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

--Manuscript Draft--

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Abstract:	<p>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.</p>
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.

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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. **Air 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 capacity² 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 percentage 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 percentage 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://bitly.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

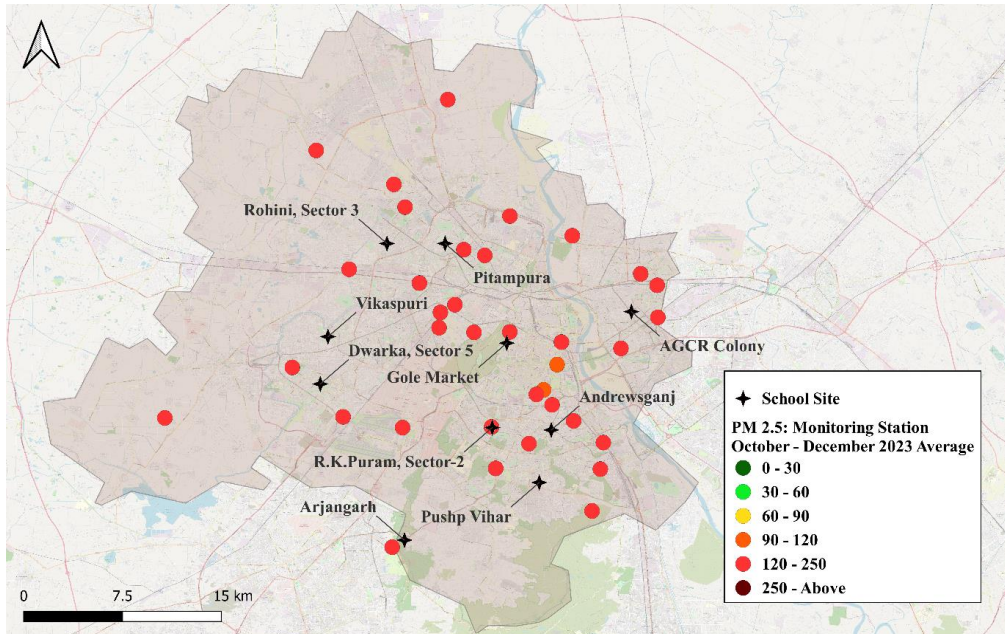
electricity expenses, it's important to note that electricity for KV schools is heavily subsidized in India. Both air purifiers and PM pollution sensors are low-energy consumption devices and, therefore, should not substantially increase electricity costs. Additionally, our research team will run regular 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, indeed, 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 $\mu g/m^3$), 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.



● 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

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2 Registered Report Stage 1: Proposal

3
4 **Technological and Behavioral Strategies to Mitigate Effects of Air**
5 **Pollution on Children: Empirical Evidence from an RCT in**
6 **Delhi's Schools**

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7
8 **Date of latest draft:** June 5th, 2024

9 **Abstract**

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

20
21 **Keywords:** Environment and Development, Air Pollution, Mitigation Strategies, Human
22 Capital.

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

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

26 **Proposed timeline:** This project plans to collect baseline data starting in October 2024.
27 The two interventions will begin in the same month and will end in December (possibly
28 extending into February 2025, depending on availability of funding). A follow-up will
29 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 et 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 et al., 2022).

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

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

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

99 This work aims to fill the gaps in the literature by providing experimental evidence on
100 the link between technological and behavioral strategies to mitigate air pollution
101 exposure and its adverse effects on accumulation of human capital, broadly defined (i.e.,
102 maintaining good health, achieving a good education, and gaining productive skills) —
103 a key factor in the pursuit of human and economic development. We believe that schools
104 are an ideal setting for enhancing awareness of air pollution problems from an early stage
105 through informational and educational campaigns. Students are used to a teaching and
106 learning environment in school, and evidence shows that they can remember specific
107 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).

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

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

127 To test these hypotheses we will conduct a randomized controlled trial (RCT) to evaluate
128 two interventions aimed at mitigating the adverse effects of air pollution in children. In
129 the first intervention we deploy HEPA purifiers in randomly selected classrooms of
130 schools in Delhi. In the second intervention we conduct an educational campaign among
131 students of these schools designed to teach them about both the effect of air pollution on
132 health and about behavioral strategies to mitigate the harmful effects of exposure, thus
133 seeking to encourage adoption of these strategies. We evaluate these interventions by
134 measuring effective exposure to particulate matter air pollution inside the classroom and
135 self-reported adoption of personal mitigation strategies. Moreover, we evaluate health
136 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.

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

142 This work makes three contributions to the broader literature of environment, health and
143 education in developing economies. First, this work contributes to the literature on
144 technology adoption for mitigating environmental hazards and improving health in
145 developing countries. For example, the literature on the adoption of clean cookstoves
146 (Pattanayak et al., 2019; Jeuland et al., 2020; Afridi et al., 2021; Berkouwer and Dean,
147 2023) has found that improved cookstoves result in an important decrease in exposure to
148 peak air pollution although finds no statistically significant decrease in average exposure
149 to air pollution nor in health biomarkers (Berkouwer and Dean, 2023). In a closely related
150 paper, Chowdhury et al. (2024) is examining the drivers of adoption of HEPA purifiers
151 and its associated effects on health and labor outcomes at the household level (although
152 results have not been reported yet). This work expands this literature by examining the
153 potential of HEPA purifiers for mitigating the adverse effects of exposure to air pollution
154 on childrens’ health in developing countries.

155 Second, this work contributes to the broad literature on development economics that
156 seeks to understand the barriers to adopting highly effective preventive behavior for
157 mitigating the burden of multiple health health hazards and diseases faced by developing
158 countries (Dupas, 2011). One possible explanation for this low adoption is a lack of
159 information on the consequences of health hazards and diseases and the effectiveness and
160 cost-effectiveness of preventative behaviors (Dupas, 2011). In this regard, our work
161 expands the limited literature that evaluates the implementation of educational
162 campaigns to incentivize better health care practices and thus improve human health.¹⁰
163 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.

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

166 Third, we assess whether these health-enhancing strategies could also positively affect
167 educational outcomes. Current empirical evidence from public health campaigns aimed
168 at eradicating persistent diseases in developing countries (e.g., malaria) shows mixed
169 results in promoting educational attainment and literacy (Lucas, 2010; Cutler et al.,
170 2010). This literature also indicates that adopting health-enhancing technologies (e.g.,
171 water treatment, clean energy) that potentially reduce human pollution risk may raise
172 educational attainments, not only through health improvements (Zhang and Xu, 2016)
173 but also via a human capital investment mechanism (Choudhuri and Desai, 2021). Our
174 work contributes to this literature by assessing an intervention that can potentially have
175 tangible effects on educational outcomes and thus improve the process of human capital
176 accumulation and its associated positive effects on long term economic and human
177 development.

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

185

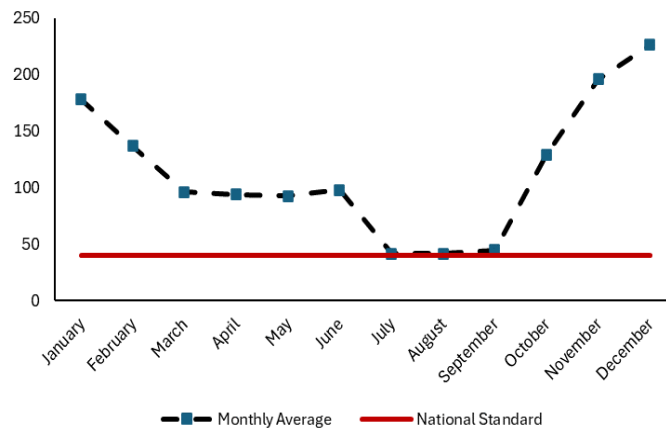
186 **2. Background and Context**

187

188 Delhi is home to about 20 million people, with an additional few million if we account
189 for surrounding satellite cities and towns. The air quality is very poor, with an average
190 $PM_{2.5}$ concentration of roughly around 120 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$) in 2018.
191 The national air quality standard for India requires annual average $PM_{2.5}$ concentrations
192 not to exceed $40 \mu\text{g}/\text{m}^3$. Delhi has been in violation of these standards for at least the past
193 two decades. Air pollution in Delhi is also highly seasonal. Colder months typically see
194 worse levels of air quality while the Monsoon (late summer) period is the cleanest. Figure
195 1 below illustrates this. This figure uses data for the year 2018 from ambient air quality

196 monitors maintained by India's Central Pollution Control Board. The horizontal red line
197 shows India's standard for annual average PM_{2.5}. Delhi's air quality typically tends to be
198 in compliance with the annual standard only during July, August and September. In the
199 winter months of November to January, in particular, the quality of the air deteriorates to
200 very high levels.¹¹

201



202

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

205

206 Since 2017 Delhi, and the surrounding satellite towns and cities that make up the National
207 Capital Region (NCR), has instituted a comprehensive policy to bring air pollution down.
208 This policy, called the Graded Response Action Plan (GRAP), consists of four stages.
209 Stage I is put in place when the predicted air quality exceeds a certain cut-off. Subsequent
210 stages - Stages II, III and IV - are invoked when air quality is predicted to exceed
211 progressively higher cut-offs. Relevant to our interventions, Stage IV of the GRAP
212 requires schools to be shut down when air quality is predicted to be particularly bad. For
213 instance, in 2023, in Delhi primary schools were shut down from November 6th to
214 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

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

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

233

234 **3. Research Design**

235

236 **a. Objectives and Main Hypothesis**

237

238 The main objective of this work is to experimentally assess technological (i.e., HEPA air
239 purifiers) and behavioral strategies for mitigating children's exposure to air pollution, the
240 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.

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

243

244 **b. Main outcomes of Interest**

245

246 We first examine the effect of air purifiers on indoor particle air pollution. To measure
247 this we will deploy indoor pollution monitors that will log real-time readings of fine and
248 coarse particulate matter pollution (PM_{2.5} and PM₁₀). These monitors will be deployed in
249 both classrooms with HEPA purifiers and control classrooms. Moreover, by means of a
250 survey questionnaire, we assess students' understanding and learning of key components
251 of the educational and behavioral intervention. Specifically, we assess understanding and
252 learning of (i) the effects of air pollution on health, (ii) identification of periods of high
253 air pollution (specifically, high Air Quality Index), and (iii) personal strategies to mitigate
254 exposure to high air pollution. In addition, the survey questionnaire will allow us to gauge
255 whether students have actually engaged in any of these behavioral strategies.

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

262 Finally, we measure students' educational outcomes in three ways. We obtain data on
263 individual-level school attendance from schools' official registry, we perform
264 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 PM_{2.5} 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).

