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The effect of air purifiers in schools *

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We randomize the installation of air purifiers across primary school classrooms to reduce children's exposure to air pollution. The intervention reduces indoor $PM_{2.5}$ concentrations by 32% and decreases student absenteeism by 12.5%. We find larger effects among students with higher pre-treatment absenteeism. The impact is also greater when outdoor air pollution is relatively low and diminishes as outdoor pollution intensifies, consistent with non-linear marginal effects of air quality on health. Treated students report fewer respiratory symptoms and exhibit greater awareness of air quality. Each avoided absence day costs approximately €11, yielding a conservative cost-benefit ratio of one-to-nine.

JEL codes: C93, I21, Q53, Q51

Keywords: Indoor air quality, air purifiers, school absences, randomized controlled trial

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1. Introduction

Air pollution is a global health issue contributing to child mortality and morbidity worldwide (Institute for Health Metrics and Evaluation, 2019; Annesi-Maesano et al., 2021). High pollution-related morbidity increases school absences (Currie et al., 2009), negatively impacting learning outcomes and educational activities (Gershenson et al., 2017; Aguilar-Gomez et al., 2022). Although average urban exposure has decreased in recent decades due to different pollution-control measures, levels often exceed WHO guidelines (World Health Organization, 2021), leading to significant health, economic, and welfare losses (Shaddick et al., 2020). Since traditional air pollution control mechanisms, such as low-emission zones or industrial policies, can be costly and complex to implement, temporary solutions are necessary to reduce exposure.

This study evaluates the efficacy and cost-effectiveness of installing portable air purifiers in school classrooms. Our main hypothesis is that air purifiers improve indoor air quality and reduce absenteeism by promoting children's health. Using a *cluster randomized controlled trial* (RCT) across five primary schools in Milan, Italy — an area known for poor air quality (EEA, 2022) — we randomly assigned 95 classes to either receive or not receive air purifiers. Additionally, we installed indoor air quality sensors in a subsample of classrooms to collect detailed data on air pollution and environmental conditions.

Air purifiers reduce indoor air pollution by 32%. The relative efficacy of the purifiers does not seem related to outdoor air pollution levels and remains rather stable throughout the study period. The treatment decreases school absences by approximately 12.5% equivalent to about 1.3 fewer missed days per year. The effect is more pronounced for students with higher baseline absenteeism. Dynamic treatment effects indicate that the reduction in absences primarily occurs in fall and spring, rather than in winter when average pollution levels are significantly higher. Supporting this observation, evidence shows that purifiers do not have statistically significant effects on absences during periods of high outdoor air pollution. Specifically, the treatment effect on absences is no longer significant when the ten-day rolling average of ambient $PM_{2.5}$ exceeds 10 micrograms per cubic meter ($\mu g/m^3$), or when more than two days in the past ten exceed the WHO threshold of 15 $\mu g/m^3$. These insights align with previous findings indicating that the marginal effect of air pollution on health is concave, i.e., improving air quality when pollution is relatively low has larger health effects than when pollution is high (Berkouwer and Dean, 2023; Miller et al., 2024; Weichenthal et al., 2022; Corrigan et al., 2018; Pope III et al., 2015; Aragón et al., 2017).

Using survey data, we find that treated students are less likely to report respiratory symptoms over the past week compared to control students. This result suggests that reduced absences likely arise from improved health. We also observe significant differences in students' perceptions of classroom air quality and their preferences for urban policies related to air quality. However, we cannot rule out experimenter demand and priming effects. To examine the potential confounding role of behavioral changes in our results, we estimate the effect on proxies for opening and closing classroom doors and windows (e.g., sudden shifts in temperature or carbon dioxide). We find no evidence that purifiers significantly alter ventilation behavior or classroom occupancy in response to the treatment, as indicated by the lack of differences in classroom CO_2 levels, temperature, and estimated ventilation episodes.

Cost-effectiveness calculations indicate that installing air purifiers leads to a cost per avoided absence of €10.6 and a lower bound rate of return 9.6 times greater than the intervention costs.

Related literature.

Air pollution is increasingly recognized as not only a health hazard but also a significant barrier to educational success. Even low levels of ambient pollution negatively affect school participation and learning across various contexts (Ebenstein et al., 2016; Carneiro et al., 2021; Sunyer et al., 2017; Roth, 2021; Persico and Venator, 2019; Gilraine and Zheng, 2022; Chiu et al., 2013; Rahai and Evans, 2023; Heyes et al., 2023; Lai et al., 2021; Yao et al., 2023). Polluted air harms children's health and cognitive function (Nauze and Severnini, 2021; Künn et al., 2019), leading to lower attendance and academic performance (Chen et al., 2018; Currie et al., 2009; Komisarow and Pakhtigian, 2022; Ransom and Pope, 1992; Persico and Venator, 2019; Heissel et al., 2022). This issue is critical, as educational outcomes have long-term implications for human capital formation, productivity, and lifetime earnings (Graff Zivin and Neidell, 2013a). Notably, the adverse effects are especially pronounced among vulnerable children with pre-existing health issues or higher baseline absenteeism (Liu and Salvo, 2018). Our paper builds on this literature by providing the first experimental evidence of the causal impact of indoor air purifiers on student absenteeism. This design addresses many common confounders in observational studies and expands the literature into a developed country setting with moderate to high ambient pollution levels. In doing so, our work corroborates the negative educational effects of air pollution.

Within education policy, cost-effectiveness is crucial for resource allocation. Policymakers must choose from various interventions to maximize educational gains. Many traditional interventions to improve educational outcomes require substantial investments, yet their cost-effectiveness varies widely (Angrist et al., 2020). Among programs to reduce absenteeism, behavioral interventions informing parents about their child's attendance proved highly cost-effective (Rogers and Feller, 2018; Robinson et al., 2018). However, few studies have assessed the cost-effectiveness of specific interventions to improve the physical learning environment and the quality of indoor air, in particular.[1] Some epidemiological studies highlight the benefits of air purifiers on reducing indoor pollution in schools (Carmona et al., 2022; Tong et al., 2020) and associated significant health benefits (Chen et al., 2015; Yang et al., 2021).Closer to our study, Gilraine (2023) find that installing air filters in schools leads to a 0.1 to 0.2 standard deviation increase in test scores, utilizing a regression discontinuity design.[2] Our experimental analysis looks at absenteeism, an important economic outcome with long-term consequences. The intervention costs approximately €11 per avoided absence day, making it a cost-effective alternative to more expensive educational initiatives. This clear benefit-cost analysis underscores the potential of indoor air purification as a viable educational policy tool.

Finally, we contribute to the literature on adaptation to environmental stressors and the role of exposure to indoor air pollution (Graff Zivin and Neidell, 2013b; Deschênes et al., 2017; Park et al., 2020; Burke et al., 2022; Coury et al., 2024; Barwick et al., 2024). As environmental stressors increasingly challenge public health and productivity, adaptive responses are essential to mitigate the negative effects of environmental hazards and minimize adverse outcomes. Studies indicate that households and firms invest in protective technologies, such as air conditioners during heat waves or air filters and masks during heavy smog, to reduce personal exposure (Deschênes et al., 2017; Ito and Zhang, 2019b; Greenstone et al., 2021b; Zhang and Mu, 2018; Baylis et al., 2024; Metcalfe and Roth, 2025). Additionally, evidence from developing countries shows that real-time air quality information encourages the adoption of mitigation measures, although these responses often vary by socioeconomic status (Ito and Zhang, 2019a; Greenstone et al., 2021a; Zhang and Mu, 2018). While adaptation does not replace pollution control, it serves as a crucial secondary defense mechanism, especially when complete hazard elimination is unfeasible. Nonetheless, research indicates that adaptive measures have limitations; for instance, when outdoor pollution reaches extreme levels, the protective behaviors may not be sufficient to mitigate the health risks (Burke et al., 2022; Barwick et al., 2024). Our study contributes to

[1] Impact assessments of general school infrastructural investments are provided, for instance, in Cellini et al. (2010). The benefits of air conditioning for learning are studied in Park et al. (2020).

[2] In an RCT, Gignac et al. (2021) find no short-term effect of purifiers on adolescent attention. Several RCTs are underway on the impact of air purifiers on schooling outcomes across different contexts and in conjunction with other interventions (Liu et al., 2024; Malik et al., 2024; Ruiz-Tagle and Sangwan, 2023; Kremer et al., 2023).

the adaptation literature by empirically testing an indoor air quality improvement technology as an adaptive strategy in schools. Our design allows us to quantify how effectively air purifiers can shield students from poor ambient conditions. The results show that while the intervention significantly reduces student absences during moderate pollution periods, its effectiveness diminishes under severe outdoor pollution. This finding highlights an important boundary condition for adaptive interventions and suggests that such measures should complement broader pollution abatement policies.

2. Experimental design

Context: Northern Italy features high population density and economic activity, along with poor orographic conditions that impede air circulation. This combination makes it one of the most polluted regions in Europe.[3]

State-owned schools dominate Italy's educational landscape, with approximately 94% of children enrolled in public institutions (Ministero Italiano dell'Istruzione e del Merito, 2023). The average Italian school buildings are over 50 years old and often do not meet current sustainability standards. Some classrooms exhibit inadequate maintenance, and environmental improvements occur infrequently (Ruggieri et al., 2019). Most schools were constructed before urban development, resulting in their proximity to high-traffic roads, which significantly increases exposure to air pollution.

