that target the sources of air pollution in Delhi have shown some progress, but these have not achieved improvements at the magnitude and speed necessary to bring air pollution down near safe levels in the foreseeable future. In lieu of the magnitude of the problem and slow progress, individuals are often left with little options other than suffer from high levels of air pollution and/or to engage in private defensive investments (such as buying air purifiers), and personal adoption of exposure mitigation strategies (henceforth, 'behavioral strategies').[2,3] We discuss these strategies in turn.

Air purifiers are a defensive technology that has proven effective at bringing down indoor air pollution and improving health (Cheek et al., 2021). The existing literature finds that High Efficiency Particulate Air (HEPA) purifiers reduced ultra fine particulate matter concentrations by 71 percent inside unoccupied school classrooms in Washington State, USA (Carmona et al., 2022)[4], and reduced $PM_{2.5}$ concentrations by 70 percent inside primary school classrooms in Hangzhou, China (Tong et al., 2020). Moreover, these HEPA air purifiers in school classrooms resulted in positive effects on a variety of children's respiratory outcomes in China (Yang et al., 2021)[5], but no effect on asthmatic children in schools in the northeast of the USA (Phipatanakul et al., 2021) where children are exposed to significantly lower levels of $PM_{2.5}$ pollution.[6] However, to the best of our knowledge, there is no experimental assessment of the potential for HEPA air purifiers to improve children's educational outcomes in a very air polluted setting.

---

[2] Private defensive strategies can serve as both complementary measures as well as a stopgap until effective long-term public policies to reduce air pollution are drafted and enacted.

[3] Personal behavioral strategies include the following: wearing masks on days in which air pollution reaches critical levels; avoiding bursting firecrackers; avoiding exercising outside and staying indoors when outdoor pollution is high; avoiding spending time near those that smoke; avoiding sources of indoor air pollution at home, such as burning incense, oil candles ('diyas'); avoiding burning biomass indoors and clear fumes/smoke in kitchen area, etc. We will discuss these in further detail in the Interventions section.

[4] For a review of the literature on the effects of HEPA air purifiers in the USA, see Cheek et al. (2021).

[5] Regarding other health outcomes associated with reduced air pollution due to deployment of HEPA air purifiers, the existing literature finds positive effects in reducing blood cadmium of pregnant women in Mongolia (Barn et al., 2018), decrease in children's visits to doctors in Ohio, USA (Lanphear et al., 2011), reductions in airway inflammation among college students in Shanghai, China (Chen at al., 2015), an improvement in airway mechanics of healthy young adults in Shanghai, China (Cui et al., 2018).

[6] Children in the USA study are exposed to average $PM_{2.5}$ concentrations of 5.4 μg/m3, whereas children in the China study are exposed to average $PM_{2.5}$ concentrations of 72 μg/m3.

On the other hand, adoption of behavioral strategies to mitigate exposure to air pollution has also been shown to be effective at mitigating the adverse effects of air pollution on health. For example, wearing face masks has been shown to reduce airway inflammation associated with particle air pollution (Guan et al., 2018), reduced decline of lung function (Shakya et al., 2016), and improved measures of blood pressure (Shi et al. 2017). Avoiding cooking with biomass and solid fuels and ventilating indoor cooking areas has been shown to improve lung function and reduce risk of chronic obstructive pulmonary disease (COPD) (Zhou et al., 2014). Staying indoors on high pollution days and limiting physical activity outdoors, or near sources of air pollution, has been shown to decrease markers of respiratory and systemic inflammation (Giles and Koehle, 2014; Madureira et al., 2019). For those that suffer from asthma, higher asthma control (with correct use of inhalers) has been shown to mitigate the adverse effects of $PM_{2.5}$ pollution on lung capacity (Mirabelli et al., 2015).[7] In terms of adoption of comprehensive behavioral strategies, Araban et al. (2017) find that an educational program can positively change behavior of pregnant women in Iran by modifying outdoor activity, particularly during episodes in which air quality alerts are issued.[8] However, to the best of our knowledge, there is no experimental evaluation of the effects of a campaign involving a comprehensive package of behavioral strategies for mitigating the effect of air pollution exposure on students' health and educational outcomes.

This work aims to fill the gaps in the literature by providing experimental evidence on the link between technological and behavioral strategies to mitigate air pollution exposure and its adverse effects on accumulation of human capital, broadly defined (i.e., maintaining good health, achieving a good education, and gaining productive skills) — a key factor in the pursuit of human and economic development. We believe that schools are an ideal setting for enhancing awareness of air pollution problems from an early stage through informational and educational campaigns. Students are used to a teaching and learning environment in school, and evidence shows that they can remember specific taught points when being taught about air pollution (Whitehouse and Grigg, 2021).

[7] For a thorough discussion of the evidence, from clinical trials, on behavioral strategies to mitigate the adverse effects of air pollution see Carlsten et al. (2020). Moreover, Laumbach and Cromar (2022) reviews the evidence for and against personal mitigation strategies and provide public health recommendations for the context of high-income countries, whereas WHO (2020) provides public health advice for low- and middle-income countries.

[8] The intervention was composed of three parts: a motivational workshop, a booklet and daily SMS text messages. See also Jasemzadeh et al. (2018).

Moreover, schools constitute a setting in which this sort of intervention could potentially be scaled up with only small changes in the teaching curriculum. On the other hand, although air purifiers have become relatively more affordable over recent years, there are still important financial constraints for households in developing countries to buy air purifiers for their homes. Moreover, as children spend a large fraction of their daily time at schools, air purifiers at home provide only a partial solution to mitigating exposure to indoor air pollution. Importantly, children are usually the least likely to be able to protect themselves from exposure to high air pollution. Children, and/or their caregivers, cannot privately engage in purchasing this technological defense for their school classrooms as only educational authorities can allow for and can carry out this sort of policies.

Thus, in this work we experimentally assess the potential of both HEPA purifiers in classrooms and a comprehensive educational campaign of behavioral strategies – tailored to students' environmental and sociocultural context – for mitigating the adverse effects of air pollution on children in Delhi's schools, a setting of very high air pollution. We hypothesize that: [H1] HEPA purifiers in classrooms and adoption of behavioral strategies mitigate students' exposure to high air pollution.[9] Moreover, we hypothesize that [H2] these technological and behavioral strategies improve students' respiratory health; and that [H3] these strategies and its associated improvements in respiratory health result in better educational outcomes.

To test these hypotheses we will conduct a randomized controlled trial (RCT) to evaluate two interventions aimed at mitigating the adverse effects of air pollution in children. In the first intervention we deploy HEPA purifiers in randomly selected classrooms of schools in Delhi. In the second intervention we conduct an educational campaign among students of these schools designed to teach them about both the effect of air pollution on health and about behavioral strategies to mitigate the harmful effects of exposure, thus seeking to encourage adoption of these strategies. We evaluate these interventions by measuring effective exposure to particulate matter air pollution inside the classroom and self-reported adoption of personal mitigation strategies. Moreover, we evaluate health effects associated with reduced exposure to air pollution – by measuring students' lung

[9] More specifically, we hypothesize that: HEPA purifiers decrease air pollution exposure while students are in the classroom; and that students learn and understand (i) the effects of air pollution in health, (ii) how to identify critical periods of air pollution (i.e., high Air Quality Index, AQI), and (iii) once taught, students change their behavior so as to adopt strategies that mitigate their personal exposure.

capacity and self-reported health – and evaluate educational outcomes — specifically, scores in standardized cognitive tests, school attendance and grades in final exams. Evidence from our pilots shows that HEPA air purifiers can effectively reduce indoor air pollution inside the classroom, and that this reduction is linked to an improvement in students' school attendance (see Appendix A.1 below).

This work makes three contributions to the broader literature of environment, health and education in developing economies. First, this work contributes to the literature on technology adoption for mitigating environmental hazards and improving health in developing countries. For example, the literature on the adoption of clean cookstoves (Pattanayak et al., 2019; Jeuland et al., 2020; Afridi et al., 2021; Berkouwer and Dean, 2023) has found that improved cookstoves result in an important decrease in exposure to peak air pollution although finds no statistically significant decrease in average exposure to air pollution nor in health biomarkers (Berkouwer and Dean, 2023). In a closely related paper, Chowdhury et al. (2024) is examining the drivers of adoption of HEPA purifiers and its associated effects on health and labor outcomes at the household level (although results have not been reported yet). This work expands this literature by examining the potential of HEPA purifiers for mitigating the adverse effects of exposure to air pollution on childrens' health in developing countries.

Second, this work contributes to the broad literature on development economics that seeks to understand the barriers to adopting highly effective preventive behavior for mitigating the burden of multiple health health hazards and diseases faced by developing countries (Dupas, 2011). One possible explanation for this low adoption is a lack of information on the consequences of health hazards and diseases and the effectiveness and cost-effectiveness of preventative behaviors (Dupas, 2011). In this regard, our work expands the limited literature that evaluates the implementation of educational campaigns to incentivize better health care practices and thus improve human health.[10] Our work expands this literature by designing an educational campaign that not simply

[10] This literature supports that health-oriented information has incentivized safe water behaviors (Madajewicz et al., 2007; Luoto et al., 2014), promoted protection strategies against tropical diseases such as malaria and dengue (Dammert et al., 2014; Cohen and Saran, 2018), reduced the exposure to indoor pollution from cooking stoves - therefore the prevalence of respiratory health problems (Afridi et al., 2021), and encouraged HIV/AIDS testing behavior (Derksen et al., 2022; Yang et al., 2023; Yu, 2023) in developing countries.

delivers information but also teaches actionable behavioral strategies for encouraging adoption of preventive behavior among school children.

Third, we assess whether these health-enhancing strategies could also positively affect educational outcomes. Current empirical evidence from public health campaigns aimed at eradicating persistent diseases in developing countries (e.g., malaria) shows mixed results in promoting educational attainment and literacy (Lucas, 2010; Cutler et al., 2010). This literature also indicates that adopting health-enhancing technologies (e.g., water treatment, clean energy) that potentially reduce human pollution risk may raise educational attainments, not only through health improvements (Zhang and Xu, 2016) but also via a human capital investment mechanism (Choudhuri and Desai, 2021). Our work contributes to this literature by assessing an intervention that can potentially have tangible effects on educational outcomes and thus improve the process of human capital accumulation and its associated positive effects on long term economic and human development.

The rest of this document is organized as follows. The next section presents the background and context of the problem of air pollution in Delhi and the schools where we will conduct the field work. Section 3 presents the research design where we state the hypotheses that will be examined, the methodological framework and conduct power analysis. Section 4 describes the data collection process and project timeline. Section 5 presents the statistical models that will be employed to test the hypotheses and section 6 states administrative project information.

2. Background and Context

Delhi is home to about 20 million people, with an additional few million if we account for surrounding satellite cities and towns. The air quality is very poor, with an average $PM_{2.5}$ concentration of roughly around 120 micrograms per cubic meter ($\mu g/m^3$) in 2018. The national air quality standard for India requires annual average $PM_{2.5}$ concentrations not to exceed 40 $\mu g/m^3$. Delhi has been in violation of these standards for at least the past two decades. Air pollution in Delhi is also highly seasonal. Colder months typically see worse levels of air quality while the Monsoon (late summer) period is the cleanest. Figure 1 below illustrates this. This figure uses data for the year 2018 from ambient air quality monitors maintained by India's Central Pollution Control Board. The horizontal red line shows India's standard for annual average $PM_{2.5}$. Delhi's air quality typically tends to be in compliance with the annual standard only during July, August and September. In the winter months of November to January, in particular, the quality of the air deteriorates to very high levels.[11]

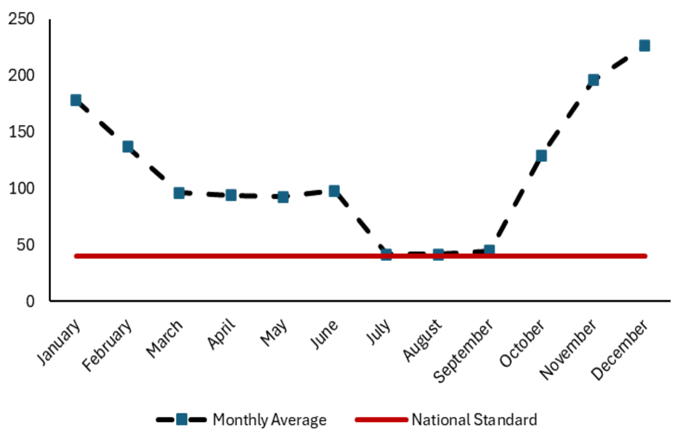


Figure 1: Monthly averages of $PM_{2.5}$ for the year of 2018 for Delhi, data taken from all active air quality monitors maintained by the Central Pollution Control Board

Since 2017 Delhi, and the surrounding satellite towns and cities that make up the National Capital Region (NCR), has instituted a comprehensive policy to bring air pollution down. This policy, called the Graded Response Action Plan (GRAP), consists of four stages. Stage I is put in place when the predicted air quality exceeds a certain cut-off. Subsequent stages - Stages II, III and IV - are invoked when air quality is predicted to exceed progressively higher cut-offs. Relevant to our interventions, Stage IV of the GRAP requires schools to be shut down when air quality is predicted to be particularly bad. For instance, in 2023, in Delhi primary schools were shut down from November 6th to November 18th, while schools at all levels were shut down from November 8th onwards.[12]

[11] This is due to several factors: the primary factor being the lower temperatures and the resulting temperature inversions that limit the ventilation of the airshed. In addition to this, other reasons can be smoke that comes from the widespread stubble burning that takes place in states northeast/upwind from Delhi (Punjab and Haryana) during November.

[12] School closures by themselves are however unlikely to be particularly useful in protecting children from air pollution. First, the decision to close schools is typically taken after air quality has already reached hazardous levels. Second, children are likely exposed to the same poor-quality air when they are at home. Closing schools may prevent some minor additional exposure during commutes, but this is unlikely to be very large. Moreover, the loss of school days that

Therefore, if HEPA purifiers in classrooms turn effective at reducing air pollution in classrooms and improving students' health and educational outcomes, Stage IV of the GRAP policy may no longer be necessary. Instead, a policy that invests and deploys this sort of air purifiers can then allow for keeping children attending and learning at school even during episodes of very high air pollution.

Our choice of school partner is the Delhi branch of the Kendriya Vidyalaya (KV) schools, which translates to *Central Government Schools* in English. India's KV schools are a nationwide system of public schools that cover all grades (called "standards" in India), from primary all the way to school completion.[13] These schools offer the same syllabus across the board and a highly standardized system of education. The major advantage of working with KV schools is that they offer very promising scope to examine how the interventions we examine could potentially be expanded on a national scale. Scaling up is important because air quality in most parts of India – particularly the northern plains region, where hundreds of millions of people live – is extremely poor, just as bad as it is in Delhi.[14] Therefore, if the behavioral strategies evaluated in this work turn effective, then a small change in the teaching curriculum can go a long way in mitigating the harmful effects of air pollution exposure throughout a vast number of geographical areas in India and other regions of the world suffering from very high air pollution.

3. Research Design

a. Objectives and Main Hypothesis

The main objective of this work is to experimentally assess technological (i.e., HEPA air purifiers) and behavioral strategies for mitigating children's exposure to air pollution, the positive health effects associated with mitigated exposure, and whether this results in

result from these school closures can hamper children's learning, and the cumulative effect of this reduction in school days is likely to show up as fewer lessons are effectively learned.

[13] These schools were initially set up to serve children of parents who work in jobs that require significant long term stays in different parts of the country, such as in the armed forces or in government. In order that their children's education does not suffer.

[14] The national scale of the problem is illustrated in Figure A.1 in Appendix A.

improved educational outcomes. We hypothesize that these strategies can result in tangible benefits for students in Delhi schools exposed to high levels of air pollution.

b. Main outcomes of Interest

We first examine the effect of air purifiers on indoor particle air pollution. To measure this we will deploy indoor pollution monitors that will log real-time readings of fine and coarse particulate matter pollution ($PM_{2.5}$ and PM_{10}). These monitors will be deployed in both classrooms with HEPA purifiers and control classrooms. Moreover, by means of a survey questionnaire, we assess students' understanding and learning of key components of the educational and behavioral intervention. Specifically, we assess understanding and learning of (i) the effects of air pollution on health, (ii) identification of periods of high air pollution (specifically, high Air Quality Index), and (iii) personal strategies to mitigate exposure to high air pollution. In addition, the survey questionnaire will allow us to gauge whether students have actually engaged in any of these behavioral strategies.

Next, we examine whether these technological and behavioral mitigation strategies result in improved health by measuring students' lung capacity using spirometry.[15] In particular, we will measure a students' Forced Expiratory Volume over 1 second (FEV1) and Peak Expiratory Flow (PEF).[16] We complement this assessment with survey questions on self-reported health, focusing on those health symptoms that are more closely associated with exposure to high air pollution.

Finally, we measure students' educational outcomes in three ways. We obtain data on individual-level school attendance from schools' official registry, we perform standardized learning and cognitive tests throughout the school year,[17] and we assess

[15] Spirometry is a tool to assess and monitor prevalence and risk of chronic respiratory diseases, such as Asthma and Chronic Obstructive Pulmonary Disease COPD (Agusti et al., 2021), that allows to identify health effects even from modest variations in short-term exposure to PM2.5 air pollution (Rice et al. 2013).

[16] Dong et al. (2019) show that portable ionization air purifiers in school classrooms, even for a short period of time (5 days), increase FEV1 among children 12 years old in Beijing, China, whereas Weichenthal et al. (2013) show similar effects among indigenous populations in Manitoba, Canada.

[17] For assessing learning of math and language, we employ the Young Lives School Survey (YLS). Whereas for cognitive assessment we employ the Reverse Corsi Block task to measure working memory (Brunetti et al., 2014). This test has been shown to be sensitive even to modest changes in average air pollution exposure (Berkower and Dean, 2023).

students' grades throughout the year and in their final exams. The survey questionnaire, spirometry sampling, questions on self-reported health and standardized cognitive tests will all be conducted several times during the data collection.

c. Testable Hypotheses

We hypothesize that

Hypothesis 1: Technological and behavioral strategies mitigate students' exposure to high air pollution

From this, we have two auxiliary hypotheses.

> *Hypothesis 1.1: Air purifiers mitigate air pollution exposure while students are in the classroom.*

and a twofold Hypothesis 1.2

> *Hypothesis 1.2.a: Students can understand and learn the following: (i) the effects of air pollution in health, (ii) how to* identify critical periods of air pollution (i.e., high Air Quality Index, AQI), and (iii) personal behavioral strategies to mitigate exposure.

> *Hypothesis 1.2.b: Once (i) through (iii) above are taught and learned, students change their behavior to adopt strategies that mitigate their personal exposure to air pollution.*

Next, we evaluate whether these strategies can reduce the harmful effects of exposure to high levels of air pollution by posing the following hypothesis.

Hypothesis 2: Technological and behavioral strategies (i.e., HEPA Purifiers in classrooms and personal behavioral strategies) improve students' respiratory health.

Finally, our last hypothesis is whether improvements in student's respiratory health leads to better educational outcomes. Thus, our third hypothesis is

Hypothesis 3: Technological and behavioral strategies, and their associated improvements in respiratory health, result in better educational outcomes.

Table 1 below summarizes the main outcome variables in relation to how they allow us to test our hypotheses.

Table 1: Hypotheses and Outcome Variables

Hypothesis	Outcome Variable	Unit of Obs.	Type	Data Source
H1: Exposure				
H1.1	Particle Pollution ($PM_{2.5}$)	$\mu g/m^3$ in classroom x 20-minutes	Continuous	Indoor pollution monitors
H1.2.a	Learning of Behavioral Strategies	Student x Round	Index	Survey questionnaire
H1.2.b	Adoption Behavioral Strategies	Student x Round	Index	Survey questionnaire
H2: Health				
H2.1	Lung capacity (FEV1 & PEF)	Student x Round	Continuous	Spirometry
H2.2	Self-Reported Health	Student x Round	Index	Survey questionnaire
H3: Education				
	Attendance	Student x Day	Count	Official School Registries
	Standardized test scores	Student x Round	Continuous	Survey Standardized Test
	Grades	Student x Year	Grading System	Official School Registries

d. Methodological Framework

We will conduct a cluster-randomized controlled trial where we will randomly assign clusters of students sharing the same classroom (a.k.a. *a class*) into one of three groups: those assigned to treatment *Purifiers*, those assigned to treatment *Educational & Behavioral Strategies (EBS)* and a *Control* group. That is, we will randomly assign all students in the same class to *only* one of these treatment arms, without overlap. This random assignment will be conducted in early October 2024 by members of the research team in a clear and transparent way. Next, we explain these three groups and the treatments in detail.

i. Treatments

Treatment Purifiers: HEPA purifiers in classrooms

The first treatment consists of deploying high-capacity HEPA purifiers inside randomly selected school classrooms. These HEPA purifiers contain a filter that filters up to 99.99 percent of particles of size 0.1 microns ($PM_{0.1}$) or larger. These air purifiers have a manufactured-stated clean air delivery rate (CADR) of 600 cubic meters per hour (21,189 cubic feet per hour) and are suitable for rooms of an area of up to 60 square meters (645 square feet). This intervention is further accompanied by simple information and education seeking to enhance the performance of the HEPA purifiers. Specifically, students and teachers will be asked to keep doors and windows shut during the time the purifier is running inside the classroom. These purifiers will be running during teaching hours and will be turned on/off by the class teacher. The field team will be in constant communication with school principals to monitor that these purifiers perform continuously during the data collection period, and any malfunctioning is promptly fixed and logged. All air purifiers will be deployed and installed in mid-October 2024, during the Autumn school break (October 8th to 17th, 2024).

To assess the reduction of indoor air pollution by these purifiers we will deploy indoor air pollution monitors inside classrooms in both those classrooms assigned to treatment

Purifier and those in the control group.[18] These devices measure fine and coarse particle air pollution ($PM_{2.5}$ and PM_{10}) concentrations and record this data internally on an SD card every 20 minutes. The field team will continuously monitor these devices, download the data stored in their SD cards to a laptop computer and then upload this data to a secured storage drive.

Treatment EBS: Education and Behavioral Strategies

The second treatment consists of an educational campaign that will have three components. Component 1 teaches students about the problem of air pollution in their city and how it impacts their own health. Component 2 teaches students that exposure to higher levels of air pollution is associated with higher risks of health hazards.[19] Finally, component 3 of this campaign teaches personal strategies to mitigate air pollution exposure and associated health risks. We will seek to deliver this teaching in a positive way that seeks to bring a sense of self-empowerment to students to 'fight against' the adverse effects of air pollution in their city. We refer to this educational and behavioral strategies treatment as treatment *EBS*. As before, assignment to this treatment will be in clusters, such that if a class is assigned to this treatment then all students in the same class will be assigned to receiving this treatment

For this intervention we will produce educational material that has educational content tailored specifically to this intervention. This includes leaflets (which will be handed out to students), posters (which will be hung inside the classroom's wall) and a short video (which will be shown to students in the computer lab, when they respond to the survey questionnaire). This educational material has simple language and is accompanied with visuals for communicating the contents in a way that is easily understandable by these

[18] These indoor air pollution monitors will also be deployed in 'pure control' classrooms.

[19] When referring to these health risks we will follow the health risks categories by the Air Quality Index (AQI) of India's Central Pollution Control Board. Under these categories 'Good' air quality (i.e., AQI between 0 and 50) is associated with "Minimal impacts" on health; 'Satisfactory' (AQI between 51 and 100) is associated with "Minor breathing discomfort to sensitive people"; 'Moderate' (AQI between 101 and 200) is associated with "Breathing discomfort to the people with lungs, asthma and heart diseases"; 'Poor' (AQI between 201 and 300) is associated with "Breathing discomfort to most people on prolonged exposure"; Very Poor (AQI between 301 and 400) is associated with "Respiratory illness on prolonged exposure", and 'Severe' (AQI between 401 and 500) is associated with "Affects healthy people and seriously impacts those with existing diseases". See https://airquality.cpcb.gov.in/AQI_India/.

students. Next, we describe in further detail the content of each of the three components of this treatment.