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

268

269 **c. Testable Hypotheses**

270

271 We hypothesize that

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

274 From this, we have two auxiliary hypotheses.

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

277 and a twofold Hypothesis 1.2

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

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

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

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

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

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

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

295

296 *Table 1: Hypotheses and Outcome Variables*

Hypothesis	Outcome Variable	Unit of Obs.	Type	Data Source
<u><i>H1: Exposure</i></u>				
<i>H1.1</i>	Particle Pollution (PM _{2.5})	µg/m ³ in classroom x 20-minutes	Continuous	Indoor pollution monitors
<i>H1.2.a</i>	Learning of Behavioral Strategies	Student x Round	Index	Survey questionnaire
<i>H1.2.b</i>	Adoption Behavioral Strategies	Student x Round	Index	Survey questionnaire
<u><i>H2: Health</i></u>				
<i>H2.1</i>	Lung capacity (FEV1 & PEF)	Student x Round	Continuous	Spirometry
<i>H2.2</i>	Self-Reported Health	Student x Round	Index	Survey questionnaire
<u><i>H3: Education</i></u>				
	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

297

298

299

300

301

302 **d. Methodological Framework**

303

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

312

313 **i. Treatments**

314

315 *Treatment Purifiers*: HEPA purifiers in classrooms

316

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

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

333 *Purifier* and those in the control group.¹⁸ These devices measure fine and coarse particle
334 air pollution (PM_{2.5} and PM₁₀) concentrations and record this data internally on an SD
335 card every 20 minutes. The field team will continuously monitor these devices, download
336 the data stored in their SD cards to a laptop computer and then upload this data to a
337 secured storage drive.

338

339 *Treatment EBS: Education and Behavioral Strategies*

340

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

352 For this intervention we will produce educational material that has educational content
353 tailored specifically to this intervention. This includes leaflets (which will be handed out
354 to students), posters (which will be hung inside the classroom’s wall) and a short video
355 (which will be shown to students in the computer lab, when they respond to the survey
356 questionnaire). This educational material has simple language and is accompanied with
357 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/.

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

360

361 *Component 1: Effects of air pollution on health*

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

366

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

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

375

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

377 The personal strategies to mitigate the adverse effects of air pollution on health include:
378 (a) avoiding physical activity, exercising and (to the extent possible) spending much time
379 outdoors when AQI is high or very high; (b) closing of doors and windows when AQI is
380 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>

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

390

391 **ii. Possible Violations of SUTVA, Spillovers and Confounders**

392

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

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

421 In addition, we anticipate that these treatments may generate spillover effects beyond the
422 intended assignment to treatment. In particular, there could be non-behavioral changes
423 in exposure to air pollution that are triggered by assignment to the treatment *EBS*. For
424 example, parents of children assigned to treatment *EBS* may decide to buy an air purifier
425 for their home if they hear from their child's increased awareness about the problem of
426 air pollution – say, they hear their child advocating and pushing for household members
427 to engage in behavioral strategies to mitigate exposure at home. While we do not
428 anticipate being able to prevent this from happening, we will ask students both at baseline
429 and follow up surveys about the presence of air purifiers at home, so that we can properly
430 account for this sort of changes in air pollution exposure mitigation in our statistical
431 analysis. Likewise, there could be behavioral changes – triggered by assignment to
432 treatment *Purifier* – in such a way that affects students' exposure to air pollution. For
433 example, students may feel that, because they are 'protected from air pollution' while in
434 the classroom, then they do not need to be protected themselves from pollution at other
435 instances – thus, they may engage in lesser pollution exposure mitigation behavior than
436 otherwise. Conversely, the presence of the air purifier in the classroom may work as a
437 salient reminder of the problem of air pollution, in such a way that students change their
438 behavior by attempting to reduce exposure, also while outside the classroom. That is,
439 those students in classrooms assigned to treatment *Purifier* may feel more interested
440 and/or engaged in taking additional measures to reduce exposure, such as engaging in
441 some of the personal exposure mitigation behaviors listed above (for example, wearing
442 face masks). To address these issues, we will include questions in the survey
443 questionnaire about behavioral strategies to mitigate exposure both at baseline and at
444 follow-ups, and we will properly account for these in our econometric analysis. Similarly,
445 if the child is in a classroom assigned to treatment *Purifier*, and his/her parents believe

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

452

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

459

460 **iii. Sample and statistical power**

461

462 We are planning to conduct this experiment in 126 classrooms across 10 schools in
463 Delhi's KV schools. Of these classrooms, 54 have two shifts of classes a day (morning
464 and afternoon), making for a total of 180 classes. Moreover, each class has an average of
465 50 students, which makes for a total of around 9,000 students. However, of these 10
466 schools we will select 2 schools to serve as 'control-only', leaving us with 8 schools and
467 between 144 and 150 classes that will be eligible for random assignment to the treatments
468 and control.²¹ For simplicity, we will refer to working with a sample of around 147
469 classes. As the treatments will be assigned at the class level, this will allow for a split of
470 roughly 49 classes in each of the three treatment arms (the two treatments and the control
471 group).

472 Our sample of classes comprises students in 6th, 7th and 8th grade. Thereby, we will
473 conduct a stratified random assignment at the school grade level (Athey and Imbens,
474 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

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

492

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

498

499 Classroom/class level outcomes (Panel A of Table 2)

500

501 *Particle Pollution (PM_{2.5}) inside classrooms.* This analysis relies on our pilot with seven
502 air purifiers in an equal number of classrooms conducted in August through December
503 2022. The average PM_{2.5} pollution inside the classrooms is 133.16 µg/m³ 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).

504 deviation is 148.17. Therefore, under equal assignment of classrooms/classes between
505 treatment and control groups this yields a MDE equal to a 84.72 $\mu\text{g}/\text{m}^3$ reduction in $\text{PM}_{2.5}$.
506 On the other hand, the average reduction in $\text{PM}_{2.5}$ pollution inside classrooms that we
507 observed in our pilot is 101.2 $\mu\text{g}/\text{m}^3$.

508

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

515

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

517

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

519

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

529

530 *Respiratory health – Lung capacity.* We rely on parameters and estimates from Foster
531 and Kumar (2011) for an index of lung capacity (as measured by spirometry) for children
532 less than 17 years old in Delhi. The mean index reported by Foster and Kumar (2011) is
533 70.44 and its associated standard deviation is 15.35. Moreover, we assume the same ICC
534 as before. This yields an MDE equal to 3.4 for an equal assignment of class clusters into

535 treatment/control groups. On the other hand, we expect to find a reduction of 12.32 points
536 in such an index from the air purifier intervention. This expected reduction comes from
537 multiplying the estimated effect of 1.023 (per $1\text{-}\mu\text{g}/\text{m}^3$ of change in $\text{PM}_{2.5}$) found by
538 Foster and Kumar (2011) by a reduction of $12.04\ \mu\text{g}/\text{m}^3$ in average $\text{PM}_{2.5}$ exposure.²³

539

540 *Respiratory health – Self reported symptoms.* We rely on parameters and estimates from
541 Berkouwer and Dean (2023) for both a (zero-mean standardized) index and a count of
542 self-reported respiratory health symptoms. Assuming the same ICC and balance split
543 between treatment and control as before this yields a MDE of 0.22, whereas the effect
544 found in Berkouwer and Dean (2024) is 0.24 for a $0.8\ \mu\text{g}/\text{m}^3$ reduction in average $\text{PM}_{2.5}$
545 exposure. Similarly, the count of respiratory symptoms has a mean of 1.7 and a standard
546 deviation of 1.76, thus yielding a MDE of 0.39, which contrasts to the effect found in
547 Berkouwer and Dean (2024) of 0.48.²⁴ As mentioned above, we expect to find a
548 considerably larger reduction in average $\text{PM}_{2.5}$ exposure than the one in Berkouwer and
549 Dean (2024).

550

551 *Cognitive/learning assessment.* We rely on parameters and estimates for a (zero-mean
552 standardized) index of cognitive memory (Corsi test) from Berkouwer and Dean (2024).
553 Assuming the same ICC and balance split of treatments/control as before, we obtain a
554 MDE equal to 0.22. This contrasts with the effect of 0.48 for this index²⁵ for $0.8\ \mu\text{g}/\text{m}^3$
555 reduction in average $\text{PM}_{2.5}$ exposure – a considerably smaller reduction than the one we
556 expect for our treatment.

557

558 *Cognitive assessment – Peabody Picture Vocabulary and Math Test*

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

²³ This $12.04\ \mu\text{g}/\text{m}^3$ reduction in average exposure to $\text{PM}_{2.5}$ is the result of a $101.2\ \mu\text{g}/\text{m}^3$ 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).

562 .55 for boys and girls, respectively, from a 1- $\mu\text{g}/\text{m}^3$ change in the annual mean of $\text{PM}_{2.5}$.²⁶
 563 On the other hand, assuming the same ICC and balance split of treatments/control as
 564 before, we obtain a MDE equal to 0.22.

565

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

567

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

Outcome Variable	Mean	S. D.	ICC	MDE	Estimated Effect	Source
<u>Panel A. Class level</u>						
<i>Indoor $\text{PM}_{2.5}$ pollution ($\mu\text{g}/\text{m}^3$)</i>	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)	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	

569

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

570 4. Data

571

572 a. Data collection and processing

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

580 The survey questionnaire is divided into multiple sections. Section 1 starts with questions
581 about simple socioeconomic indicators and questions about self-reported respiratory
582 health symptoms experienced over a recent period of time. Then it moves onto questions
583 about air pollution. These include questions about knowledge and understanding of the
584 problem of air pollution, questions about capacity to identify periods of time with high
585 air pollution (by means of the Air Quality Index, AQI), and questions about knowledge
586 and practice of behavioral strategies to mitigate exposure to high air pollution. Sections
587 2 and 3 have questions for assessing learning of language and math (this is borrowed
588 from the India chapter of the *Young Lives survey*).²⁷ Finally, section 4 has questions on a
589 memory test consisting of connecting visual shapes (Corsi memory test). A working draft
590 of the questionnaires is attached in [Appendix B](#).

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

594 For collecting data on indoor PM pollution we will be using a low-cost monitor
595 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/>).

596 This monitor records PM_{2.5} and PM₁₀ every 20 minutes and records this data in its built-
597 in SD card.

598

599 **b. Timeline and implementation**

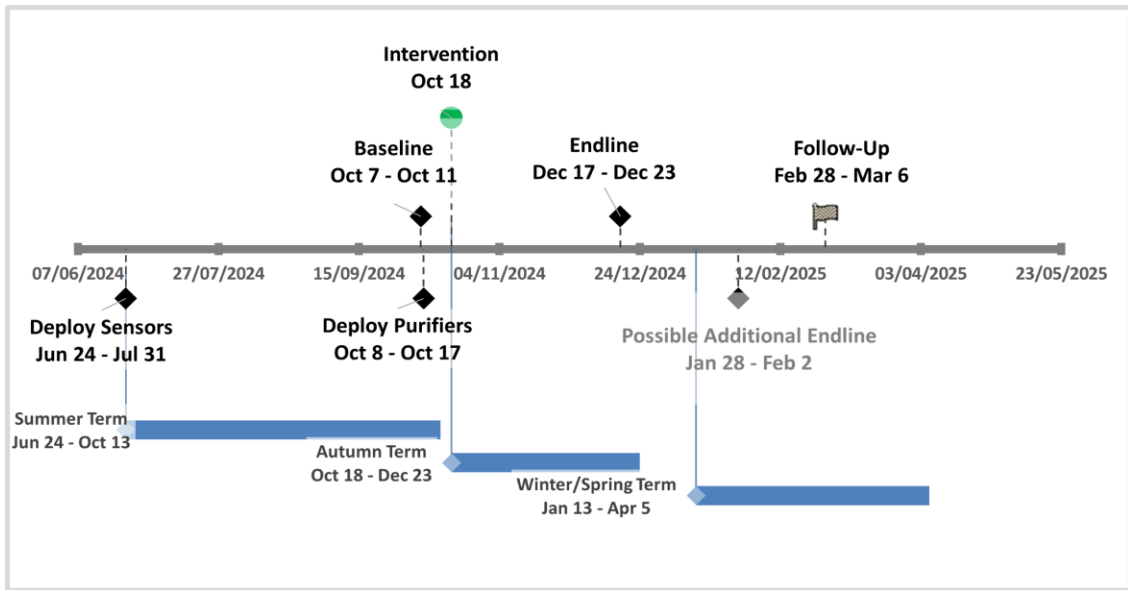
600

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

616

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.



