Clean Air in the Classroom: Environmental Inputs and Human Capital Formation

Pre-Analysis Plan

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Abstract

Poor air quality has become endemic in many parts of the world due to its negative impact on health and cognitive abilities, with several developing countries shutting down their education and economic activities for weeks when air quality is bad. Early exposure to bad air quality is linked with serious health impacts that could limit one's potential (Prunicki et al., 2021), making young children particularly vulnerable. While improving outdoor air quality is costly and requires collective action from numerous stakeholders, improving indoor air pollution (IAP) may not only aid in mitigating some of the negative impacts of exposure to bad air quality but also serve as a relatively cheap and feasible policy alternative to shutting down education and economic activities. Our understanding of the efficacy of improving IAP is limited. To that end, we are currently running a randomized field experiment in a private school network in and around Lahore – one of the most polluted cities in Pakistan – through which we provide randomly selected schools in the network with air purifiers and monitors to investigate whether improved IAP impacts young children's health, cognitive, and non-cognitive outcomes and how those effects change with cumulative exposure.

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1 Introduction

Exposure to severe air pollution has been shown to reduce life expectancy (Ebenstein et al., 2017), increase the risk of premature death and illness (Murray et al., 2020), and cause mental health disorders. It also leads to poor test scores (Lavy et al., 2014; Carneiro et al., 2021), lower college attendance and completion (Voorheis et al., 2017), and lower wages (Voorheis et al., 2017). However, our understanding of whether better indoor air quality can undo the existing health, cognitive and non-cognitive damages from ambient pollution, and the frequency at which such improvements can take place, is limited. Improving our understanding of these issues, therefore, may play an important role in helping policymakers design effective remedies to the damages caused by pervasive air pollution and achieve sustainable growth in developing countries. This is particularly important in places like Pakistan, where limited state capacity and the imperatives of growth likely mean that air quality will remain poor for some time. This project aims to contribute to this nascent and underdeveloped literature.

Households have been a primary focus of the existing strand of the literature investigating the impact of indoor air pollution (IAP), due to the common use within homes of highly polluting energy sources for cooking. Verma and Imelda (2023) show that using clean energy for cooking improves women's health and labor supply and increases men's work hours. In another study, Hanna et al. (2016) shows that using laboratory-validated stoves helps reduce smoke inhalation, but the effect disappears after two years as households use and maintain them irregularly. This literature has improved our understanding of the impacts of IAP from traditional cooking practices, and the potential for improvements through the adoption of cleaner technologies. However, there is a dearth of research on the efficacy of improving IAP through the use of air purifiers in schools – a setting attractive from a policy perspective – where children spend roughly 5 hours per day. This intervention has the potential of wide and efficient means of providing improved air quality.

Children are the most vulnerable to air pollution, as their airways are smaller and still developing. They breathe more rapidly, ending up inhaling more than an average adult. Early exposure to bad air is therefore particularly concerning for children with serious health impacts (asthma, cancer, etc.,) which may limit their lifetime potential Prunicki et al. (2021). For developing countries like Pakistan, where the population is particularly young, and which should be experiencing a "demographic dividend," this could negatively impact the country's economic growth. Thus, paying careful attention to pollution and its effects on students is essential from a policy perspective and constitutes an important contribution to the literature on the human capital formation of children (Cunha and Heckman, 2007; Cunha et al., 2010), particularly in developing countries.

To that end, our study aims to provide evidence on how improving IAP impacts young students/children's health, cognitive, and non-cognitive outcomes and how those effects change with cumulative exposure. In addition, our study is novel in the literature that aims to look at the impact of air pollution on various economically relevant outcomes, as we employ a randomized control trial instead of an IV strategy, giving researchers control over exogenous variation in the air quality.

We are running a randomized field experiment with a private school network, Allied Schools, in and around Lahore. We install air purifiers and monitors in grade 2 classrooms among a randomly selected set of schools in the network, with one air purifier and monitor per school. Our sample comprises 132 schools; 60 received the air purifier, and the rest serve as our control group. We collect novel data on students' cognitive abilities, such as test scores, cognitive endurance, and different measures of IQ; non-cognitive outcomes, such as disruption, bullying, and attention; and health outcomes, such as respiratory conditions and doctor visits.