Component 1: Effects of air pollution on health

For explaining the effects of air pollution on health we have produced a draft of this educational content (see Appendix C.1 below). In addition, based on this content we will produce a short video that will be similar to this video from the United Nations Children's Fund (UNICEF, 2016) and the 'Freedom to Breathe' campaign for India.[20]

Component 2: Identification of critical levels of air pollution by means of checking the AQI

Another important component of this intervention is to create awareness about the current level of ambient air pollutants, at any given period of time, by explaining the Air Quality Index (AQI) and getting students (and/or getting them to ask their caregivers) to check the AQI on a regular basis (see Appendix C.2). This component seeks to aid students in identifying when air pollution has reached critical levels, and it is indeed the first behavioral strategy for mitigating exposure to high ambient air pollution.

Component 3: Personal strategies to mitigate exposure and its effects on health

The personal strategies to mitigate the adverse effects of air pollution on health include: (a) avoiding physical activity, exercising and (to the extent possible) spending much time outdoors when AQI is high or very high; (b) closing of doors and windows when AQI is high and the indoor environment is clear of air pollution; (c) running an air purifier if it

[20] This video explains – for an Indian context – the problem of air pollution on health and a few personal strategies for mitigating exposure. The `Freedom to Breathe' campaign provided an opportunity for children to call for their right to clean air to be acknowledged by the United Nations Convention on the Rights of the Child (UNCRC). The campaign worked with partners across the world to deliver a curriculum-linked education program that helped young people understand the state of air quality in their cities, the health harms of poor air quality, and simple measures they could take at home and in school to protect themselves from breathing harmful pollutants. The campaign was run globally by Blueair -- a Swedish subsidiary of the Unilever company that manufactures air purifiers -- in partnership with Global Action Plan, Association for the Promotion of Youth Leadership Advocacy and Volunteerism Cameroon (APYLAV), Centre for Environment Education, Coalition for Clean Air, and Safekids Worldwide. https://www.blueair.com/us/freedomtobreathe.html

is available at home; (d) avoiding spending time near people that smoke; (e) asking parents to avoid burning incense and oil candles indoors, (f) asking parents to avoid burning biomass (such as wood fuel, charcoal or dung) for cooking or heating indoors, (g) avoiding busy roads when going to school, (h) avoiding bursting firecrackers (which is widespread during the Diwali festivities) and/or spending time near where this happens; (i) considering wearing an N95-type face mask when AQI is very or extremely high; (j) paying attention to own health and seek care early on if symptoms arise; (k) using inhaler more often if the student suffers from asthma. The figures in Appendix C.3 below illustrate some of these strategies.

ii. Possible Violations of SUTVA, Spillovers and Confounders

We take several provisions to prevent 'contamination' of treatments across subjects, or, more technically, violations of the Stable Unit Treatment Value Assumption (SUTVA). First, SUTVA may be violated if students in treatment *EBS* share information from the educational campaign with students in either treatment *Purifier* or in the *Control* group. This problem is more likely to occur within the same school than across different schools. To address this potential problem, we will conduct a multi-stage assignment. More specifically, in the first stage we will select schools that will serve as 'control-only' schools, and in the second stage we will conduct the random assignment of clusters of students into treatments and control groups. For classes and classrooms in 'control-only' schools we will conduct the same surveys and will deploy the same indoor air pollution monitors. We believe that, if there is any spillover effect between students in treatment(s) and control groups, we expect that this spillover will occur between classes within the same school, but it will not occur across classes from different schools. Therefore, having classes in 'control-only' schools would allow us to assess whether those students in classes that have been randomly assigned to the *Control* group effectively remain free of any possible spillover from those students in classes randomly assigned to any of the treatment groups. If spillovers exist, then observing those students in classes in 'control-only' schools would allow us to identify that spillover and properly account for it in our statistical analysis.

Second, SUTVA may be violated if classrooms in treatment *Purifier* have students switching in and out of this classroom during the time of the field experiment. For example, it might be that, due to the novelty of having an air purifier in the classroom, students from classes selected for treatment *EBS* or *Control* group may want to spend time inside classrooms assigned to treatment *Purifier*. To minimize this possibility, we will make it explicit to teachers and educators to enforce that only students in the treatment *Purifier* classes should be allowed in those classrooms. We will ask them to inform us if this is not feasible to enforce and we will keep a log of instances in which students swap classrooms.

In addition, we anticipate that these treatments may generate spillover effects beyond the intended assignment to treatment. In particular, there could be non-behavioral changes in exposure to air pollution that are triggered by assignment to the treatment *EBS*. For example, parents of children assigned to treatment *EBS* may decide to buy an air purifier for their home if they hear from their child's increased awareness about the problem of air pollution – say, they hear their child advocating and pushing for household members to engage in behavioral strategies to mitigate exposure at home. While we do not anticipate being able to prevent this from happening, we will ask students both at baseline and follow up surveys about the presence of air purifiers at home, so that we can properly account for this sort of changes in air pollution exposure mitigation in our statistical analysis. Likewise, there could be behavioral changes – triggered by assignment to treatment *Purifier* – in such a way that affects students' exposure to air pollution. For example, students may feel that, because they are 'protected from air pollution' while in the classroom, then they do not need to be protected themselves from pollution at other instances – thus, they may engage in lesser pollution exposure mitigation behavior than otherwise. Conversely, the presence of the air purifier in the classroom may work as a salient reminder of the problem of air pollution, in such a way that students change their behavior by attempting to reduce exposure, also while outside the classroom. That is, those students in classrooms assigned to treatment *Purifier* may feel more interested and/or engaged in taking additional measures to reduce exposure, such as engaging in some of the personal exposure mitigation behaviors listed above (for example, wearing face masks). To address these issues, we will include questions in the survey questionnaire about behavioral strategies to mitigate exposure both at baseline and at follow-ups, and we will properly account for these in our econometric analysis. Similarly, if the child is in a classroom assigned to treatment *Purifier*, and his/her parents believe that the child will be protected from air pollution while in the school classroom, then the child's parents may decide to send the student to school more often than otherwise. Due to this reason, we can expect a direct increase in students' attendance rate in classrooms assigned to treatment *Purifier* that is not directly linked to improvements in the child's health. To address this issue, in our empirical strategy we implement an instrumental variable regression approach (see section 5 below).

Finally, a potential confounder effect can occur as schools close due to a government mandate as air pollution reaches very high peaks (Stage IV of GRAP policy response, as discussed in section 2 above). But as schools in the control and the treatment group are impacted similarly by closures, we expect a similar exposure outside the classroom premises. However, we will keep track of the occurrence of school closures for any reason.

iii. Sample and statistical power

We are planning to conduct this experiment in 126 classrooms across 10 schools in Delhi's KV schools. Of these classrooms, 54 have two shifts of classes a day (morning and afternoon), making for a total of 180 classes. Moreover, each class has an average of 50 students, which makes for a total of around 9,000 students. However, of these 10 schools we will select 2 schools to serve as 'control-only', leaving us with 8 schools and between 144 and 150 classes that will be eligible for random assignment to the treatments and control.[21] For simplicity, we will refer to working with a sample of around 147 classes. As the treatments will be assigned at the class level, this will allow for a split of roughly 49 classes in each of the three treatment arms (the two treatments and the control group).

Our sample of classes comprises students in 6th, 7th and 8th grade. Thereby, we will conduct a stratified random assignment at the school grade level (Athey and Imbens, 2017). The rationale for this stratified random assignment is as follows. One of the

[21] The exact number will depend on the actual 2 schools that we select out for the 'control-only' group

important factors likely driving many of our primary outcomes is the student's age and their associated school grade and cognitive/learning capacity. An older student should have a more resilient health system that can better withstand adverse environmental conditions, such as exposure to high levels of air pollution. Thereby, the effects of mitigating exposure to air pollution on respiratory health (and thus, educational outcomes) may be less pronounced among older students than among younger students. Moreover, older students should be better equipped to grasp the content of an educational campaign aimed at reducing personal exposure, they have more agency on determining their actual behavior, and thus could possibly mitigate their exposure to air pollution to a greater extent than younger students. Furthermore, older students should be able to perform better in cognitive and learning tests than younger students. For these reasons, we believe that we should have a balanced sample of students in 6th, 7th and 8th grade assigned to each of the treatments and to the control group. Therefore, conducting a stratified random assignment at the school grade level will guarantee that the treatments and control groups are balanced for each school grade. That is, for a given school grade, there will be (roughly) as many classrooms in treatment *Purifier* as in treatment *EBS* as in *Control* groups.[22]

Next, we present our power analysis for the Minimum Detectable Effect (MDE) assuming statistical significance of 5 percent and 80 percent of statistical power. We present this analysis at the classroom/class level as well as at the student level, depending on the unit of measurement of the outcome variable. Table 2 below summarizes the power analysis.

<u>Classroom/class level outcomes</u> (Panel A of Table 2)

Particle Pollution ($PM_{2.5}$) inside classrooms. This analysis relies on our pilot with seven air purifiers in an equal number of classrooms conducted in August through December 2022. The average $PM_{2.5}$ pollution inside the classrooms is 133.16 $\mu g/m^3$ and the standard

[22] In our case there will be roughly 14 classrooms, per school grade, assigned to each group. Moreover, when conducting the regression analysis we will not control for the strata of randomization (i.e., we will not control for school grade), although we will control for all the dimensions of fixed-effects as well as their interactions (Athey and Imbens, 2017).

deviation is 148.17. Therefore, under equal assignment of classrooms/classes between treatment and control groups this yields a MDE equal to a 84.72 μg/m^3 reduction in $PM_{2.5}$. On the other hand, the average reduction in $PM_{2.5}$ pollution inside classrooms that we observed in our pilot is 101.2 μg/m^3.

School attendance. This analysis relies on the absenteeism rate reported by (Singh, 2022) for schools in Delhi. Singh (2022) reports an average absenteeism rate of 26.24 for 6th to 8th graders in Delhi schools and a standard deviation of 1.4. Therefore, assuming equal assignment of classes into treatment and control groups, this yields a MDE equal to 0.8 reduction in absenteeism rate. On the other hand, the estimated reduction in absenteeism rate we find in our pilot with air purifiers is 6 percentage points.

<u>Student level outcomes, clustered at the class/classroom level</u> (Panel B of Table 2)

Learning Behavioral Strategies. Not currently available (N/A).

Adoption of behavioral strategies. Although we did not conduct a pilot for the educational and behavioral intervention, we rely on Araban et al. (2017) for a feasible mean and standard deviation of an index of behavioral strategy adoption. In addition, for the class-level intra-cluster correlation (ICC) we rely on estimates from the 'Balsakhi' program of remedial education for schools in urban India (Banerjee et al., 2007). Thus, we assume a mean adoption index of 11.2 (for an index that goes from 5 to 20), an associated standard deviation of 2.3, and an ICC of 0.1356. Under equal assignment of class-level clusters of students among treatments/control groups, this yields a MDE equal to 0.51. On the other hand, Araban et al. (2017) finds an effect of 8.8 for that same index.

Respiratory health – Lung capacity. We rely on parameters and estimates from Foster and Kumar (2011) for an index of lung capacity (as measured by spirometry) for children less than 17 years old in Delhi. The mean index reported by Foster and Kumar (2011) is 70.44 and its associated standard deviation is 15.35. Moreover, we assume the same ICC as before. This yields an MDE equal to 3.4 for an equal assignment of class clusters into treatment/control groups. On the other hand, we expect to find a reduction of 12.32 points in such an index from the air purifier intervention. This expected reduction comes from multiplying the estimated effect of 1.023 (per 1-μg/m^3 of change in $PM_{2.5}$) found by Foster and Kumar (2011) by a reduction of 12.04 μg/m^3 in average $PM_{2.5}$ exposure.[23]

Respiratory health – Self reported symptoms. We rely on parameters and estimates from Berkouwer and Dean (2023) for both a (zero-mean standardized) index and a count of self-reported respiratory health symptoms. Assuming the same ICC and balance split between treatment and control as before this yields a MDE of 0.22, whereas the effect found in Berkouwer and Dean (2024) is 0.24 for a 0.8 μg/m^3 reduction in average $PM_{2.5}$ exposure. Similarly, the count of respiratory symptoms has a mean of 1.7 and a standard deviation of 1.76, thus yielding a MDE of 0.39, which contrasts to the effect found in Berkouwer and Dean (2024) of 0.48.[24] As mentioned above, we expect to find a considerably larger reduction in average $PM_{2.5}$ exposure than the one in Berkouwer and Dean (2024).

Cognitive/learning assessment. We rely on parameters and estimates for a (zero-mean standardized) index of cognitive memory (Corsi test) from Berkouwer and Dean (2024). Assuming the same ICC and balance split of treatments/control as before, we obtain a MDE equal to 0.22. This contrasts with the effect of 0.48 for this index[25] for 0.8 μg/m^3 reduction in average $PM_{2.5}$ exposure – a considerably smaller reduction than the one we expect for our treatment.

Cognitive assessment – Peabody Picture Vocabulary and Math Test

We rely on parameters and estimates from Balakrishnan and Tsaneva (2021) for a (zero-mean standardized) index of the Peabody Picture Vocabulary Test from the India Chapter of the *Young Lives Survey*. Balakrishnan and Tsaneva (2021) find an effect of 0.18 and

[23] This 12.04 μg/m^3 reduction in average exposure to $PM_{2.5}$ is the result of a 101.2 μg/m3 reduction (from the air purifier) for a period of 4 hours a day spent inside the classroom over 5 days a week.
[24] For the effect of the index and count of respiratory symptoms see Table B.13 in Berkouwer and Dean (2024).
[25] See Table B.15 in Berkouwer and Dean (2024).

.55 for boys and girls, respectively, from a 1-μg/m^3 change in the annual mean of $PM_{2.5}$.[26] On the other hand, assuming the same ICC and balance split of treatments/control as before, we obtain a MDE equal to 0.22.

Grade in Final Exams. Not currently available (N/A).

Table 2: Power Analysis – Input Parameters, Minimum Detectable Effect and Effect Size.

Outcome Variable	Mean	S. D.	ICC	MDE	Estimated Effect	Source
Panel A. Class level						
Indoor $PM_{2.5}$ pollution (μg/m^3)	133.2	148.2	-	84.72	101.2	Pilot
Absenteeism rate (%)	26.24	1.4	-	0.8	6	Pilot, Singh (2022).
Panel B. Student level						
Learning behavioral strategies	N/A	N/A	N/A	N/A	N/A	
Adoption of behavioral strategies (index)	11.2	2.3	0.136	0.51	8.8	Araban et al. (2017), Banerjee et al., (2007).
Respiratory health effects (index of lung capacity)	70.44	15.35	0.136	3.4	12.32	Foster and Kumar (2011), Pilot.
Respiratory health symptoms (index)	0	1	0.136	0.22	0.24	Berkouwer and Dean (2023), Pilot.
Respiratory health symptoms (count)	1.7	1.76	0.136	0.39	0.48	Berkouwer and Dean (2023), Pilot.
Cognitive Test, Corsi working memory (index)	0	1	0.136	0.22	0.48	Berkouwer and Dean (2023), Pilot.
Cognitive assessment, Peabody Picture Test (index)	0	1	0.136	0.22	0.18 (Boys) 0.55 (Girls)	Balakrishnan and Tsaneva (2021)
Final Exams	N/A	N/A	N/A	N/A	N/A	

[26] We expect to find an effect in the annual mean of $PM_{2.5}$ from our interventions in the order of two to three times as large as that in Balakrishnan and Tsaneva (2021).

4. Data

a. Data collection and processing

As stated above, we collaborate with Kendriya Vidyalaya (KV) schools in Delhi. To collect student-level data we will use a combination of survey instruments (both questionnaires and a low-cost medical device for spirometry) and administrative data on attendance and grades in final exams. The survey instruments would be executed with the help of a survey team with prior experience and training for collecting data from school students. Moreover, we will deploy air pollution monitors inside classrooms to assess exposure to indoor PM air pollution while in the classroom.

The survey questionnaire is divided into multiple sections. Section 1 starts with questions about simple socioeconomic indicators and questions about self-reported respiratory health symptoms experienced over a recent period of time. Then it moves onto questions about air pollution. These include questions about knowledge and understanding of the problem of air pollution, questions about capacity to identify periods of time with high air pollution (by means of the Air Quality Index, AQI), and questions about knowledge and practice of behavioral strategies to mitigate exposure to high air pollution. Sections 2 and 3 have questions for assessing learning of language and math (this is borrowed from the India chapter of the *Young Lives survey*).[27] Finally, section 4 has questions on a memory test consisting of connecting visual shapes (Corsi memory test). A working draft of the questionnaires is attached in Appendix B.

For collecting spirometry data on a student's lung capacity we will be using a low cost portable spirometer from Medical International Research company.[28] Spirometer tests will be administered individually to each student by well-trained enumerators.

For collecting data on indoor PM pollution we will be using a low-cost monitor manufactured by Purelogic Labs India, an air quality company based in Delhi, India.[29]

[27] The questionnaires are borrowed from the India chapter of the Young Lives School survey https://www.younglives.org.uk/india-school-survey.
[28] Specifically, we will be using Medical International Research's Spirobank II Smart https://www.spirometry.com/en/products/spirobank-ii-smart/.
[29] Specifically, we will deploy procure and deploy Purelogic Labs' Prana Air Smart Indoor PM Monitor (https://www.pranaair.com/air-quality-monitor/smart-indoor-pm-monitor/).

This monitor records $PM_{2.5}$ and PM_{10} every 20 minutes and records this data in its built-in SD card.

b. Timeline and implementation

We will conduct the intervention during the last quarter of 2024 (October through December 2024). As shown in Figure 1 above, this is the period of time in which PM pollution in Delhi peaks up and reaches its highest levels.[30] The deployment of the PM pollution monitors in KV School classrooms will begin earlier, in the summer of 2024 (thus, allowing for pre-treatment data collection). The main data collection, however, will be carried out in October and December of 2024. The baseline data survey and spirometry tests will be conducted on October 7th through 11th. During this time, we will also conduct the *Educational and Behavioral Strategies* treatment in randomly selected school classes. During the Autumn break, on October 8th through 17th, we will deploy the HEPA purifiers in randomly selected classrooms, and these will be running throughout the Autumn teaching term. In addition, there will be an endline survey and spirometry tests before the Christmas break (on December 17th to 13th).[31] Finally, there will be a follow-up data collection in which we will obtain administrative data on students' attendance and grades in final examinations. Figure 2 below shows a visual timeline of events.

[30] The reason for termination in December 2024 is to meet the expenditure schedule required by the current funding organizations. However, depending on the availability of funds, we may extend the intervention and data collection into early 2025 and we may conduct an additional round of surveys around February 2025.

[31] This could eventually be relabeled as a 'midline survey' in case we could extend the data collection into early 2025.

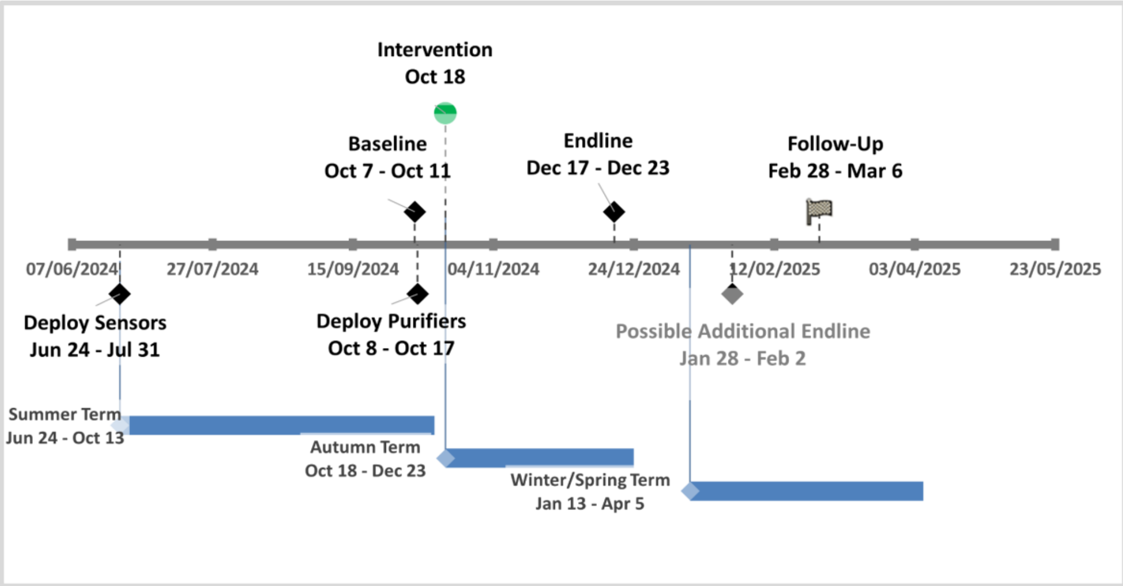


Figure 2: Project Timeline

5. Statistical Analysis

In this work we aim to assess whether technological and behavioral strategies to mitigate effects of high air pollution can result in improved health and better educational outcomes for students in heavily air polluted cities. To that end, here we outline an empirical strategy to first estimate the effects of these strategies on mitigating pollution exposure. Specifically, we want to empirically test the following hypotheses.

Hypothesis H1.1: *Air purifiers Reduce air pollution while students are in the classroom*.

Our empirical strategy consists of estimating the following equation.

$$Pollution_{cst} = \alpha + \beta Purifier_{cst} + \lambda_{cs} + \Gamma_t + \epsilon_{cst} \qquad (1)$$

Where $Pollution_{ct}$ denotes particle pollution (say, fine particulate matter, $PM_{2.5}$) in classroom c in school s in period t. $Purifier_{cst}$ is a dummy equal to one if the classroom has been randomly assigned a purifier and zero otherwise. We control for school-classroom-specific fixed effect λ_{cs}, which may capture factors such as: different levels of principal's engagement and awareness about air pollution issues, whether schools/classrooms are differentially exposed to ambient air pollution, whether classrooms vary in the level of air exchange with outdoor air pollutants, classroom volumetric size, etc. Moreover, we control for a set of time-specific fixed effects, Γ_t, accounting for the differential exposure during different periods of time throughout the year (days, season), as well as during different times of the day (morning, afternoon, etc.). Finally, ϵ_{cst} is an unobserved error term. The parameter β captures the effect of the HEPA purifier on indoor particle pollution. We estimate β by running an OLS regression of equation (1), clustering standard errors at the school-classroom level. To test Hypothesis H1.1. we test the null hypothesis that $\hat{\beta} < 0$ against the alternative that $\hat{\beta} = 0$.

<u>Hypothesis 1.2.a</u>: *Students learn and understand (i) the effects of air pollution in health, (ii) how to identify critical periods of air pollution (i.e., high AQI), and (iii) strategies to mitigate exposure*.

We estimate the following equation:

$$Learning_{icst} = \alpha + \beta_t EBS_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \qquad (2)$$

Where $Learning_{icst}$ refers to three separate indices of learning and understanding of the concepts in (i), (ii) and (iii) (where these are detailed in section 2 above) for student i in classroom c in school s and survey-round t. In this equation EBS_{ics} is a dummy that denotes whether a student and his/her classroom has been randomly assigned to receiving treatment *EBS*, δ_i denotes student-specific fixed effect, λ_{cs} denotes school-classroom-specific fixed effects, D_t denotes survey-round specific dummies and ϵ_{icst} is an error term. The parameter of interest β_t captures the differential effect on learning and understanding of (i) through (iii) of assignment to treatment *EBS*, while allowing for this effect to change over consecutive survey rounds t. A more general specification aggregates over all survey-rounds t and, accordingly, estimates β instead of β_t.

We estimate β_t in equation (2) by running an OLS regression clustering standard errors at the school-classroom and survey-round level. To test Hypothesis H1.2.a. we test the null hypothesis that $\widehat{\beta_t} < 0$ against the alternative that $\widehat{\beta_t} = 0$. We evaluate the more general specification, with only β, as before.