In the Italian school system, at the beginning of the year, students are assigned to a single classroom where they spend most of their day. They leave daily for lunch at the school canteen and can visit the garden or courtyard during breaks.[4] The choice between spending breaks indoors vs. outdoors depends on the weather and teachers' preferences. Teachers may teach multiple classes and move between different physical classrooms throughout the day.

Intervention and randomization: Our intervention installed 43 consumer-grade portable air purifiers in randomly selected classrooms across five schools. We assigned classrooms to treatment and control groups, stratifying by school and grade. All purifiers were installed outside school hours in early November 2023. The intervention did not include targeted information campaigns or communications to teachers or parents. All purifiers operated continuously from November 2023 to June 2024. The research team monitored purifier functionality through

[3] More information is provided in Appendix B.

[4] Students spend a few hours per week attending lab sessions in specialized classrooms and exercising in the school gym.

monthly statistical analyses of indoor air pollution data in a subsample of classrooms and bi-monthly on-site visits.

We installed NETCO NIVEUS NV100 air purifiers equipped with U15 Ultra Low Particulate Air (ULPA) filters, capable of capturing up to 99.99% of particles larger than 0.026 microns—the highest efficiency in mechanical filtration technology. These devices are energy-efficient, with power consumption comparable to a 60-watt incandescent bulb, and operate quietly, producing sound levels between 29 and 45 dB(A). Following the manufacturer's guidelines, we selected the model based on the average classroom volume. Purifiers operated at 60% capacity to ensure effective air purification with minimal noise, achieving an average Air Exchange Rate of 1.04. In addition to the purifiers, we randomly installed 31 indoor air quality sensors in a subsample of classrooms.[5] Sensors' installations were stratified by school, treatment status, and grade to ensure balanced representation across treatment and control groups. The sensors measure concentrations of $PM_{2.5}$, PM_{10}, carbon dioxide (CO_2), carbon monoxide (CO), as well as temperature, humidity, and atmospheric pressure. Once powered and connected to the internet, the sensors transmit data every 30 seconds to an online data platform.

Teachers administered paper-and-pencil surveys to students at two time points: before the intervention in October 2023 and after the intervention in April 2024. Teachers selected survey administration dates within a two-week window based on availability. To improve comprehension, we used capital letters and visual Likert scales with emoticons. First-grade teachers adhered to a dedicated protocol, projecting and reading each question aloud to support student understanding. Participation was optional for first-grade students. The survey took approximately 15 minutes to complete.[6]

2.1. Sample, Data and Outcome Variables

Sample: The study sample includes students from the 2023–24 school year, with absence and demographic data obtained from official school ledgers and registries. It comprises 95 classes and 2,050 students across five grades. Data on indoor environmental conditions were collected using 31 air quality sensors; one sensor was excluded from the analysis after data quality checks (see Appendix D for details).

The survey completion rate is approximately 88%, with 1,822 responses in the first wave and

[5] Appendix C provides technical details on the purifiers and monitors.

[6] The English translation of the survey is available at https://drive.google.com/file/d/1xxGPG3gAREeUooPk4cVDqA3LYQSJ1pH5/view?usp=sharing.

1,815 in the second. This rate is primarily explained by two factors. (1) Many schools chose not to administer the survey to first-grade students in either wave, and (2) student absences on the survey day. Appendix Tables A.1 and A.2 show that survey participation rates do not differ significantly between treatment and control groups.

Indoor air quality: We aggregate air pollution concentration data from monitors into daily averages, using measurements recorded between 8:00 AM and 5:00 PM to align with class hours. To assess the potential impact of measurement error on the evaluation, we co-located all sensors in a single space for four consecutive days. Overall, we find no evidence that measurement imprecision in indoor variables differs systematically between treatment and control classrooms.[7]

Absenteeism: Schools collected daily absence data digitally and shared it with researchers in anonymized form at the end of the 2023–24 school year. However, the reasons for student absences are neither systematically recorded nor digitized, preventing us from identifying whether health-related issues are the primary cause. Our outcome variable for absenteeism is a binary indicator equal to one if a student is absent on a given day, and zero otherwise.

Subjective health symptoms: We use students' self-reported symptoms as a proxy for health conditions. Children reported the frequency of various respiratory and non-respiratory symptoms experienced over the past week using a four-point Likert scale: never, sometimes, often, and every day.[8] The symptoms include: runny nose, blocked nose, sneezing, cough, shortness of breath, tiredness, headache, and stomachache. We classify the first four symptoms as respiratory, the last two as non-respiratory (placebo), and the remaining two as general. For each symptom, we create a binary indicator equal to one if the student reported experiencing it at least "sometimes," and zero if they selected "never."

Perceptions, Beliefs, and Behavioral responses: The intervention did not include explicit communication or awareness campaigns about indoor air quality or environmental issues; however, it may have implicitly raised environmental awareness. We assess perceptions of air quality across different settings (overall, city, classroom, and courtyard) using a four-point Likert scale: very bad, bad, good, and very good. Responses received a score from 1 to 4. We also evaluated children's views on the importance of addressing urban challenges such as street garbage, lack of green areas or playgrounds, insufficient sports facilities, air pollution, and road traffic. These were rated on a four-point Likert scale: to a great extent, to some extent, to a limited extent,

[7] Details are in Appendix D.

[8] These questions are adapted from a validated survey on acute respiratory illnesses for children aged 4 to 10, developed by Schmit et al. (2021).

and not at all, and similarly coded as a score from 1 to 4.[9]

To measure teachers' behavioral responses to the purifiers, we monitored indoor environmental conditions—specifically CO_2 levels, temperature, and the frequency of window openings. These parameters are influenced by classroom occupancy and ventilation, but are not directly affected by the purifiers. We calculated daily averages of CO_2 and temperature using data from the air quality sensors. We identified ventilation episodes with sharp drops in CO_2 levels alongside increases in $PM_{2.5}$. Further details are provided in Appendix E.

Controls and dimensions of heterogeneity: We obtained students' socio-demographic information from school administrative records, focusing specifically on gender and nationality. We created a binary variable, assigning a value of one for female students and zero for male students, along with a binary indicator for foreign citizenship.[10]

Outdoor air pollution: We used outdoor pollution data from the European Environmental Agency (EEA) database (EEA, 2024). We calculated daily average $PM_{2.5}$ levels for each school by applying inverse distance weighting from the two nearest background air quality monitoring stations.

3. Descriptive Statistics

3.1. Sample characteristics and balance

Table 1 presents descriptive statistics for the student sample. Overall, 47% of students are female, and 37% have foreign citizenship. The distribution across the five grades is relatively balanced. In the pre-treatment period, students were absent for approximately 4.6% of school days, averaging about nine missed days in a standard 200-day school year.

At baseline, between 46% and 62% of students reported experiencing runny nose, blocked nose, sneezing, cough, or shortness of breath in the previous week, 61% reported tiredness, 48% headaches, and 42% stomach aches. Perceptions of air quality averaged 3.1 on a 1-to-5 scale, with lower ratings for city air quality (2.7) and higher ratings for classrooms (3.2). Students regarded outdoor school spaces, such as courtyards, as safer in terms of air quality (3.5) compared to the broader urban environment (2.7). Regarding urban priorities, students emphasized city cleanliness and air quality (both around 3.5), followed by green areas, playgrounds, traffic (3.2),

[9]This block of questions was inspired by the scales used in Cori et al. (2020).

[10]Under Italian law, children born in Italy to non-Italian parents acquire Italian citizenship at the age of 18.

and sports infrastructure (3.1). Administrative and survey-based measures show no significant differences between treatment and control groups (see Columns 4–5).

Survey measures are affected by missing data at both baseline and endline. Appendix Tables A.1 and A.2 present the extent of missingness and test for correlations with treatment status. At baseline, approximately one-quarter of students—and 13–15% at endline—did not respond to health-related questions. Non-response rates for items on air quality perceptions and policy preferences ranged from 15% to 18% at baseline and from 4% to 6% at endline. We find no evidence of differential missingness by treatment status at either time point.

4. Empirical strategy and results

Our empirical strategy leverages the random assignment of air purifiers across classrooms. Identification relies on the assumption that treated and control students are comparable in both observable and unobservable characteristics. We also assume that control students do not receive indirect benefits from the treatment or change their behavior due to the absence of purifiers. We discuss potential threats to these assumptions in Section 4.3. Most analyses were pre-registered, and deviations from the Pre-Analysis Plan (PAP) are detailed in Appendix F.