617

618 Figure 2: Project Timeline

619

620 5. Statistical Analysis

621

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

627

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

629 Our empirical strategy consists of estimating the following equation.

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

630 Where $Pollution_{ct}$ denotes particle pollution (say, fine particulate matter, $PM_{2.5}$) in
 631 classroom c in school s in period t . $Purifier_{cst}$ is a dummy equal to one if the classroom
 632 has been randomly assigned a purifier and zero otherwise. We control for school-
 633 classroom-specific fixed effect λ_{cs} , which may capture factors such as: different levels
 634 of principal's engagement and awareness about air pollution issues, whether
 635 schools/classrooms are differentially exposed to ambient air pollution, whether

636 classrooms vary in the level of air exchange with outdoor air pollutants, classroom
637 volumetric size, etc. Moreover, we control for a set of time-specific fixed effects, Γ_t ,
638 accounting for the differential exposure during different periods of time throughout the
639 year (days, season), as well as during different times of the day (morning, afternoon,
640 etc.). Finally, ϵ_{cst} is an unobserved error term. The parameter β captures the effect of the
641 HEPA purifier on indoor particle pollution. We estimate β by running an OLS regression
642 of equation (1), clustering standard errors at the school-classroom level. To test
643 Hypothesis H1.1. we test the null hypothesis that $\hat{\beta} < 0$ against the alternative that $\hat{\beta} = 0$.

644

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

648 We estimate the following equation:

$$\text{Learning}_{icst} = \alpha + \beta_t EBS_{ics} + \delta_i + \lambda_{cs} D_t + \epsilon_{icst} \quad (2)$$

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

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

663 It could be that the effect of treatment EBS on learning varies by student's school grade,
664 such that those students in 8th grade could more easily grasp the content of the educational
665 campaign than, say, those students in 6th or 7th grade. To examine this possible differential

666 effect by school grade we interact EBS_{ics} with D_g , where D_g is a school grade-specific
 667 dummy.³²

668

669 Hypothesis 1.2.b: *Students change their behavior so as to mitigate their personal*
 670 *exposure.*

671 We estimate the following equation:

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

672 Where $Behavior_{icst}$ refers to an index of self-reported behaviors to mitigate exposure to
 673 high air pollution for student i in classroom c in school s and in survey-round t .
 674 Moreover, EBS_{ics} , δ_i , λ_{cs} , D_t and ϵ_{icst} are defined as in equation (2) above. To assess
 675 Hypothesis 1.2.b we test the null hypothesis that $\hat{\beta}_t < 0$, against the alternative that $\hat{\beta}_t =$
 676 0 , where we obtain $\hat{\beta}_t$ by OLS with cluster-robust standard errors. We also test the more
 677 general version substituting β for β_t . Additionally, to examine school grade-specific
 678 effects of treatment EBS on adoption of behavioral strategies we test the school grade-
 679 specific model by interacting EBS_{ics} with the grade-specific dummy D_g .

680

681 Hypothesis 2: *HEPA Purifiers in classrooms and personal mitigation strategies improve*
 682 *students' health.*

683 We estimate the following equation:

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

684 Where $Health_{icst}$ refers to respiratory health of student i in classroom c in school s and
 685 survey-round t . Specifically, lung capacity (FEV1 and PEF, as measured by spirometry)
 686 and an index of self-reported health. Variables δ_i , λ_{cs} , D_t , and ϵ_{icst} are defined as before.
 687 Moreover, $Mitigation_{ics}$ refers to either $Purifier_{cs}$ (for treatment *Purifier*) or EBS_{ics}
 688 (for treatment *EBS*), and β_t captures the effect of assignment to any of the mitigation
 689 strategy treatments on students' respiratory health. A more general version substitutes β_t
 690 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.

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

693 Moreover, to assess whether there is a differential effect of the two treatments (treatment
694 *Purifier* vs. treatment *EBS*), we estimate equation (4) with both treatments and conduct
695 an F-test of equality of the parameter estimates associated to each treatment. In addition,
696 it could be that the effect of mitigation strategies on health varies by student's age. As
697 student's age is almost perfectly correlated with student's school grade, we examine the
698 differential effects of the mitigation strategies by school grade by interacting
699 $Mitigation_{ics}$ with the grade-specific dummy D_g .

700

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

703 We estimate the following equation:

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

704 Where $Education_{icst}$ refers to scores in standardized cognitive tests, school attendance
705 and grades in final exams of student i in classroom c in school s and survey-round t .³³
706 $Mitigation_{ics}$, δ_i , λ_{cs} , D_t and ϵ_{icst} are defined as before. When running these
707 regressions, we also evaluate whether there is a differential effect of each of the two
708 treatments on educational outcomes by means of running (5) with the two treatments and
709 then conducting an F-test of equality of treatment effects. Moreover, it could be that the
710 effects of mitigation strategies on educational outcomes are mediated by the student's
711 age (proxied by his/her school grade). Thereby, we also interact $Mitigation_{ics}$ with the
712 grade-specific dummy D_g .

713 In addition, to identify effects on education that are directly linked to the effect of
714 assignment to treatment – via its associated effect on student's respiratory health – we
715 estimate equation (6) below instrumenting $Health_{icst}$ for $Mitigation_{ics}$ (as in equation
716 (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

717

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

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

725

726 **Other Heterogeneous Effects**

727

728 We may also look at gender heterogeneity. Recent evidence from rural India suggests
729 that girls are more sensitive than boys to the adverse effect of air pollution on math and
730 language test scores (Balakrishnan and Tsaneva, 2021). Balakrishnan and Tsaneva
731 (2021) hypothesize that this could be due to girls experiencing worse health and worse
732 access to health care at baseline. However, this gender heterogeneity has not been
733 examined for urban areas in India, which are exposed to much higher levels of air
734 pollution than rural areas. To examine and test for heterogeneous effects we will interact
735 the main dependent variable in equations (5) and (6) with a dummy variable that captures
736 this heterogeneity (i.e., a gender indicator).

737

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

738 **6. Administrative information**

739

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743

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747

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750

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1011 **Appendices**

1012 **A. Additional Materials**

1013 **1. Pilot Analysis**

1014

1015 A pilot study was conducted on a sample of 7 schools during the period August through
1016 December 2022. The intervention consisted of deploying large-capacity HEPA purifiers
1017 in 3rd grade classrooms. Due to the reduced number of devices all schools were treated
1018 (i.e., there was no control group), benefiting a total of 157 children. The pilot’s objective
1019 was to assess the performance of the air purifier devices in a school environment over a
1020 long period of time, and to estimate the potential effects on students’ attendance resulting
1021 from reductions in PM pollution inside the classroom.

1022

1023 To measure air pollution exposure, the head teacher in each class was asked to record
1024 indoor PM pollution levels – as displayed by the devices – four times per day (i.e., at the
1025 start of the days, before and after each recess, and at the end of the day). Daily attendance
1026 at the individual level data was provided by each school and month-level attendance at
1027 the class-level was obtained for comparable schools. We calculated attendance rates for
1028 both treated schools and non-treated schools for classes in 2nd, 3rd and 4th grade.
1029 Moreover, we generated a dummy variable for before and after the air purifiers were
1030 deployed (dummy ‘After’) and a dummy variable denoting those schools that received
1031 the air purifier (dummy ‘AirPurSchool’), and a third dummy variable denoting the
1032 interaction of these two (dummy ‘WithAirPur’). The parameter associated with this
1033 interactive dummy represents the difference-in-difference estimate of the effect of an air
1034 purifier in the classroom on school attendance rate (the standard errors are clustered at
1035 the school-level). Results from Table A.1 below show that the deployment of air purifiers
1036 resulted in an increase of 6 percentual points in attendance rate, which translates into an
1037 8 percent increase in school attendance.

	Attendance Rate		
	Second Grade	Third Grade	Fourth Grade
WithAirPur	0.017 [0.018]	0.060** [0.023]	0.009 [0.034]
AirPurSchool	0.038 [0.063]	-0.012 [0.051]	0.025 [0.029]
After	0.014 [0.011]	0.006 [0.009]	0.015 [0.008]
Constant	0.684*** [0.032]	0.749*** [0.028]	0.736*** [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.