It could be that the effect of treatment *EBS* on learning varies by student's school grade, such that those students in 8th grade could more easily grasp the content of the educational campaign than, say, those students in 6th or 7th grade. To examine this possible differential effect by school grade we interact EBS_{ics} with D_g, where D_g is a school grade-specific dummy.[32]

<u>Hypothesis 1.2.b</u>: *Students change their behavior so as to mitigate their personal exposure.*

We estimate the following equation:

$$Behavior_{icst} = \alpha + \beta_t EBS_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \tag{3}$$

Where $Behavior_{icst}$ refers to an index of self-reported behaviors to mitigate exposure to high air pollution for student i in classroom c in school s and in survey-round t. Moreover, EBS_{ics}, δ_i, λ_{cs}, D_t and ϵ_{icst} are defined as in equation (2) above. To assess Hypothesis 1.2.b we test the null hypothesis that $\widehat{\beta_t} < 0$, against the alternative that $\widehat{\beta_t} = 0$, where we obtain $\widehat{\beta_t}$ by OLS with cluster-robust standard errors. We also test the more general version substituting β for β_t. Additionally, to examine school grade-specific effects of treatment *EBS* on adoption of behavioral strategies we test the school grade-specific model by interacting EBS_{ics} with the grade-specific dummy D_g.

<u>Hypothesis 2</u>: HEPA Purifiers in classrooms and personal mitigation strategies improve students' health.

We estimate the following equation:

$$Health_{icst} = \alpha + \beta_t Mitigation_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \tag{4}$$

Where $Health_{icst}$ refers to respiratory health of student i in classroom c in school s and survey-round t. Specifically, lung capacity (FEV1 and PEF, as measured by spirometry) and an index of self-reported health. Variables δ_i, λ_{cs}, D_t, and ϵ_{icst} are defined as before. Moreover, $Mitigation_{ics}$ refers to either $Purifier_{cs}$ (for treatment *Purifier*) or EBS_{ics} (for treatment *EBS*), and β_t captures the effect of assignment to any of the mitigation strategy treatments on students' respiratory health. A more general version substitutes β_t simply for β. As before, we estimate β_t with cluster-robust standard errors accounting

[32] Recall that we will randomize assignment to treatment at the school grade level, so that, as recommended by Athey and Imbens (2017), we should not be including school-grade-specific fixed effects in our model.

for serial correlation. To assess Hypothesis 2 we test the null of $\beta_t > 0$ against the alternative $\beta_t = 0$.

Moreover, to assess whether there is a differential effect of the two treatments (treatment *Purifier* vs. treatment *EBS*), we estimate equation (4) with both treatments and conduct an F-test of equality of the parameter estimates associated to each treatment. In addition, it could be that the effect of mitigation strategies on health varies by student's age. As student's age is almost perfectly correlated with student's school grade, we examine the differential effects of the mitigation strategies by school grade by interacting $Mitigation_{ics}$ with the grade-specific dummy D_g.

<u>Hypothesis 3</u>: *Technological and behavioral strategies, and their associated improvements in respiratory health, result in better educational outcomes.*

We estimate the following equation:

$$Education_{icst} = \alpha + \beta_t Mitigation_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \tag{5}$$

Where $Education_{icst}$ refers to scores in standardized cognitive tests, school attendance and grades in final exams of student i in classroom c in school s and survey-round t.[33] $Mitigation_{ics}$, δ_i, λ_{cs}, D_t and ϵ_{icst} are defined as before. When running these regressions, we also evaluate whether there is a differential effect of each of the two treatments on educational outcomes by means of running (5) with the two treatments and then conducting an F-test of equality of treatment effects. Moreover, it could be that the effects of mitigation strategies on educational outcomes are mediated by the student's age (proxied by his/her school grade). Thereby, we also interact $Mitigation_{ics}$ with the grade-specific dummy D_g.

In addition, to identify effects on education that are directly linked to the effect of assignment to treatment – via its associated effect on student's respiratory health – we estimate equation (6) below instrumenting $Health_{icst}$ for $Mitigation_{ics}$ (as in equation (4) above) for each mitigation strategy as well as for both strategies simultaneously.[34]

[33] Notice that for school attendance and exam grades we will not be using midlines survey rounds but will be using and endline survey round only.

[34] It could be that parents and/or children believe that students should attend school because there is a HEPA purifier in the classroom or because students are learning about PMS, even though

$$Education_{icst} = \alpha + \beta_t Health_{icst} + \delta_i + \lambda_c + D_t + \epsilon_{ict} \tag{6}$$

Thus, we estimate equation (6) using predicted health, $\widehat{Health}_{icst}$, running a GMM-IV regression with $Mitigation_{ics}$ as instruments, and with cluster-robust standard errors accounting for serial correlation. We also estimate school-grade specific effects of predicted health by interacting it with the dummy D_g. Therefore, to assess Hypothesis 3 we test the null of $\beta_t > 0$ against the alternative $\beta_t = 0$ for standardized cognitive tests and the more general model, using β, for school attendance, exam grades and standardized cognitive tests.

Other Heterogeneous Effects

We may also look at gender heterogeneity. Recent evidence from rural India suggests that girls are more sensitive than boys to the adverse effect of air pollution on math and language test scores (Balakrishnan and Tsaneva, 2021). Balakrishnan and Tsaneva (2021) hypothesize that this could be due to girls experiencing worse health and worse access to health care at baseline. However, this gender heterogeneity has not been examined for urban areas in India, which are exposed to much higher levels of air pollution than rural areas. To examine and test for heterogeneous effects we will interact the main dependent variable in equations (5) and (6) with a dummy variable that captures this heterogeneity (i.e., a gender indicator).

---

these strategies may have no real effect on health. To address this potential effect we use instrumental variable regression.

6. Administrative information

Funding: This work is supported by Environment for Development, Swedish International Development Agency (Grant # MS-1481), and the Northern Ireland Department for the Economy (Grant # R3661QMS).

Institutional Review Board (ethics approval): Ethics approval has been requested from the Institutional Review Board of the Indian Statistical Institute (isical.ac.in). The decision is currently pending.

Declaration of interest: The authors declare having no competing interests nor they have any material or financial interests related to this project.

Acknowledgments: We benefited from valuable discussions with Sefi Roth (LSE), Joshua Graff Zivin (UC San Diego) and Subhrendu K. Pattanayak (Duke University). We acknowledge valuable research assistance from Kritika Chauhan and Valentina González Ortiz.

References

Afridi, F., Debnath, S., and Somanathan, E. (2021). A breath of fresh air: Raising awareness for clean fuel adoption. Journal of Development Economics, 151, 102674.

Aguilar-Gomez, S., Dwyer, H., Graff Zivin, J., & Neidell, M. (2022). This is air: The "Nonhealth" Effects of Air Pollution. Annual Review of Resource Economics, 14, 403-425.

Agusti, A., Fabbri, L. M., Baraldi, E., Celli, B., Corradi, M., Faner, R., ... & Papi, A. (2021). Spirometry: a practical lifespan predictor of global health and chronic respiratory and non-respiratory diseases. European Journal of Internal Medicine, 89, 3-9.

AQLI. The Air Quality Life Index - Annual Update August 2023. (2023). Energy Policy Institute at the University of Chicago. URL: https://aqli.epic.uchicago.edu/reports/

Araban, M., Tavafian, S. S., Zarandi, S. M., Hidarnia, A. R., Burri, A., & Montazeri, A. (2017). A behavioral strategy to minimize air pollution exposure in pregnant women: a randomized controlled trial. Environmental health and preventive medicine, 22(1), 1-8.

Athey, S., & Imbens, G. W. (2017). The econometrics of randomized experiments. In Handbook of economic field experiments (Vol. 1, pp. 73-140). North-Holland.

Balakrishnan, U., & Tsaneva, M. (2021). Air pollution and academic performance: Evidence from India. World Development, 146, 105553.

Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. The quarterly journal of economics, 122(3), 1235-1264.

Barn, P., Gombojav, E., Ochir, C., Laagan, B., Beejin, B., Naidan, G., ... & Allen, R. W. (2018). The effect of portable HEPA filter air cleaners on indoor PM2. 5 concentrations and second hand tobacco smoke exposure among pregnant women in Ulaanbaatar, Mongolia: The UGAAR randomized controlled trial. Science of the Total Environment, 615, 1379-1389.

Berkouwer, S. B., and Dean, J. T. (2023). Private Actions in the Presence of Externalities: The Health Impacts of Reducing Air Pollution Peaks but not Ambient Exposure (No. w31614). National Bureau of Economic Research.

Bharadwaj, P., Gibson, M., Zivin, J. G., & Neilson, C. (2017). Gray matters: Fetal pollution exposure and human capital formation. Journal of the Association of Environmental and Resource Economists, 4(2), 505-542.

Brunetti, R., Del Gatto, C., & Delogu, F. (2014). eCorsi: implementation and testing of the Corsi block-tapping task for digital tablets. Frontiers in psychology, 5, 104751.

Carlsten, C., Salvi, S., Wong, G. W., & Chung, K. F. (2020). Personal strategies to minimise effects of air pollution on respiratory health: advice for providers, patients and the public. European Respiratory Journal, 55(6).

Carmona, N., Seto, E., Gould, T. R., Rasyid, E., Shirai, J. H., Cummings, B. J., ... & Austin, E. (2022). Indoor Air Quality Intervention in Schools: Effectiveness of a Portable

HEPA Filter Deployment in Five Schools Impacted by Roadway and Aircraft Pollution Sources. Atmosphere, 13(10), 1623.

Carneiro, J., Cole, M. A., & Strobl, E. (2021). The effects of air pollution on students' cognitive performance: Evidence from brazilian university entrance tests. Journal of the Association of Environmental and Resource Economists, 8(6), 1051-1077.

Cerami, C., Galandra, C., Santi, G. C., Dodich, A., Cappa, S. F., Vecchi, T., & Crespi, C. (2021). Risk-aversion for negative health outcomes may promote individual compliance to containment measures in Covid-19 pandemic. Frontiers in Psychology, 12, 666454.

Chowdhury, A., Garg, T., Jagnani, M. and Mattson , M. (2024). Adoption and Use of Air Purifiers in Households, (registered report accepted based on pre-results review), Journal of Development Economics.

Cheek, E., Guercio, V., Shrubsole, C., & Dimitroulopoulou, S. (2021). Portable air purification: Review of impacts on indoor air quality and health. Science of the total environment, 766, 142585.

Chen, R., Zhao, A., Chen, H., Zhao, Z., Cai, J., Wang, C., ... & Kan, H. (2015). Cardiopulmonary benefits of reducing indoor particles of outdoor origin: a randomized, double-blind crossover trial of air purifiers. Journal of the American College of Cardiology, 65(21), 2279-2287.

Chen, Siyu, Chongshan Guo, and Xinfei Huang. 2018. Air pollution, student health, and school absences: Evidence from China. Journal of Environmental Economics and Management 92:465–97.

Choudhuri, P., & Desai, S. (2021). Lack of access to clean fuel and piped water and children's educational outcomes in rural India. World Development, 145, 105535.

Cohen, J., & Saran, I. (2018). The impact of packaging and messaging on adherence to malaria treatment: evidence from a randomized controlled trial in Uganda. Journal of Development Economics, 134, 68-95.

Cui, X., Li, F., Xiang, J., Fang, L., Chung, M. K., Day, D. B., ... & Zhang, J. J. (2018). Cardiopulmonary effects of overnight indoor air filtration in healthy non-smoking adults: a double-blind randomized crossover study. Environment international, 114, 27-36.

Currie, Janet, and Matthew Neidell. "Air pollution and infant health: what can we learn from California's recent experience?." The Quarterly Journal of Economics 120, no. 3 (2005): 1003-1030.

Currie, Janet, Eric A. Hanushek, E. Megan Kahn, Matthew Neidell, and Steven G. Rivkin. "Does pollution increase school absences?." The Review of Economics and Statistics 91, no. 4 (2009): 682-694.

Currie, Janet, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell. "What do we know about short-and long-term effects of early-life exposure to pollution?." Annu. Rev. Resour. Econ. 6, no. 1 (2014): 217-247.

Cutler, D., Fung, W., Kremer, M., Singhal, M., & Vogl, T. (2010). Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in India. American Economic Journal: Applied Economics, 2(2), 72-94.

Dammert, A. C., Galdo, J. C., & Galdo, V. (2014). Preventing dengue through mobile phones: evidence from a field experiment in Peru. Journal of Health Economics, 35, 147-161.

Derksen, L., Muula, A., & van Oosterhout, J. (2022). Love in the time of HIV: How beliefs about externalities impact health behavior. Journal of Development Economics, 159, 102993.

Dirks, K. N., Wang, J. Y., Khan, A., & Rushton, C. (2016). Air pollution exposure in relation to the commute to school: a Bradford UK case study. International journal of environmental research and public health, 13(11), 1064.

Dong, W., Liu, S., Chu, M., Zhao, B., Yang, D., Chen, C., ... & Deng, F. (2019). Different cardiorespiratory effects of indoor air pollution intervention with ionization air purifier: findings from a randomized, double-blind crossover study among school children in Beijing. Environmental Pollution, 254, 113054.

Dupas, P. (2011). Health behavior in developing countries. Annual Review of Economics, 3(1), 425-449.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth, "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution," American Economic Journal: Applied Economics, 10 2016, 8 (4), 36–65.

Foster, A., & Kumar, N. (2011). Health effects of air quality regulations in Delhi, India. Atmospheric Environment, 45(9), 1675-1683.

Giles, L. V., & Koehle, M. S. (2014). The health effects of exercising in air pollution. Sports Medicine, 44, 223-249.

Gilraine, M. (2023). Air Filters, Pollution, and Student Achievement. Journal of Human Resources.

Goldizen, F. C., Sly, P. D., & Knibbs, L. D. (2016). Respiratory effects of air pollution on children. Pediatric pulmonology, 51(1), 94-108.

Guan, T., Hu, S., Han, Y., Wang, R., Zhu, Q., Hu, Y., ... & Zhu, T. (2018). The effects of facemasks on airway inflammation and endothelial dysfunction in healthy young adults: a double-blind, randomized, controlled crossover study. Particle and fibre toxicology, 15, 1-12.

Hankey, S., Lindsey, G., & Marshall, J. D. (2017). Population-level exposure to particulate air pollution during active travel: planning for low-exposure, health-promoting cities. Environmental health perspectives, 125(4), 527-534.

HEI. Health Effects Institute. (2020). State of Global Air 2020. Special Report. Boston, MA:Health Effects Institute. URL: https://www.healthdata.org/research-analysis/library/state-global-air-2020.

Heissel, J. A., Persico, C., and Simon, D. (2022). Does pollution drive achievement? The effect of traffic pollution on academic performance. Journal of Human Resources, 57(3), 747-776.

Heyes, A., and Saberian, S. (2024). Pollution and learning: Causal evidence from Obama's Iran Sanctions. Journal of Environmental Economics and Management, 102965.

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

IQAir. (2024). Most polluted city ranking based on annual average PM2.5 concentration ($\mu g/m^3$) URL: https://www.iqair.com/us/world-most-polluted-cities

Jasemzadeh, M., Khafaie, M. A., Jaafarzadeh, N., & Araban, M. (2018). Effectiveness of a theory-based mobile phone text message intervention for improving protective behaviors of pregnant women against air pollution: a randomized controlled trial. Environmental Science and Pollution Research, 25, 6648-6655.

Jeuland, M., Pattanayak, S. K., Tan Soo, J. S., & Usmani, F. (2020). Preferences and the effectiveness of behavior-change interventions: Evidence from adoption of improved cookstoves in India. Journal of the Association of Environmental and Resource Economists, 7(2), 305-343.

Ke, L., Zhang, Y., Fu, Y., Shen, X., Zhang, Y., Ma, X., & Di, Q. (2022). Short-term $PM_{2.5}$ exposure and cognitive function: Association and neurophysiological mechanisms. Environment International, 170, 107593.

Krebs, B., Burney, J., Zivin, J. G., & Neidell, M. (2021). Using crowd-sourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. Environmental Science & Technology, 55(9), 6107-6115.

Lanphear, B. P., Hornung, R. W., Khoury, J., Yolton, K., Lierl, M., & Kalkbrenner, A. (2011). Effects of HEPA air cleaners on unscheduled asthma visits and asthma symptoms for children exposed to secondhand tobacco smoke. Pediatrics, 127(1), 93-101.

Laumbach, R., Meng, Q., & Kipen, H. (2015). What can individuals do to reduce personal health risks from air pollution?. Journal of thoracic disease, 7(1), 96.

Laumbach, R. J., & Cromar, K. R. (2022). Personal interventions to reduce exposure to outdoor air pollution. Annual Review of Public Health, 43, 293-309.

Lucas, A. M. (2010). Malaria eradication and educational attainment: evidence from Paraguay and Sri Lanka. American Economic Journal: Applied Economics, 2(2), 46-71.

Luoto, J., Levine, D., Albert, J., & Luby, S. (2014). Nudging to use: Achieving safe water behaviors in Kenya and Bangladesh. Journal of Development Economics, 110, 13-21.

Madajewicz, M., Pfaff, A., Van Geen, A., Graziano, J., Hussein, I., Momotaj, H., Sylvi, R., and Ahsan, H. (2007). Can information alone change behavior? Response to arsenic contamination of groundwater in Bangladesh. Journal of Development Economics, 84(2), 731-754.

Madureira, J., Brancher, E. A., Costa, C., de Pinho, R. A., & Teixeira, J. P. (2019). Cardio-respiratory health effects of exposure to traffic-related air pollutants while exercising outdoors: A systematic review. Environmental research, 178, 108647.

Mirabelli, M. C., Golan, R., Greenwald, R., Raysoni, A. U., Holguin, F., Kewada, P., ... & Sarnat, J. A. (2015). Modification of traffic-related respiratory response by asthma control in a population of car commuters. Epidemiology, 26(4), 546-555.

Nhung, N. T. T., Amini, H., Schindler, C., Joss, M. K., Dien, T. M., Probst-Hensch, N., ... & Künzli, N. (2017). Short-term association between ambient air pollution and pneumonia in children: A systematic review and meta-analysis of time-series and case-crossover studies. Environmental Pollution, 230, 1000-1008.

Pattanayak, S. K., Jeuland, M., Lewis, J. J., Usmani, F., Brooks, N., Bhojvaid, V., ... & Ramanathan, V. (2019). Experimental evidence on promotion of electric and improved biomass cookstoves. Proceedings of the National Academy of Sciences, 116(27), 13282-13287.

Petrocchi, S., Iannello, P., Ongaro, G., Antonietti, A., & Pravettoni, G. (2022). The interplay between risk and protective factors during the initial height of the COVID-19 crisis in Italy: The role of risk aversion and intolerance of ambiguity on distress. Current psychology, 41, 437-448.

Phipatanakul, W., Koutrakis, P., Coull, B. A., Petty, C. R., Gaffin, J. M., Sheehan, W. J., ... & School Inner-City Asthma Intervention study team. (2021). Effect of school integrated pest management or classroom air filter purifiers on asthma symptoms in students with active asthma: a randomized clinical trial. Jama, 326(9), 839-850.

Rice, M. B., Ljungman, P. L., Wilker, E. H., Gold, D. R., Schwartz, J. D., Koutrakis, P., ... & Mittleman, M. A. (2013). Short-term exposure to air pollution and lung function in the Framingham Heart Study. American journal of respiratory and critical care medicine, 188(11), 1351-1357.

Roth, S. (2020). The effect of indoor air pollution on cognitive performance: Evidence from the UK. Manuscript, London School of Economics https://personal. lse.ac.uk/roths/JMP.pdf.

Schwartz, J. (2004). Air pollution and children's health. Pediatrics, 113(Supplement_3), 1037-1043.

Shakya, K. M., Rupakheti, M., Aryal, K., & Peltier, R. E. (2016). Respiratory effects of high levels of particulate exposure in a cohort of traffic police in Kathmandu, Nepal. Journal of Occupational and Environmental Medicine, 58(6), e218-e225.

Zhang, X., Chen, X., & Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. Proceedings of the National Academy of Sciences, 115(37), 9193-9197.

Shi, J., Lin, Z., Chen, R., Wang, C., Yang, C., Cai, J., ... & Kan, H. (2017). Cardiovascular benefits of wearing particulate-filtering respirators: a randomized crossover trial. Environmental health perspectives, 125(2), 175-180.

Sinharay, R., Gong, J., Barratt, B., Ohman-Strickland, P., Ernst, S., Kelly, F. J., ... & Chung, K. F. (2018). Respiratory and cardiovascular responses to walking down a traffic-polluted road compared with walking in a traffic-free area in participants aged 60 years and older with chronic lung or heart disease and age-matched healthy controls: a randomised, crossover study. The Lancet, 391(10118), 339-349.

Singh, D., Gupta, I., & Dey, S. (2022). Effect of Air Pollution on Cognitive Performance in India (No. 452). Institute of Economic Growth.

Singh, Tejendra Pratap, Beyond The Haze: Air Pollution and Student Absenteeism - Evidence from India (May 2, 2022). Available at SSRN: https://ssrn.com/abstract=3680588 or http://dx.doi.org/10.2139/ssrn.3680588

Steffen, J., & Cheng, J. (2021). The influence of gain-loss framing and its interaction with political ideology on social distancing and mask wearing compliance during the COVID-19 pandemic. Current Psychology, 1-11.

Tong, Z., Li, Y., Westerdahl, D., & Freeman, R. B. (2020). The impact of air filtration units on primary school students’ indoor exposure to particulate matter in China. Environmental Pollution, 266, 115107.

UNICEF, United Nations Children’s Fund (2016). Clear the air for children - The impact of air pollution on children. https://www.unicef.org/reports/clean-air-children. ISBN: 978-92-806-4854-6.

Vyas, S., Srivastav, N., & Spears, D. (2016). An experiment with air purifiers in Delhi during Winter 2015-2016. PloS one, 11(12), e0167999.

Weichenthal, S., Mallach, G., Kulka, R., Black, A., Wheeler, A., You, H., ... & Sharp, D. (2013). A randomized double-blind crossover study of indoor air filtration and acute changes in cardiorespiratory health in a First Nations community. Indoor air, 23(3), 175-184.

Whitehouse, A., & Grigg, J. M. (2018). The air they breathe; where children are exposed to air pollution. In B23. ENVIRONMENTAL EPIDEMIOLOGICAL INVESTIGATIONS IN ASTHMA (pp. A2803-A2803). American Thoracic Society.

Whitehouse, A., & Grigg, J. (2021). Teaching Air Pollution to Children-Clinical research and education colliding.

WHO. World Health Organization. (2016). Ambient air pollution: A global assessment of exposure and burden of disease. https://www.who.int/publications/i/item/9789241511353. ISBN: 978 92 4 151135 3.

WHO. World Health Organization (2020), Personal Interventions and Risk Communication on Air Pollution. Meeting Report. https://www.who.int/publications/i/item/9789240000278. ISBN: 978 92 4 000027 8.

Yang, D., Allen Iv, J., Mahumane, A., Riddell Iv, J., & Yu, H. (2023). Knowledge, stigma, and HIV testing: An analysis of a widespread HIV/AIDS program. Journal of Development Economics, 160, 102958.

Yang, X., Wang, Q., Han, F., Dong, B., Wen, B., Li, L., ... & Xu, D. (2021). Pulmonary Benefits of Intervention with HEPA Air Purifier in Schoolchildren: A Double-Blind Crossover Study.

Yao, Z., Zhang, W., Ji, X., & Weng, W. (2023). Short-Term Exposure to Air Pollution and Cognitive Performance: New Evidence from China's College English Test. Environmental and Resource Economics, 1-27.

Yu, H. (2023). Social stigma as a barrier to HIV testing: Evidence from a randomized experiment in Mozambique. Journal of Development Economics, 161, 103035.

Zhang, J., & Xu, L. C. (2016). The long-run effects of treated water on education: The rural drinking water program in China. Journal of Development Economics, 122, 1-15.

Zhou, Y., Zou, Y., Li, X., Chen, S., Zhao, Z., He, F., ... & Ran, P. (2014). Lung function and incidence of chronic obstructive pulmonary disease after improved cooking fuels and kitchen ventilation: a 9-year prospective cohort study. PLoS medicine, 11(3), e1001621.

Appendices

A. Additional Materials

1. Pilot Analysis

A pilot study was conducted on a sample of 7 schools during the period August through December 2022. The intervention consisted of deploying large-capacity HEPA purifiers in 3rd grade classrooms. Due to the reduced number of devices all schools were treated (i.e., there was no control group), benefiting a total of 157 children. The pilot's objective was to assess the performance of the air purifier devices in a school environment over a long period of time, and to estimate the potential effects on students' attendance resulting from reductions in PM pollution inside the classroom.