4.1. Impact on indoor air quality

We assess the impact of air purifiers on indoor air quality using Equation 1, where Y_{ct} represents the indoor air quality measure in classroom c on day t; $AirPurifier_c$ indicates whether the classroom received a purifier.[11] We include time fixed effects (λ_t) for calendar day, school-by-weekday, and school-by-month. Calendar day fixed effects capture daily pollution shocks affecting all schools. School-by-weekday and school-by-month interactions control for location-specific seasonal factors, such as school events, that may influence air quality. We also control for grade fixed effects, X_c, to account for the stratified randomization procedure (Bruhn and McKenzie, 2009).

$$Y_{ct} = \alpha + \beta AirPurifier_c + \gamma X_c + \lambda_t + \varepsilon_{ct} \tag{1}$$

Table 2 presents the treatment effects on $PM_{2.5}$ and PM_{10} (Panel A, Columns 1-2). Purifiers significantly reduce concentrations by approximately 4.5 $\mu g/m^3$, which corresponds to a 32%

[11] We do not have pre-treatment measurements, as air quality monitors and purifiers were installed simultaneously.

reduction compared to control classes. As expected, we observe no effects on CO since air purifiers do not target this pollutant. To focus on student impacts, we limit the sample to school days; however, results remain consistent when including non-school days (see Appendix Table A.3).

Panel B presents the dynamic treatment effects, with each coefficient capturing the monthly impact of the intervention. The absolute difference in $PM_{2.5}$ concentrations between treated and control classrooms is largest during the winter months, at 7.9 in February and 6.2 in January. In contrast, the absolute differences in April and June are smaller, at 1.7 and 2.1 $\mu g/m^3$, respectively. Although the absolute differences are greater in winter, the relative reduction does not seem to correlate with outdoor air pollution. At its peak, the reduction reached approximately 39.2% in May. However, sustained levels above 32% are found from November to June, with a slight dip in December and January.

Indoor air pollution levels appear to be influenced by several factors: outdoor pollution levels, the indoor/outdoor (I/O) ratio, which indicates the extent of $PM_{2.5}$ penetration, and the presence of air purifiers. Outdoor $PM_{2.5}$ concentrations exceeded the WHO daily limit of 15 $\mu g/m^3$ on 48% of days during the study period. The I/O ratio ranged from 55.8% to 121% (with a weighted average of 0.64%), typically decreasing in winter due to reduced ventilation. Consequently, indoor $PM_{2.5}$ levels in control classrooms exceeded the WHO threshold on 28.2% of days. This percentage drops to 18.7% in treated classrooms, reflecting the purifiers' mitigating effect.

4.2. Impact on absences

We test the impact of air purifiers on absences using:

$$Absent_{ict} = \beta_1 AirPurifier_c * Post_t + \lambda_i + \lambda_t + \varepsilon_{ict} \tag{2}$$

In this equation, $Absent_{ict}$ is a binary variable equal to one if student i in class c is absent on date t, and zero otherwise. $AirPurifier_c$ indicates whether class c received an air purifier, while $Post_t$ equals one for dates after the purifiers were installed on November 8, 2023. The model includes student fixed effects (λ_i) to control for time-invariant individual characteristics. To address unobserved temporal heterogeneity across days, schools, and seasons, we include calendar date, school-by-weekday, and school-by-month fixed effects (λ_t). We cluster standard errors at the treatment level to account for within-class correlation in absences, following Abadie et al. (2023). We estimate Equation 2 using a Probit Maximum Likelihood Estimator.

Air purifiers reduce concentrations of various airborne substances that can affect respiratory health, such as pollen and viruses. Thus, we cannot use the random installation of purifiers as an instrumental variable for $PM_{2.5}$, as it likely violates the exclusion restriction. Also note that purifiers may introduce unintended effects beyond reducing the concentration of airborne particles, such as noise or light emissions. To mitigate these risks, we turned off all indicator lights and operated the purifiers at reduced speeds, maintaining noise levels within the WHO-recommended threshold for classrooms (35 dB(A)).

Panel A of Table 3 shows that purifiers reduce absences by approximately 0.7 percentage points (Column 1), equivalent to about 12.5% of post-treatment absences in the control group or 0.03 standard deviations. This result is significant at the 10% level.[12] Panel A reports heterogeneous treatment effects by pre-treatment absence levels (Columns 2–5). We interact $Post_t$ and $AirPurifier_c \times Post_t$ with quartiles of the pre-treatment absence distribution. The point estimates indicate that the treatment effect strengthens with higher baseline absence levels. In particular, the interaction term for the fourth quartile is negative and statistically significant at the 10% level.[13] Two potential mechanisms may explain this pattern. First, students who are more fragile or vulnerable may benefit disproportionately from improved air quality, resulting in fewer illnesses and, consequently, reduced absenteeism. Second, while purifiers may produce uniform health improvements across students, families with more health-sensitive children may be more likely to respond to symptoms by keeping them at home. Although the first mechanism is more strongly supported in the literature (Currie et al., 2009; Mendoza et al., 2020), the research design does not allow us to distinguish between the two channels.

We examine whether treatment effects vary based on students' socio-demographic characteristics, including gender and citizenship (Columns 6–9). There is no evidence of differential effects by gender. However, we find suggestive evidence that the treatment is more effective for students with foreign citizenship (p-value = 0.102), who tend to have higher pre-treatment absence rates. For instance, the average number of pre-treatment absences among Italian students is approximately 25% lower than that of foreign students. Additionally, we explore heterogeneity by grade level and find no significant differences (Appendix Table A.5).

The right panel of Figure 1 presents dynamic treatment effects on absences by month. The

[12] The results remain qualitatively consistent when using linear probability models ($p - value = 0.131$), Poisson and Zero-Inflated Poisson (ZIP) models at the classroom level ($p - value = 0.093$ and $p - value = 0.034$, respectively), as reported in Appendix Table A.4.

[13] Results remain consistent when using a continuous measure of pre-treatment absences (Appendix Table A.5).

treatment effect is statistically significant or borderline significant in November, April, May, and June, but not during the winter months (December, January, and February), when outdoor pollution levels peak. The left panel displays the seasonality of absences in the control group. The seasonal pattern of treatment effects does not appear to result from seasonal trends in absenteeism.

We examine heterogeneous treatment effects by outdoor air pollution levels in Panel B of Table 3. We compute the 10-day rolling average of outdoor $PM_{2.5}$ concentrations and count the number of days exceeding the WHO's daily threshold of 15 $\mu g/m^3$ within that period. From these metrics, we create indicator variables for the quartiles of both the number of exceedance days and the rolling average. Columns 1–4 and 5–8 present results, using the lowest quartile as the reference group for each specification. Both exceedance counts and pollution averages show that air purifiers significantly reduce absences in the lowest quartile. The effects in the second and third quartiles do not significantly differ from the first quartile, but the effects in the fourth quartile are significantly smaller. In both specifications, treatment effects in the third and fourth quartiles are not statistically distinguishable from zero, indicating that purifiers lose effectiveness at high outdoor pollution levels. We further explore this relationship using a linear interaction model to estimate the pollution threshold at which the treatment effect becomes statistically indistinguishable from zero (Appendix Table A.6). The results indicate that when the ten-day rolling average of $PM_{2.5}$ exceeds approximately 10 $\mu g/m^3$, or when more than two days in the previous ten exceed the 15 $\mu g/m^3$ threshold, the impact of purifiers on absences is no longer statistically significant.[14] In the study context, these situations occur in 65% and 58% of school days, respectively.

4.3. Impact on self-reported health symptoms, perceptions, preferences, and behaviors

We assess the intervention's impact on self-reported health symptoms, perceptions of air quality in different environments, and preferences for various urban policies. For binary outcomes, we use Probit models, while for ordinal outcomes (e.g., perception and preference scores), we use Ordered Probit models. Each endline outcome is regressed on a treatment indicator and a vector of student characteristics, including gender, citizenship, and grade, along with school fixed effects. We cluster standard errors at the classroom level.

[14] We calculate this value by estimating the X value for which the following expression holds true: $Abs\left|\beta_{tr} + \left(\alpha_{tr} \cdot \Phi^{-1}(0.95)\right)\right| < \left[\beta_{inter} + \left(\alpha_{inter} \cdot \Phi^{-1}(0.95)\right)\right] \times X$. In it, β_{tr} and α_{tr} is the estimate and standard error of the treatment effect. β_{inter} and α_{inter} the counterparts from the linear interaction model. We multiply both by its 90% confidence interval $\Phi^{-1}(0.95)$.

Table 4 reports the estimated effects on self-reported health symptoms. We observe negative treatment effects for respiratory-related symptoms, with statistically significant reductions in the incidence of runny nose and blocked nose at the 10% level. The effect sizes for these symptoms range from 4.6 to 5.9 percentage points, indicating decreases of approximately 9% and 11% relative to the control group mean. Columns 6 to 8 show no significant effects for general or unrelated (placebo) symptoms. These results provide suggestive evidence that the treatment operates through improvements in respiratory health.

We investigate how classroom air purifiers affect students' perceptions of air quality in different environments. Panel B of Table 4 shows that students in treated classrooms report significantly higher perceptions of air quality than students in control classrooms. In contrast, we find no significant differences in perceptions of overall city air quality or the schoolyard (Columns 1–4). Moreover, the treatment significantly increased priority scores for green policies, including city cleaning, green playgrounds, and air quality. However, the effect is statistically significant only for air quality (Columns 5-9).