1038

1039 Table A.1: Parameter estimates from Difference-in-Difference regressions analysis.

1040

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

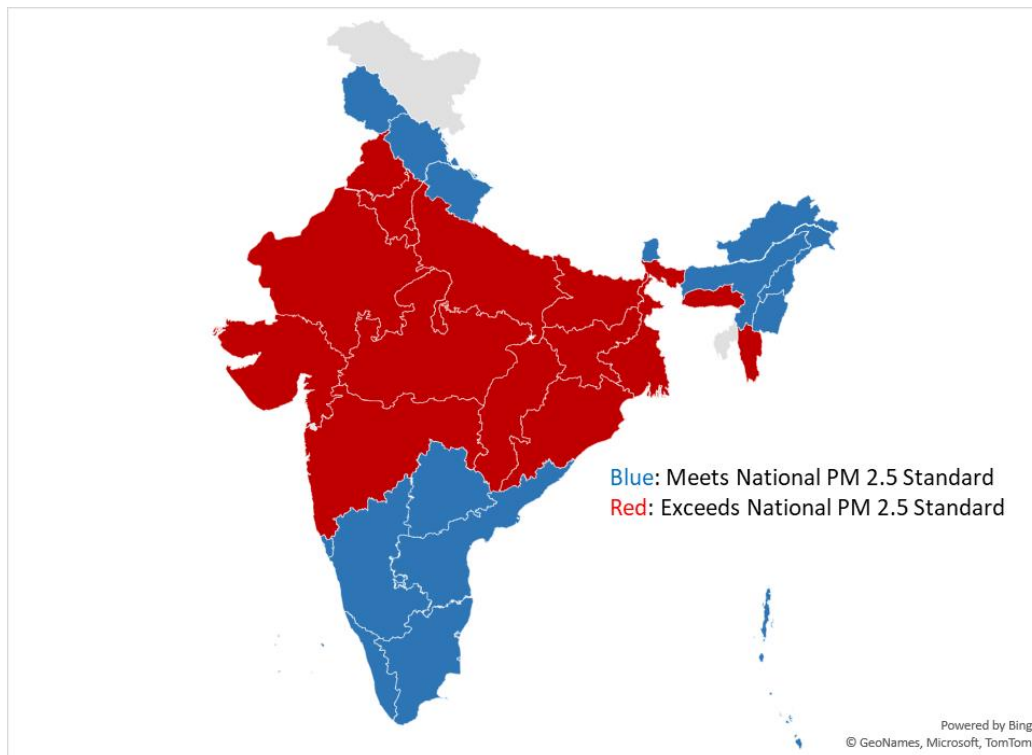
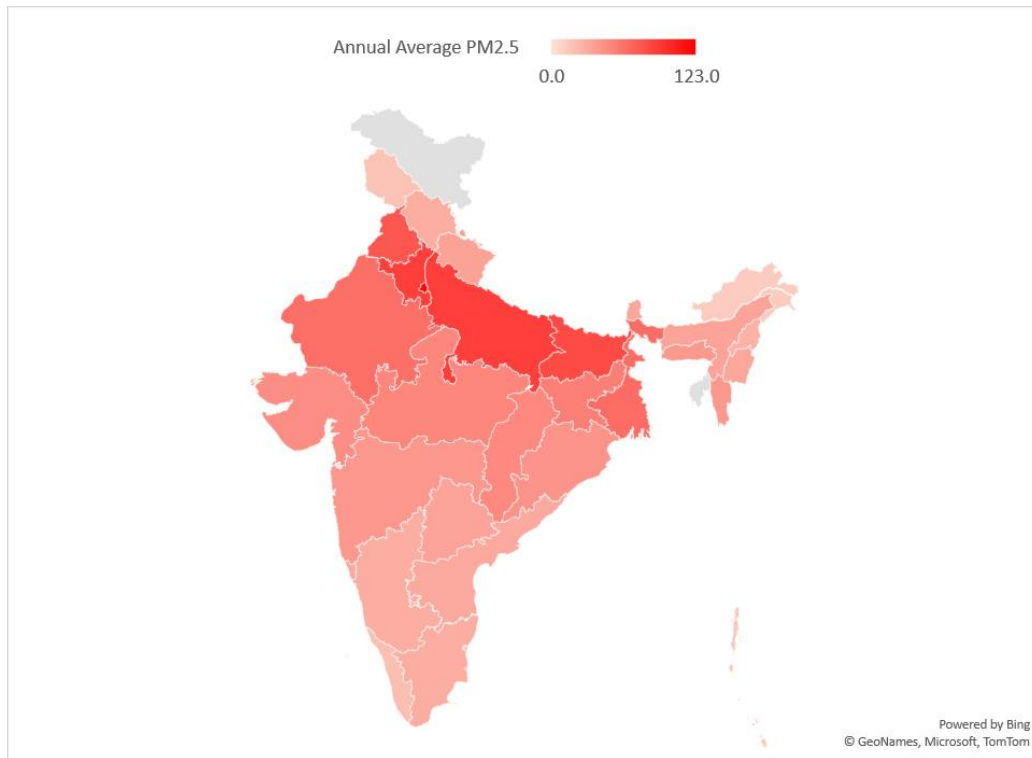


Figure 2: Annual average PM 2.5 for Indian states, in 2018. Source: urbanemissions.info

1042 The top panel shows state wise average annual PM_{2.5} concentrations in 2018. Darker
 1043 colors imply higher concentrations, while lighter colors imply lower concentrations. The
 1044 scale ranges from 0 to 123 μm^3 . The states that are located in the northern part of the
 1045 country are much more polluted, in particular the states located just south of the

1046 Himalayan Mountain range. Using the national standard of $40 \mu/m^3$, the bottom panel in
1047 Figure 2 splits states into whether their annual averages were above or below this national
1048 standard. States colored blue had annual average $PM_{2.5}$ concentrations below the national
1049 standard, and thus met the national standard. States colored red had annual average $PM_{2.5}$
1050 concentrations above the national standard, and thus exceeded the national standard. As
1051 is clear, most states located in the central or northern parts of the country had $PM_{2.5}$ levels
1052 above the national standard.
1053

1054 **B. Survey Questionnaires**

1055 **1. Air Pollution, Respiratory Symptoms & Socioeconomics**

1056 For our project-specific questionnaire, please open this document:

1057 <https://drive.google.com/file/d/1wggeTLQKyOiHShsCCcTy4h9Mt47ZIWFP/view?usp=sharing>

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2. Young Lives School Survey – Language Questionnaire

1085 For the language questionnaire (in English), please open this document:

1086 [https://www.younglives.org.uk/sites/default/files/migrated/TEST_English%20Form_Wave%20](https://www.younglives.org.uk/sites/default/files/migrated/TEST_English%20Form_Wave%20%20FINAL.pdf)
1087 [%20FINAL.pdf](https://www.younglives.org.uk/sites/default/files/migrated/TEST_English%20Form_Wave%20%20FINAL.pdf)

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3. Young Lives School Survey – Math Questionnaire

1118

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

1119

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

1120

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

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4. Corsi Memory Test

1125

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.

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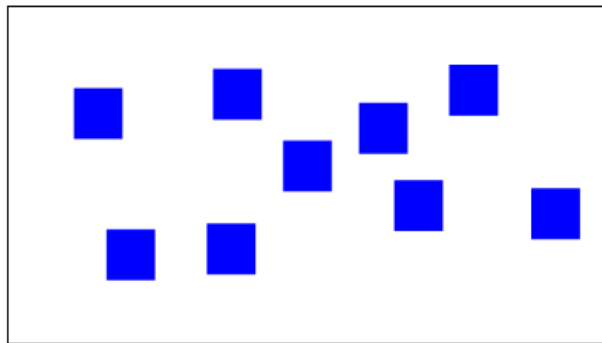
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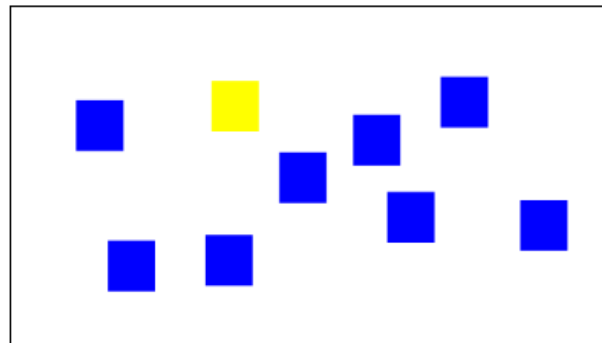
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(a) Blocks appear in random positions



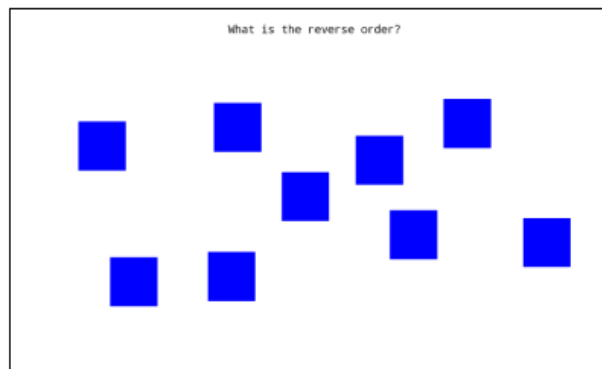
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(b) Blocks light up yellow randomly



1134

(c) Respondents tap blocks in reverse order



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C. Figures for Educational and Behavioral Strategies

1139

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

1140

LET US LEARN TOGETHER

HI, FRIENDS!!
I AM RAJ

AND
I AM MINA

HEY!
I AM ALI

Tell us your name _____

We live in different parts of Delhi. Come with us to learn about air pollution.

Please tell me about Air Pollution!!!!

Air pollution refers to the presence of harmful or excessive quantities of substances in the air that can harm human health. One major pollutant is particulate matter which is so small that it is not even visible!!

This means these small particles can enter our body and can cause a myriad of health problems, including respiratory illnesses like asthma, bronchitis, and chronic obstructive pulmonary disease, as well as cardiovascular diseases and even lung cancer.

But where does it come from?

Look the reasons!!!!

- VEHICLES
- TOO MANY INCENSE AND CANDLES
- WASTE BURNING AND NATURAL WILDFIRES
- INDUSTRIES AND MINING ACTIVITIES
- CONSTRUCTION ACTIVITIES
- INDOOR BURNING OF WOOD AND CHARCOAL
- OUTDOOR DUST AND POLLUTION

1141

1142

1143

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

1144

SO, HOW CAN WE MEASURE AIR POLLUTION

We can assess pollution using the Air Quality Index (AQI). It's a numerical scale that tells us about the air quality in a specific location at a given time.

Found it!!!!

Discomfort to the people with lungs, asthma and heart diseases

Discomfort to most people on prolonged exposure

Minor breathing discomfort to sensitive people

Respiratory illness on prolonged exposure

Minimal Impact

Affects healthy people and seriously impacts those with existing diseases

We can use different Websites such as https://airquality.cpcb.gov.in/AQI_India_iframe/ to check the AQI in Delhi.

Furthermore, multiple weather apps show AQI. We can just check once before we plan our outings

TELL US THE AQI IN YOUR NEIGHBOURHOOD

Q & A

Did you know that children and young people are more affected by air pollution than adults?

This is because you breathe faster than adults and take in more pollutants. Also, because your bodies and brains are still growing, and these pollutants can be way more harmful for your overall growth.

Next time you plan your hiking or cricket activity, make sure to check AQI.

Try playing indoors just like us, if AQI is too high

OK!

1145

1146

1147

1148

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

1149

STAY SAFE FROM POLLUTION

but how??

- Ask parents to not burn wood/ incense indoors.
- Avoid busy roads while going to school
- Say NO to firecrackers
- Stay away from people who smoke
- Shut your windows and stay indoors when AQI is too high.
- try to stay in clean spaces.
- Wear Masks when AQI is very high

Now we are ready!!!

The infographic features a central title 'STAY SAFE FROM POLLUTION' in large, bold, black letters. To the right of the title is a cartoon girl with a thinking expression and a speech bubble that says 'but how??'. Below the title are eight rectangular boxes, each containing a tip and an illustration. The tips are: 1. 'Ask parents to not burn wood/ incense indoors.' with illustrations of a wood burner, a fire, a candle, and incense. 2. 'Avoid busy roads while going to school' with an illustration of a busy street with cars and a person walking. 3. 'Say NO to firecrackers' with an illustration of exploding firecrackers. 4. 'Stay away from people who smoke' with a 'no smoking' sign and an illustration of a person smoking. 5. 'Shut your windows and stay indoors when AQI is too high.' with an illustration of a person sitting on a windowsill. 6. 'try to stay in clean spaces.' with an illustration of a person standing next to an air purifier. 7. 'Wear Masks when AQI is very high' with illustrations of two children wearing face masks. 8. A final speech bubble from the girl saying 'Now we are ready!!!'. The background is light yellow with decorative elements like stars and green leaf shapes.