We have completed the baseline, midline, and intervention (i.e., the installation of air purifiers in schools and outreach that these be kept on during school hours). The baseline survey was conducted in early November 2023, and the intervention started immediately after the baseline survey. The midline survey took place in the second and third week of December 2023, and the endline is scheduled for the last two weeks of January 2024.

The following section outlines the experimental design, including randomization and treatment assignment. The last section covers our proposed analysis plan, including the specifications we would run and how we would account for multiple hypothesis testing, missing values, attrition, and breach of protocol.

2 Experimental Design

2.1 Treatment and Randomization

2.1.1 Treatment

We assigned schools to air purifier treatment, i.e., the schools randomly assigned to the treatment status receive an air purifier. The air purifier is placed in the grade-2 classroom, and in the case of a school with multiple sections, a random section is drawn to receive the air purifier. The treatment school/classroom also receives an air monitor, which is used to track the air quality. The intervention started in November 2023 and is scheduled to continue until March 2024.

2.2 Experimental Sample

We received baseline administrative data on 175 Allied schools in Lahore, Pakistan; this data was retrieved from the central administration of the Allied School network, our partner for the study.[1] Of these, we are conducting a randomized control experiment with 132 schools.[2] Our experimental sample is grade-2 students, parents, teachers and principals of these 132 schools. Allied Schools operates under a franchise-based model wherein the brand is licensed to individual school proprietors while the head office establishes the curriculum and educational objectives centrally. This standardized structure ensures uniformity across schools concerning holidays, curriculum, and supplementary teacher training programs, creating a homogenous administrative framework.

2.2.1 Protocol

In theory, all schools must provide updated student academic/nonacademic data to the central head office. Through this channel, we aimed to acquire the student rosters and parental contact information. Nonetheless, during our initial visits to the schools, discrepancies arose in the accuracy of the information provided by the head office. Consequently, we relied on the head office to secure access to these schools and acquire updated information from the schools directly.

Our strategy with the Allied Schools was to request the head office to dispatch emails to the school principals, informing them about the study's details and soliciting their participation. Additionally, we procured a formal permission letter from the head office, which our enumerators carried along to gain entry into the schools. Prior to our official visits, we organized preliminary trips to the schools to update and verify student and parental

[1] Allied School network is one of the biggest networks of schools in Pakistan, with over 1000 campuses in around 62 cities of Pakistan. It has been operating in Pakistan since 2010.

[2] Even though the central office of the Allied Schools maintains the list of all schools in the school network, it is not in real-time, especially the contact details of principals. Hence, we conducted the first round of visits to get up-to-date information. After the first round of visits, our initial sample was reduced to 141 schools with information on their exact location (lat/long), number of sections in grade two, number of students in each section, and the principals' and class teachers' contact details. We dropped nine schools as they were too small - total students of less than eight in a single-section school, or each section in a multi-section school has less than eight students. Thus, we were left with 132 schools.

information. Having received this updated data, we proceeded with the initial phase of our research, engaging parents and obtaining consent for their children's involvement in our study.

We planned our school visits in the following way. In the first visit to the school, the enumerator took notes on the school infrastructure and collected parents' contact information, which we used to take parental consent (see Appendix) and their short survey. We informed schools before contacting parents, and school administration informed parents beforehand about the call (through schools), which helped in the smooth conduct of the parent phone survey.

In the second enumerators' visit, a baseline survey of the principal, class teachers, and all students in grade 2 is conducted. We covered all sections in multi-section schools irrespective of whether they received any air purifier or monitor. On the same day, after school hours, a technical team comprising electricians, carpenters, and surveyors visited the school and installed the necessary equipment, including: air purifiers, air quality monitors in treatment schools, and air quality monitors in the 44 randomly selected control schools.[3]

2.3 Treatment Assignment

We adopted a stratified randomization design, assigning 132 schools to treatment and control within each stratum. The strata are based on a combination of three variables: location (whether the school is located inside or outside the ring road[4]), school size (whether the school is a single or multi-section school) and batch (total of four batches) in which we received the up-to-date data on the school from our first visit.[5] Within each batch (except the last batch), we divide the schools into four types: inside ring road and single section, inside ring road and multi-section, outside ring road and single section, inside ring road and multi-section. In the last batch, since there were only 8 schools (all outside the ring

[3]Three schools in the treatment group refused to participate, even though they did not know about them being in the treatment or control group. Their main reason was that they were unhappy with the frequent incoming of outsiders in school. To avoid the non-usage of devices, we placed these three air purifiers and monitors in a randomly chosen section of a multi-section treatment school.