Changes in classroom air quality perception may prompt behavioral adaptations. Students and teachers in treated classrooms might modify ventilation practices, such as reducing the frequency of window openings, or alter decisions about classroom occupancy. These behavioral responses could compromise the study's identification strategy if indoor pollution levels correlate with treatment status, leading to conflated treatment effect estimates that mix the direct impact of purifiers with the effects of behavioral adaptation. To assess potential behavioral adaptation, we compare average daily levels of indoor CO_2, temperature, and estimated window-opening events between treatment and control classrooms, using a specification similar to Equation 1. These variables depend on student density, class duration, and ventilation frequency. As shown in Panel A of Table 2 (Columns 4–6), we observe no significant differences in these environmental measures between the treatment and control groups. Since window-opening behavior may vary seasonally, we also test whether treatment affects ventilation patterns across seasons. We find no significant relationship between treatment status and window-opening frequency, either overall or by season (Appendix E).

Due to data and power limitations, we cannot assess the impact of air purifiers on academic achievement. Furthermore, we observe no significant effects of the intervention on cognitive skills, mood, or aggressive behavior—three pre-specified, survey-based outcomes. We present and discuss these results in detail in Appendix Section F.

5. Discussion

Significant improvements in indoor air quality (-32% in $PM_{2.5}$) resulted in 1.34 fewer missed days per student annually. In comparison, Komisarow and Pakhtigian (2022) report a smaller reduction of 0.66 missed days per student each year following the closure of three coal-fired power plants in Chicago. Similarly, Chen et al. (2018) find that in China, a 10-unit increase in the Air Quality Index (AQI) raises the total absence rate by approximately 2.31% of the daily mean. In Texas, Currie et al. (2009) indicate that high levels of outdoor carbon monoxide (CO) significantly reduce school attendance. Persico and Venator (2019) find that the opening of Toxic Release Inventory sites near schools in the U.S. is associated with 0.6 fewer annual absences per student, while Heissel et al. (2022) show that relocating upwind of major highways in Florida reduces yearly absences by 0.82 days. The effect of air purifiers is especially pronounced among those with higher baseline absence rates, reinforcing existing evidence on the unequal burden of air pollution (Liu and Salvo, 2018).

We observe seasonal effects of purifiers on absences: absences decrease in November, April, May, and June, showing borderline significant or significant reductions. However, we find no significant decrease in absences in December, January, and February, when outdoor pollution levels peak. This pattern aligns with a concave relationship between air quality and health outcomes. Reducing pollution from very high to moderately high levels yields limited health benefits, as both levels remain above the recommended "healthy" exposure thresholds. Our results support prior evidence on non-linear relationships between air pollution and morbidity. For instance, Berkouwer and Dean (2023) find no clinical health improvements after installing clean stoves in rural households in India because average pollution exposure remains high due to significant outdoor levels. Similarly, Miller et al. (2024) show that health impacts rise steeply when transitioning from small to medium smoke shocks but flatten and slightly decline from medium to large shocks.

Another possible explanation for the dynamic effects relates to absenteeism caused by allergic respiratory symptoms in spring. During this season, purifiers may improve indoor air quality by reducing high concentrations of dust, allergens, and pollen. To test this hypothesis, we estimate heterogeneous treatment effects based on pollen concentration, using a 10-day rolling average. Following the approach in Panel B of Table 3, we find no evidence that the effectiveness of purifiers varies with pollen levels (Appendix Table A.7). This finding reduces the likelihood that our dynamic treatment effect arises from purifiers' impact on pollen.

We find that purifiers reduce students' self-reported respiratory symptoms and influence their perceptions of air quality and preferences for urban policies aimed at reducing pollution. However, one limitation is the potential for experimenter demand effects—treated students may feel pressured to report symptoms, perceptions, and preferences that align with the perceived goals of the intervention. Additionally, the physical presence of purifiers may prime students' responses. To support the validity of self-reported health measures, we examine their correlation with pre-treatment absences. We find a positive and statistically significant relationship between baseline reports of runny nose and blocked nose and pre-treatment absences (Appendix Table A.8).

5.1. Cost-effectiveness

We assess the cost-effectiveness of our intervention by calculating the cost per avoided student absence. The total cost is approximately €3,070 per purifier over a 10-year lifespan, which includes purchase, maintenance, and energy use.[15] In a typical classroom with 21.6 students, this results in an annual cost of about €14.20 per student. Since the intervention reduces absences by approximately 1.34 days per student per year, the estimated cost per avoided absence day is €10.60.

In high-income contexts, interventions designed to reduce absenteeism among at-risk students often include mentorship programs and behaviorally informed attendance reports sent to parents (Rogers and Feller, 2018; Heppen et al., 2018; Robinson et al., 2018; Bergman, 2021). In lower-income settings, deworming is considered one of the most cost-effective strategies for improving both attendance and academic outcomes (Miguel and Kremer, 2001). The cost per additional day of attendance varies widely across interventions—from approximately €7.10 for deworming to €9–15 for behavioral interventions that reduce information frictions, and over €580 for hiring dedicated support staff.[16] Our intervention falls at the lower end of this cost range. Additionally, unlike information-based treatments, air purifiers are likely to produce lasting effects without behavioral mean reversion or externalities.

The benefits of our intervention significantly exceed its costs when considering the broader economic impacts of school absences. Extensive research shows that missed school days adversely affect both short-term academic performance and long-term earnings potential (Liu et al., 2021; Cattan et al., 2022; Goodman, 2014). Using a health-cost framework, Federici et al. (2018)

[15] This includes a bulk purchase price of €2,000, three replacement filters at €250 each (every 3 years), and €320 in electricity costs (assuming 0.8 KW/h per day over 2,000 days at the current Italian price of €0.20/KWh).

[16] Original cost values were converted to euros and adjusted for inflation to ensure comparability in 2024.

estimate the societal cost of a single school day missed due to influenza-related illness in Italy at approximately €102, which includes costs related to childcare, lost parental productivity, and healthcare expenditures. Based on this estimate, our intervention results in a benefit-cost ratio of 9.62 when considering only the immediate economic costs of absenteeism.

6. Conclusion

In this paper, we evaluate the impact of installing portable air purifiers in schools. The study occurs in a developed region characterized by moderate ambient pollution and standard school infrastructure. Our findings indicate that air purifiers effectively lower indoor pollution and decrease student absenteeism, especially among the most vulnerable students. The intervention proves to be cost-effective, scalable, and easily replicable.

The effects are most pronounced during periods of moderate outdoor pollution. During high-pollution episodes, the reduction in $PM_{2.5}$ achieved by purifiers is insufficient, as students remain exposed to elevated pollution levels both indoors and outdoors. This indicates that in areas with severe air pollution, purifiers alone may not significantly improve health outcomes or reduce absences. Improving indoor air quality in such contexts may require reducing infiltration through better infrastructure or increasing the capacity and operational speed of purifiers. Furthermore, using air purifiers should complement—not replace—broader efforts to reduce emissions, raise awareness, and promote adaptive behaviors.

This study presents the first experimental evidence on the effect of air purifiers on absenteeism among primary school students and establishes a conservative estimate of their cost-effectiveness. Future research should examine the impact on academic achievement across various educational levels and assess potential effects on teachers to quantify the intervention's benefits more comprehensively.

Tables and Figures

Table 1: Descriptive statistics and balance

	(1)	(2)	(3)	(4)	(5)
	Obs	Control		ATE	
Variable		Mean	(SD)	Estimate	(SE)
Female	2051	0.469	0.499	0.002	0.016
Grade 1	2051	0.184	0.388	0.016	0.081
Grade 2	2051	0.215	0.411	-0.020	0.086
Grade 3	2051	0.209	0.407	-0.017	0.085
Grade 4	2051	0.195	0.396	-0.012	0.081
Grade 5	2051	0.197	0.398	0.033	0.087
Foreign citizenship	2051	0.369	0.483	0.025	0.020
Pre-treat absences	2049	0.046	0.074	0.004	0.004
Class size	95	21.58	2.57	0.196	0.414
Some symptoms: runny nose	1451	0.456	0.498	-0.008	0.040
Some symptoms: blocked nose	1437	0.541	0.499	-0.001	0.039
Some symptoms: sneezing	1430	0.620	0.486	0.007	0.038
Some symptoms: cough	1433	0.556	0.497	0.030	0.038
Some symptoms: short of breath	1375	0.249	0.433	-0.004	0.033
Some symptoms: tiredness	1397	0.615	0.487	-0.002	0.039
Some symptoms: headache	1405	0.482	0.500	-0.039	0.035
Some symptoms: stomach ache	1389	0.424	0.494	-0.057	0.037
AQ perception: overall	1557	3.091	0.850	-0.036	0.092
AQ perception: city	1554	2.716	0.954	-0.142	0.089
AQ perception: class	1553	3.230	0.747	-0.036	0.059
AQ perception: schoolyard	1551	3.513	0.680	-0.112	0.059
Priority policy score: cleaning	1559	3.467	0.900	-0.014	0.067
Priority policy score: green and playgrounds	1540	3.278	0.982	-0.004	0.083
Priority policy score: sport infrastructures	1525	3.098	1.087	-0.105	0.099
Priority policy score: air quality	1536	3.486	0.955	-0.061	0.068
Priority policy score: less traffic	1513	3.169	0.997	-0.061	0.081

Notes: The table presents the mean and standard deviation in the control group (columns 2-3) for student socio-demographic characteristics and survey variables at the baseline, and the treatment effect with its standard error (columns 4-5). Air Quality (AQ) perception indexes are expressed on a scale from 1 (very bad) to 4 (very good). Priority policy scores are expressed on a scale from 1 (not important at all) to 4 (very important).