To measure air pollution exposure, the head teacher in each class was asked to record indoor PM pollution levels – as displayed by the devices – four times per day (i.e., at the start of the days, before and after each recess, and at the end of the day). Daily attendance at the individual level data was provided by each school and month-level attendance at the class-level was obtained for comparable schools. We calculated attendance rates for both treated schools and non-treated schools for classes in 2nd, 3rd and 4th grade. Moreover, we generated a dummy variable for before and after the air purifiers were deployed (dummy 'After') and a dummy variable denoting those schools that received the air purifier (dummy 'AirPurSchool'), and a third dummy variable denoting the interaction of these two (dummy 'WithAirPur'). The parameter associated with this interactive dummy represents the difference-in-difference estimate of the effect of an air purifier in the classroom on school attendance rate (the standard errors are clustered at the school-level). Results from Table A.1 below show that the deployment of air purifiers resulted in an increase of 6 percentual points in attendance rate, which translates into an 8 percent increase in school attendance.

	Attendance Rate		
	Second Grade	Third Grade	Fourth Grade
WithAirPur	0.017	0.060**	0.009
	[0.018]	[0.023]	[0.034]
AirPurSchool	0.038	-0.012	0.025
	[0.063]	[0.051]	[0.029]
After	0.014	0.006	0.015
	[0.011]	[0.009]	[0.008]
Constant	0.684***	0.749***	0.736***
	[0.032]	[0.028]	[0.016]
Mean of Dep. Var.	0.693	0.744	0.741
N	2,436	1,562	2,033

Notes: Parameter estimates from an OLS regression of attendance rate (defined as number of attended days over the number of days the school was in session) on a set of DiD dummies: 'AirPurSchool' denotes whether the school was assigned to receiving an air purifier, 'After' denotes observations once this purifier was in place (Aug 1st, 2022), and 'WithAirPur' denotes the interaction of these two dummies. Each individual observation is weighted by the number of days the school was in session during the month. Standard errors clustered at the school level in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table A.1: Parameter estimates from Difference-in-Difference regressions analysis.

1. Figure A.1: Average $PM_{2.5}$ Pollution in Indian States

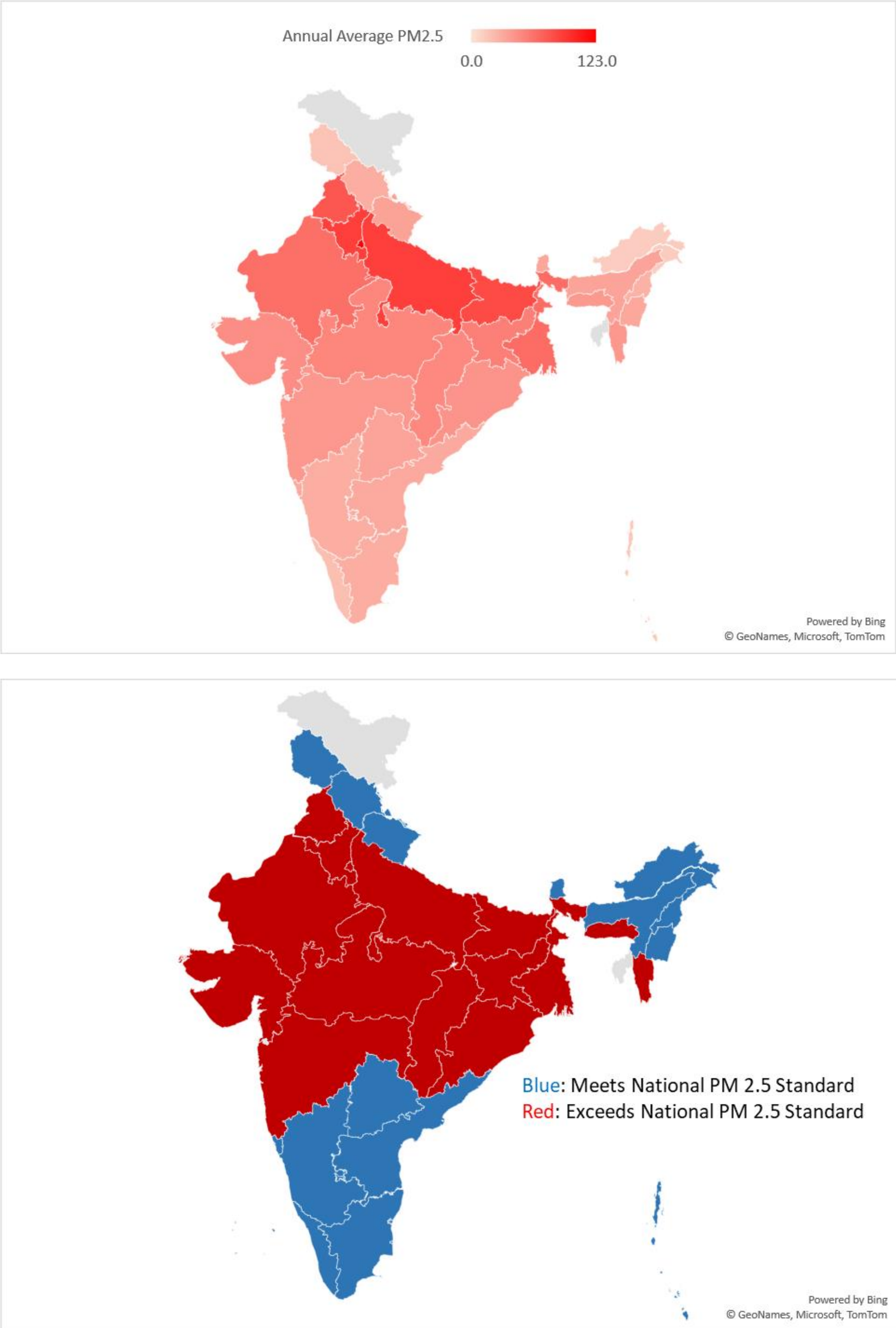


Figure 2: Annual average PM 2.5 for Indian states, in 2018. Source: urbanemissions.info

The top panel shows state wise average annual $PM_{2.5}$ concentrations in 2018. Darker colors imply higher concentrations, while lighter colors imply lower concentrations. The scale ranges from 0 to 123 μ/m^3. The states that are located in the northern part of the country are much more polluted, in particular the states located just south of the

Himalayan Mountain range. Using the national standard of 40 μ/m^3, the bottom panel in Figure 2 splits states into whether their annual averages were above or below this national standard. States colored blue had annual average $PM_{2.5}$ concentrations below the national standard, and thus met the national standard. States colored red had annual average $PM_{2.5}$ concentrations above the national standard, and thus exceeded the national standard. As is clear, most states located in the central or northern parts of the country had $PM_{2.5}$ levels above the national standard.

B. Survey Questionnaires

1. Air Pollution, Respiratory Symptoms & Socioeconomics

For our project-specific questionnaire, please open this document:

https://drive.google.com/file/d/1wqgeTLQKyOiHShsCCcTy4h9Mt47ZIWFP/view?usp=sharing

2. Young Lives School Survey – Language Questionnaire

For the language questionnaire (in English), please open this document:

https://www.younglives.org.uk/sites/default/files/migrated/TEST_English%20Form_Wave%201%20FINAL.pdf

3. Young Lives School Survey – Math Questionnaire

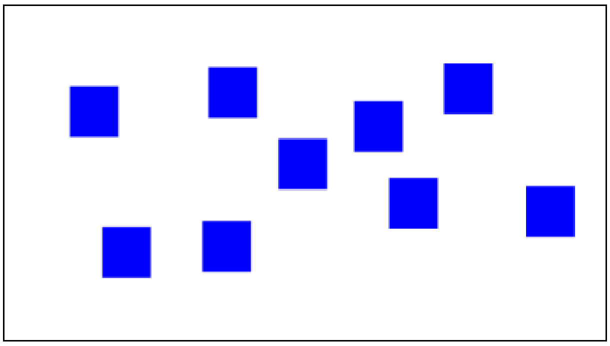
For the math questionnaire (in English), please open this document:

https://www.younglives.org.uk/sites/default/files/2021-12/School%20survey%202016-17_in_w1_Students%20Maths%20Test_0.pdf

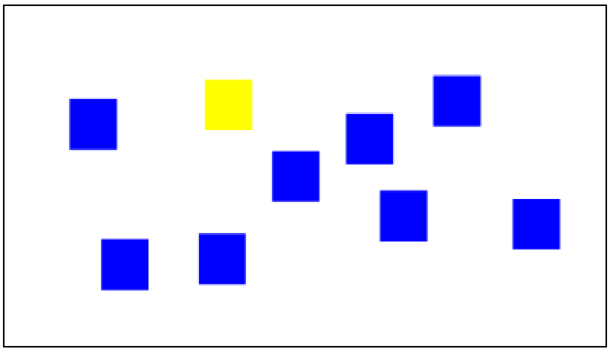
4. Corsi Memory Test

Following Berkouwer and Dean (2024), we will implement the Reverse Corsi Block task on a Tablet device. For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up yellow. Students are then asked to tap the blocks in reverse order as how they lit up (see figure below). For each block in the sequence, if the student taps on the correct block, it turns on green and the student can proceed to tapping on the next block in the sequence. If the respondent taps on the wrong block, it flashes red and the trial ends. The student then moves on to the next trial. The first trial sequence contains only two blocks, and consecutive trials keep on adding one additional block.

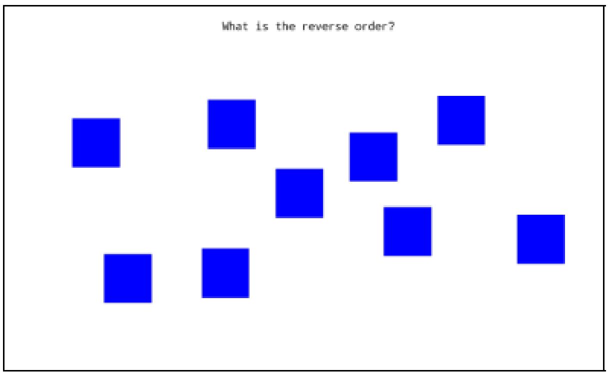
(a) Blocks appear in random positions



(b) Blocks light up yellow randomly

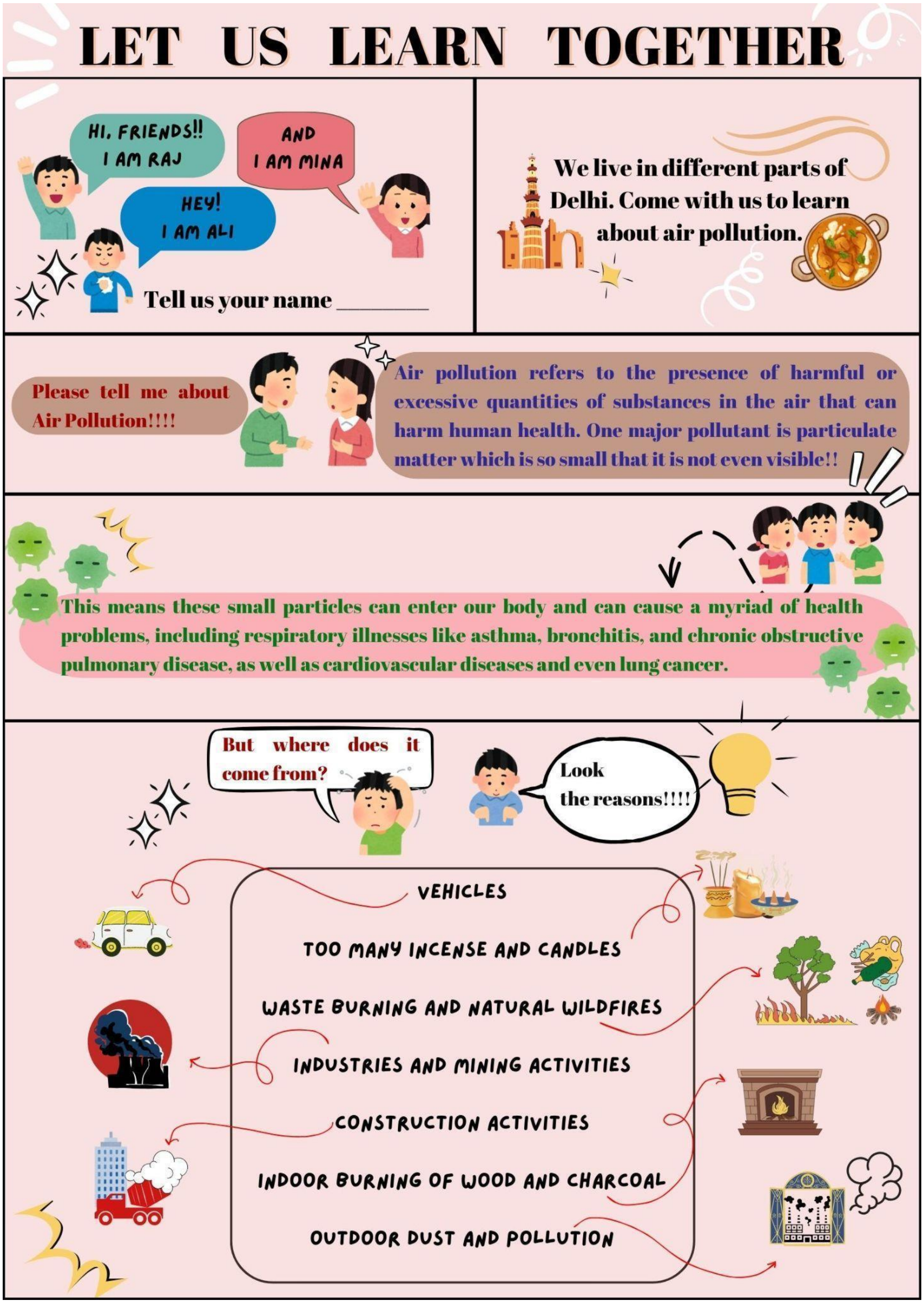


(c) Respondents tap blocks in reverse order

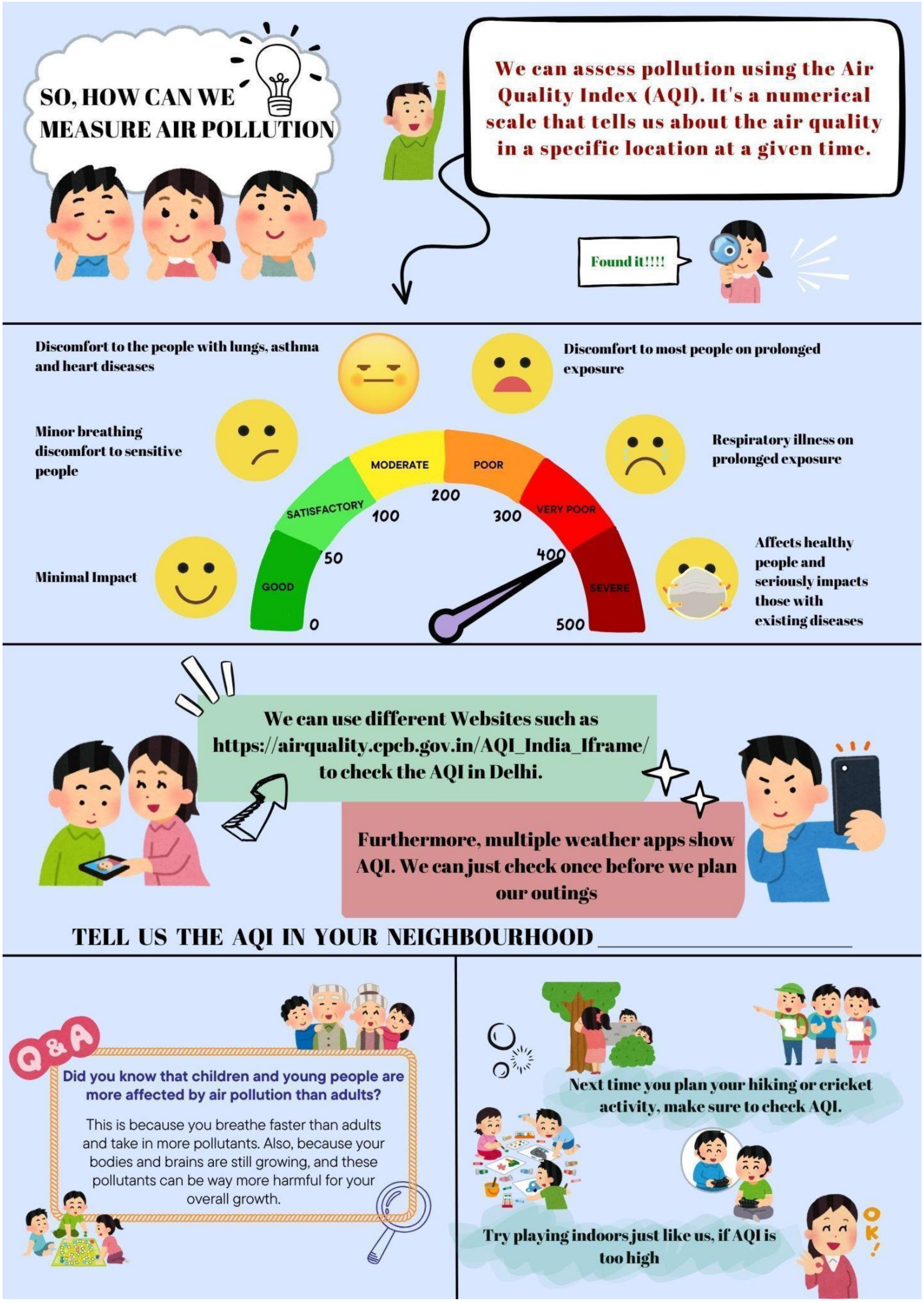


C. Figures for Educational and Behavioral Strategies

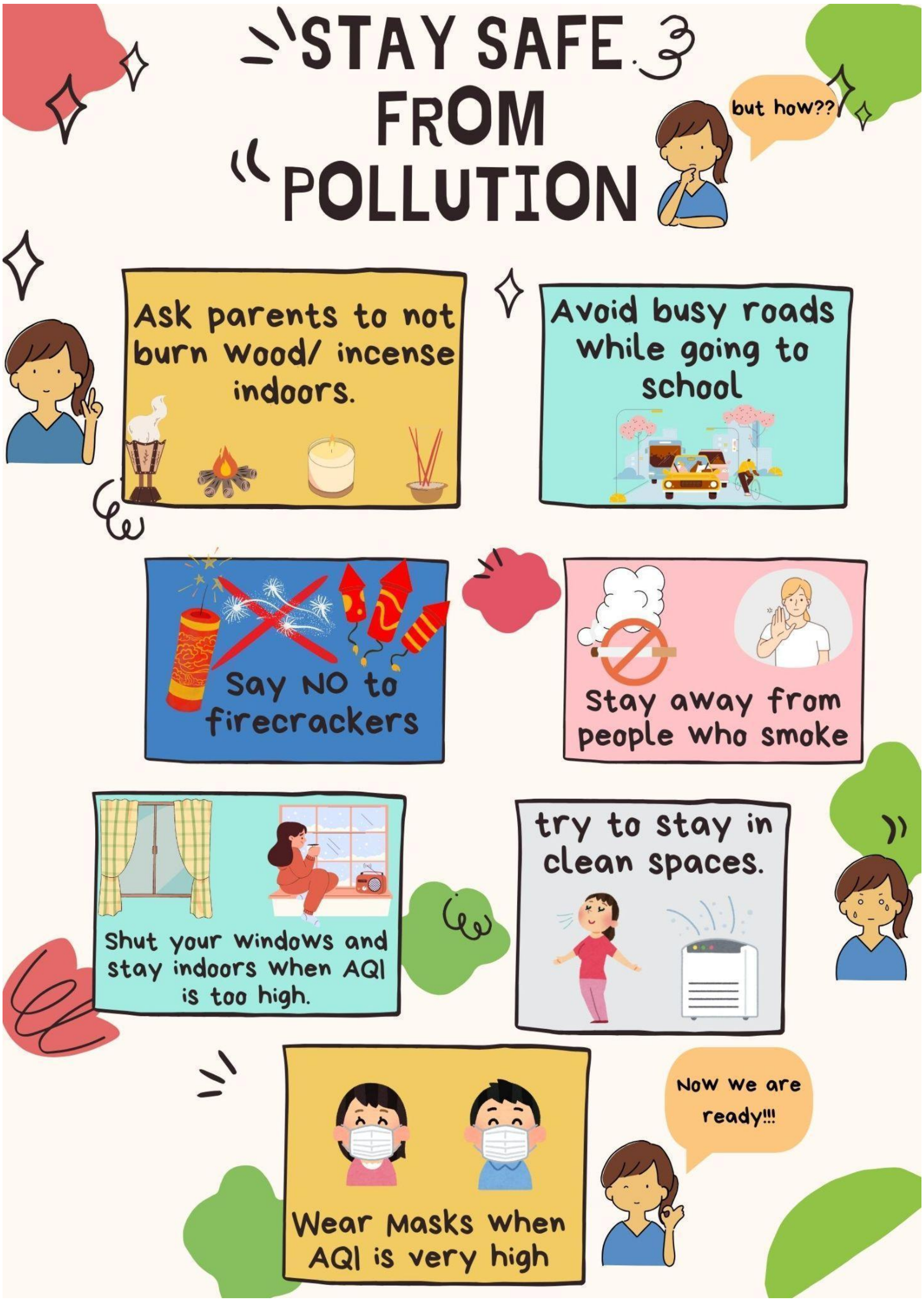
1. Example of Educational Material for Teaching About the Effects of Air Pollution on Health.



2. Example of Educational Material for Teaching Students How to Identify When Air Pollution Has Reached Critical Levels.



3. Example of Educational Material for Teaching About Strategies to Mitigate the Effects of Air Pollution on Health.



Author Statement

J. Cristobal Ruiz-Tagle

Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing

Nikita Sangwan

Conceptualization, Funding acquisition, Project administration, Supervision

M. Marcela Jaime

Funding acquisition, Investigation, Resources

César Salazar

Funding acquisition, Investigation, Resources

Kanishka Kacker

Data curation, Funding acquisition, Investigation, Resources, Supervision

Pankaj Kumar

Investigation, Project administration, Resources, Supervision

1. Introduction

Air pollution is linked to millions of deaths in the developing world and a myriad of other health problems (WHO 2016, HEI 2020). South Asia, and India in particular, suffers from some of the highest air pollution concentrations, where Delhi consistently ranks at the very top of the most polluted cities in the world (IQAir, 2024). Air pollution is linked to 5.3 fewer years of life expectancy for India and 11.9 fewer years of life expectancy for Delhi (AQLI 2023), on average. In this work we experimentally assess technological and behavioral strategies to mitigate the adverse effects of air pollution on the health and educational outcomes of school children in Delhi.

Air pollution also negatively impacts education and human capital accumulation, thus hampering human and economic development (Aguilar-Gomez et al., 2022). Avoiding exposure to air pollutants is especially important for children (Nhung et al., 2017; Goldizen et al., 2016; Schwartz, 2014) and for those suffering from chronic pulmonary diseases, such as asthma, which is more prevalent in children (Laumbach et al., 2015).[1] Air pollution is causally linked to adverse effects on children's health (Currie and Neidell, 2005), school absenteeism (Currie et al., 2009; Chen et al., 2018), standardized test scores (Bharadwaj et al., 2017; Carneiro et al., 2021; Heissel at al., 2022; Heyes and Saberian, 2024) as well as test-takers' future wages (Ebenstein et al., 2016). For India, fine particulate matter (i.e., particulates of size of 2.5 microns or smaller, $PM_{2.5}$) is causally linked to increased school absenteeism (Singh,2022) and reduced academic performance of children in rural (Balakrishnan and Tsaneva, 2021) and urban areas (Singh et al., 2022). Moreover, high levels of air pollution in childhood can carry long-lasting negative consequences well into adulthood (Isen and Walker, 2017).