1150

Author Statement

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

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29 **1. Introduction**

30

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

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

53 Control of air pollution has proven very challenging for developing countries. Air
54 pollution is a multifaceted problem involving many actors, economic sectors and even
55 varying geographies as the source of air pollutants. Moreover, developing countries often
56 seek to raise living standards through added manufacturing activity of highly polluting
57 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 et al., 2022).

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

66 Adoption of behavioral strategies to mitigate exposure to air pollution has been shown to
67 be effective at mitigating the adverse effects of air pollution on health. For example,
68 wearing face masks has been shown to reduce airway inflammation associated with
69 particle air pollution (Guan et al., 2018), reduce the decline of lung function (Shakya et
70 al., 2016), and improve measures of blood pressure (Shi et al. 2017). Avoiding cooking
71 with biomass and solid fuels and ventilating indoor cooking areas has been shown to
72 improve lung function and reduce the risk of chronic obstructive pulmonary disease
73 (COPD) (Zhou et al., 2014). Staying indoors on high-pollution days and limiting physical
74 activity outdoors, or near sources of air pollution, has been shown to decrease markers
75 of respiratory and systemic inflammation (Giles and Koehle, 2014; Madureira et al.,
76 2019). For those who suffer from asthma, higher asthma control (with the correct use of
77 inhalers) has been shown to mitigate the adverse effects of PM_{2.5} pollution on lung
78 capacity (Mirabelli et al., 2015).⁴ In terms of adoption of comprehensive behavioral
79 strategies, Araban et al. (2017) find that an educational program can positively change
80 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.

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

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

97 This work aims to fill the gaps in the literature by providing experimental evidence on
98 the link between both behavioral strategies to mitigate air pollution exposure and
99 technological strategies to reduce air pollution in classrooms, and the associated effects
100 on accumulation of human capital, broadly defined (i.e., maintaining good health,
101 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 et 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 $\mu\text{g}/\text{m}^3$, whereas children in the China study are exposed to average PM_{2.5} concentrations of 72 $\mu\text{g}/\text{m}^3$.

⁹ For our sample of KV schools in Delhi the average PM_{2.5} concentrations ranges from 142 $\mu\text{g}/\text{m}^3$ to 231 $\mu\text{g}/\text{m}^3$ 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.

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

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

126 To test these hypotheses, we will conduct a randomized controlled trial (RCT) in about
127 9,000 students from 180 classes in KV Schools in Delhi. We will evaluate two
128 interventions aimed at mitigating the adverse effects of air pollution in children. In the
129 first intervention we conduct an educational campaign among students of these schools
130 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.

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

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

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

152 Second, this work contributes to the literature on technology adoption for mitigating
153 environmental hazards and improving health in developing countries. For example, the
154 literature on the adoption of clean cookstoves (Pattanayak et al., 2019; Jeuland et al.,
155 2020; Afridi et al., 2021; Berkouwer and Dean, 2023) has found that improved
156 cookstoves result in a significant decrease in peak indoor air pollution although finds no
157 statistically significant decrease in average exposure to air pollution nor in health
158 biomarkers (Berkouwer and Dean, 2023). In a closely related paper, Chowdhury et al.
159 (2024) is examining the drivers of adoption of HEPA purifiers and their associated effects
160 on health and labor outcomes at the household level (although results have not been
161 reported yet). This work expands this literature by examining the potential of HEPA
162 purifiers for mitigating the adverse effects of indoor air pollution on children’s health
163 and educational performance in developing countries.

164 Third, this work contributes to the broad literature on development economics that seeks
165 to understand the barriers to adopting highly effective preventive behavior for mitigating
166 the burden of multiple health hazards and diseases faced by developing countries (Dupas,
167 2011). One possible explanation for this low adoption is a lack of information on the
168 consequences of health hazards and diseases and the effectiveness of preventative
169 behaviors (Dupas, 2011). In this regard, our work expands the limited literature that
170 evaluates the implementation of educational campaigns to incentivize better healthcare
171 practices and thus improve human health.¹² Our work expands this literature by designing
172 an educational campaign that not only delivers information but also teaches actionable
173 behavioral strategies for encouraging adoption of preventive behavior among school
174 children.

175 Fourth, we assess whether these health-enhancing strategies could also positively affect
176 educational outcomes. Current empirical evidence from public health campaigns aimed
177 at eradicating persistent diseases in developing countries (e.g., malaria) shows mixed
178 results in promoting educational attainment and literacy (Lucas, 2010; Cutler et al.,
179 2010). This literature also indicates that adopting health-enhancing technologies (e.g.,
180 water treatment, clean energy) that potentially reduce human pollution risk may raise
181 educational attainments, not only through health improvements (Zhang and Xu, 2016)
182 but also via a human capital investment mechanism (Choudhuri and Desai, 2021). Our
183 work contributes to this literature by assessing interventions that can potentially
184 disentangle the direct and indirect effects of behavioral and technological interventions
185 on educational performance, having as mediator health improvements.

186 The rest of this document is organized as follows. The next section presents the
187 background and context of the problem of air pollution in Delhi and the schools where
188 we will conduct the fieldwork. Section 3 presents the research design, where we state the
189 hypotheses that will be examined, the methodological framework, and conduct power
190 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.

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

193

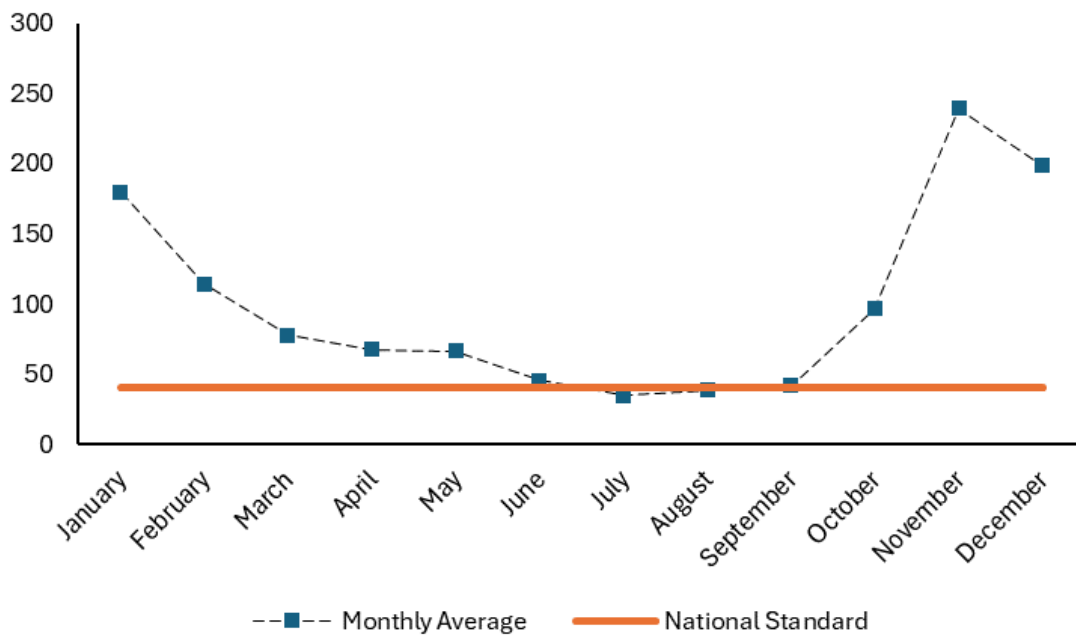
194 **2. Background and Context**

195

196 Delhi is home to about 20 million people, with an additional few million if we account
197 for surrounding satellite cities and towns. The air quality is very poor, with an average
198 PM_{2.5} concentration of roughly 120 micrograms per cubic meter ($\mu\text{g}/\text{m}^3$) in 2023. The
199 national air quality standard for India requires annual average PM_{2.5} concentrations not
200 to exceed 40 $\mu\text{g}/\text{m}^3$. Delhi has been in violation of these standards for at least the past
201 two decades. Air pollution in Delhi is also highly seasonal. Colder months typically see
202 worse air quality levels, while the Monsoon (late summer) period is the cleanest. Figure
203 1 below illustrates this. This figure uses data for the year 2023 from ambient air quality
204 monitors maintained by India's Central Pollution Control Board. The horizontal red line
205 shows India's standard for annual average PM_{2.5}. Delhi's air quality typically tends to be
206 in compliance with the annual standard only during July, August, and September. In the
207 winter months of November to January, in particular, the quality of the air deteriorates to
208 very high levels.¹³

209

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.



210

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

213

214 Since 2017 Delhi, and the surrounding satellite towns and cities that make up the National
 215 Capital Region (NCR), has instituted a comprehensive policy to reduce air pollution. This
 216 policy, called the Graded Response Action Plan (GRAP), consists of four stages. Stage I
 217 is put in place when the predicted air pollution exceeds a certain cut-off. Subsequent
 218 stages - Stages II, III and IV - are invoked when air pollution is predicted to exceed
 219 progressively higher cut-offs. Relevant to our interventions, Stage IV of the GRAP
 220 requires schools to be shut down when air quality is predicted to be particularly bad. For
 221 instance, in 2023 in Delhi, primary schools were shut down from November 6th to
 222 November 18th, while schools at all levels were shut down from November 8th onwards.¹⁴
 223 Therefore, if HEPA purifiers in classrooms turn effective at reducing air pollution in
 224 classrooms and improving students' health and educational outcomes, Stage IV of the
 225 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.

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

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

241

242 **3. Research Design**

243

244 **a. Objectives and Main Hypothesis**

245

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

251

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.

252 **b. Main outcomes of Interest**

253

254 By means of a survey questionnaire, we assess students' understanding and learning of
255 key components of the educational and behavioral intervention. Specifically, we assess
256 understanding and learning of (i) the effects of air pollution on health, (ii) identification
257 of periods of high air pollution (specifically, high Air Quality Index), and (iii) personal
258 strategies to mitigate exposure to high air pollution. In addition, the survey questionnaire
259 will allow us to gauge whether students have actually engaged in any of these behavioral
260 strategies. Moreover, we examine the effect of air purifiers on indoor particle air
261 pollution. To measure this, we will deploy indoor pollution monitors that will log real-
262 time readings of fine and coarse particulate matter pollution (PM_{2.5} and PM₁₀). These
263 monitors will be deployed in both classrooms with HEPA purifiers and control
264 classrooms. Moreover,

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

271 Finally, we measure students' educational outcomes in three ways. We obtain data on
272 individual-level school attendance from schools' official registries, perform standardized
273 learning and cognitive tests throughout the school year¹⁹, and assess students' grades
274 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).

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

277

278 **c. Testable Hypotheses**

279

280 We hypothesize that

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

283

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

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

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

292 and

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

295

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

298

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.