Table 2: Average and dynamic treatment effects on indoor air quality and environmental variables

Panel A: Average treatment effects on indoor environmental variables

	(1)	(2)	(3)	(4)	(5)	(6)
	Indoor air quality			Other environmental variables		
	$PM_{2.5}$	PM_{10}	CO	CO_2	Temp.	N. Ventilation episodes
Estimate	-4.489***	-4.595***	-0.1731	30.53	-0.1666	0.148
	(0.5206)	(0.5807)	(0.2933)	(69.07)	(0.2803)	(0.240)
N.Obs	3,417	3,417	3,417	3,417	3,417	3,422
Control Mean	14.15	14.85	1.31	805.9	20.97	1.4
Rel. Change %	31.72	30.94	13.25	3.79	0.79	−10.6

Panel B: Dynamic treatment effects on indoor $PM_{2.5}$

	(1) 11-2023	(2) 12-2023	(3) 01-2024	(4) 02-2024	(5) 03-2024	(6) 04-2024	(7) 05-2024	(8) 06-2024
Estimate	-3.819***	-4.397***	-6.178***	-7.947***	-2.952***	-1.686***	-2.308***	-2.119***
	(0.5814)	(0.9762)	(0.9354)	(0.9306)	(0.4362)	(0.2231)	(0.3509)	(0.5275)
N.Obs	515	712	797	751	847	819	820	186
Control Mean	11.59	18.24	21.64	21.39	8.03	5.12	5.88	5.84
Treated Mean	7.70	13.84	15.46	13.93	5.11	3.45	3.59	3.63
Outdoor Mean	18.53	26.33	32.92	35.21	13.30	8.60	6.98	4.48
Rel. Change %	-32.95	-24.11	-28.54	-37.16	-36.78	-32.94	-39.24	-36.27
I/O Ratio	0.625	0.693	0.657	0.607	0.604	0.595	0.843	1.304

Notes: Panel A reports the average treatment effects (ATE) on indoor air quality measures ($PM_{2.5}$, PM_{10}, CO) alongside effects on other environmental variables (CO_2 and temperature) and the number of ventilation episodes. The sample is restricted to school days. Panel B presents the dynamic treatment effects on indoor $PM_{2.5}$ by calendar month. Due to some missing observations at the sub-daily level, the sample size is slightly different in Column (6). All models include calendar date, day of the week, school-by-weekday, school-by-month, and grade fixed effects. Standard errors are clustered at the treatment (classroom) level. Significance levels: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 3: Main and heterogenous effects on school absences

Panel A: Average treatment effects and heterogeneity

	(1) *Main effect*	(2) *Pre-treat absences*	(3)	(4)	(5)	(6) *Student characteristics*	(7)	(8)	(9)
		Q1	Tr×Q2	Tr×Q3	Tr×Q4	Male	Tr×Female	Italian	Tr×Foreign
Estimate	−0.064*	0.004	−0.024	−0.028	−0.103*	−0.108**	0.099	−0.013	−0.123
	(0.038)	(0.007)	(0.052)	(0.054)	(0.061)	(0.050)	(0.081)	(0.044)	(0.075)
N.Obs	336,716	335,861	335,861	335,861	335,861	336,716	336,716	336,716	336,716
Marginal Effect	−0.007	0.0004	-0.0025	-0.0028	-0.0109	−0.006	−0.001	−0.002	−0.015
Control Mean	0.056	0.044	0.056	0.059	0.101	0.062	0.060	0.058	0.067

Panel B: Heterogeneity by outdoor air pollution:

	(1) *WHO exceedances in the last ten days*	(2)	(3)	(4)	(5) *Ten days rolling average of $PM_{2.5}$*	(6)	(7)	(8)
	Q1	Tr×Q2	Tr×Q3	Tr×Q4	Q1	Tr×Q2	Tr×Q3	Tr×Q4
Estimate	−0.106**	0.029	0.050	0.087**	−0.097**	0.003	0.043	0.079**
	(0.042)	(0.036)	(0.040)	(0.040)	(0.042)	(0.036)	(0.043)	(0.039)
N.Obs	336,716	336,716	336,716	336,716	336,716	336,716	336,716	336,716
Marginal Effect	−0.011	0.003	−0.005	0.009	−0.010	−0.000	0.004	0.008
Control Mean	0.064	0.067	0.059	0.058	0.063	0.068	0.061	0.055
P-val ($Q1 + Tr \times Qx = 0$)	-	0.081	0.239	0.657	-	0.0426	0.290	0.684

Notes: The dependent variable is an indicator for student-day absences. All models include student, date, school-by-weekday, and school-by-month fixed effects, and are estimated with a Probit Maximum Likelihood Estimator panel model. Coefficients are effects on log-odds. Marginal effects are reported at the table bottom. The bottom line reports the average post-treatment absences in the control group in the specific sub-groups. Panel A reports the main effect (Column 1); interactions of the treatment indicator (Treat×Post) with quartiles of pre-treatment absence rates (the lowest quartile is the reference) in Columns 2-5; interactions with student characteristics (sex and citizenship) in Columns 6-9. The sample size decreases slightly in columns 2–5 because there was no data on pre-treatment absences for a small number of students. Panel B reports heterogeneous treatment effects estimates by the 10-day rolling sum of days with outdoor average $PM_{2.5}$ exceeding the daily WHO thresholds (15 $\mu g/m^3$) and the 10-day rolling lagged outdoor $PM_{2.5}$ levels. Both variables are constructed using the quartile split (with the lowest category as the reference). The bottom line shows the p-values of the treatment effect in the different quartiles, obtained from the test of $Q1 + Tr \times QX$, for the second, third and fourth quartiles. Standard errors are clustered at the treatment level (classroom). Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

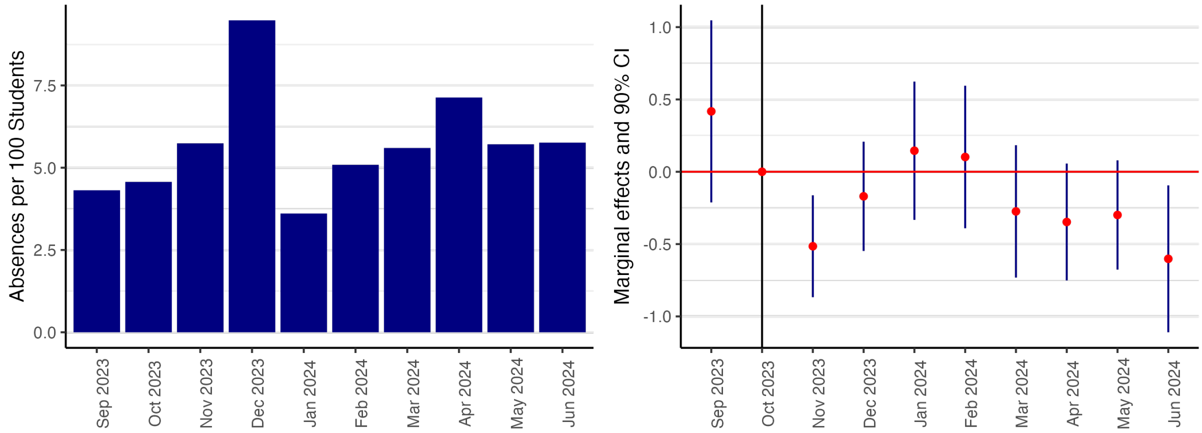

Figure 1: Dynamic effects on absences

Notes: The left panel figure shows the seasonality of absences in the control group, expressed as average absences per 100 students in the month. The right panel figure shows the dynamic treatment effects on daily absences and 90% confidence intervals. Models are estimated with Probit. Marginal effects are reported. The reference probability at t-1 (October 2023) is 4.7%. The models include calendar date, day of the week, school-by-weekday, and school-by-month, and grade fixed effects. Standard errors are clustered at the treatment level (classroom).