Control of air pollution has proven very challenging for developing countries. Air pollution is a multifaceted problem involving many actors, economic sectors and even varying geographies as the source of air pollutants. Moreover, developing countries often seek to raise living standards through added manufacturing activity of highly polluting industries, a view in which air pollution control is not a priority. The problem is made

[1] Children are more sensitive than adults to air pollution because they have a faster breathing rate, a relatively immature respiratory system and overall lower immunity. Moreover, due to their young ages, children are more likely to suffer from cumulative cognitive impacts from air pollution exposure (Ke at al., 2022).

worse by weak regulatory capacity. Recent policies that target the sources of air pollution in Delhi have shown some progress, but these have not achieved improvements at the magnitude and speed necessary to bring air pollution down near safe levels in the foreseeable future. In lieu of the magnitude of the problem and slow progress, individuals are often left with few options other than suffering from high levels of air pollution and/or engage in private defensive investments (such as buying air purifiers) and personal adoption of exposure mitigation strategies (henceforth, ‘behavioral strategies’).[2,3] We discuss these strategies in turn.

Adoption of behavioral strategies to mitigate exposure to air pollution has been shown to be effective at mitigating the adverse effects of air pollution on health. For example, wearing face masks has been shown to reduce airway inflammation associated with particle air pollution (Guan et al., 2018), reduce the decline of lung function (Shakya et al., 2016), and improve measures of blood pressure (Shi et al. 2017). Avoiding cooking with biomass and solid fuels and ventilating indoor cooking areas has been shown to improve lung function and reduce the risk of chronic obstructive pulmonary disease (COPD) (Zhou et al., 2014). Staying indoors on high-pollution days and limiting physical activity outdoors, or near sources of air pollution, has been shown to decrease markers of respiratory and systemic inflammation (Giles and Koehle, 2014; Madureira et al., 2019). For those who suffer from asthma, higher asthma control (with the correct use of inhalers) has been shown to mitigate the adverse effects of $PM_{2.5}$ pollution on lung capacity (Mirabelli et al., 2015).[4] In terms of adoption of comprehensive behavioral strategies, Araban et al. (2017) find that an educational program can positively change the behavior of pregnant women in Iran by modifying outdoor activity, particularly

---

[2] Private defensive strategies can serve as both complementary measures as well as a stopgap until effective long-term public policies to reduce air pollution are drafted and enacted.

[3] Some key personal behavioral strategies for the Indian context include the following: wearing masks on days in which air pollution reaches critical levels; avoiding bursting firecrackers; avoiding exercising outside and staying indoors when outdoor pollution is high; avoiding spending time near those that smoke; avoiding sources of indoor air pollution at home, such as minimizing burning incense, oil candles ('diyas'); avoiding burning biomass indoors and clear fumes/smoke in kitchen area, etc. We will discuss these in further detail in the Interventions section.

[4] For a thorough discussion of the evidence, from clinical trials, on behavioral strategies to mitigate the adverse effects of air pollution see Carlsten et al. (2020). Moreover, Laumbach and Cromar (2022) reviews the evidence for and against personal mitigation strategies and provide public health recommendations for the context of high-income countries, whereas WHO (2020) provides public health advice for low- and middle-income countries.

during episodes in which air quality alerts are issued.[5] However, to the best of our knowledge, there is no experimental evaluation of the effects of a campaign involving a comprehensive package of behavioral strategies for mitigating the effect of air pollution exposure on students' health and educational outcomes.

On the other hand, air purifiers are a defensive technology that has proven effective at reducing indoor air pollution and improving health (Cheek et al., 2021). The existing literature finds that High-Efficiency Particulate Air (HEPA) purifiers reduced ultra fine particulate matter concentrations by 71 percent inside unoccupied school classrooms in Washington State, USA (Carmona et al., 2022)[6], and reduced $PM_{2.5}$ concentrations by 70 percent inside primary school classrooms in Hangzhou, China (Tong et al., 2020). Moreover, these HEPA air purifiers in school classrooms resulted in positive effects on a variety of children's respiratory outcomes in China (Yang et al., 2021)[7], but no effect on asthmatic children in schools in the northeast of the USA (Phipatanakul et al., 2021) where children are exposed to significantly lower levels of $PM_{2.5}$ pollution.[8] However, to the best of our knowledge, there is no experimental assessment of the potential for HEPA air purifiers to improve children's educational outcomes in any major city in India.[9]

This work aims to fill the gaps in the literature by providing experimental evidence on the link between both behavioral strategies to mitigate air pollution exposure and technological strategies to reduce air pollution in classrooms, and the associated effects on accumulation of human capital, broadly defined (i.e., maintaining good health, achieving a good education, and gaining productive skills) — a key factor in the pursuit

[5] The intervention was composed of three parts: a motivational workshop, a booklet and daily SMS text messages. See also Jasemzadeh et al. (2018).

[6] For a review of the literature on the effects of HEPA air purifiers in the USA, see Cheek et al. (2021).

[7] Importantly, Yang et al. (2021) does not link children's respiratory outcomes to their educational performance. Regarding other health outcomes associated with reduced air pollution due to deployment of HEPA air purifiers, the existing literature finds positive effects in reducing blood cadmium of pregnant women in Mongolia (Barn et al., 2018), decrease in children's visits to doctors in Ohio, USA (Lanphear et al., 2011), reductions in airway inflammation among college students in Shanghai, China (Chen at al., 2015), an improvement in airway mechanics of healthy young adults in Shanghai, China (Cui et al., 2018).

[8] Children in the USA study are exposed to average $PM_{2.5}$ concentrations of 5.4 $\mu g/m^3$, whereas children in the China study are exposed to average $PM_{2.5}$ concentrations of 72 $\mu g/m^3$.

[9] For our sample of KV schools in Delhi the average $PM_{2.5}$ concentrations ranges from 142 $\mu g/m^3$ to 231 $\mu g/m^3$ for the period October 2023 to January 2024 (a period of time comparable to that of our intervention). This is twice as large as the average $PM_{2.5}$ concentrations for children in China reported by Yang et al., (2021). This is important because there is compelling evidence that the effect of air pollution on health needs not be linear, so that extrapolation from existing literature to a setting with air pollution concentrations such as in India may yield bias results.

of human and economic development. We believe that schools are an ideal setting for enhancing awareness of air pollution problems from an early stage through informational and educational campaigns. Students are used to a teaching and learning environment in school, and evidence shows that they can remember specific taught points when being taught about air pollution (Whitehouse and Grigg, 2021). Moreover, schools constitute a setting in which this sort of intervention could potentially be scaled up with only small changes in the teaching curriculum. On the other hand, although air purifiers have become relatively more affordable over recent years, there are still important financial constraints for households in developing countries to buy air purifiers for their homes.[10] Moreover, as children spend a large fraction of their daily time at school, air purifiers at home provide only a partial solution to mitigating exposure to indoor air pollution. Importantly, children are usually the least likely to be able to protect themselves from high air pollution. Children, and/or their caregivers, cannot privately engage in purchasing this technological defense for their school classrooms as only educational authorities can allow for and can carry out this sort of policy.

Thus, in this work we experimentally assess the potential of both a comprehensive educational campaign of behavioral strategies – tailored to students' environmental and sociocultural context – and HEPA purifiers in classrooms and for mitigating the adverse effects of air pollution on children in Delhi's schools, a setting of very high air pollution. We hypothesize that: [H1] Adoption of behavioral strategies mitigates students' exposure to high air pollution and HEPA purifiers in classrooms reduce indoor air pollution.[11] Moreover, we hypothesize that [H2] these behavioral and technological strategies improve students' respiratory health; and that [H3] these strategies and their associated improvements in respiratory health result in better educational outcomes.

To test these hypotheses, we will conduct a randomized controlled trial (RCT) in about 9,000 students from 180 classes in KV Schools in Delhi. We will evaluate two interventions aimed at mitigating the adverse effects of air pollution in children. In the first intervention we conduct an educational campaign among students of these schools designed to teach them about both the effect of air pollution on health and about

[10] Due to economies of scale for large spaces, HEPA purifiers for purifying indoor air in classrooms are relatively cheaper than for purifying indoor air in homes.

[11] More specifically, we hypothesize that students learn and understand (i) the effects of air pollution in health, (ii) how to identify critical periods of air pollution (i.e., high Air Quality Index, AQI), and (iii) once taught, students change their behavior so as to adopt strategies that mitigate their personal exposure.

behavioral strategies to mitigate the harmful effects of exposure, thus seeking to encourage adoption of these strategies for students in Delhi's KV schools. In the second intervention, in addition to the educational campaign, we also deploy HEPA purifiers in randomly selected classrooms of these schools. We evaluate these interventions by measuring self-reported adoption of personal mitigation strategies and monitoring air pollution inside the classrooms. Moreover, we evaluate health effects associated with reduced indoor air pollution and exposure – by measuring students' lung capacity and self-reported health – and evaluate educational outcomes — specifically, scores in standardized cognitive tests, school attendance, and grades in final exams. Evidence from our pilots shows that HEPA air purifiers can effectively reduce indoor air pollution inside the classroom, and that this reduction is linked to an improvement in students' school attendance (see Appendix A.1 below).

This work makes four contributions to the broader literature of environment, health and education in developing economies.

First, this work advances the literature by focusing on the role of information and education in protecting children's health. More specifically, this work proposes to examine the added effect of a tailored educational campaign that seeks to promote behavioral change for reducing exposure to air pollution among school children. Information-based interventions can be easily scaled up. Therefore, assessing experimentally the effect of this intervention can inform policymakers about the cost-effectiveness of this type of policy.

Second, this work contributes to the literature on technology adoption for mitigating environmental hazards and improving health in developing countries. For example, the literature on the adoption of clean cookstoves (Pattanayak et al., 2019; Jeuland et al., 2020; Afridi et al., 2021; Berkouwer and Dean, 2023) has found that improved cookstoves result in a significant decrease in peak indoor air pollution although finds no statistically significant decrease in average exposure to air pollution nor in health biomarkers (Berkouwer and Dean, 2023). In a closely related paper, Chowdhury et al. (2024) is examining the drivers of adoption of HEPA purifiers and their associated effects on health and labor outcomes at the household level (although results have not been reported yet). This work expands this literature by examining the potential of HEPA purifiers for mitigating the adverse effects of indoor air pollution on children's health and educational performance in developing countries.

Third, this work contributes to the broad literature on development economics that seeks to understand the barriers to adopting highly effective preventive behavior for mitigating the burden of multiple health hazards and diseases faced by developing countries (Dupas, 2011). One possible explanation for this low adoption is a lack of information on the consequences of health hazards and diseases and the effectiveness of preventative behaviors (Dupas, 2011). In this regard, our work expands the limited literature that evaluates the implementation of educational campaigns to incentivize better healthcare practices and thus improve human health.[12] Our work expands this literature by designing an educational campaign that not only delivers information but also teaches actionable behavioral strategies for encouraging adoption of preventive behavior among school children.

Fourth, we assess whether these health-enhancing strategies could also positively affect educational outcomes. Current empirical evidence from public health campaigns aimed at eradicating persistent diseases in developing countries (e.g., malaria) shows mixed results in promoting educational attainment and literacy (Lucas, 2010; Cutler et al., 2010). This literature also indicates that adopting health-enhancing technologies (e.g., water treatment, clean energy) that potentially reduce human pollution risk may raise educational attainments, not only through health improvements (Zhang and Xu, 2016) but also via a human capital investment mechanism (Choudhuri and Desai, 2021). Our work contributes to this literature by assessing interventions that can potentially disentangle the direct and indirect effects of behavioral and technological interventions on educational performance, having as mediator health improvements.

The rest of this document is organized as follows. The next section presents the background and context of the problem of air pollution in Delhi and the schools where we will conduct the fieldwork. Section 3 presents the research design, where we state the hypotheses that will be examined, the methodological framework, and conduct power analysis. Section 4 describes the data collection process and project timeline. Section 5

[12] This literature supports that health-oriented information has incentivized safe water behaviors (Madajewicz et al., 2007; Luoto et al., 2014), promoted protection strategies against tropical diseases such as malaria and dengue (Dammert et al., 2014; Cohen and Saran, 2018), reduced indoor pollution from cooking stoves - therefore the prevalence of respiratory health problems (Afridi et al., 2021), and encouraged HIV/AIDS testing behavior (Derksen et al., 2022; Yang et al., 2023; Yu, 2023) in developing countries.

presents the statistical models that will be employed to test the hypotheses and section 6 states administrative project information.

2. Background and Context

Delhi is home to about 20 million people, with an additional few million if we account for surrounding satellite cities and towns. The air quality is very poor, with an average $PM_{2.5}$ concentration of roughly 120 micrograms per cubic meter ($\mu g/m^3$) in 2023. The national air quality standard for India requires annual average $PM_{2.5}$ concentrations not to exceed 40 $\mu g/m^3$. Delhi has been in violation of these standards for at least the past two decades. Air pollution in Delhi is also highly seasonal. Colder months typically see worse air quality levels, while the Monsoon (late summer) period is the cleanest. Figure 1 below illustrates this. This figure uses data for the year 2023 from ambient air quality monitors maintained by India's Central Pollution Control Board. The horizontal red line shows India's standard for annual average $PM_{2.5}$. Delhi's air quality typically tends to be in compliance with the annual standard only during July, August, and September. In the winter months of November to January, in particular, the quality of the air deteriorates to very high levels.[13]

[13] This is due to several factors: the primary factor being the lower temperatures and the resulting temperature inversions that limit the ventilation of the airshed. In addition to this, other reasons can be smoke that comes from the widespread stubble burning that takes place in states northeast/upwind from Delhi (Punjab and Haryana) during November.

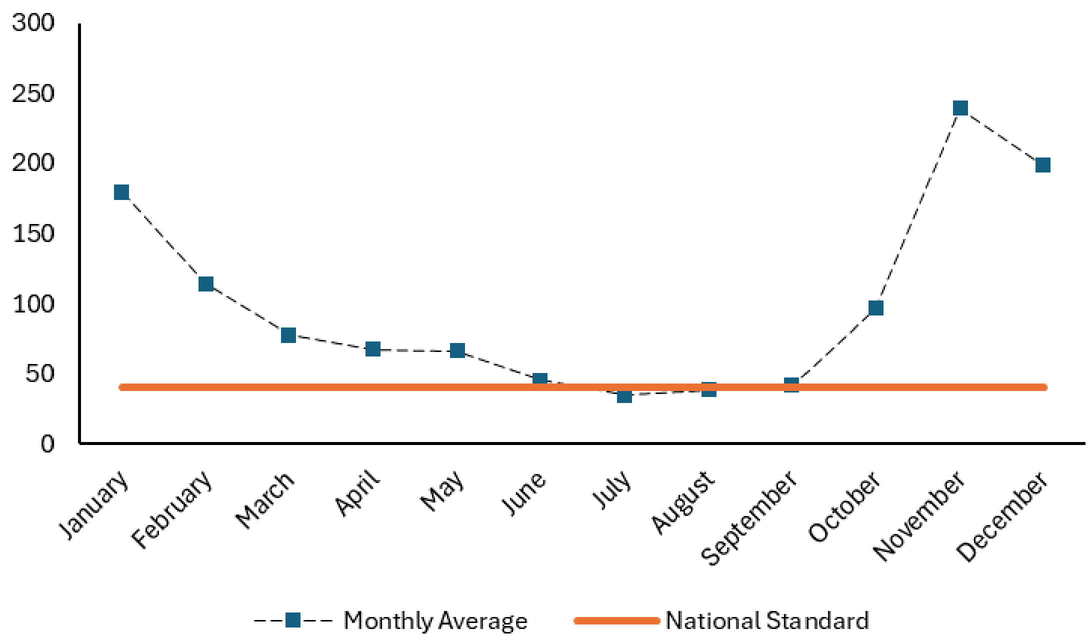


Figure 1: Monthly averages of $PM_{2.5}$ for Delhi in 2023. Data taken from all active air quality monitors maintained by the Central Pollution Control Board

Since 2017 Delhi, and the surrounding satellite towns and cities that make up the National Capital Region (NCR), has instituted a comprehensive policy to reduce air pollution. This policy, called the Graded Response Action Plan (GRAP), consists of four stages. Stage I is put in place when the predicted air pollution exceeds a certain cut-off. Subsequent stages - Stages II, III and IV - are invoked when air pollution is predicted to exceed progressively higher cut-offs. Relevant to our interventions, Stage IV of the GRAP requires schools to be shut down when air quality is predicted to be particularly bad. For instance, in 2023 in Delhi, primary schools were shut down from November 6th to November 18th, while schools at all levels were shut down from November 8th onwards.[14] Therefore, if HEPA purifiers in classrooms turn effective at reducing air pollution in classrooms and improving students' health and educational outcomes, Stage IV of the GRAP policy may no longer be necessary. Instead, a policy that invests and deploys this

[14] School closures by themselves are however unlikely to be particularly useful in protecting children from air pollution. First, the decision to close schools is typically taken after air quality has already reached hazardous levels. Second, children are likely exposed to the same poor-quality air when they are at home. Closing schools may prevent some minor additional exposure during commutes, but this is unlikely to be very large. Moreover, the loss of school days that result from these school closures can hamper children's learning, and the cumulative effect of this reduction in school days is likely to show up as fewer lessons are effectively learned.

sort of air purifier can then allow for keeping children attending and learning at school even during episodes of very high air pollution.

Our choice of school partner is the Delhi branch of the Kendriya Vidyalaya (KV) schools, which translates to *Central Government Schools* in English. India's KV schools are a nationwide system of public schools that cover all grades (called "standards" in India), from primary all the way to school completion.[15] These schools offer the same syllabus across the board and a highly standardized education system. The major advantage of working with KV schools is that they offer a very promising scope to examine how the interventions we examine could potentially be expanded on a national scale. Scaling up is important because air quality in most parts of India – particularly the northern plains region, where hundreds of millions of people live – is extremely poor, just as bad as it is in Delhi.[16] Therefore, if the behavioral strategies evaluated in this work turn effective, then a small change in the teaching curriculum can go a long way in mitigating the harmful effects of air pollution exposure throughout a vast number of geographical areas in India and other regions of the world suffering from very high air pollution.

3. Research Design

a. Objectives and Main Hypothesis

The main objective of this work is to experimentally assess behavioral strategies for mitigating children's exposure and technological (i.e., HEPA air purifiers) for mitigating indoor air pollution in classrooms, the positive health effects associated with this mitigation, and whether this results in improved educational outcomes. We hypothesize that these strategies can result in important benefits for students in Delhi schools.

[15] These schools were initially set up to serve children of parents who work in jobs that require significant long term stays in different parts of the country, such as in the armed forces or in government. In order that their children's education does not suffer.
[16] The national scale of the problem is illustrated in Figure A.1 in Appendix A.

b. Main outcomes of Interest

By means of a survey questionnaire, we assess students' understanding and learning of key components of the educational and behavioral intervention. Specifically, we assess understanding and learning of (i) the effects of air pollution on health, (ii) identification of periods of high air pollution (specifically, high Air Quality Index), and (iii) personal strategies to mitigate exposure to high air pollution. In addition, the survey questionnaire will allow us to gauge whether students have actually engaged in any of these behavioral strategies. Moreover, we examine the effect of air purifiers on indoor particle air pollution. To measure this, we will deploy indoor pollution monitors that will log real-time readings of fine and coarse particulate matter pollution ($PM_{2.5}$ and PM_{10}). These monitors will be deployed in both classrooms with HEPA purifiers and control classrooms. Moreover,

Next, we examine whether these behavioral and technological mitigation strategies result in improved respiratory health by measuring students' lung capacity using Peak Expiratory Flow (PEF) meters.[17] In particular, we will measure a students' PEF over 1 second.[18] We complement this assessment with survey questions on self-reported health, focusing on those health symptoms that are more closely associated with high air pollution.

Finally, we measure students' educational outcomes in three ways. We obtain data on individual-level school attendance from schools' official registries, perform standardized learning and cognitive tests throughout the school year[19], and assess students' grades throughout the year and in their final exams. The survey questionnaire, PEF 1s sampling,

---

[17] Peak Expiratory Flow meters is a low-cost device to assess and monitor prevalence and risk of chronic respiratory diseases, such as Asthma and Chronic Obstructive Pulmonary Disease COPD (Agusti et al., 2021), that allows to identify health effects even from modest variations in short-term exposure to $PM_{2.5}$ air pollution (Rice et al. 2013).

[18] Dong et al. (2019) show that portable ionization air purifiers in school classrooms, even for a short period of time (5 days), increase PEF 1s among children 12 years old in Beijing, China, whereas Weichenthal et al. (2013) show similar effects among indigenous populations in Manitoba, Canada.

[19] For assessing learning of math and language, we employ the Young Lives School Survey (YLS). Whereas for cognitive assessment we employ the Reverse Corsi Block task to measure working memory (Brunetti et al., 2014). This test has been shown to be sensitive even to modest changes in average air pollution exposure (Berkower and Dean, 2023).

questions on self-reported health,, and standardized cognitive tests will all be conducted several times during the data collection.

c. Testable Hypotheses

We hypothesize that

Hypothesis 1: Behavioral strategies mitigate students' exposure to high air pollution and technological strategies reduce air pollution in classrooms

From this, we have two auxiliary hypotheses. A twofold Hypothesis 1.1

> *Hypothesis 1.1.a: Students can understand and learn the following: (i) the effects of air pollution on health, (ii) how to* identify critical periods of air pollution (i.e., high Air Quality Index, AQI), and (iii) personal behavioral strategies to mitigate exposure.[20]

> *Hypothesis 1.1.b: Once (i) through (iii) above are taught and learned, students change their behavior to adopt strategies that mitigate their personal exposure to air pollution.*

and

> *Hypothesis 1.2: Air purifiers reduce indoor air pollution while students are in the classroom.*

Next, we evaluate whether these strategies can reduce the harmful effects of air pollution by posing the following hypothesis.

[20] We are planning on teaching students ten personal exposure mitigation strategies. These include: avoidance behaviors of ambient and indoor air pollution, defensive behaviors for ambient and indoor air pollution, behavioral change to minimize emissions of indoor air pollution, and heightened awareness of own respiratory health. Section 3.d.i. below explains these personal behavioral strategies in further detail.

Hypothesis 2: Behavioral and technological strategies (i.e., personal behavioral strategies and HEPA Purifiers in classrooms) improve students' respiratory health.

Finally, our last hypothesis is whether improvements in student's respiratory health leads to better educational outcomes. Thus, our third hypothesis is

Hypothesis 3: Behavioral and technological and strategies, and their associated improvements in respiratory health, result in better educational outcomes.

Table 1 below summarizes the main outcome variables in relation to how they allow us to test our hypotheses.

Table 1: Hypotheses and Outcome Variables

Hypothesis	**Outcome Variable**	**Unit of Obs.**	**Type**	**Data Source**
H1: Air Pollution & Exposure				
H1.1.a	Learning of Behavioral Strategies	Student x Round	Index	Survey questionnaire
H1.1.b	Adoption Behavioral Strategies	Student x Round	Index	Survey questionnaire
H1.2	Particle Pollution ($PM_{2.5}$)	$\mu g/m^3$ in classroom x 20-minutes	Continuous	Indoor pollution monitors
H2: Health				
H2.1	Lung capacity (FEV1 & PEF)	Student x Round	Continuous	Spirometry
H2.2	Self-Reported Health	Student x Round	Index	Survey questionnaire

H3: Education				
	Attendance	Student x Day	Count	Official School Registries
	Standardized test scores	Student x Round	Continuous	Survey Standardized Test
	Grades	Student x Year	Grading System	Official School Registries

d. Methodological Framework

We will conduct a cluster-randomized controlled trial where we will randomly assign clusters of students sharing the same classroom (a.k.a. *a class*) into one of three groups: (Group 1) those assigned to treatment *Educational & Behavioral Strategies (EBS)*, (Group 2) those assigned to both treatment EBS and treatment *Purifiers*, jointly, and (Group 3) a *Control* group. That is, we will randomly assign all students in the same class to *only* one of these treatment arms. This random assignment will be conducted in October 2024 by members of the research team in a clear and transparent way. Next, we explain these treatments in detail.

i. Treatments

Treatment EBS: Education and Behavioral Strategies

The first treatment consists of an educational campaign that will have three components. Component 1 teaches students about the problem of air pollution in their city and how it impacts their own health. Component 2 teaches students that exposure to higher levels of air pollution is associated with higher risks of health hazards.[21] Finally, component 3 of

[21] When referring to these health risks we will follow the health risks categories by the Air Quality Index (AQI) of India's Central Pollution Control Board. Under these categories 'Good' air quality (i.e., AQI between 0 and 50) is associated with "Minimal impacts" on health; 'Satisfactory' (AQI between 51 and 100) is associated with "Minor breathing discomfort to

this campaign teaches personal strategies to mitigate air pollution exposure and associated health risks. We seek to deliver this teaching in a positive way that seeks to bring a sense of self-empowerment to students to 'fight against' the adverse effects of air pollution in their city. We refer to this educational and behavioral strategies treatment as treatment *EBS*. As before, assignment to this treatment will be in clusters, such that if a class is assigned to this treatment then all students in the same class will be assigned to receiving this treatment

For this intervention we have produced educational material that has educational content tailored specifically to this intervention. This includes leaflets – which will be handed out to students and then collected – and a short video – which will be shown to students in the classroom. This educational material has simple language and is accompanied by visuals for communicating the contents in a way that is easily understandable by these students. Next, we describe in further detail the content of each of the three components of this treatment.