[4]The Lahore ring road divides the city into inner and outer zones.

[5]One practical issue that came up during the first visit was that school principals provided us with the date when we could make another visit to conduct the baseline survey. This restricted us from waiting until we finished the first round of visits to get the complete list of schools. We received a total of 141 schools in 4 batches. The first batch was of 80 schools (including 5 small schools), the second batch of 27 schools (including one small school), 26 schools (including three small schools) in the third batch, and 8 in the last batch.

road and only 1 multi-section), we formed it into one stratum. In total, there are 13 strata.

We assigned 60 schools to the treatment group and 72 to the control group. Within multi-section schools, we randomly select a section where equipment is installed. The treatment schools (or the randomly selected section if the school is multi-section) are provided with an air purifier and an air quality monitor. In control schools, we randomly selected 44 schools (out of 72) to receive air quality monitors.[6]

In effect, our sample comprises approximately 4500 students (roughly 2000 in treatment and 2500 in control) with approximately 34 students per school. We summarize the distribution of schools by treatment status in the Appendix.

2.4 Data

Our data consists of information collected through surveys (provided in the Appendix). In addition to the baseline and midline data collection, we plan to obtain the following data from our sample:

1. We will conduct surveys with students, parents and teacher. The follow-up survey with students is mainly their cognitive and (possibly) non-cognitive tests.
2. We will also access administrative records of students, primarily their test scores and school performance, directly from the school.
3. We will retrieve air quality data from air quality monitors in each subsequent school visit. Air quality monitors store air quality (PM2.5, PM1, PM10, temperature, humidity, pressure, etc.) every 2 minutes.

3 Analysis

3.1 Outcome Variables

We are primarily focused on four key set of outcomes. The first pertains to air quality measures, the second is about cognitive measures, the third relates to non-cognitive measures, and the last is on children's health. While the first outcome is measured at the school level with a granular frequency (2 minutes), the remainder of the outcomes are collected at the

[6]This is because we have 104 air monitors due to budget constraints.

student-level. We custom design the tests, and integrate multifaceted assessment components into our study as described below. Through these tests, we aim to comprehensively capture the potential effects of air quality on students' cognitive performance, providing a holistic understanding of the impact of environmental factors on educational outcomes. For the non-cognitive outcomes, we use information from parental surveys, direct student assessments on moral reasoning, and teacher-reported classroom dynamics. Using these sources, we aim to gain a comprehensive understanding of the multiple dimensions influencing conduct in the school environment. For health outcomes, we rely on parental surveys and their reported health-related information. Wherever possible we will form indices where we standardize all components, average them, and re-standardize them.

Primary Outcomes:

Air Quality. We use air monitoring devices (from Purple Air) to quantify the variations in air quality resulting from our intervention (Smart air purifier). These monitoring instruments directly capture and record data concerning the concentration of particulate matter present in the air. Specifically, we focus on particulate matter within the diameter range of 2.5 to 10 microns. The information will be retrieved during the midline and endline visits.

Cognitive Outcomes. One aspect of student learning that can be impacted due to bad air quality is their ability to learn and their performance on cognitive tests. In our study, we have developed a customized test that aligns closely with the school's curriculum standards. This assessment comprises sections covering mathematics, reading, and visual comprehension, reflecting the key domains of scholastic achievement.

Secondary Outcomes:

Additional Cognitive Outcomes. Our test design intentionally incorporates a comprehensive array of questions related to math, reading, and picture comprehension. While the primary outcome is the total test score, in the secondary outcomes we will use the disaggregate test scores by the type of questions.

Our customized tests allow us to evaluate both fluid and crystallized IQ among students. Fluid IQ is pattern recognition drawn from the Weschler Intelligence Scale for Children or Raven's Progressive Matrices, whereas crystallized IQ is measured using student's test score in questions related to vocabulary drawn from the Weschler Intelligence Scale for

Children or Peabody Picture Vocabulary Test.

Furthermore, following Brown et al. (2022) we consider cognitive endurance to be "the ability to sustain effortful mental activity over a continuous stretch of time." A key feature in the design of our tests is that we randomize the order of the questions at the student level, allowing us to capture the effect on endurance and not necessarily on the type of questions the student has to answer. Our methodology of randomizing the sequence of questions therefore helps us discern any potential variance in correct responses between earlier and later questions.