Table 4: Impact on Self-Reported Health Symptoms, Perceptions, and Preferences

Panel A: Impact on Self-Reported Health

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Symptoms							
	Runny nose	Blocked nose	Sneezing	Cough	Short breath	Tiredness	Headache	Stomach ache
Estimate	-0.150*	-0.118*	-0.093	-0.058	0.082	0.030	0.006	0.034
	(0.079)	(0.068)	(0.070)	(0.084)	(0.093)	(0.081)	(0.068)	(0.068)
N.Obs	1,589	1,597	1,587	1,621	1,555	1,570	1,571	1,574
Marginal effect	-0.059	-0.046	-0.034	-0.023	0.027	0.011	0.002	0.013
Control Mean	0.532	0.569	0.664	0.576	0.259	0.646	0.452	0.403

Panel B: Impact on Perceptions and Preferences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Air Quality Perception				Urban Policy Priorities				
	General	City	Class	Schoolyard	City cleaning	Green playgrounds	Sport infrastructure	Air quality	Less traffic
Estimate	0.132	-0.043	0.247**	-0.038	0.089	0.101	0.002	0.181**	-0.011
	(0.099)	(0.092)	(0.093)	(0.101)	(0.076)	(0.088)	(0.079)	(0.081)	(0.068)
N.Obs	1,715	1,742	1,733	1,725	1,729	1,720	1,704	1,716	1,695
N.Class	95	95	95	95	95	95	95	95	
Control Mean	2.978	2.559	3.109	3.360	3.509	3.280	3.088	3.456	3.158

Notes: Panel A reports Probit estimates of the treatment effect on self-reported health symptoms. Marginal effects are reported at the bottom of the table. The dependent variables equal one if the student reported the symptom at least some time over the previous week and zero otherwise. Panel B presents estimates of the impact on perceptions and policy preferences using Ordered Probit models. The first four columns report an air quality perception index (scored from 1 (very bad) to 4 (very good)), and the next five columns report a policy priority score on urban issues (scored from 1 (not important at all) to 4 (very important)). Models control for gender and foreign nationality and include grade and school fixed effects; standard errors are clustered at the treatment (classroom) level. Significance levels: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

References

Abadie A., Athey S., Imbens G. W., and Wooldridge J. M. (2023) When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1): 1–35. 10

Aguilar-Gomez S., Dwyer H., Graff Zivin J., and Neidell M. (2022) This Is Air: The "Nonhealth" Effects of Air Pollution. *Annual Review of Resource Economics*, 14(Volume 14, 2022): 403–425. 2

Angrist J. et al. (2020) *How to Improve Education Outcomes Most Efficiently?: A Comparison of 150 Interventions Using the New Learning-adjusted Years of Schooling Metric*: World Bank Group. 4

Annesi-Maesano I., Maesano C. N., Biagioni B., D'Amato G., and Cecchi L. (2021) Call to action: Air pollution, asthma, and allergy in the exposome era. *Journal of Allergy and Clinical Immunology*, 148(1): 70–72. 2

Aragón F. M., Miranda J. J., and Oliva P. (2017) Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management*, 86: 295–309, Special issue on environmental economics in developing countries. 2

Barwick P. J., Li S., Lin L., and Zou E. Y. (2024) From Fog to Smog: The Value of Pollution Information. *American Economic Review*, 114(5): 1338–1381. 4

Barwick P., Li S., Lin L., and Zou E. (2024) From Fog to Smog: The Value of Pollution Information. *American Economic Review*, 114(5): 1338–1381. 4

Baylis P., Greenstone M., Lee K., and Sahai H. (2024) Is the Demand for Clean Air Too Low? Experimental Evidence from Delhi. 4

Benjamini Y., Krieger A. M., and Yekutieli D. (2006) Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3): 491–507. 39, 40

Bergman P. (2021) Parent-child information frictions and human capital investment: Evidence from a field experiment. *Journal of political economy*, 129(1): 286–322. 15

Berkouwer S. B. and Dean J. T. (2023) Private Actions in the Presence of Externalities: The Health Impacts of Reducing Air Pollution Peaks but not Ambient Exposure. September. 2, 14

Bruhn M. and McKenzie D. (2009) In Pursuit of Balance: Randomization in Practice in Development Field Experiments. *American Economic Journal: Applied Economics*, 1(4): 200–232, Publisher: American Economic Association. 9

Burke M. et al. (2022) Exposures and Behavioural Responses to Wildfire Smoke. *Nature Human Behaviour*, 6(10): 1351–1361. 4

Burke M., Heft-Neal S., Li J., Driscoll A., Baylis P., Stigler M., Weill J. A., Burney J. A., Wen J., Childs M. L., and Gould C. F. (2022) Exposures and behavioural responses to wildfire smoke. *Nature Human Behaviour*, 6(10): 1351–1361, Publisher: Nature Publishing Group. 4

Carmona N., Seto E., Gould T. R., Rasyid E., Shirai J. H., Cummings B. J., Hayward L., Larson T. V., and Austin E. (2022) Indoor Air Quality Intervention in Schools: Effectiveness of a Portable HEPA Filter Deployment in Five Schools Impacted by Roadway and Aircraft Pollution Sources. *Atmosphere*, 13(10): 1623, Number: 10 Publisher: Multidisciplinary Digital Publishing Institute. 4

Carneiro J., Cole M., and Strobl E. (2021) The Effects of Air Pollution on Students' Cognitive Performance: Evidence from Brazilian University Entrance Tests. *Journal of the Association of Environmental and Resource Economists*. 3

Cattan S., Kamhöfer D. A., Karlsson M., and Nilsson T. (2022) The Long-Term Effects of Student Absence: Evidence from Sweden. *The Economic Journal*, 133(650): 888–903. 15

Cellini S. R., Ferreira F., and Rothstein J. (2010) The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design*. *The Quarterly Journal of Economics*, 125(1): 215–261. 4

Chen R., Zhao A., Chen H., Zhao Z., Cai J., Wang C., Yang C., Li H., Xu X., Ha S. et al. (2015) Cardiopulmonary benefits of reducing indoor particles of outdoor origin: a randomized, double-blind crossover trial of air purifiers. *Journal of the American College of Cardiology*, 65(21): 2279–2287. 4

Chen S., Guo C., and Huang X. (2018) Air Pollution, Student Health, and School Absences: Evidence from China. *Journal of Environmental Economics and Management*, 92: 465–497. 3, 14

Chiu Y.-H. M., Bellinger D. C., Coull B. A., Anderson S., Barber R., Wright R. O., and Wright R. J. (2013) Associations between Traffic-Related Black Carbon Exposure and Attention in a Prospective Birth Cohort of Urban Children. *Environmental Health Perspectives*, 121(7): 859–864. 3

Cori L., Donzelli G., Gorini F., Bianchi F., and Curzio O. (2020) Risk Perception of Air Pollution: A Systematic Review Focused on Particulate Matter Exposure. *International Journal of Environmental Research and Public Health*, 17(17): 6424. 8

Corrigan A. E., Becker M. M., Neas L. M., Cascio W. E., and Rappold A. G. (2018) Fine particulate matters: The impact of air quality standards on cardiovascular mortality. *Environmental research*, 161: 364–369. 2

Coury M., Falconer L., and La Nauze A. (2024) Wildfire smoke and private provision of public air-quality monitoring. *Journal of Environmental Economics and Management*, 127: 103036. 4

Currie J., Hanushek E. A., Kahn E. M., Neidell M., and Rivkin S. G. (2009) Does pollution increase school absences? *The Review of Economics and Statistics*, 91(4): 682–694. 2, 3, 11, 14

Deschênes O., Greenstone M., and Shapiro J. S. (2017) Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program. *American Economic Review*, 107(10): 2958–2989. 4

Ebenstein A., Lavy V., and Roth S. (2016) The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution. *American Economic Journal: Applied Economics*, 8(4): 36–65. 3

EEA (2022) Air Quality e-Reporting: Air quality annual statistics calculated by the EEA. 2

——— (2024) https://www.eea.europa.eu/en. 8

ENVIRA (2024a) https://envira.global/nanoenvi-iaq/. 34

——— (2024b) https://envira.global/wp-content/uploads/2022/03/EN_IAQ_LORA_Data_Sheet_V1.3.3.pdf. 34

Federici C., Cavazza M., Costa F., and Jommi C. (2018) Health care costs of influenza-related episodes in high income countries: A systematic review. *PLOS ONE*, 13(9): e0202787, Publisher: Public Library of Science. 15

Gehrsitz M. (2017) The effect of low emission zones on air pollution and infant health. *Journal of Environmental Economics and Management*, 83: 121–144. 32

Gershenson S., Jacknowitz A., and Brannegan A. (2017) Are student absences worth the worry in US primary schools? *Education Finance and Policy*, 12(2): 137–165. 2

Gignac F., Barrera-Gómez J., Persavento C., Solé C., Tena È., López-Vicente M., Foraster M., Amato F., Alastuey A., Querol X. et al. (2021) Short-term effect of air pollution on attention function in adolescents (ATENC! Ó): A randomized controlled trial in high schools in Barcelona, Spain. *Environment international*, 156: 106614. 4

Gilraine M. (2023) Air Filters, Pollution, and Student Achievement. *Journal of Human Resources*. 4

Gilraine M. and Zheng A. (2022) Air Pollution and Student Performance in the U.S.. Working Paper 30061. 3

Goodman J. (2014) Flaking Out: Student Absences and Snow Days as Disruptions of Instructional Time. Working Paper 20221. 15

Graff Zivin J. and Neidell M. (2013a) Environment, Health, and Human Capital. *Journal of Economic Literature*, 51(3): 689–730. 3

——— (2013b) Environment, Health, and Human Capital. *Journal of Economic Literature*, 51(3): 689–730. 4

——— (2021b) Indoor Air Quality, Information, and Socioeconomic Status: Evidence from Delhi. *AEA Papers and Proceedings*, 111: 420–424. 4

Greenstone M., Lee K., and Sahai H. (2021a) Indoor Air Quality, Information, and Socioeconomic Status: Evidence from Delhi. *AEA Papers and Proceedings*, 111: 420–424. 4