Component 1: Effects of air pollution on health

For explaining the effects of air pollution on health we have produced a draft of this educational content (see Appendix C.1 below). In addition, based on this content we have produced a short video that is similar to this video from the United Nations Children's Fund (UNICEF, 2016) and the 'Freedom to Breathe' campaign for India.[22]

---

sensitive people"; 'Moderate' (AQI between 101 and 200) is associated with "Breathing discomfort to the people with lungs, asthma and heart diseases"; 'Poor' (AQI between 201 and 300) is associated with "Breathing discomfort to most people on prolonged exposure"; Very Poor (AQI between 301 and 400) is associated with "Respiratory illness on prolonged exposure", and 'Severe' (AQI between 401 and 500) is associated with "Affects healthy people and seriously impacts those with existing diseases". See https://airquality.cpcb.gov.in/AQI_India/.

[22] This video explains – for an Indian context – the problem of air pollution on health and a few personal strategies for mitigating exposure. The `Freedom to Breathe' campaign provided an opportunity for children to call for their right to clean air to be acknowledged by the United Nations Convention on the Rights of the Child (UNCRC). The campaign worked with partners across the world to deliver a curriculum-linked education program that helped young people understand the state of air quality in their cities, the health harms of poor air quality, and simple measures they could take at home and in school to protect themselves from breathing harmful pollutants. The campaign was run globally by Blueair -- a Swedish subsidiary of the Unilever company that manufactures air purifiers -- in partnership with Global Action Plan, Association for the Promotion of Youth Leadership Advocacy and Volunteerism Cameroon (APYLAV), Centre for Environment Education, Coalition for Clean Air, and Safekids Worldwide. https://www.blueair.com/us/freedomtobreathe.html

Component 2: Identification of critical levels of air pollution by means of checking the AQI

Another important component of this intervention is to create awareness about the current level of ambient air pollutants, at any given period of time, by explaining the Air Quality Index (AQI) and getting students (and/or getting them to ask their caregivers) to check the AQI on a regular basis (see Appendix C.2). This component seeks to aid students in identifying when air pollution has reached critical levels. It is indeed the first behavioral strategy for mitigating exposure to high ambient air pollution.

Component 3: Personal strategies to mitigate exposure and its effects on health

The personal strategies to mitigate the adverse effects of air pollution on health include: (a) avoiding physical activity, exercising and (to the extent possible) spending much time outdoors when AQI is high or very high; (b) closing of doors and windows when AQI is high and the indoor environment is clear of air pollution; (c) running an air purifier if it is available at home; (d) avoiding spending time near people that smoke; (e) asking parents to minimize burning of incense and oil candles indoors, (f) asking parents to avoid burning biomass (such as wood fuel, charcoal or dung) for cooking or heating indoors, (g) avoiding busy roads when going to school, (h) avoiding bursting firecrackers (which is widespread during the Diwali festivities) and/or spending time near where this happens; (i) considering wearing an N95-type face mask when AQI is very or extremely high; (j) paying attention to own health and seek care early on if symptoms arise; (k) if the student suffers from asthma, remind the student to use his/her inhaler as often as recommended by the doctor. The figures in Appendix C.3 below illustrate some of these strategies.

We will use the figures in appendices C1 through C3 to produce a leaflet that will be handed to students at the time of delivering the educational intervention. Moreover, we will show this video that we have produced for the purposes of this intervention that presents the content of these figures in a more entertaining and pedagogical way. Importantly, to prevent any possible informational spillovers, we will collect these leaflets immediately after showing the video.

Treatment Purifiers: HEPA purifiers in classrooms

The second treatment consists of deploying high-capacity HEPA purifiers inside randomly selected school classrooms. These HEPA purifiers contain a filter that filters up to 99.99 percent of particles of size 0.1 microns ($PM_{0.1}$) or larger. These air purifiers have a manufactured-stated clean air delivery rate (CADR) of 600 cubic meters per hour (21,189 cubic feet per hour) and are suitable for rooms of an area of up to 60 square meters (645 square feet). This intervention is further accompanied by simple information and education seeking to enhance the performance of the HEPA purifiers. Specifically, students and teachers will be asked to keep doors and windows shut during the time the purifier is running inside the classroom. These purifiers will be running during teaching hours and will be turned on/off by the class teacher. The field team will be in constant communication with school principals to ensure that these purifiers perform continuously during the data collection period and that any malfunction is promptly fixed and logged. All air purifiers will be deployed and installed in late October and early November 2024 (October 28th to November 4th, 2024).

To assess the reduction of indoor air pollution by these purifiers we will deploy indoor air pollution monitors inside classrooms in both those classrooms assigned to treatment *Purifier* and those in the control group.[23] These devices measure fine and coarse particle air pollution ($PM_{2.5}$ and PM_{10}) concentrations and record this data internally on an SD card every 20 minutes. The field team will continuously monitor these devices, download the data stored in their SD cards to a laptop computer, and then upload th-is data to a secured storage drive.

ii. Possible Indirect Effects of Assignment to Treatment Arms

We anticipate that these treatments may generate effects on indoor air pollution and exposure that are beyond those directly intended by the assignment to treatment. There could be non-behavioral changes in indoor air pollution that are triggered by assignment

[23] These indoor air pollution monitors will also be deployed in 'pure control' classrooms.

to the treatment arm *EBS*. For example, parents of children assigned to treatment arm *EBS* may decide to buy an air purifier for their home if they hear from their child's increased awareness about the problem of air pollution – say, they hear their child advocating and pushing for household members to engage in behavioral strategies to mitigate exposure at home. While we do not anticipate being able to prevent this from happening, we will ask students both at baseline and at follow-up surveys about the presence of air purifiers at home so that we can properly account for this sort of changes in indoor air pollution mitigation and examine the possible indirect effects in our statistical analysis.

Likewise, there could be behavioral changes – triggered by assignment to treatment arm *EBS+Purifier* – in such a way that affects students' exposure to air pollution. For example, students may feel that, because they are 'protected from air pollution' while in a classroom with an air purifier, then they do not need to be protected themselves from pollution in other instances – thus, they may engage in lesser pollution exposure mitigation behavior than otherwise. Conversely, the presence of the air purifier in the classroom may work as a salient reminder of the problem of air pollution, in such a way that students change their behavior by more intensively trying to reduce their exposure while outside the classroom. That is, an effect that may go beyond that of the EBS treatment alone. In other words, those students in classrooms assigned to treatment arm *EBS+Purifier* may feel more interested and/or engaged in taking additional measures to reduce their exposure. To examine these possible responses to treatment assignment we will include questions in the survey questionnaire about adoption of behavioral strategies to mitigate exposure both at baseline and at follow-ups, and we will properly account for these to examine these possible indirect effects in our econometric analysis.

Similarly, if the child is in a classroom assigned to treatment arm *EBS+Purifier*, and his/her parents believe that the child will be protected from air pollution while in the school classroom, then the child's parents may decide to send the student to school more often than otherwise. Due to this reason, we can expect a direct increase in students' attendance rate in classrooms assigned to treatment arm *EBS+Purifier* that is not directly linked to improvements in the child's health. To address this issue, we implement an instrumental variable regression approach in our empirical strategy (see section 5 below).

iii. Possible Violations of SUTVA and Confounding Effects

We take several provisions to prevent 'contamination' of treatments across subjects, or, more technically, violations of the Stable Unit Treatment Value Assumption (SUTVA). First, SUTVA may be violated if students in treatment arm *EBS* share information from the educational campaign with students in the *Control* group. This problem is more likely to occur within the same school than across different schools. To address this potential problem, we will conduct a multi-stage assignment. More specifically, in the first stage we will select schools that will serve as 'control-only' schools, and in the second stage we will conduct the random assignment of clusters of students into treatments and control groups. For classes and classrooms in 'control-only' schools, we will conduct the same surveys and will deploy the same indoor air pollution monitors. We believe that, if there is any spillover effect between students in treatment(s) and control groups, we expect that this spillover will occur between classes within the same school, but it will not occur across classes from different schools. Therefore, having classes in 'control-only' schools would allow us to assess whether those students in classes that have been randomly assigned to the *Control* group effectively remain free of any possible spillover from those students in classes randomly assigned to any of the treatment groups. If spillovers exist, then observing those students in classes in 'control-only' schools would allow us to identify that spillover and properly account for it in our statistical analysis.

Second, SUTVA may be violated if classrooms in treatment arm EBS only have students switching in and out of this classroom during the time of the field experiment. For example, it might be that, due to the novelty of having an air purifier in the classroom, students from classes assigned to the treatment arm *EBS* or *Control* group may want to spend time inside classrooms assigned to treatment arm *EBS+Purifier*. To minimize this possibility, we will make it explicit to teachers and educators to enforce that only students in the treatment *EBS+Purifier* classes should be allowed in those classrooms. We will ask them to inform us if this is not feasible to enforce, and we will keep a log of instances in which students swap classrooms. If this situation arises, we expect that this will not be in a regular basis and therefore exposure will not be long enough to generate a significant change in children's health status.

On the other hand, a potential confounder effect can occur as schools close due to a government mandate as air pollution reaches very high peaks (Stage IV of GRAP policy response, as discussed in section 2 above). But as schools in the control and the treatment group are impacted similarly by closures, we expect a similar exposure outside the classroom premises. However, we will keep track of the occurrence of school closures for any reason.

iv. Sample and statistical power

We are planning to conduct this experiment in 126 classrooms across 10 schools in Delhi's KV schools. Of these classrooms, 54 have two shifts of classes a day (morning and afternoon), making for a total of 180 classes. Moreover, each class has an average of 50 students, which makes for a total of around 9,000 students. However, of these 10 schools we will select 2 schools to serve as 'control-only', leaving us with 8 schools and between 144 and 150 classes that will be eligible for random assignment to the treatments and control.[24] For simplicity, we will refer to working with a sample of around 147 classes. As the treatments will be assigned at the class level, this will allow for a split of roughly 49 classes in each of the three treatment arms (the two treatments and the control group).

Our sample of classes comprises students in 6th, 7th and 8th grade. Thereby, we will conduct a stratified random assignment at the school grade level (Athey and Imbens, 2017). The rationale for this stratified random assignment is as follows. One of the important factors likely driving many of our primary outcomes is the student's age and their associated school grade and cognitive/learning capacity. An older student should have a more resilient health system that can better withstand adverse environmental conditions, such as exposure to high levels of air pollution. Thereby, the effects of mitigating indoor air pollution and exposure to high air pollution on respiratory health (and thus, educational outcomes) may be less pronounced among older students than among younger students. Moreover, older students should be better equipped to grasp the content of an educational campaign aimed at reducing personal exposure, they have more agency on determining their actual behavior, and thus could possibly mitigate their exposure to air pollution to a greater extent than younger students. Furthermore, older

[24] The exact number will depend on the actual 2 schools that we select out for the 'control-only' group

students should be able to perform better in cognitive and learning tests than younger students. For these reasons, we believe that we should have a balanced sample of students in 6th, 7th and 8th grade assigned to each of the treatments and to the control group. Therefore, conducting a stratified random assignment at the school grade level will guarantee that the treatments and control groups are balanced for each school grade. That is, for a given school grade, there will be (roughly) as many classrooms in treatment *Purifier* as in treatment *EBS* as in *Control* groups.[25]

Next, we present our power analysis for the Minimum Detectable Effect (MDE) assuming statistical significance of 5 percent and 80 percent of statistical power. We present this analysis at the classroom/class level as well as at the student level, depending on the unit of measurement of the outcome variable. Table 2 below summarizes the power analysis.

<u>Classroom/class level outcomes</u> (Panel A of Table 2)

Particle Pollution ($PM_{2.5}$) inside classrooms. This analysis relies on our pilot with seven air purifiers in an equal number of classrooms conducted in August through December 2022. The average $PM_{2.5}$ pollution inside the classrooms is 133.16 $\mu g/m^3$ and the standard deviation is 148.17. Therefore, under equal assignment of classrooms/classes between treatment and control groups this yields a MDE equal to a 84.72 $\mu g/m^3$ reduction in $PM_{2.5}$. On the other hand, the average reduction in $PM_{2.5}$ pollution inside classrooms that we observed in our pilot is 101.2 $\mu g/m^3$.

School attendance. This analysis relies on the absenteeism rate reported by (Singh, 2022) for schools in Delhi. Singh (2022) reports an average absenteeism rate of 26.24 for 6th to 8th graders in Delhi schools and a standard deviation of 1.4. Therefore, assuming equal assignment of classes into treatment and control groups, this yields a MDE equal to 0.8

[25] In our case there will be roughly 14 classrooms, per school grade, assigned to each group. Moreover, when conducting the regression analysis we will not control for the strata of randomization (i.e., we will not control for school grade), although we will control for all the dimensions of fixed-effects as well as their interactions (Athey and Imbens, 2017).

reduction in absenteeism rate. On the other hand, the estimated reduction in absenteeism rate we find in our pilot with air purifiers is 6 percentage points.

<u>Student level outcomes, clustered at the class/classroom level</u> (Panel B of Table 2)

Learning Behavioral Strategies. Not currently available (N/A).

Adoption of behavioral strategies. Although we did not conduct a pilot for the educational and behavioral intervention, we rely on Araban et al. (2017) for a feasible mean and standard deviation of an index of adoption of behavioral strategies.[26] In addition, for the class-level intra-cluster correlation (ICC) we rely on estimates from the 'Balsakhi' program of remedial education for schools in urban India (Banerjee et al., 2007). Thus, we assume a mean adoption index of 11.2 (for an index that goes from 5 to 20), an associated standard deviation of 2.3, and an ICC of 0.1356.[27] Under equal assignment of class-level clusters of students among treatments/control groups, this yields a MDE equal to 0.51. On the other hand, Araban et al. (2017) finds an effect of 8.8 for that same index.

Respiratory health – Lung capacity. We rely on parameters and estimates from Foster and Kumar (2011) for an index of lung capacity (as measured by spirometry) for children less than 17 years old in Delhi. The mean index reported by Foster and Kumar (2011) is

[26] The index of behavioral strategy adoption in Araban et al. (2017) ranges from 5 to 20. This was generated by asking four questions to participating individuals and rating the answers in a 5-point scale. The specific questions were the following: (Q1) "How often did you stay indoors in the peak hours of the air pollution - from 7 to 9 am?"; (Q2) "How often did you stay indoors in the peak hours of the air pollution - from 6 to 9 pm?"; (Q3) "How often did you stay indoors in the days that air quality is in the crisis situation?"; and (Q4) "How often did you avoid entering into the high traffic area of the city?". Answers ranged from 'never' (rating = 1) to 'always' (rating = 5).

[27] In practice, however, our index will range from 10 to 60, so that to compare with those results in Araban et al. (2017), once would need to rescale accordingly. The reason for this difference in range comes from evaluating ten strategies (as opposed to only four in Araban et al. (2017)) and allowing for answers in a 6-point scale. More precisely, for all ten strategies we will create an index of adoption of these ten strategies by calculating a score of intensity of adoption of each of one of these strategies (where intensity of adoption refers to: 'always' adopting a specific personal exposure mitigation strategy, 'usually'…, 'often'…, 'seldom'…, 'rarely'…, and 'never' adopting a specific personal exposure mitigation strategy).

70.44 and its associated standard deviation is 15.35. Moreover, we assume the same ICC as before. For ease of testing and depending on parents' authorizations, we expect to conducting these tests on a subsample of no less than 10 percent of students in each class (about no less than 5 students per class). This yields a MDE equal to 4.8 for an equal assignment of class clusters into treatment/control groups. On the other hand, we expect to find a reduction of 12.32 points in such an index from the air purifier intervention. This expected reduction comes from multiplying the estimated effect of 1.023 (per 1-$\mu g/m^3$ of change in $PM_{2.5}$) found by Foster and Kumar (2011) by a reduction of 12.04 $\mu g/m^3$ in average ambient $PM_{2.5}$.[28]

Respiratory health – Self reported symptoms. We rely on parameters and estimates from Berkouwer and Dean (2023) for both a (zero-mean standardized) index and a count of self-reported respiratory health symptoms. Assuming the same ICC and balance split between treatment and control as before this yields a MDE of 0.22, whereas the effect found in Berkouwer and Dean (2024) is 0.24 for a 0.8 $\mu g/m^3$ reduction in average $PM_{2.5}$. Similarly, the count of respiratory symptoms has a mean of 1.7 and a standard deviation of 1.76, thus yielding a MDE of 0.39, which contrasts to the effect found in Berkouwer and Dean (2024) of 0.48.[29] As mentioned above, we expect to find a considerably larger reduction in average $PM_{2.5}$ than the one in Berkouwer and Dean (2024).

Cognitive/learning assessment. We rely on parameters and estimates for a (zero-mean standardized) index of cognitive memory (Corsi test) from Berkouwer and Dean (2024). Assuming the same ICC and balance split of treatments/control as before, we obtain a MDE equal to 0.22. This contrasts with the effect of 0.48 for this index[30] for 0.8 $\mu g/m^3$ reduction in average $PM_{2.5}$ – a considerably smaller reduction than the one we expect for our treatment.

---

[28] This 12.04 $\mu g/m^3$ reduction in average $PM_{2.5}$ is the result of a 101.2 μg/m3 reduction in indoor pollution inside the classrooms (from the air purifier) for a period of 4 hours a day spent inside the classroom over 5 days a week.

[29] For the effect of the index and count of respiratory symptoms see Table B.13 in Berkouwer and Dean (2024).

[30] See Table B.15 in Berkouwer and Dean (2024).

Cognitive assessment – Peabody Picture Vocabulary and Math Test

We rely on parameters and estimates from Balakrishnan and Tsaneva (2021) for a (zero-mean standardized) index of the Peabody Picture Vocabulary Test from the India Chapter of the *Young Lives Survey*. Balakrishnan and Tsaneva (2021) find an effect of 0.18 and .55 for boys and girls, respectively, from a 1-μg/m^3 change in the annual mean of $PM_{2.5}$.[31] On the other hand, assuming the same ICC and balance split of treatments/control as before, we obtain a MDE equal to 0.22.

Grade in Final Exams. Not currently available (N/A).

Table 2: Power Analysis – Input Parameters, Minimum Detectable Effect and Effect Size.

Outcome Variable	Mean	S. D.	ICC	MDE	Expected Effect	Source
<u>Panel A. Class level</u>						
Indoor $PM_{2.5}$ pollution (μg/m^3)	133.2	148.2	-	84.72	101.2	Pilot
Absenteeism rate (%)	26.24	1.4	-	0.8	6	Pilot, Singh (2022).
<u>Panel B. Student level</u>						
Learning behavioral strategies	N/A	N/A	N/A	N/A	N/A	
Adoption of behavioral strategies (index)	10.6	2.1	0.136	0.42	8.8	Araban et al. (2017), Banerjee et al., (2007).
Respiratory health effects (index of lung capacity)	70.44	15.35	0.136	4.8	12.32	Foster and Kumar (2011), Pilot.
Respiratory health symptoms (index)	0	1	0.136	0.22	0.24	Berkouwer and Dean (2023), Pilot.
Respiratory health symptoms (count)	1.7	1.76	0.136	0.39	0.48	Berkouwer and Dean (2023), Pilot.
Cognitive Test, Corsi working memory (index)	0	1	0.136	0.22	0.48	Berkouwer and Dean (2023), Pilot.

[31] We expect to find an effect in the annual mean of $PM_{2.5}$ from our interventions in the order of two to three times as large as that in Balakrishnan and Tsaneva (2021).

Cognitive assessment, Peabody Picture Test (index)	0	1	0.136	0.22	0.18 (Boys) 0.55 (Girls)	Balakrishnan and Tsaneva (2021)
Final Exams	N/A	N/A	N/A	N/A	N/A	

4. Data

a. Data collection and processing

As stated above, we collaborate with Kendriya Vidyalaya (KV) schools in Delhi. To collect student-level data we will use a combination of survey instruments (both questionnaires and a low-cost medical device for assessing lung capacity and administrative data on attendance and grades in final exams. The survey instruments would be executed with the help of a survey team with prior experience and training for collecting data from school students. Moreover, we will deploy air pollution monitors inside classrooms to assess indoor PM air pollution while students are in the classroom.

The survey questionnaire is divided into multiple sections. Section 1 starts with questions about simple socioeconomic indicators and questions about self-reported respiratory health symptoms experienced over a recent period of time. Then it moves onto questions about air pollution. These include questions about knowledge and understanding of the problem of air pollution, questions about capacity to identify periods of time with high air pollution (by means of the Air Quality Index, AQI), and questions about knowledge and practice of behavioral strategies to mitigate exposure to high air pollution. Sections 2 and 3 have questions for assessing learning of language and math (this is borrowed from the India chapter of the *Young Lives survey*).[32] Finally, section 4 has questions on a memory test consisting of connecting visual shapes (Corsi memory test). A working draft of the questionnaires is attached in Appendix B.

For collecting data on a student's lung capacity we will be using a low cost Peak Expiratory Flow (PEF) meter.[33] PEF tests will be administered individually by well-trained enumerators to a subsample of students in each classroom.

For collecting data on indoor PM pollution we will be using a low-cost monitor manufactured by Purelogic Labs India, an air quality company based in Delhi, India.[34] This monitor records $PM_{2.5}$ and PM_{10} every 20 minutes and records this data in its built-in SD card.

[32] The questionnaires are borrowed from the India chapter of the Young Lives School survey https://www.younglives.org.uk/india-school-survey.
[33] Specifically, we will be using a Rossmax PF102C Peak Flow Meter (https://amz.run/9Zah).
[34] Specifically, we will deploy procure and deploy Purelogic Labs' Prana Air Smart Indoor PM Monitor (https://www.pranaair.com/air-quality-monitor/smart-indoor-pm-monitor/).

b. Timeline and implementation

We will conduct the intervention during late 2024 and into early 2025 (November 2024 through January 2025). As shown in Figure 1 above, this is the period of time in which PM pollution in Delhi peaks up and reaches its highest levels.[35] The deployment of the PM pollution monitors in KV School classrooms will begin earlier, in the summer of 2024 (thus, allowing for pre-treatment data collection). The main data collection, however, will be carried out in November-December of 2024, and early February 2025. The baseline data survey and lung capacity tests will be conducted on October 28th through November 4th. During this time, we will also conduct the *Educational and Behavioral Strategies* treatment in randomly selected school classes. At this time we will also deploy the HEPA purifiers in randomly selected classrooms, and these will be running throughout the Winter teaching term. In addition, there will be a midline survey and lung capacity tests before the Christmas break (on December 17th to 13th).[36] And there will be an endline on February 3rd to the 7th. Finally, there will be a follow-up data collection in which we will obtain administrative data on students' attendance and grades in final examinations. Figure 2 below shows a visual timeline of events.

[35] The reason for termination in December 2024 is to meet the expenditure schedule required by the current funding organizations. However, depending on the availability of funds, we may extend the intervention and data collection into early 2025 and we may conduct an additional round of surveys around February 2025.

[36] This could eventually be relabeled as a 'midline survey' in case we could extend the data collection into early 2025.