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

301

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

304

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

307

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

310

311 *Table 1: Hypotheses and Outcome Variables*

Hypothesis	Outcome Variable	Unit of Obs.	Type	Data Source
<u>H1: Air Pollution & Exposure</u>				
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})	µg/m ³ in classroom x 20-minutes	Continuous	Indoor pollution monitors
<u>H2: Health</u>				
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

312

313

d. Methodological Framework

314

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

323

324

i. Treatments

325

326 Treatment EBS: Education and Behavioral Strategies

327

328 The first treatment consists of an educational campaign that will have three components.
329 Component 1 teaches students about the problem of air pollution in their city and how it
330 impacts their own health. Component 2 teaches students that exposure to higher levels of
331 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

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

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

346

347 *Component 1: Effects of air pollution on health*

348 For explaining the effects of air pollution on health we have produced a draft of this
349 educational content (see [Appendix C.1](#) below). In addition, based on this content we have
350 produced a short video that is similar to [this video](#) from the United Nations Children's
351 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>

352

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

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

361

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

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

377

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

384

385 Treatment Purifiers: HEPA purifiers in classrooms

386

387 The second treatment consists of deploying high-capacity HEPA purifiers inside
388 randomly selected school classrooms. These HEPA purifiers contain a filter that filters
389 up to 99.99 percent of particles of size 0.1 microns (PM_{0.1}) or larger. These air purifiers
390 have a manufactured-stated clean air delivery rate (CADR) of 600 cubic meters per hour
391 (21,189 cubic feet per hour) and are suitable for rooms of an area of up to 60 square
392 meters (645 square feet). This intervention is further accompanied by simple information
393 and education seeking to enhance the performance of the HEPA purifiers. Specifically,
394 students and teachers will be asked to keep doors and windows shut during the time the
395 purifier is running inside the classroom. These purifiers will be running during teaching
396 hours and will be turned on/off by the class teacher. The field team will be in constant
397 communication with school principals to ensure that these purifiers perform continuously
398 during the data collection period and that any malfunction is promptly fixed and logged.
399 All air purifiers will be deployed and installed in late October and early November 2024
400 (October 28th to November 4th, 2024).

401 To assess the reduction of indoor air pollution by these purifiers we will deploy indoor
402 air pollution monitors inside classrooms in both those classrooms assigned to treatment
403 *Purifier* and those in the control group.²³ These devices measure fine and coarse particle
404 air pollution (PM_{2.5} and PM₁₀) concentrations and record this data internally on an SD
405 card every 20 minutes. The field team will continuously monitor these devices, download
406 the data stored in their SD cards to a laptop computer, and then upload th-is data to a
407 secured storage drive.

408

409 **ii. Possible Indirect Effects of Assignment to Treatment Arms**

410

411 We anticipate that these treatments may generate effects on indoor air pollution and
412 exposure that are beyond those directly intended by the assignment to treatment. There
413 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.

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

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

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

445

iii. Possible Violations of SUTVA and Confounding Effects

446

447

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

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

477 On the other hand, a potential confounder effect can occur as schools close due to a
478 government mandate as air pollution reaches very high peaks (Stage IV of GRAP policy

479 response, as discussed in section 2 above). But as schools in the control and the treatment
480 group are impacted similarly by closures, we expect a similar exposure outside the
481 classroom premises. However, we will keep track of the occurrence of school closures
482 for any reason.

483

484 **iv. Sample and statistical power**

485

486 We are planning to conduct this experiment in 126 classrooms across 10 schools in
487 Delhi's KV schools. Of these classrooms, 54 have two shifts of classes a day (morning
488 and afternoon), making for a total of 180 classes. Moreover, each class has an average of
489 50 students, which makes for a total of around 9,000 students. However, of these 10
490 schools we will select 2 schools to serve as 'control-only', leaving us with 8 schools and
491 between 144 and 150 classes that will be eligible for random assignment to the treatments
492 and control.²⁴ For simplicity, we will refer to working with a sample of around 147
493 classes. As the treatments will be assigned at the class level, this will allow for a split of
494 roughly 49 classes in each of the three treatment arms (the two treatments and the control
495 group).

496 Our sample of classes comprises students in 6th, 7th and 8th grade. Thereby, we will
497 conduct a stratified random assignment at the school grade level (Athey and Imbens,
498 2017). The rationale for this stratified random assignment is as follows. One of the
499 important factors likely driving many of our primary outcomes is the student's age and
500 their associated school grade and cognitive/learning capacity. An older student should
501 have a more resilient health system that can better withstand adverse environmental
502 conditions, such as exposure to high levels of air pollution. Thereby, the effects of
503 mitigating indoor air pollution and exposure to high air pollution on respiratory health
504 (and thus, educational outcomes) may be less pronounced among older students than
505 among younger students. Moreover, older students should be better equipped to grasp
506 the content of an educational campaign aimed at reducing personal exposure, they have
507 more agency on determining their actual behavior, and thus could possibly mitigate their
508 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

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

516

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

522

523 Classroom/class level outcomes (Panel A of Table 2)

524

525 *Particle Pollution (PM_{2.5}) inside classrooms.* This analysis relies on our pilot with seven
526 air purifiers in an equal number of classrooms conducted in August through December
527 2022. The average PM_{2.5} pollution inside the classrooms is 133.16 µg/m³ and the standard
528 deviation is 148.17. Therefore, under equal assignment of classrooms/classes between
529 treatment and control groups this yields a MDE equal to a 84.72 µg/m³ reduction in PM_{2.5}.
530 On the other hand, the average reduction in PM_{2.5} pollution inside classrooms that we
531 observed in our pilot is 101.2 µg/m³.

532

533 *School attendance.* This analysis relies on the absenteeism rate reported by (Singh, 2022)
534 for schools in Delhi. Singh (2022) reports an average absenteeism rate of 26.24 for 6th
535 to 8th graders in Delhi schools and a standard deviation of 1.4. Therefore, assuming equal
536 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).

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

539

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

541

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

543

544 *Adoption of behavioral strategies.* Although we did not conduct a pilot for the
545 educational and behavioral intervention, we rely on Araban et al. (2017) for a feasible
546 mean and standard deviation of an index of adoption of behavioral strategies.²⁶ In
547 addition, for the class-level intra-cluster correlation (ICC) we rely on estimates from the
548 ‘Balsakhi’ program of remedial education for schools in urban India (Banerjee et al.,
549 2007). Thus, we assume a mean adoption index of 11.2 (for an index that goes from 5 to
550 20), an associated standard deviation of 2.3, and an ICC of 0.1356.²⁷ Under equal
551 assignment of class-level clusters of students among treatments/control groups, this
552 yields a MDE equal to 0.51. On the other hand, Araban et al. (2017) finds an effect of
553 8.8 for that same index.

554

555 *Respiratory health – Lung capacity.* We rely on parameters and estimates from Foster
556 and Kumar (2011) for an index of lung capacity (as measured by spirometry) for children
557 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), one 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).

558 70.44 and its associated standard deviation is 15.35. Moreover, we assume the same ICC
559 as before. For ease of testing and depending on parents' authorizations, we expect to
560 conducting these tests on a subsample of no less than 10 percent of students in each class
561 (about no less than 5 students per class). This yields a MDE equal to 4.8 for an equal
562 assignment of class clusters into treatment/control groups. On the other hand, we expect
563 to find a reduction of 12.32 points in such an index from the air purifier intervention.
564 This expected reduction comes from multiplying the estimated effect of 1.023 (per 1-
565 $\mu\text{g}/\text{m}^3$ of change in $\text{PM}_{2.5}$) found by Foster and Kumar (2011) by a reduction of 12.04
566 $\mu\text{g}/\text{m}^3$ in average ambient $\text{PM}_{2.5}$.²⁸

567

568 *Respiratory health – Self reported symptoms.* We rely on parameters and estimates from
569 Berkouwer and Dean (2023) for both a (zero-mean standardized) index and a count of
570 self-reported respiratory health symptoms. Assuming the same ICC and balance split
571 between treatment and control as before this yields a MDE of 0.22, whereas the effect
572 found in Berkouwer and Dean (2024) is 0.24 for a 0.8 $\mu\text{g}/\text{m}^3$ reduction in average $\text{PM}_{2.5}$.
573 Similarly, the count of respiratory symptoms has a mean of 1.7 and a standard deviation
574 of 1.76, thus yielding a MDE of 0.39, which contrasts to the effect found in Berkouwer
575 and Dean (2024) of 0.48.²⁹ As mentioned above, we expect to find a considerably larger
576 reduction in average $\text{PM}_{2.5}$ than the one in Berkouwer and Dean (2024).

577

578 *Cognitive/learning assessment.* We rely on parameters and estimates for a (zero-mean
579 standardized) index of cognitive memory (Corsi test) from Berkouwer and Dean (2024).
580 Assuming the same ICC and balance split of treatments/control as before, we obtain a
581 MDE equal to 0.22. This contrasts with the effect of 0.48 for this index³⁰ for 0.8 $\mu\text{g}/\text{m}^3$
582 reduction in average $\text{PM}_{2.5}$ – a considerably smaller reduction than the one we expect for
583 our treatment.

584

²⁸ This 12.04 $\mu\text{g}/\text{m}^3$ reduction in average $\text{PM}_{2.5}$ is the result of a 101.2 $\mu\text{g}/\text{m}^3$ 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).

585 *Cognitive assessment – Peabody Picture Vocabulary and Math Test*

586 We rely on parameters and estimates from Balakrishnan and Tsaneva (2021) for a (zero-
 587 mean standardized) index of the Peabody Picture Vocabulary Test from the India Chapter
 588 of the *Young Lives Survey*. Balakrishnan and Tsaneva (2021) find an effect of 0.18 and
 589 .55 for boys and girls, respectively, from a 1- $\mu\text{g}/\text{m}^3$ change in the annual mean of $\text{PM}_{2.5}$.³¹
 590 On the other hand, assuming the same ICC and balance split of treatments/control as
 591 before, we obtain a MDE equal to 0.22.

592

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

594

595 *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 $\text{PM}_{2.5}$ pollution ($\mu\text{g}/\text{m}^3$)	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 $\text{PM}_{2.5}$ 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	

596

597 4. Data

598

599 a. Data collection and processing

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

607 The survey questionnaire is divided into multiple sections. Section 1 starts with questions
608 about simple socioeconomic indicators and questions about self-reported respiratory
609 health symptoms experienced over a recent period of time. Then it moves onto questions
610 about air pollution. These include questions about knowledge and understanding of the
611 problem of air pollution, questions about capacity to identify periods of time with high
612 air pollution (by means of the Air Quality Index, AQI), and questions about knowledge
613 and practice of behavioral strategies to mitigate exposure to high air pollution. Sections
614 2 and 3 have questions for assessing learning of language and math (this is borrowed
615 from the India chapter of the *Young Lives survey*).³² Finally, section 4 has questions on a
616 memory test consisting of connecting visual shapes (Corsi memory test). A working draft
617 of the questionnaires is attached in [Appendix B](#).