Heissel J. A., Persico C., and Simon D. (2022) Does Pollution Drive Achievement? The Effect of Traffic Pollution on Academic Performance. *Journal of Human Resources*, 57(3): 747–776. 3, 14

Heppen J. B., Zeiser K., Holtzman D. J., O'Cummings M., Christenson S., and Pohl A. (2018) Efficacy of the Check & Connect mentoring program for at-risk general education high school students. *Journal of Research on Educational Effectiveness*, 11(1): 56–82. 15

Heyes A., Cook N., and Rivers N. (2023) Clean Air and Cognitive Productivity: Effect and Adaptation. *Journal of the Association of Environmental and Resource Economists*. 3

IHME (2023) Air Pollution. Accessed: 07-08-2023. 31

Institute for Health Metrics and Evaluation (2019) Global Health Data Exchange - Global Burden of Disease Study 2019 (GBD 2019). 2, 31

Italian Republic (2010) DECRETO LEGISLATIVO 13 agosto 2010, n. 155, "Attuazione della direttiva 2008/50/CE relativa alla qualita' dell'aria ambiente e per un'aria piu' pulita in Europa." (10G0177), in G. U. 15/09/2010, n. 217/L). 31

Ito K. and Zhang S. (2019a) Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy*: —. 4

——— (2019b) Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China. *Journal of Political Economy*: 000–000. 4

Klauber H., Holub F., Koch N., Pestel N., Ritter N., and Rohlf A. (2024) Killing Prescriptions Softly: Low Emission Zones and Child Health from Birth to School. *American Economic Journal: Economic Policy*, 16(2): 220–48. 32

Komisarow S. and Pakhtigian E. L. (2022) Are power plant closures a breath of fresh air? Local air quality and school absences. *Journal of Environmental Economics and Management*, 112: 102569. 3, 14

Kremer M., Romero M., and Saavedra S. (2023) Air filters and student learning. AEA RCT Registry. 4

Künn S., Palacios J., and Pestel N. (2019) Indoor Air Quality and Cognitive Performance. IZA Discussion Papers 12632. 3

Lai W., Li S., Li Y., and Tian X. (2021) Air Pollution and Cognitive Functions: Evidence from Straw Burning in China. *American Journal of Agricultural Economics*, n/a(n/a). 3

Liu H. and Salvo A. (2018) Severe air pollution and child absences when schools and parents respond. *Journal of Environmental Economics and Management*, 92: 300–330. 3, 14

Liu J., Lee M., and Gershenson S. (2021) The short- and long-run impacts of secondary school absences. *Journal of Public Economics*, 199: 104441. 15

Liu T., Yan W., and Peng K. (2024) A large-scale examination of the efficacy of air quality intervention in Chinese middle schools. AEA RCT Registry. 4

Lombardy Region (2006) LEGGE REGIONALE 11 dicembre 2006, n. 24, "Norme per la prevenzione e la riduzione delle emissioni in atmosfera a tutela della salute e dell'ambiente.". 31

——— (2013) DECRETO REGIONALE 11/09/2013, n. 593, "Approvazione del Piano Regionale degli interventi per la qualità dell'aria e dei relativi documenti previsti dalla procedura di valutazione ambientale strategica - (atto da trasmettere al consiglio regionale". 31

Malik S., Walter T. F., Naeem T., Bharti N. K., and Blakeslee D. (2024) Clean Air in the Classroom: Environmental Inputs and Human Capital Formation. AEA RCT Registry. 4

Mendoza D. L., Pirozzi C. S., Crosman E. T., Liou T. G., Zhang Y., Cleeves J. J., Bannister S. C., Anderegg W. R., and Robert P. I. (2020) Impact of low-level fine particulate matter and ozone exposure on absences in K-12 students and economic consequences. *Environmental Research Letters*, 15(11): 114052. 11

Metcalfe R. D. and Roth S. (2025) Making the Invisible Visible: The Impact of Revealing Indoor Air Pollution on Behavior and Welfare. Working Paper 33510, National Bureau of Economic Research. 4

Miguel E. and Kremer M. (2001) Worms: education and health externalities in Kenya. 15

Miller N. H., Molitor D., and Zou E. (2024) The Nonlinear Effects of Air Pollution on Health: Evidence from Wildfire Smoke. Working Paper 32924, National Bureau of Economic Research. 2, 14

Ministero Italiano dell'Istruzione e del Merito (2023) Portale Unico dei Dati della Scuola. 5

Municipality of Milan (2022a) Atto n. DD 8014 del 30/09/2022 - Approvazione del "Programma di Monitoraggio del Piano Aria e Clima" del Comune di Milano, 30/09/2022. 32

——— (2022b) Atto n. DD 8519 del 12/10/2022 - Approvazione del "Programma di Monitoraggio del Piano Aria e Clima" del Comune di Milano, 12/10/2022. 32

——— (2023) Atto n. DD 6121 del 13/07/2023, "Approvazione del disciplinare dei sistemi di pagamento, di comunicazione e di registrazione della targa per l'accesso dei veicoli nella ZTL Cerchia dei Bastioni – Area C.". 32

Nauze A. L. and Severnini E. R. (2021) Air Pollution and Adult Cognition: Evidence from Brain Training.Technical report. 3

Park R. J., Goodman J., Hurwitz M., and Smith J. (2020) Heat and learning. *American Economic Journal: Economic Policy*, 12(2): 306–39. 4

Percoco M. (2013) Is road pricing effective in abating pollution? Evidence from Milan. *Transportation Research Part D: Transport and Environment*, 25: 112–118. 32

——— (2014) The effect of road pricing on traffic composition: Evidence from a natural experiment in Milan, Italy. *Transport Policy*, 31: 55–60. 32

Persico C. L. and Venator J. (2019) The Effects of Local Industrial Pollution on Students and Schools. *Journal of Human Resources*: 0518–9511R2. 3, 14

Pestel N. and Wozny F. (2021) Health effects of Low Emission Zones: Evidence from German hospitals. *Journal of Environmental Economics and Management*, 109: 102512. 32

Pope III C. A., Cropper M., Coggins J., and Cohen A. (2015) Health benefits of air pollution abatement policy: Role of the shape of the concentration–response function. *Journal of the Air & Waste Management Association*, 65(5): 516–522. 2

Rahai R. and Evans G. W. (2023) Cumulative Neurotoxicological Air Pollution Exposure Is Associated with Lower Reading Improvement and Diminished Benefits of Literacy Interventions for Urban Elementary Students of Color. *Journal of Urban Health*, 100(3): 493–503. 3

Ransom M. R. and Pope C. A. (1992) Elementary school absences and PM10 pollution in Utah Valley. *Environmental Research*, 58(1): 204–219. 3

Robinson C. D., Lee M. G., Dearing E., and Rogers T. (2018) Reducing student absenteeism in the early grades by targeting parental beliefs. *American educational research journal*, 55(6): 1163–1192. 4, 15

Rogers T. and Feller A. (2018) Reducing student absences at scale by targeting parents' misbeliefs. *Nature Human Behaviour*, 2(5): 335–342. 4, 15

Roth S. (2021) The Effect of Indoor Air Pollution on Cognitive Performance: Evidence from the UK.Technical report. 3

Rubalcava L. and Teruel G. (2006) Mexican Family Life Survey, First Wave. 39

Ruggieri S., Longo V., Perrino C., Canepari S., Drago G., L'Abbate L., Balzan M., Cuttitta G., Scaccianoce G., Minardi R. et al. (2019) Indoor air quality in schools of a highly polluted south Mediterranean area. *Indoor Air*, 29(2): 276–290. 5

Ruiz-Tagle J. C. and Sangwan N. S. (2023) Technological and Behavioral Strategies to Mitigate the Effects of Air Pollution on Children in Delhi's Schools. AEA RCT Registry. 4

Schmit K. M., Brown R., Hayer S., Checovich M. M., Gern J. E., Wald E. R., and Barrett B. (2021) Wisconsin Upper Respiratory Symptom Survey for Kids: Validation of an Illness-specific Quality of Life Instrument. *Pediatric Research*, 90(6): 1207–1214. 7

Shaddick G., Thomas M. L., Mudu P., Ruggeri G., and Gumy S. (2020) Half the world's population are exposed to increasing air pollution. *NPJ Climate and Atmospheric Science*, 3(1): 23. 2

Sunyer J., Suades-González E., García-Esteban R., Rivas I., Pujol J., Alvarez-Pedrerol M., Forns J., Querol X., and Basagaña X. (2017) Traffic-related Air Pollution and Attention in Primary School Children. *Epidemiology*, 28(2): 181–189. 3

Tong Z., Li Y., Westerdahl D., and Freeman R. B. (2020) The impact of air filtration units on primary school students' indoor exposure to particulate matter in China. *Environmental Pollution (Barking, Essex: 1987)*, 266(Pt 2): 115107. 4

Weichenthal S., Pinault L., Christidis T., Burnett R. T., Brook J. R., Chu Y., Crouse D. L., Erickson A. C., Hystad P., Li C. et al. (2022) How low can you go? Air pollution affects mortality at very low levels. *Science Advances*, 8(39): eabo3381. 2

World Health Organization (2021) *WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*, Genève, Switzerland: World Health Organization. 2