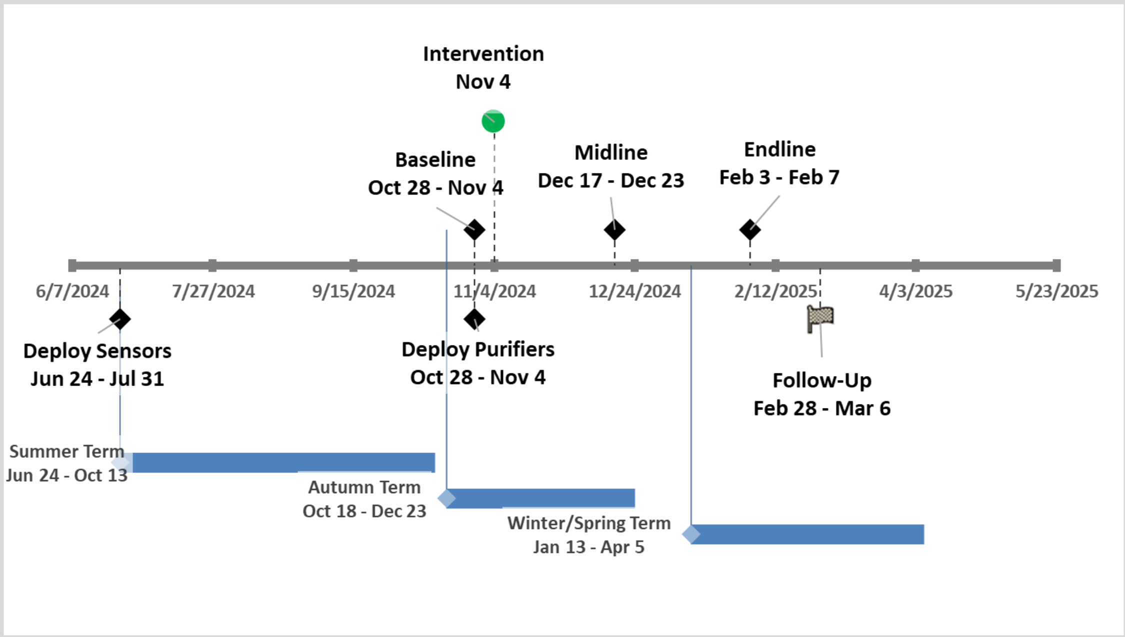


Figure 2: Project Timeline

5. Statistical Analysis

In this work we aim to assess whether technological and behavioral strategies to mitigate effects of high air pollution can result in improved health and better educational outcomes for students in heavily air polluted cities. To that end, here we outline an empirical strategy to first estimate the effects of these strategies on mitigating indoor air pollution and exposure. Specifically, we want to empirically test the following hypotheses.

<u>Hypothesis 1.1.a</u>: *Students learn and understand (i) the effects of air pollution in health, (ii) how to identify critical periods of air pollution (i.e., high AQI), and (iii) strategies to mitigate exposure.*

We estimate the following equation:

$$Learning_{icst} = \alpha + \beta_t EBS_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \tag{2}$$

Where $Learning_{icst}$ refers to three separate indices of learning and understanding of the concepts in components 1, 2 and 3 (as in section 3 above[37]) for student i in classroom c

[37] Component 3 lists personal behavioral strategies. We will create a score of the intensity of adoption of each one of the strategies (listed as *a* through *k* above) as well as an index of average

in school s and survey-round t. In this equation EBS_{ics} is a dummy that denotes whether a student and his/her classroom has been randomly assigned to receiving treatment *EBS*, δ_i denotes student-specific fixed effect, λ_{cs} denotes school-classroom-specific fixed effects, D_t denotes survey-round specific dummies and ϵ_{icst} is an error term. The parameter of interest β_t captures the differential effect on learning and understanding of (i) through (iii) of assignment to treatment *EBS*, while allowing for this effect to change over consecutive survey rounds t. A more general specification aggregates over all survey-rounds t and, accordingly, estimates β instead of β_t.

We estimate β_t in equation (2) by running an OLS regression clustering standard errors at the school-classroom and survey-round level. To test Hypothesis H1.1.a. we test the null hypothesis that $\widehat{\beta_t} < 0$ against the alternative that $\widehat{\beta_t} = 0$. We also evaluate the more general specification, with only β.

Moreover, it could be that the effect of treatment *EBS* on learning varies by student's school grade, such that those students in 8^{th} grade could more easily grasp the content of the educational campaign than, say, those students in 6^{th} or 7^{th} grade. To examine this possible differential effect by school grade we interact EBS_{ics} with D_g, where D_g is a school grade-specific dummy.[38]

<u>Hypothesis 1.1.b</u>: *Students change their behavior so as to mitigate their personal exposure.*

We estimate the following equation:

$$Behavior_{icst} = \alpha + \beta_t EBS_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \quad (3)$$

Where $Behavior_{icst}$ refers to an index of self-reported behaviors to mitigate exposure to high air pollution for student i in classroom c in school s and in survey-round t. Moreover, EBS_{ics}, δ_i, λ_{cs}, D_t and ϵ_{icst} are defined as in equation (2) above. To assess Hypothesis 1.2.b we test the null hypothesis that $\widehat{\beta_t} < 0$, against the alternative that $\widehat{\beta_t} = 0$, where we obtain $\widehat{\beta_t}$ by OLS with cluster-robust standard errors. We also test the more

intensity of adoption. Where, as before, intensity of adoption refers to: 'always', 'usually', 'often' 'seldom', 'rarely', and 'never'.

[38] Recall that we will randomize assignment to treatment at the school grade level, so that, as recommended by Athey and Imbens (2017), we should not be including school-grade-specific fixed effects in our model.

general version substituting β for β_t. Additionally, to examine school grade-specific effects of treatment *EBS* on adoption of behavioral strategies we test the school grade-specific model by interacting EBS_{ics} with the grade-specific dummy D_g.

<u>Hypothesis H1.2</u>: *Air purifiers Reduce air pollution while students are in the classroom*. Our empirical strategy consists of estimating the following equation.

$$Pollution_{cst} = \alpha + \beta Purifier_{cst} + \lambda_{cs} + \Gamma_t + \epsilon_{cst} \tag{1}$$

Where $Pollution_{ct}$ denotes particle pollution (say, fine particulate matter, $PM_{2.5}$) in classroom c in school s in period t. $Purifier_{cst}$ is a dummy equal to one if the classroom has been randomly assigned a purifier and zero otherwise. We control for school-classroom-specific fixed effect λ_{cs}, which may capture factors such as: different levels of principal's engagement and awareness about air pollution issues, whether schools/classrooms are differentially exposed to ambient air pollution, whether classrooms vary in the level of air exchange with outdoor air pollutants, classroom volumetric size, etc. Moreover, we control for a set of time-specific fixed effects, Γ_t, accounting for the differential air pollution during different periods of time throughout the year (days, season), as well as during different times of the day (morning, afternoon, etc.). Finally, ϵ_{cst} is an unobserved error term. The parameter β captures the effect of the HEPA purifier on indoor particle pollution. We estimate β by running an OLS regression of equation (1), clustering standard errors at the school-classroom level. To test Hypothesis H1.2. we test the null hypothesis that $\hat{\beta} < 0$ against the alternative that $\hat{\beta} = 0$.

<u>Hypothesis 2</u>: HEPA Purifiers in classrooms and personal mitigation strategies improve students' health.

We estimate the following equation:

$$Health_{icst} = \alpha + \beta_t Mitigation_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \tag{4}$$

Where $Health_{icst}$ refers to respiratory health of student i in classroom c in school s and survey-round t. Specifically, lung capacity (FEV1 and PEF, as measured by spirometry) and an index of self-reported health. Variables δ_i, λ_{cs}, D_t, and ϵ_{icst} are defined as before. Moreover, $Mitigation_{ics}$ refers to either $Purifier_{cs}$ (for treatment *Purifier*) or EBS_{ics}

(for treatment *EBS*), and β_t captures the effect of assignment to any of the mitigation strategy treatments on students' respiratory health. A more general version substitutes β_t simply for β. As before, we estimate β_t with cluster-robust standard errors accounting for serial correlation. To assess Hypothesis 2 we test the null of $\beta_t > 0$ against the alternative $\beta_t = 0$.

Moreover, to assess whether there is a differential effect of the two treatments (treatment *Purifier* vs. treatment *EBS*), we estimate equation (4) with both treatments and conduct an F-test of equality of the parameter estimates associated to each treatment. In addition, it could be that the effect of mitigation strategies on health varies by student's age. As student's age is almost perfectly correlated with student's school grade, we examine the differential effects of the mitigation strategies by school grade by interacting $Mitigation_{ics}$ with the grade-specific dummy D_g.

<u>Hypothesis 3</u>*: Technological and behavioral strategies, and their associated improvements in respiratory health, result in better educational outcomes.*

We estimate the following equation:

$$Education_{icst} = \alpha + \beta_t Mitigation_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \quad (5)$$

Where $Education_{icst}$ refers to scores in standardized cognitive tests, school attendance and grades in final exams of student i in classroom c in school s and survey-round t.[39] $Mitigation_{ics}$, δ_i, λ_{cs}, D_t and ϵ_{icst} are defined as before. When running these regressions, we also evaluate whether there is a differential effect of each of the two treatments on educational outcomes by means of running (5) with the two treatments and then conducting an F-test of equality of treatment effects. Moreover, it could be that the effects of mitigation strategies on educational outcomes are mediated by the student's age (proxied by his/her school grade). Thereby, we also interact $Mitigation_{ics}$ with the grade-specific dummy D_g.

In addition, to identify effects on education that are directly linked to the effect of assignment to treatment – via its associated effect on student's respiratory health – we

[39] Notice that for school attendance and exam grades we will not be using midlines survey rounds but will be using and endline survey round only.

estimate equation (6) below instrumenting $Health_{icst}$ for $Mitigation_{ics}$ (as in equation (4) above) for each mitigation strategy as well as for both strategies simultaneously.[40]

$$Education_{icst} = \alpha + \beta_t Health_{icst} + \delta_i + \lambda_c + D_t + \epsilon_{ict} \quad (6)$$

Thus, we estimate equation (6) using predicted health, $\widehat{Health}_{icst}$, running a GMM-IV regression with $Mitigation_{ics}$ as instruments, and with cluster-robust standard errors accounting for serial correlation. We also estimate school-grade specific effects of predicted health by interacting it with the dummy D_g. Therefore, to assess Hypothesis 3 we test the null of $\beta_t > 0$ against the alternative $\beta_t = 0$ for standardized cognitive tests and the more general model, using β, for school attendance, exam grades and standardized cognitive tests.

Other Heterogeneous Effects

We may also look at gender heterogeneity. Recent evidence from rural India suggests that girls are more sensitive than boys to the adverse effect of air pollution on math and language test scores (Balakrishnan and Tsaneva, 2021). Balakrishnan and Tsaneva (2021) hypothesize that this could be due to girls experiencing worse health and worse access to health care at baseline. However, this gender heterogeneity has not been examined for urban areas in India, which are exposed to much higher levels of air pollution than rural areas. To examine and test for heterogeneous effects we will interact the main dependent variable in equations (5) and (6) with a dummy variable that captures this heterogeneity (i.e., a gender indicator).

[40] It could be that parents and/or children believe that students should attend school because there is a HEPA purifier in the classroom or because students are learning about personal exposure mitigation strategies, even though these strategies may have no real effect on health. To address this potential effect we use instrumental variable regression.

6. Administrative information

Funding: This work is supported by Environment for Development, Swedish International Development Agency (Grant # MS-1481), and the Northern Ireland Department for the Economy (Grant # R3661QMS).

Institutional Review Board (ethics approval): Ethics approval has been requested from the Institutional Review Board of the Indian Statistical Institute (isical.ac.in). The decision is currently pending.

Declaration of interest: The authors declare having no competing interests nor they have any material or financial interests related to this project.

Acknowledgments: We are grateful for valuable feedback and suggestions from two anonymous referees and the journal's editor. We benefited from insightful discussions with Sefi Roth (LSE), Joshua Graff Zivin (UC San Diego) and Subhrendu K. Pattanayak (Duke University). We acknowledge valuable research assistance from Kritika Chauhan and Valentina González Ortiz.

References

Afridi, F., Debnath, S., and Somanathan, E. (2021). A breath of fresh air: Raising awareness for clean fuel adoption. Journal of Development Economics, 151, 102674.

Aguilar-Gomez, S., Dwyer, H., Graff Zivin, J., & Neidell, M. (2022). This is air: The “Nonhealth” Effects of Air Pollution. Annual Review of Resource Economics, 14, 403-425.

Agusti, A., Fabbri, L. M., Baraldi, E., Celli, B., Corradi, M., Faner, R., ... & Papi, A. (2021). Spirometry: a practical lifespan predictor of global health and chronic respiratory and non-respiratory diseases. European Journal of Internal Medicine, 89, 3-9.

AQLI. The Air Quality Life Index - Annual Update August 2023. (2023). Energy Policy Institute at the University of Chicago. URL: https://aqli.epic.uchicago.edu/reports/

Araban, M., Tavafian, S. S., Zarandi, S. M., Hidarnia, A. R., Burri, A., & Montazeri, A. (2017). A behavioral strategy to minimize air pollution exposure in pregnant women: a randomized controlled trial. Environmental health and preventive medicine, 22(1), 1-8.

Athey, S., & Imbens, G. W. (2017). The econometrics of randomized experiments. In Handbook of economic field experiments (Vol. 1, pp. 73-140). North-Holland.

Balakrishnan, U., & Tsaneva, M. (2021). Air pollution and academic performance: Evidence from India. World Development, 146, 105553.

Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. The quarterly journal of economics, 122(3), 1235-1264.

Barn, P., Gombojav, E., Ochir, C., Laagan, B., Beejin, B., Naidan, G., ... & Allen, R. W. (2018). The effect of portable HEPA filter air cleaners on indoor PM2. 5 concentrations and second hand tobacco smoke exposure among pregnant women in Ulaanbaatar, Mongolia: The UGAAR randomized controlled trial. Science of the Total Environment, 615, 1379-1389.

Berkouwer, S. B., and Dean, J. T. (2023). Private Actions in the Presence of Externalities: The Health Impacts of Reducing Air Pollution Peaks but not Ambient Exposure (No. w31614). National Bureau of Economic Research.

Bharadwaj, P., Gibson, M., Zivin, J. G., & Neilson, C. (2017). Gray matters: Fetal pollution exposure and human capital formation. Journal of the Association of Environmental and Resource Economists, 4(2), 505-542.

Brunetti, R., Del Gatto, C., & Delogu, F. (2014). eCorsi: implementation and testing of the Corsi block-tapping task for digital tablets. Frontiers in psychology, 5, 104751.

Carlsten, C., Salvi, S., Wong, G. W., & Chung, K. F. (2020). Personal strategies to minimise effects of air pollution on respiratory health: advice for providers, patients and the public. European Respiratory Journal, 55(6).

Carmona, N., Seto, E., Gould, T. R., Rasyid, E., Shirai, J. H., Cummings, B. J., ... & Austin, E. (2022). Indoor Air Quality Intervention in Schools: Effectiveness of a Portable

HEPA Filter Deployment in Five Schools Impacted by Roadway and Aircraft Pollution Sources. Atmosphere, 13(10), 1623.

Carneiro, J., Cole, M. A., & Strobl, E. (2021). The effects of air pollution on students' cognitive performance: Evidence from brazilian university entrance tests. Journal of the Association of Environmental and Resource Economists, 8(6), 1051-1077.

Cerami, C., Galandra, C., Santi, G. C., Dodich, A., Cappa, S. F., Vecchi, T., & Crespi, C. (2021). Risk-aversion for negative health outcomes may promote individual compliance to containment measures in Covid-19 pandemic. Frontiers in Psychology, 12, 666454.

Chowdhury, A., Garg, T., Jagnani, M. and Mattson , M. (2024). Adoption and Use of Air Purifiers in Households, (registered report accepted based on pre-results review), Journal of Development Economics.

Cheek, E., Guercio, V., Shrubsole, C., & Dimitroulopoulou, S. (2021). Portable air purification: Review of impacts on indoor air quality and health. Science of the total environment, 766, 142585.

Chen, R., Zhao, A., Chen, H., Zhao, Z., Cai, J., Wang, C., ... & Kan, H. (2015). Cardiopulmonary benefits of reducing indoor particles of outdoor origin: a randomized, double-blind crossover trial of air purifiers. Journal of the American College of Cardiology, 65(21), 2279-2287.

Chen, Siyu, Chongshan Guo, and Xinfei Huang. 2018. Air pollution, student health, and school absences: Evidence from China. Journal of Environmental Economics and Management 92:465–97.

Choudhuri, P., & Desai, S. (2021). Lack of access to clean fuel and piped water and children's educational outcomes in rural India. World Development, 145, 105535.

Cohen, J., & Saran, I. (2018). The impact of packaging and messaging on adherence to malaria treatment: evidence from a randomized controlled trial in Uganda. Journal of Development Economics, 134, 68-95.

Cui, X., Li, F., Xiang, J., Fang, L., Chung, M. K., Day, D. B., ... & Zhang, J. J. (2018). Cardiopulmonary effects of overnight indoor air filtration in healthy non-smoking adults: a double-blind randomized crossover study. Environment international, 114, 27-36.

Currie, Janet, and Matthew Neidell. "Air pollution and infant health: what can we learn from California's recent experience?." The Quarterly Journal of Economics 120, no. 3 (2005): 1003-1030.

Currie, Janet, Eric A. Hanushek, E. Megan Kahn, Matthew Neidell, and Steven G. Rivkin. "Does pollution increase school absences?." The Review of Economics and Statistics 91, no. 4 (2009): 682-694.

Currie, Janet, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell. "What do we know about short-and long-term effects of early-life exposure to pollution?." Annu. Rev. Resour. Econ. 6, no. 1 (2014): 217-247.

Cutler, D., Fung, W., Kremer, M., Singhal, M., & Vogl, T. (2010). Early-life malaria exposure and adult outcomes: Evidence from malaria eradication in India. American Economic Journal: Applied Economics, 2(2), 72-94.

Dammert, A. C., Galdo, J. C., & Galdo, V. (2014). Preventing dengue through mobile phones: evidence from a field experiment in Peru. Journal of Health Economics, 35, 147-161.

Derksen, L., Muula, A., & van Oosterhout, J. (2022). Love in the time of HIV: How beliefs about externalities impact health behavior. Journal of Development Economics, 159, 102993.

Dirks, K. N., Wang, J. Y., Khan, A., & Rushton, C. (2016). Air pollution exposure in relation to the commute to school: a Bradford UK case study. International journal of environmental research and public health, 13(11), 1064.

Dong, W., Liu, S., Chu, M., Zhao, B., Yang, D., Chen, C., ... & Deng, F. (2019). Different cardiorespiratory effects of indoor air pollution intervention with ionization air purifier: findings from a randomized, double-blind crossover study among school children in Beijing. Environmental Pollution, 254, 113054.

Dupas, P. (2011). Health behavior in developing countries. Annual Review of Economics, 3(1), 425-449.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth, “The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution,” American Economic Journal: Applied Economics, 10 2016, 8 (4), 36–65.

Foster, A., & Kumar, N. (2011). Health effects of air quality regulations in Delhi, India. Atmospheric Environment, 45(9), 1675-1683.

Giles, L. V., & Koehle, M. S. (2014). The health effects of exercising in air pollution. Sports Medicine, 44, 223-249.

Gilraine, M. (2023). Air Filters, Pollution, and Student Achievement. Journal of Human Resources.

Goldizen, F. C., Sly, P. D., & Knibbs, L. D. (2016). Respiratory effects of air pollution on children. Pediatric pulmonology, 51(1), 94-108.

Guan, T., Hu, S., Han, Y., Wang, R., Zhu, Q., Hu, Y., ... & Zhu, T. (2018). The effects of facemasks on airway inflammation and endothelial dysfunction in healthy young adults: a double-blind, randomized, controlled crossover study. Particle and fibre toxicology, 15, 1-12.

Hankey, S., Lindsey, G., & Marshall, J. D. (2017). Population-level exposure to particulate air pollution during active travel: planning for low-exposure, health-promoting cities. Environmental health perspectives, 125(4), 527-534.

HEI. Health Effects Institute. (2020). State of Global Air 2020. Special Report. Boston, MA:Health Effects Institute. URL: https://www.healthdata.org/research-analysis/library/state-global-air-2020.

Heissel, J. A., Persico, C., and Simon, D. (2022). Does pollution drive achievement? The effect of traffic pollution on academic performance. Journal of Human Resources, 57(3), 747-776.

Heyes, A., and Saberian, S. (2024). Pollution and learning: Causal evidence from Obama's Iran Sanctions. Journal of Environmental Economics and Management, 102965.

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

IQAir. (2024). Most polluted city ranking based on annual average PM2.5 concentration (μg/m^3) URL: https://www.iqair.com/us/world-most-polluted-cities

Jasemzadeh, M., Khafaie, M. A., Jaafarzadeh, N., & Araban, M. (2018). Effectiveness of a theory-based mobile phone text message intervention for improving protective behaviors of pregnant women against air pollution: a randomized controlled trial. Environmental Science and Pollution Research, 25, 6648-6655.

Jeuland, M., Pattanayak, S. K., Tan Soo, J. S., & Usmani, F. (2020). Preferences and the effectiveness of behavior-change interventions: Evidence from adoption of improved cookstoves in India. Journal of the Association of Environmental and Resource Economists, 7(2), 305-343.

Ke, L., Zhang, Y., Fu, Y., Shen, X., Zhang, Y., Ma, X., & Di, Q. (2022). Short-term PM$_{2.5}$ exposure and cognitive function: Association and neurophysiological mechanisms. Environment International, 170, 107593.

Krebs, B., Burney, J., Zivin, J. G., & Neidell, M. (2021). Using crowd-sourced data to assess the temporal and spatial relationship between indoor and outdoor particulate matter. Environmental Science & Technology, 55(9), 6107-6115.

Lanphear, B. P., Hornung, R. W., Khoury, J., Yolton, K., Lierl, M., & Kalkbrenner, A. (2011). Effects of HEPA air cleaners on unscheduled asthma visits and asthma symptoms for children exposed to secondhand tobacco smoke. Pediatrics, 127(1), 93-101.

Laumbach, R., Meng, Q., & Kipen, H. (2015). What can individuals do to reduce personal health risks from air pollution?. Journal of thoracic disease, 7(1), 96.

Laumbach, R. J., & Cromar, K. R. (2022). Personal interventions to reduce exposure to outdoor air pollution. Annual Review of Public Health, 43, 293-309.

Lucas, A. M. (2010). Malaria eradication and educational attainment: evidence from Paraguay and Sri Lanka. American Economic Journal: Applied Economics, 2(2), 46-71.

Luoto, J., Levine, D., Albert, J., & Luby, S. (2014). Nudging to use: Achieving safe water behaviors in Kenya and Bangladesh. Journal of Development Economics, 110, 13-21.

Madajewicz, M., Pfaff, A., Van Geen, A., Graziano, J., Hussein, I., Momotaj, H., Sylvi, R., and Ahsan, H. (2007). Can information alone change behavior? Response to arsenic contamination of groundwater in Bangladesh. Journal of Development Economics, 84(2), 731-754.

Madureira, J., Brancher, E. A., Costa, C., de Pinho, R. A., & Teixeira, J. P. (2019). Cardio-respiratory health effects of exposure to traffic-related air pollutants while exercising outdoors: A systematic review. Environmental research, 178, 108647.

Mirabelli, M. C., Golan, R., Greenwald, R., Raysoni, A. U., Holguin, F., Kewada, P., ... & Sarnat, J. A. (2015). Modification of traffic-related respiratory response by asthma control in a population of car commuters. Epidemiology, 26(4), 546-555.

Nhung, N. T. T., Amini, H., Schindler, C., Joss, M. K., Dien, T. M., Probst-Hensch, N., ... & Künzli, N. (2017). Short-term association between ambient air pollution and pneumonia in children: A systematic review and meta-analysis of time-series and case-crossover studies. Environmental Pollution, 230, 1000-1008.

Pattanayak, S. K., Jeuland, M., Lewis, J. J., Usmani, F., Brooks, N., Bhojvaid, V., ... & Ramanathan, V. (2019). Experimental evidence on promotion of electric and improved biomass cookstoves. Proceedings of the National Academy of Sciences, 116(27), 13282-13287.