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

621 For collecting data on indoor PM pollution we will be using a low-cost monitor
622 manufactured by Purelogic Labs India, an air quality company based in Delhi, India.³⁴
623 This monitor records PM_{2.5} and PM₁₀ every 20 minutes and records this data in its built-
624 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.pranair.com/air-quality-monitor/smart-indoor-pm-monitor/>).

625

626

b. Timeline and implementation

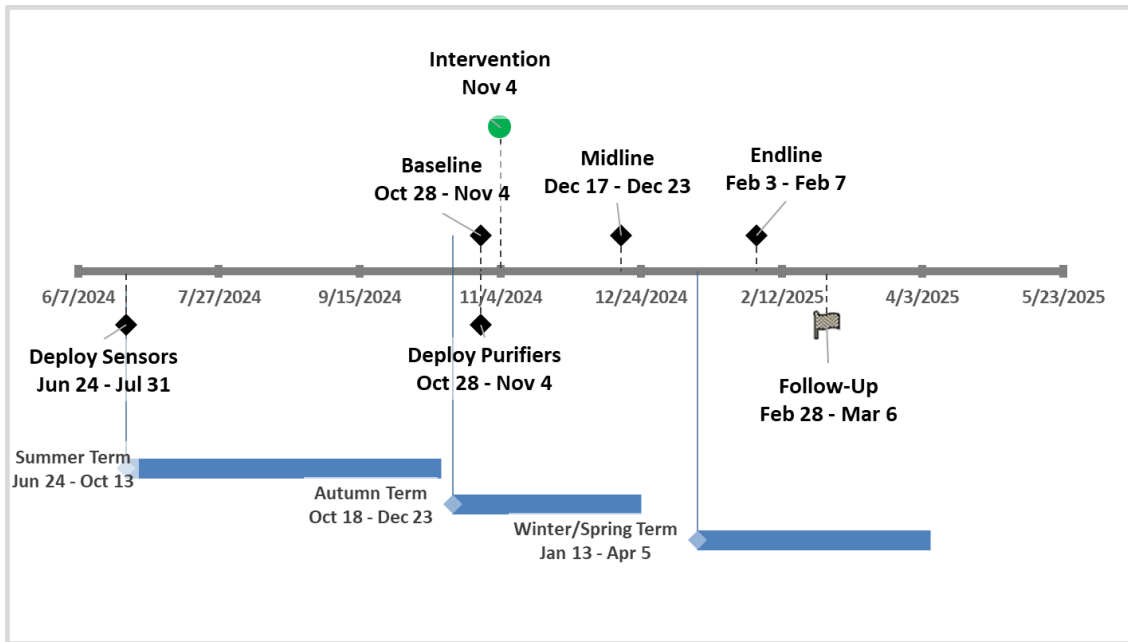
627

628 We will conduct the intervention during late 2024 and into early 2025 (November 2024
629 through January 2025). As shown in Figure 1 above, this is the period of time in which
630 PM pollution in Delhi peaks up and reaches its highest levels.³⁵ The deployment of the
631 PM pollution monitors in KV School classrooms will begin earlier, in the summer of
632 2024 (thus, allowing for pre-treatment data collection). The main data collection,
633 however, will be carried out in November-December of 2024, and early February 2025.
634 The baseline data survey and lung capacity tests will be conducted on October 28th
635 through November 4th. During this time, we will also conduct the *Educational and*
636 *Behavioral Strategies* treatment in randomly selected school classes. At this time we will
637 also deploy the HEPA purifiers in randomly selected classrooms, and these will be
638 running throughout the Winter teaching term. In addition, there will be a midline survey
639 and lung capacity tests before the Christmas break (on December 17th to 13th).³⁶ And
640 there will be an endline on February 3rd to the 7th. Finally, there will be a follow-up data
641 collection in which we will obtain administrative data on students' attendance and grades
642 in final examinations. Figure 2 below shows a visual timeline of events.

643

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.



644

645 Figure 2: Project Timeline

646

647 5. Statistical Analysis

648

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

654

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

658 We estimate the following equation:

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

659 Where $Learning_{icst}$ refers to three separate indices of learning and understanding of the
 660 concepts in components 1, 2 and 3 (as in section 3 above³⁷) 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

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

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

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

678

679 Hypothesis 1.1.b: *Students change their behavior so as to mitigate their personal*
 680 *exposure.*

681 We estimate the following equation:

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

682 Where $Behavior_{icst}$ refers to an index of self-reported behaviors to mitigate exposure to
 683 high air pollution for student i in classroom c in school s and in survey-round t .
 684 Moreover, EBS_{ics} , δ_i , λ_{cs} , D_t and ϵ_{icst} are defined as in equation (2) above. To assess
 685 Hypothesis 1.2.b we test the null hypothesis that $\hat{\beta}_t < 0$, against the alternative that $\hat{\beta}_t =$
 686 0 , where we obtain $\hat{\beta}_t$ 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.

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

690

691 Hypothesis H1.2: *Air purifiers Reduce air pollution while students are in the classroom.*

692 Our empirical strategy consists of estimating the following equation.

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

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

707

708 Hypothesis 2: *HEPA Purifiers in classrooms and personal mitigation strategies improve*
 709 *students' health.*

710 We estimate the following equation:

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

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

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

720 Moreover, to assess whether there is a differential effect of the two treatments (treatment
 721 *Purifier* vs. treatment *EBS*), we estimate equation (4) with both treatments and conduct
 722 an F-test of equality of the parameter estimates associated to each treatment. In addition,
 723 it could be that the effect of mitigation strategies on health varies by student's age. As
 724 student's age is almost perfectly correlated with student's school grade, we examine the
 725 differential effects of the mitigation strategies by school grade by interacting
 726 $Mitigation_{ics}$ with the grade-specific dummy D_g .

727

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

730 We estimate the following equation:

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

731 Where $Education_{icst}$ refers to scores in standardized cognitive tests, school attendance
 732 and grades in final exams of student i in classroom c in school s and survey-round t .³⁹
 733 $Mitigation_{ics}$, δ_i , λ_{cs} , D_t and ϵ_{icst} are defined as before. When running these
 734 regressions, we also evaluate whether there is a differential effect of each of the two
 735 treatments on educational outcomes by means of running (5) with the two treatments and
 736 then conducting an F-test of equality of treatment effects. Moreover, it could be that the
 737 effects of mitigation strategies on educational outcomes are mediated by the student's
 738 age (proxied by his/her school grade). Thereby, we also interact $Mitigation_{ics}$ with the
 739 grade-specific dummy D_g .

740 In addition, to identify effects on education that are directly linked to the effect of
 741 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.

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

744

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

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

752

753 **Other Heterogeneous Effects**

754

755 We may also look at gender heterogeneity. Recent evidence from rural India suggests
756 that girls are more sensitive than boys to the adverse effect of air pollution on math and
757 language test scores (Balakrishnan and Tsaneva, 2021). Balakrishnan and Tsaneva
758 (2021) hypothesize that this could be due to girls experiencing worse health and worse
759 access to health care at baseline. However, this gender heterogeneity has not been
760 examined for urban areas in India, which are exposed to much higher levels of air
761 pollution than rural areas. To examine and test for heterogeneous effects we will interact
762 the main dependent variable in equations (5) and (6) with a dummy variable that captures
763 this heterogeneity (i.e., a gender indicator).

764

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.

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766

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770

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774

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1039 **Appendices**

1040 **A. Additional Materials**

1041 **1. Pilot Analysis**

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1043 A pilot study was conducted on a sample of 7 schools during the period August through
1044 December 2022. The intervention consisted of deploying large-capacity HEPA purifiers
1045 in 3rd grade classrooms. Due to the reduced number of devices all schools were treated
1046 (i.e., there was no control group), benefiting a total of 157 children. The pilot’s objective
1047 was to assess the performance of the air purifier devices in a school environment over a
1048 long period of time, and to estimate the potential effects on students’ attendance resulting
1049 from reductions in PM pollution inside the classroom.

1050

1051 To measure air pollution, the head teacher in each class was asked to record indoor PM
1052 pollution levels – as displayed by the devices – four times per day (i.e., at the start of the
1053 days, before and after each recess, and at the end of the day). Daily attendance at the
1054 individual level data was provided by each school and month-level attendance at the
1055 class-level was obtained for comparable schools. We calculated attendance rates for both
1056 treated schools and non-treated schools for classes in 2nd, 3rd and 4th grade. Moreover, we
1057 generated a dummy variable for before and after the air purifiers were deployed (dummy
1058 ‘After’) and a dummy variable denoting those schools that received the air purifier
1059 (dummy ‘AirPurSchool’), and a third dummy variable denoting the interaction of these
1060 two (dummy ‘WithAirPur’). The parameter associated with this interactive dummy
1061 represents the difference-in-difference estimate of the effect of an air purifier in the
1062 classroom on school attendance rate (the standard errors are clustered at the school-level).
1063 Results from Table A.1 below show that the deployment of air purifiers resulted in an
1064 increase of 6 percentage points in attendance rate, which translates into an 8 percent
1065 increase in school attendance.

	Attendance Rate		
	Second Grade	Third Grade	Fourth Grade
WithAirPur	0.017 [0.018]	0.060** [0.023]	0.009 [0.034]
AirPurSchool	0.038 [0.063]	-0.012 [0.051]	0.025 [0.029]
After	0.014 [0.011]	0.006 [0.009]	0.015 [0.008]
Constant	0.684*** [0.032]	0.749*** [0.028]	0.736*** [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.

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1067 Table A.1: Parameter estimates from Difference-in-Difference regressions analysis.