Non-Cognitive Outcomes. The second aspect revolves around moral judgment, absenteeism and classroom behavior, adaptation behavior, and the perception of parents/teachers relating to the air quality.

Our assessment extends beyond traditional academic measures, and integrates questions aimed at investigating students' moral judgment as in Keller et al. (2003) and Gummerum et al. (2010). This segment comprises hypothetical characters in hypothetical scenarios designed to elicit responses that gauge students' perceptions of ethically appropriate actions and the associated emotions in various situations. This is called a happy victimizer task and constitutes a prosocial moral dilemma (Eisenberg, 2014), in which a person's (selfish) desires conflict with prosocial moral norms.

Apart from instances where students are absent during our survey, absenteeism data will be obtained directly from administrative records. Our goal is to get access to comprehensive administrative data on students' attendance and test scores. If we acquire this dataset, we will analyze its impact on the variables we collect systematically from this data.

Furthermore, we collect information from teachers' logbooks (these are filled by the teacher for each student) regarding each student's classroom issues like bullying, fights, disruptions, and other behavioral problems observed by the parents. The questions posed to parents include bullying/fighting, and throwing a tantrum, whereas those to teachers include general disruptive behavior, a child being involved in fights and whether they pay attention in class.

Finally, in parental survey, we ask parents about their perception of air quality at their child's school and any measures (e.g., installing air purifiers, wearing masks, restricting outdoor activity) that they take to protect their child against poor air quality. We would use these instruments to investigate the impact of our treatment on adaptation and perception of parents in relation to air pollution.

Health Outcomes Within health outcomes, the first outcome regarding students' overall health and sleep patterns comes from the parental survey that contains parent's perception of their child's general happiness, chronic health problems, short-term health problems restricting activities, and any visits to doctors.

Control variables. We consider additional covariates in our analysis to get more precision of estimates. These covariates are at the: (i) student level, such as socioeconomic controls, and baseline test performance; (ii) teacher level such as teacher quality, and experience; and (iii) school level, such as amenities and the environmental variables in and surrounding the school such as traffic, building sites, air quality using a handheld device (which is the only reading that is available at the baseline before the intervention).

3.2 Basic estimating specification

For most of our outcome variables, the level of analysis is at the student level, whereas for the air quality measures we do the analysis at the school level. Thus, we present two separate basic specifications that we would use in our analysis.

Air Quality. Consider, an outcome of air quality, denoted by y_s, where s stands for school.

$$y_s = \alpha + \beta \cdot \mathrm{T}_s + \eta_{b(s)} + \epsilon_s \tag{1}$$

where T_s is a dummy for treatment, and $\eta_{b(s)}$ represents strata fixed effects where b is stratum defined earlier (see Treatment Assignment Section).

Student Outcomes. Consider, generically, an outcome variable $y_{i,c(i),s(i),t}$, for student i, in classroom $c(i)$, in school $s(i)$, and time t, whose baseline value is $y_{i,c(i),s(i),0}$. Then our basic estimating specification will be:

$$y_{i,c(i),s(i),t} = \beta \cdot \mathrm{T}_{s(i)} + \alpha \cdot y_{i,c(i),s(i),0} + \gamma \cdot X_{i,c(i),s(i),0} + \eta_{b(s(i))} + \epsilon_{i,c(i),s(i),t} \tag{2}$$

where $\mathrm{T}_{s(i)}$ is a dummy for treatment, and $\eta_{b(s(i))}$ represents strata fixed effects where b is stratum defined earlier (see Treatment Assignment Section). Our identification strategy does not require including covariates from the baseline $X_{i,c(i),s(i),0}$ at the student or school level. However, we plan to include covariates to increase precision. These covariates are listed in the control section above. We will cluster standard errors at the school level $s(i)$.

We will report the following hypothesis test, i.e. $H_0 : \beta = 0$ (that air purifier provision has no effect).

Additional Specifications. The above specification is ANCOVA. However, we will also run the specification without the baseline outcome variable in one version, because it is possible for some students to be absent on the day we conduct the baseline tests.

For the student-level cognitive outcomes, we have data from the baseline, midline, and endline. To exploit all the available data, in another version we will run the pooled specification where each student will have two observations over time.

Finally, we will also consider another estimation strategy using the instrumental variable approach. Using treatment as the instrument for air quality, we will see how air quality impacts student-level outcomes. This will allow us to compare results of our study with those studies in the literature that focus on how ambient air quality impacts cognitive and health outcomes using different instruments for air quality.