Petrocchi, S., Iannello, P., Ongaro, G., Antonietti, A., & Pravettoni, G. (2022). The interplay between risk and protective factors during the initial height of the COVID-19 crisis in Italy: The role of risk aversion and intolerance of ambiguity on distress. Current psychology, 41, 437-448.

Phipatanakul, W., Koutrakis, P., Coull, B. A., Petty, C. R., Gaffin, J. M., Sheehan, W. J., ... & School Inner-City Asthma Intervention study team. (2021). Effect of school integrated pest management or classroom air filter purifiers on asthma symptoms in students with active asthma: a randomized clinical trial. Jama, 326(9), 839-850.

Rice, M. B., Ljungman, P. L., Wilker, E. H., Gold, D. R., Schwartz, J. D., Koutrakis, P., ... & Mittleman, M. A. (2013). Short-term exposure to air pollution and lung function in the Framingham Heart Study. American journal of respiratory and critical care medicine, 188(11), 1351-1357.

Roth, S. (2020). The effect of indoor air pollution on cognitive performance: Evidence from the UK. Manuscript, London School of Economics https://personal. lse.ac.uk/roths/JMP.pdf.

Schwartz, J. (2004). Air pollution and children's health. Pediatrics, 113(Supplement_3), 1037-1043.

Shakya, K. M., Rupakheti, M., Aryal, K., & Peltier, R. E. (2016). Respiratory effects of high levels of particulate exposure in a cohort of traffic police in Kathmandu, Nepal. Journal of Occupational and Environmental Medicine, 58(6), e218-e225.

Zhang, X., Chen, X., & Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. Proceedings of the National Academy of Sciences, 115(37), 9193-9197.

Shi, J., Lin, Z., Chen, R., Wang, C., Yang, C., Cai, J., ... & Kan, H. (2017). Cardiovascular benefits of wearing particulate-filtering respirators: a randomized crossover trial. Environmental health perspectives, 125(2), 175-180.

Sinharay, R., Gong, J., Barratt, B., Ohman-Strickland, P., Ernst, S., Kelly, F. J., ... & Chung, K. F. (2018). Respiratory and cardiovascular responses to walking down a traffic-polluted road compared with walking in a traffic-free area in participants aged 60 years and older with chronic lung or heart disease and age-matched healthy controls: a randomised, crossover study. The Lancet, 391(10118), 339-349.

Singh, D., Gupta, I., & Dey, S. (2022). Effect of Air Pollution on Cognitive Performance in India (No. 452). Institute of Economic Growth.

Singh, Tejendra Pratap, Beyond The Haze: Air Pollution and Student Absenteeism - Evidence from India (May 2, 2022). Available at SSRN: https://ssrn.com/abstract=3680588 or http://dx.doi.org/10.2139/ssrn.3680588

Steffen, J., & Cheng, J. (2021). The influence of gain-loss framing and its interaction with political ideology on social distancing and mask wearing compliance during the COVID-19 pandemic. Current Psychology, 1-11.

Tong, Z., Li, Y., Westerdahl, D., & Freeman, R. B. (2020). The impact of air filtration units on primary school students' indoor exposure to particulate matter in China. Environmental Pollution, 266, 115107.

UNICEF, United Nations Children's Fund (2016). Clear the air for children - The impact of air pollution on children. https://www.unicef.org/reports/clean-air-children. ISBN: 978-92-806-4854-6.

Vyas, S., Srivastav, N., & Spears, D. (2016). An experiment with air purifiers in Delhi during Winter 2015-2016. PloS one, 11(12), e0167999.

Weichenthal, S., Mallach, G., Kulka, R., Black, A., Wheeler, A., You, H., ... & Sharp, D. (2013). A randomized double-blind crossover study of indoor air filtration and acute changes in cardiorespiratory health in a First Nations community. Indoor air, 23(3), 175-184.

Whitehouse, A., & Grigg, J. M. (2018). The air they breathe; where children are exposed to air pollution. In B23. ENVIRONMENTAL EPIDEMIOLOGICAL INVESTIGATIONS IN ASTHMA (pp. A2803-A2803). American Thoracic Society.

Whitehouse, A., & Grigg, J. (2021). Teaching Air Pollution to Children-Clinical research and education colliding.

WHO. World Health Organization. (2016). Ambient air pollution: A global assessment of exposure and burden of disease. https://www.who.int/publications/i/item/9789241511353. ISBN: 978 92 4 151135 3.

WHO. World Health Organization (2020), Personal Interventions and Risk Communication on Air Pollution. Meeting Report. https://www.who.int/publications/i/item/9789240000278. ISBN: 978 92 4 000027 8.

Yang, D., Allen Iv, J., Mahumane, A., Riddell Iv, J., & Yu, H. (2023). Knowledge, stigma, and HIV testing: An analysis of a widespread HIV/AIDS program. Journal of Development Economics, 160, 102958.

Yang, X., Wang, Q., Han, F., Dong, B., Wen, B., Li, L., ... & Xu, D. (2021). Pulmonary Benefits of Intervention with HEPA Air Purifier in Schoolchildren: A Double-Blind Crossover Study.

Yao, Z., Zhang, W., Ji, X., & Weng, W. (2023). Short-Term Exposure to Air Pollution and Cognitive Performance: New Evidence from China's College English Test. Environmental and Resource Economics, 1-27.

Yu, H. (2023). Social stigma as a barrier to HIV testing: Evidence from a randomized experiment in Mozambique. Journal of Development Economics, 161, 103035.

Zhang, J., & Xu, L. C. (2016). The long-run effects of treated water on education: The rural drinking water program in China. Journal of Development Economics, 122, 1-15.

Zhou, Y., Zou, Y., Li, X., Chen, S., Zhao, Z., He, F., ... & Ran, P. (2014). Lung function and incidence of chronic obstructive pulmonary disease after improved cooking fuels and kitchen ventilation: a 9-year prospective cohort study. PLoS medicine, 11(3), e1001621.

Appendices

A. Additional Materials

1. Pilot Analysis

A pilot study was conducted on a sample of 7 schools during the period August through December 2022. The intervention consisted of deploying large-capacity HEPA purifiers in 3rd grade classrooms. Due to the reduced number of devices all schools were treated (i.e., there was no control group), benefiting a total of 157 children. The pilot's objective was to assess the performance of the air purifier devices in a school environment over a long period of time, and to estimate the potential effects on students' attendance resulting from reductions in PM pollution inside the classroom.

To measure air pollution, the head teacher in each class was asked to record indoor PM pollution levels – as displayed by the devices – four times per day (i.e., at the start of the days, before and after each recess, and at the end of the day). Daily attendance at the individual level data was provided by each school and month-level attendance at the class-level was obtained for comparable schools. We calculated attendance rates for both treated schools and non-treated schools for classes in 2nd, 3rd and 4th grade. Moreover, we generated a dummy variable for before and after the air purifiers were deployed (dummy 'After') and a dummy variable denoting those schools that received the air purifier (dummy 'AirPurSchool'), and a third dummy variable denoting the interaction of these two (dummy 'WithAirPur'). The parameter associated with this interactive dummy represents the difference-in-difference estimate of the effect of an air purifier in the classroom on school attendance rate (the standard errors are clustered at the school-level). Results from Table A.1 below show that the deployment of air purifiers resulted in an increase of 6 percentual points in attendance rate, which translates into an 8 percent increase in school attendance.

	Attendance Rate		
	Second Grade	Third Grade	Fourth Grade
WithAirPur	0.017	0.060**	0.009
	[0.018]	[0.023]	[0.034]
AirPurSchool	0.038	-0.012	0.025
	[0.063]	[0.051]	[0.029]
After	0.014	0.006	0.015
	[0.011]	[0.009]	[0.008]
Constant	0.684***	0.749***	0.736***
	[0.032]	[0.028]	[0.016]
Mean of Dep. Var.	0.693	0.744	0.741
N	2,436	1,562	2,033

Notes: Parameter estimates from an OLS regression of attendance rate (defined as number of attended days over the number of days the school was in session) on a set of DiD dummies: 'AirPurSchool' denotes whether the school was assigned to receiving an air purifier, 'After' denotes observations once this purifier was in place (Aug 1st, 2022), and 'WithAirPur' denotes the interaction of these two dummies. Each individual observation is weighted by the number of days the school was in session during the month. Standard errors clustered at the school level in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table A.1: Parameter estimates from Difference-in-Difference regressions analysis.

1. Figure A.1: Average $PM_{2.5}$ Pollution in Indian States

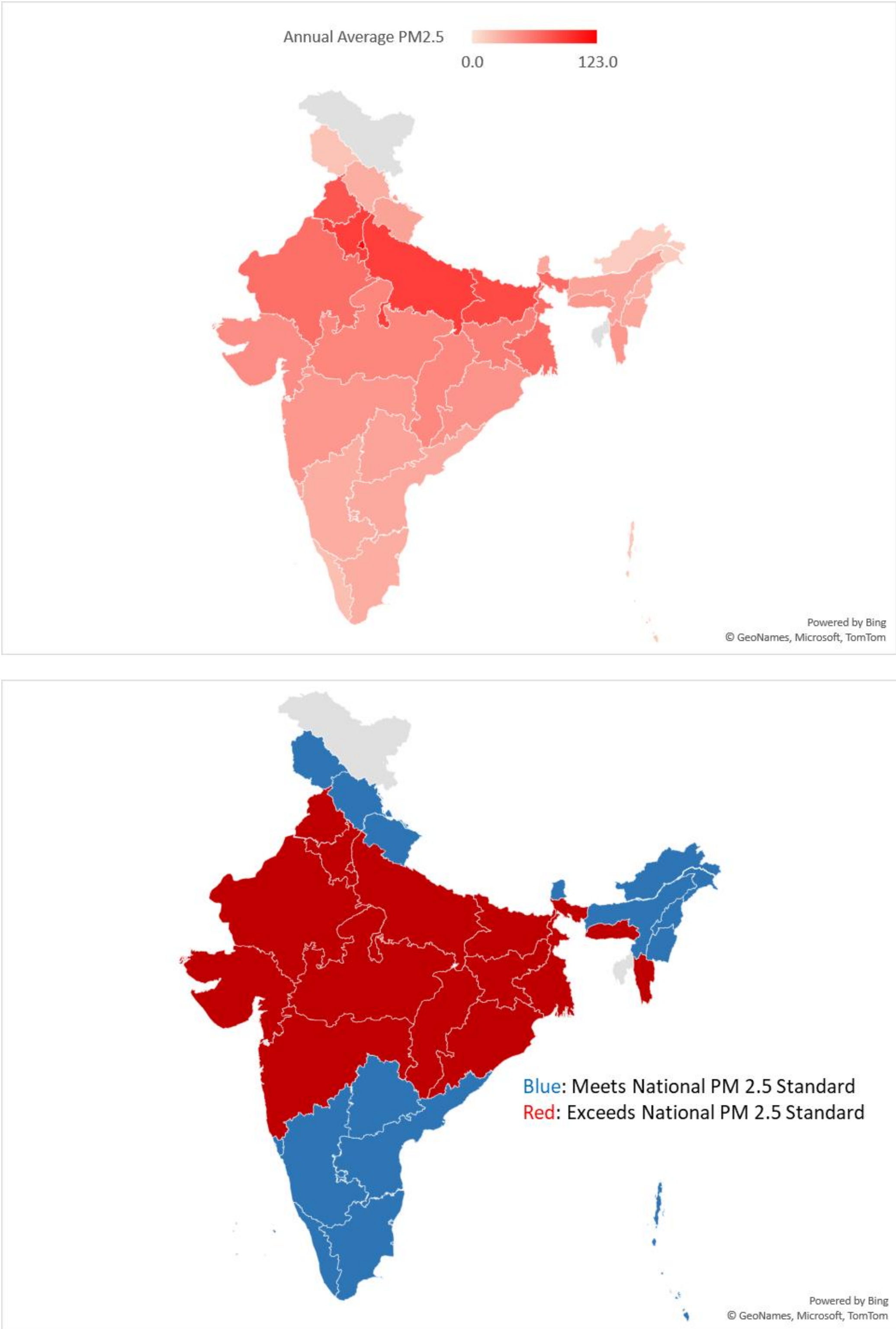


Figure 2: Annual average PM 2.5 for Indian states, in 2018. Source: urbanemissions.info

The top panel shows state wise average annual $PM_{2.5}$ concentrations in 2018. Darker colors imply higher concentrations, while lighter colors imply lower concentrations. The scale ranges from 0 to 123 μ/m^3. The states that are located in the northern part of the country are much more polluted, in particular the states located just south of the

Himalayan Mountain range. Using the national standard of 40 μ/m^3, the bottom panel in Figure 2 splits states into whether their annual averages were above or below this national standard. States colored blue had annual average $PM_{2.5}$ concentrations below the national standard, and thus met the national standard. States colored red had annual average $PM_{2.5}$ concentrations above the national standard, and thus exceeded the national standard. As is clear, most states located in the central or northern parts of the country had $PM_{2.5}$ levels above the national standard.

B. Survey Questionnaires

1. Air Pollution, Respiratory Symptoms & Socioeconomics

For our project-specific questionnaire, please open this document:

https://drive.google.com/file/d/1wqgeTLQKyOiHShsCCcTy4h9Mt47ZIWFP/view?usp=sharing

2. Young Lives School Survey – Language Questionnaire

For the language questionnaire (in English), please open this document:

https://www.younglives.org.uk/sites/default/files/migrated/TEST_English%20Form_Wave%201%20FINAL.pdf

3. Young Lives School Survey – Math Questionnaire

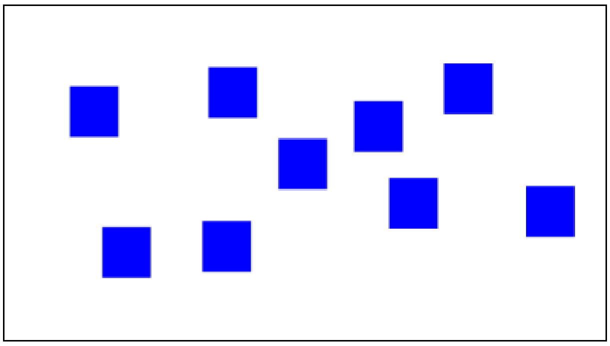
For the math questionnaire (in English), please open this document:

https://www.younglives.org.uk/sites/default/files/2021-12/School%20survey%202016-17_in_w1_Students%20Maths%20Test_0.pdf

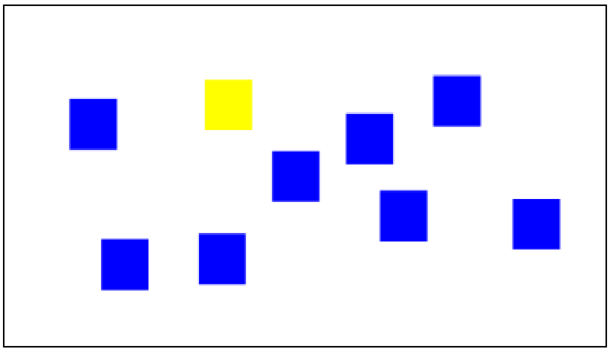
4. Corsi Memory Test

Following Berkouwer and Dean (2024), we will implement the Reverse Corsi Block task on a Tablet device. For each trial, nine blue blocks appear in random locations on the screen. They take turns lighting up yellow. Students are then asked to tap the blocks in reverse order as how they lit up (see figure below). For each block in the sequence, if the student taps on the correct block, it turns on green and the student can proceed to tapping on the next block in the sequence. If the respondent taps on the wrong block, it flashes red and the trial ends. The student then moves on to the next trial. The first trial sequence contains only two blocks, and consecutive trials keep on adding one additional block.

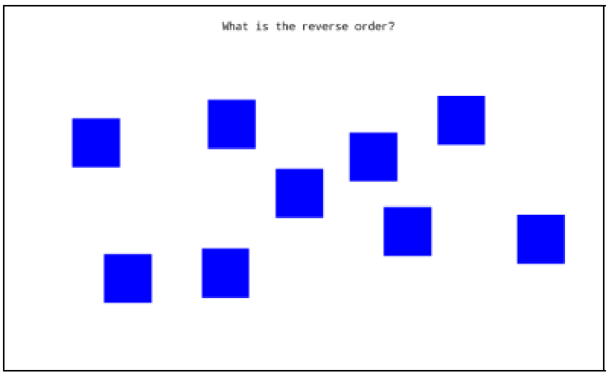
(a) Blocks appear in random positions



(b) Blocks light up yellow randomly

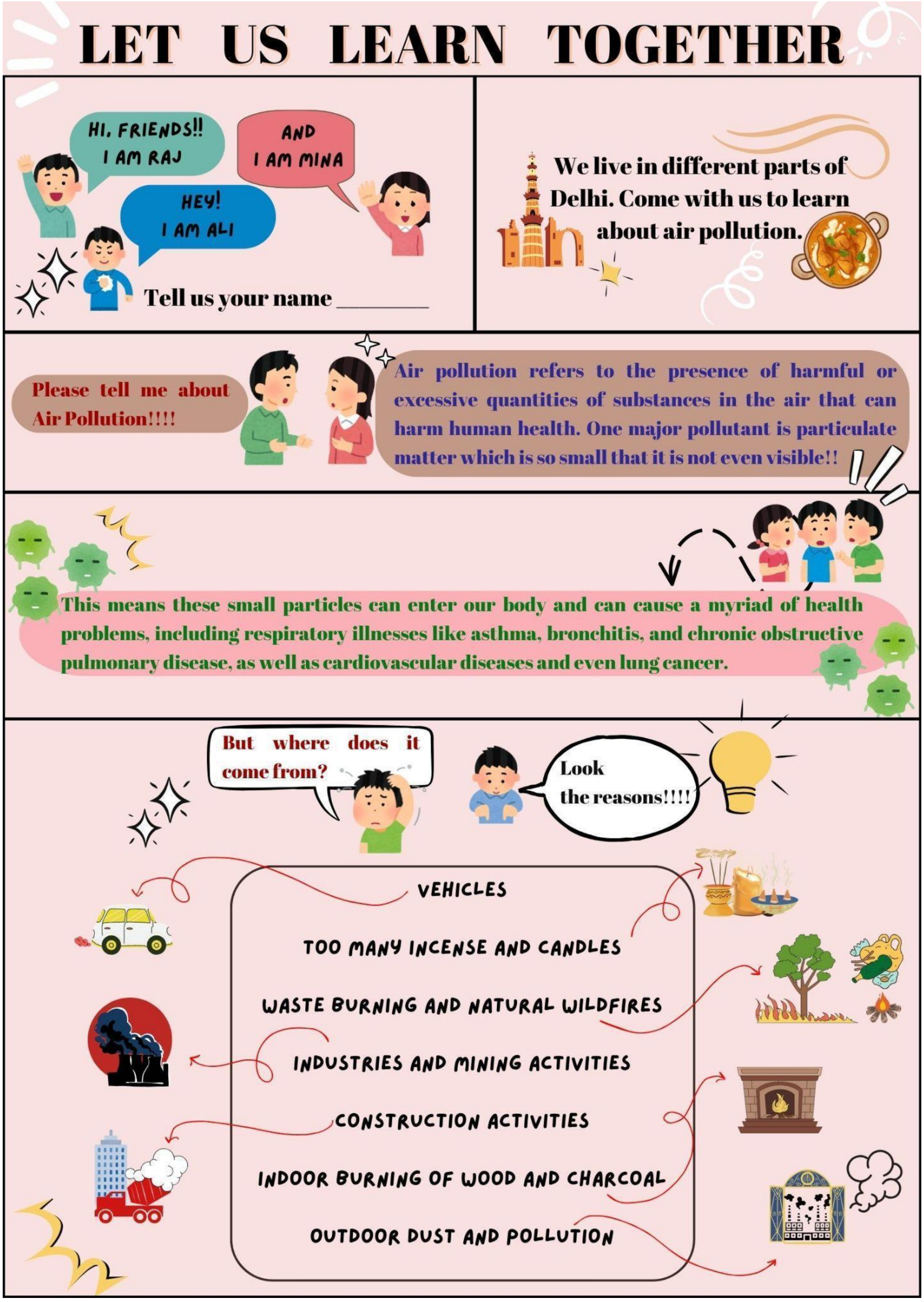


(c) Respondents tap blocks in reverse order

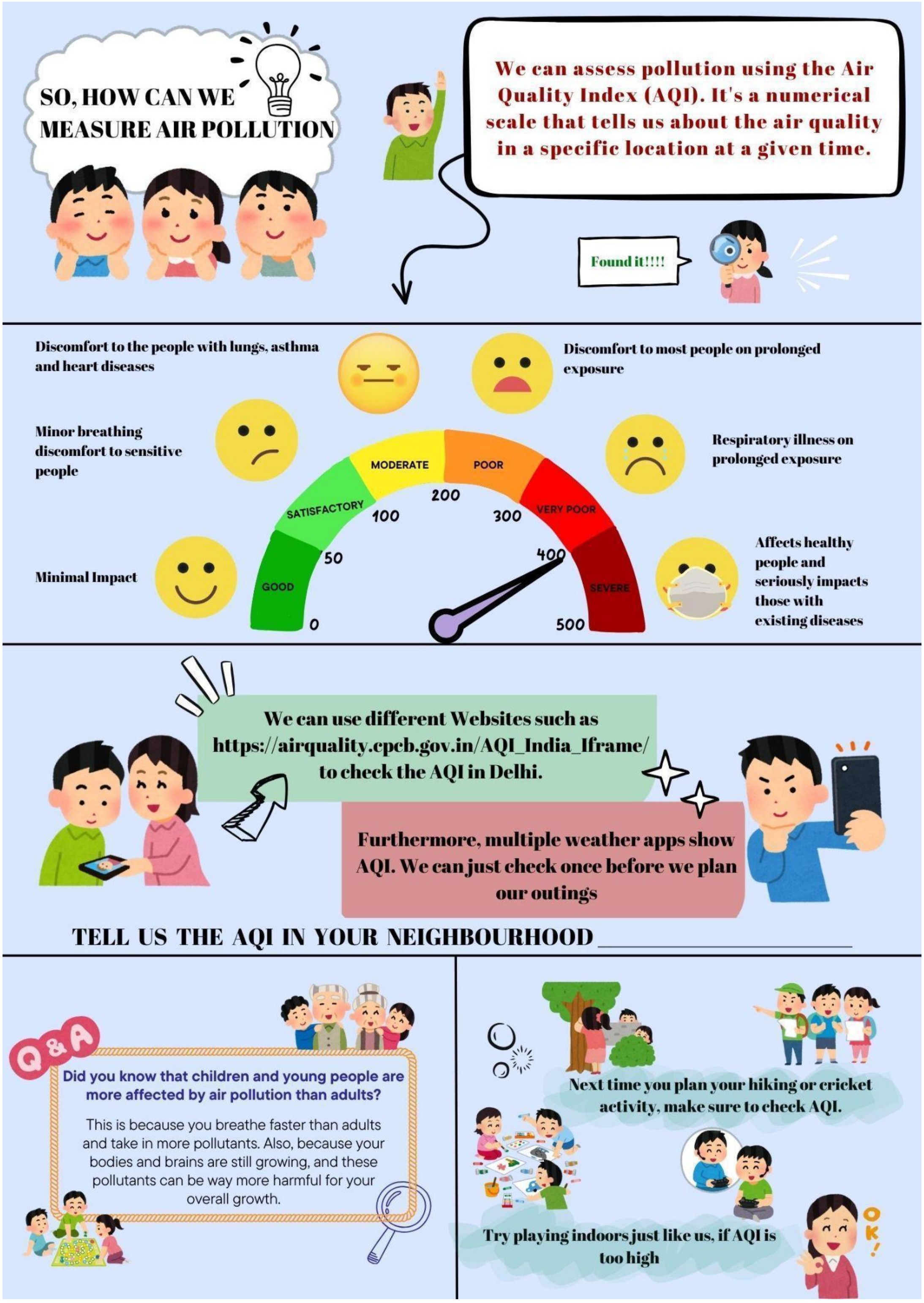


C. Figures for Educational and Behavioral Strategies

1. Example of Educational Material for Teaching About the Effects of Air Pollution on Health.



2. Example of Educational Material for Teaching Students How to Identify When Air Pollution Has Reached Critical Levels.



3. Example of Educational Material for Teaching About Strategies to Mitigate the Effects of Air Pollution on Health.