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

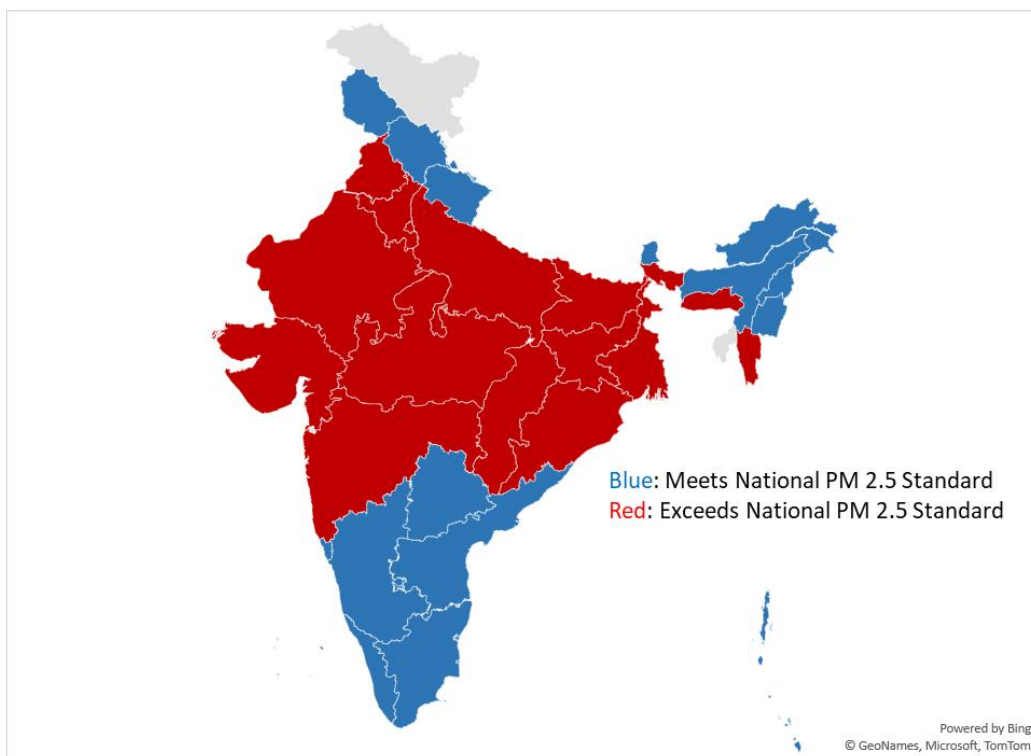
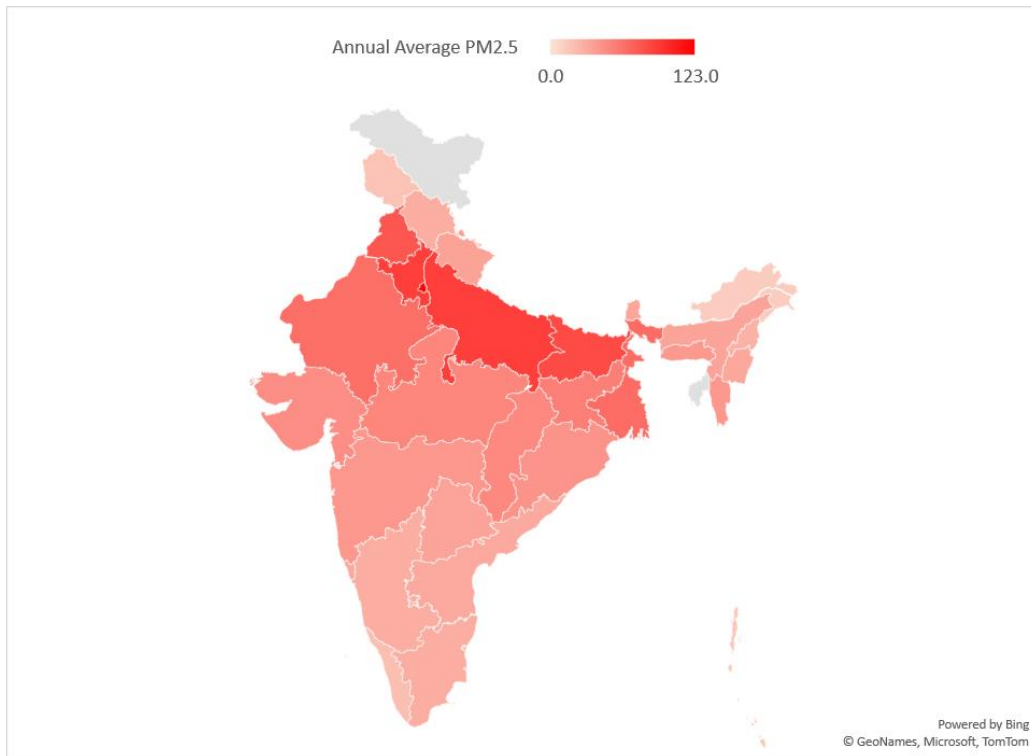


Figure 2: Annual average PM 2.5 for Indian states, in 2018. Source: urbanemissions.info

1070 The top panel shows state wise average annual PM_{2.5} concentrations in 2018. Darker
 1071 colors imply higher concentrations, while lighter colors imply lower concentrations. The
 1072 scale ranges from 0 to 123 μm^3 . The states that are located in the northern part of the
 1073 country are much more polluted, in particular the states located just south of the

1074 Himalayan Mountain range. Using the national standard of $40 \mu/m^3$, the bottom panel in
1075 Figure 2 splits states into whether their annual averages were above or below this national
1076 standard. States colored blue had annual average $PM_{2.5}$ concentrations below the national
1077 standard, and thus met the national standard. States colored red had annual average $PM_{2.5}$
1078 concentrations above the national standard, and thus exceeded the national standard. As
1079 is clear, most states located in the central or northern parts of the country had $PM_{2.5}$ levels
1080 above the national standard.
1081

1082 **B. Survey Questionnaires**

1083 **1. Air Pollution, Respiratory Symptoms & Socioeconomics**

1084 For our project-specific questionnaire, please open this document:

1085 <https://drive.google.com/file/d/1wggeTLQKyOiHShsCCcTy4h9Mt47ZIWFP/view?usp=sharing>

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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%20%20FINAL.pdf

1145

3. Young Lives School Survey – Math Questionnaire

1146

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

1147

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

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

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4. Corsi Memory Test

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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.

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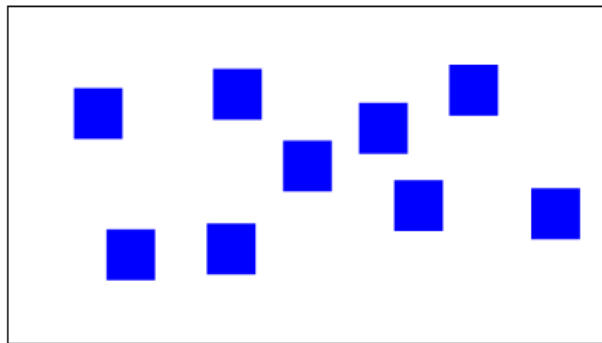
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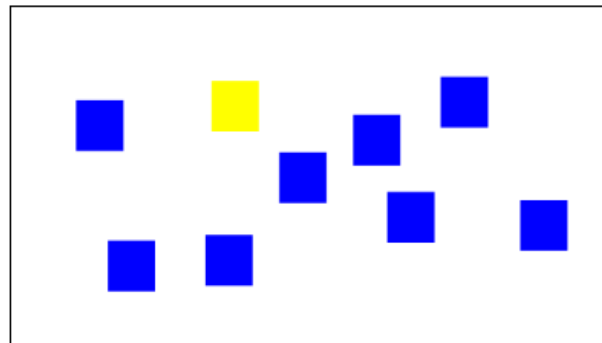
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(a) Blocks appear in random positions



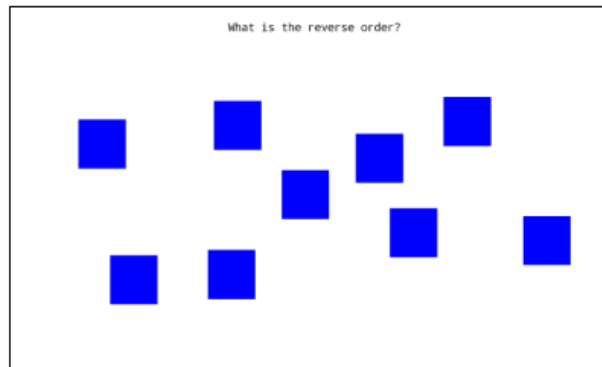
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(b) Blocks light up yellow randomly



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(c) Respondents tap blocks in reverse order



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C. Figures for Educational and Behavioral Strategies

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

1168

LET US LEARN TOGETHER

HI, FRIENDS!!
I AM RAJ

AND
I AM MINA

HEY!
I AM ALI

Tell us your name _____

We live in different parts of Delhi. Come with us to learn about air pollution.

Please tell me about Air Pollution!!!!

Air pollution refers to the presence of harmful or excessive quantities of substances in the air that can harm human health. One major pollutant is particulate matter which is so small that it is not even visible!!

This means these small particles can enter our body and can cause a myriad of health problems, including respiratory illnesses like asthma, bronchitis, and chronic obstructive pulmonary disease, as well as cardiovascular diseases and even lung cancer.

But where does it come from?

Look the reasons!!!!

VEHICLES

TOO MANY INCENSE AND CANDLES

WASTE BURNING AND NATURAL WILDFIRES

INDUSTRIES AND MINING ACTIVITIES

CONSTRUCTION ACTIVITIES

INDOOR BURNING OF WOOD AND CHARCOAL

OUTDOOR DUST AND POLLUTION

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1172

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

SO, HOW CAN WE MEASURE AIR POLLUTION

We can assess pollution using the **Air Quality Index (AQI)**. It's a numerical scale that tells us about the air quality in a specific location at a given time.

Found it!!!!

Discomfort to the people with lungs, asthma and heart diseases

Discomfort to most people on prolonged exposure

Minor breathing discomfort to sensitive people

Respiratory illness on prolonged exposure

Minimal Impact

Affects healthy people and seriously impacts those with existing diseases

GOOD 0 50 100 **SATISFACTORY** 200 **MODERATE** 300 **POOR** 400 **VERY POOR** 500 **SEVERE**

We can use different Websites such as https://airquality.cpcb.gov.in/AQI_India_iframe/ to check the AQI in Delhi.

Furthermore, multiple weather apps show AQI. We can just check once before we plan our outings

TELL US THE AQI IN YOUR NEIGHBOURHOOD _____

Q & A

Did you know that children and young people are more affected by air pollution than adults?

This is because you breathe faster than adults and take in more pollutants. Also, because your bodies and brains are still growing, and these pollutants can be way more harmful for your overall growth.

Next time you plan your hiking or cricket activity, make sure to check AQI.

Try playing indoors just like us, if AQI is too high

OK!

1173
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3. Example of Educational Material for Teaching About Strategies to Mitigate the Effects of Air Pollution on Health.

STAY SAFE FROM POLLUTION

but how??

- Ask parents to not burn wood/ incense indoors.
- Avoid busy roads while going to school
- Say NO to firecrackers
- Stay away from people who smoke
- Shut your windows and stay indoors when AQI is too high.
- try to stay in clean spaces.
- Wear Masks when AQI is very high

Now we are ready!!!

The infographic features a central title 'STAY SAFE FROM POLLUTION' in large, bold, black letters. To the right of the title is a cartoon girl with a thinking expression and a speech bubble that says 'but how??'. Below the title are seven rectangular boxes, each containing a tip and an illustration. The tips are: 1. 'Ask parents to not burn wood/ incense indoors.' with illustrations of a wood burner, a fire, a candle, and incense. 2. 'Avoid busy roads while going to school' with an illustration of a busy street with cars and a person walking. 3. 'Say NO to firecrackers' with an illustration of exploding firecrackers. 4. 'Stay away from people who smoke' with a 'no smoking' sign and an illustration of a person smoking. 5. 'Shut your windows and stay indoors when AQI is too high.' with an illustration of a person sitting on a windowsill. 6. 'try to stay in clean spaces.' with an illustration of a person standing next to an air purifier. 7. 'Wear Masks when AQI is very high' with illustrations of two children wearing face masks. To the right of the last tip is a cartoon girl with a speech bubble that says 'Now we are ready!!!'. The background is light yellow with decorative green and red shapes and white starburst icons.