3.3 Heterogeneity

We conduct tests to examine diverse treatment effects across multiple dimensions, collated through various sources including the parent survey, teacher survey, enumerator observations, and principal survey. We will consider several heterogeneities along several dimensions such as baseline pollution levels, gender and socioeconomic background of students, baseline health of students, school/classroom size, and length of exposure. Several of these dimensions will also serve as additional covariates in our analysis.

Our specification with heterogeneity is an extension of the baseline specification, with an interaction term:

$$\begin{aligned} y_{i,c(i),s(i),t} &= \beta \cdot \mathrm{T}_{s(i)} + \lambda \cdot Z_{c(i),s(i),0} + \delta \cdot \mathrm{T}_{s(i)} * \mathrm{Z}_{c(i),s(i),0} + \alpha \cdot y_{i,c(i),s(i),0} + \gamma \cdot X_{i,c(i),s(i),0} \\ &+ \eta_{b(s(i))} + \epsilon_{i,c(i),s(i),t} \qquad (3) \end{aligned}$$

where **Z** is the dimension of heterogeneity we test, and δ is the coefficient of interest when we expect heterogeneous treatment effects. In cases where the variable in **Z** coincides the variable in **X**, we will drop **X** from our specification, as it would be redundant.

We will also use the split sample regressions to allow for baseline covariate (Z) to interact with every independent variable in the specification above.

3.4 Multiple Hypothesis Testing

Given that we will be testing the impact of the treatment on several outcome variables, we will make multiple-testing corrections and report sharpened False Discovery Rate (FDR) q-values Anderson (2008), which does not allow for correlation among p-values across outcome variables; as well as the bootstrap procedure developed by List et al. (2016), which does allow for correlation among p-values across outcome variables. We will adjust for multiple hypothesis testing within the family of outcomes, but not across them.

We will correct for multiple hypothesis testing using a step-down procedure to adjust p-values for the false discovery rate (FDR) among groups of outcomes, and report the resulting "q-values" (Benjamini and Hochberg, 1995). We will adjust for multiple hypothesis testing within a family of outcomes, but not across them.

3.5 Missing values, Attrition, and breach of protocol

Attrition: We do not anticipate substantial problems with school attrition. There is a possibility of attrition in terms of schools' continuous post-baseline engagement during our visits for the midline and endline. However, we do not think that there will be differential attrition across the control and treatment.

A more serious challenge is that schools may not fully comply with the program that requires them to keep the air purifier on and the doors and windows closed. We have tried to minimize this by directly sending the messages to the control and treatment school teachers. Wherever the air purifier is placed, we thanked the teacher for their participation and continuous support, and included a suggestion to keep the doors and windows closed. For the control classes (even within the treated schools with multiple sections), we sent the same message without the suggestion. Despite this, we may have some compliance issues in the midline and endline. Where this does occur, it will adversely affect the estimated ITT.

Additional Concerns: Below we list additional concerns we may encounter over the course of our study and how we will address those in our analysis.

If we become aware of any serious breaches of protocol that are not attributable to the intervention itself, we will omit the relevant observations from our analysis. We would still check the robustness of the results to an ITT in which these schools continue to be included, but our baseline analysis would omit them.

When some variables show little variation, we will assess if this means that almost all observations within the treatment and control group share the same value for these variables (around 95 percent). If that is the case, we will omit these variables from our analysis, including any related index measures. If this process results in excluding all variables that make up an index, we will simply remove the entire index from our evaluation. This way, we will focus on using only the most relevant and diverse set of variables for our analysis, ensuring we do not rely on redundant or limited information in our assessments.

Given the extensive nature of the project, with surveys conducted with parents, teachers, principals, and students, as well as the enumerator observations, each survey round takes more than 3 weeks to conduct. To address this variability, we plan to incorporate a control mechanism in our analysis by factoring in the time when the survey was completed. This inclusion will help mitigate potential influences stemming from the timing differences and ensure a more accurate evaluation of the collected data.

There are potential technical challenges associated with the devices utilized in our study. First, the air monitor relies on a mini chip, and improper insertion or removal of this chip may result in a failure to collect air quality data effectively. Second, though the continuous operation of the air purifiers has been imposed to prevent inadvertent shutdowns by teachers or students, there exist additional issues that may impair the optimal functioning of the air purifiers, including the obstruction of airflow.

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