Yang X., Wang Q., Han F., Dong B., Wen B., Li L., Ruan H., Zhang S., Kong J., Zhi H., Wang C., Wang J., Zhang M., and Xu D. (2021) Pulmonary Benefits of Intervention with HEPA Air Purifier in Schoolchildren: A Double-Blind Crossover Study. February. 4

Yao Z., Zhang W., Ji X., and Weng W. (2023) Short-Term Exposure to Air Pollution and Cognitive Performance: New Evidence from China's College English Test. *Environmental and Resource Economics*, 85(1): 211–237. 3

Zhang J. and Mu Q. (2018) Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management*, 92: 517–536. 4

Zhang Y. and Mu D. (2018) Demand for Clean Indoor Air: The Role of Pollutant Concentrations in Household Decisions. *Journal of Environmental Economics*, xx(x): xxx–xxx. 4

Appendix

A. Additional tables and figures

Table A.1: Survey attrition and missing values at the baseline

	(1) Obs	(2) Control Mean	(3) Control SD	(4) ATE Estimate	(5) ATE SE
Surveyed in wave 1	2051	0.888	0.315	-0.006	0.057
Missing values in:					
Some symtoms: runny nose	1822	0.223	0.417	-0.040	0.038
Some symtoms: blocked nose	1822	0.228	0.420	-0.035	0.041
Some symtoms: sneezing	1822	0.225	0.418	-0.019	0.041
Some symtoms: cough	1822	0.232	0.422	-0.039	0.040
Some symtoms: short of breath	1822	0.265	0.441	-0.039	0.043
Some symtoms: tiredness	1822	0.257	0.437	-0.049	0.044
Some symtoms: head ache	1822	0.244	0.430	-0.030	0.043
Some symtoms: stomach ache	1822	0.259	0.438	-0.043	0.043
Air quality perception: overall	1822	0.149	0.356	-0.007	0.026
Air quality perception: city	1822	0.145	0.352	0.006	0.025
Air quality perception: class	1822	0.150	0.357	-0.004	0.027
Air quality perception: school yard	1822	0.153	0.360	-0.008	0.027
Prioriy policy score: cleaning	1822	0.153	0.360	-0.020	0.027
Prioriy policy score:: green and playgrounds	1822	0.161	0.368	-0.016	0.026
Prioriy policy score: sport infrastructures	1822	0.169	0.375	-0.016	0.026
Prioriy policy score: air quality	1822	0.159	0.366	-0.007	0.026
Prioriy policy score: less traffic	1822	0.177	0.382	-0.020	0.030

Notes: The table presents the mean and standard deviation in the control group for the probability of participating in the baseline survey and for the probability of non-reporting a given question in the first survey wave, conditional on participating in it (Columns 2-3). It reports the estimate and standard error of the difference in mean between treatment and control group in Columns 4-5.

Table A.2: Survey attrition and missing values at the endline

	(1) Obs	(2) Control Mean	(3) Control SD	(4) ATE Estimate	(5) ATE SE
Surveyed in wave 2	2051	0.876	0.330	0.024	0.034
Missing values in:					
Some symtoms: runny nose	1815	0.132	0.338	-0.018	0.034
Some symtoms: blocked nose	1815	0.128	0.334	-0.020	0.035
Some symtoms: sneezing	1815	0.139	0.346	-0.032	0.034
Some symtoms: cough	1815	0.124	0.329	-0.042	0.034
Some symtoms: short of breath	1815	0.155	0.362	-0.028	0.036
Some symtoms: tiredness	1815	0.152	0.359	-0.041	0.036
Some symtoms: head ache	1815	0.155	0.362	-0.048	0.037
Some symtoms: stomach ache	1815	0.151	0.358	-0.043	0.036
AQ perception: overall	1815	0.052	0.222	0.008	0.016
AQ perception: city	1815	0.040	0.196	0.003	0.013
AQ perception: class	1815	0.042	0.200	0.009	0.015
AQ perception: school yard	1815	0.049	0.216	0.002	0.015
Prioriy policy score: cleaning	1815	0.048	0.214	-0.002	0.012
Prioriy policy score+A35:D55: green and playgrounds	1815	0.049	0.216	0.007	0.015
Prioriy policy score: sport infrastructures	1815	0.065	0.246	-0.009	0.015
Prioriy policy score: air quality	1815	0.056	0.230	-0.004	0.014
Prioriy policy score: less traffic	1815	0.063	0.243	0.007	0.018

Notes: This table presents the mean and standard deviation in the control group for the probability of participating in the endline survey and for the probability of non-reporting a given question in the second wave survey, conditional on participating in it (Columns 2-3). It reports the estimate and standard error of the difference in mean between treatment and control group in Columns 4-5.

Table A.3: Average treatment effects on indoor air quality and environmental variables, including non-school days

	(1)	(2)	(3)	(4)	(5)
	Indoor air quality			Other environmental variables	
	$PM_{2.5}$	PM_{10}	CO	CO_2	Temp.
Estimate	-3.353***	-3.395***	-0.1197	12.43	-0.3516
	(0.8421)	(0.8761)	(0.2954)	(57.23)	(0.3026)
N.Obs	5,651	5,651	5,651	5,651	5,651
Control Mean	11.959	12.405	1.207	678.380	20.444
Rel. Change %	−28.04	−27.36	−9.90	1.83	1.72

Notes: This table reports the average treatment effects (ATE) on indoor air quality measures ($PM_{2.5}$, PM_{10}, CO) alongside effects on other environmental variables (CO_2 and temperature). The sample includes school and non-school days. All models include calendar date, day of the week, school-by-weekday, school-by-month, and grade fixed effects. Standard errors are clustered at the treatment (classroom) level. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.

Table A.4: Average treatment effect on absences, robustness check

	(1)	(2)	(3)
	Daily absence		
	LPM	Poisson	ZIP count
Estimate	-0.006	-0.123*	-0.125**
	(0.004)	(0.073)	(0.059)
N.Obs	336,716	16,203	16,203
Control Mean.	0.061	1.27	1.27

Notes: The table reports the average treatment effects on daily absences. The dependent variable is daily student absence (Column 1) and the count of daily classroom absences (Columns 2-3). The models include student (LPM) and classroom (Poisson and ZIP), date, school-by-weekday, school-by-month fixed effects. The control group mean and standard deviation of the outcome in the post-treatment period are reported at the bottom. Standard errors clustered at the treatment level (classroom). *** significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A.5: Heterogeneous treatment effects on school absences by grade

	(1)	(2)	(1)	(2)	(3)	(4)	(5)
	Pre-treat Absences		Daily absence by Grade				
	Tr	Tr× *PreAbs*	1st Grade	Tr×2nd	Tr×3rd	Tr×4th	Tr×5th
Estimate	0.027	-0.009*	-0.083	-0.045	-0.011	0.154	-0.013
	(0.043)	(0.004)	(0.057)	(0.103)	(0.090)	(0.118)	(0.089)
N.Obs	335,861	335,861	336,716	336,716	336,716	336,716	336,716
Marginal Effect	0.0027	-0.0008	-0.008	-0.005	0.001	0.016	0.001

Notes: The dependent variable is an indicator variable for student-day absences. The empirical model includes student, date, school-by-weekday, and school-by-month fixed effects, and is estimated with a Probit Maximum Likelihood Estimator panel model. Coefficients are effects on log-odds. Marginal effects are reported at the table bottom. In Columns 1-5, the treatment indicator (Treat ×Post) is interacted with binary variables for the grade (grades 1 through 5), where grade 1 serves as the reference category. Standard errors are clustered at the treatment (classroom) level. *** significance at the 1% level, ** at the 5% level, * at the 10% level.

Table A.6: Heterogeneous treatment effects by outdoor levels of air pollution (linear interaction)

	(1)	(2)	(3)	(4)
	Daily absence			
	WHO exceedances last ten days		*Ten days $PM_{2.5}$ rolling average*	
	Tr	Tr× WHO	Tr	Tr× $PM_{2.5}$
Estimate	−0.104**	0.009**	−0.120***	0.003**
	(0.041)	(0.004)	(0.044)	(0.001)
N.Obs	336,716	336,716	336,716	336,716
Marginal Effect	−0.011	0.001	−0.012	0.000

Notes: The dependent variable is an indicator for student-day absences. All models include student, date, school-by-weekday, and school-by-month fixed effects, and are estimated with a Probit Maximum Likelihood Estimator panel model. Coefficients are effects on log-odds. Marginal effects are reported at the table bottom. We reports heterogeneous treatment effects estimates by the 10-day rolling sum of days exceeding the daily WHO threshold of 15 *micrograms per cubic meter* (μg/m^3) (Columns 1-2) and 10-day rolling mean $PM_{2.5}$ level (Columns 3-4). Standard errors are clustered at the treatment level (classroom). Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Heterogeneous treatment effects by outdoor levels of pollen: Quartile interaction model

	(1)	(2)	(3)	(4)
	Daily absence			
	Q1	Tr×Q2	Tr×Q3	Tr×Q4
All Pollens	-0.063	-0.016	0.016	-0.003
	(0.046)	(0.039)	(0.045)	(0.044)
Selected Pollens	-0.067	-0.001	-0.015	0.024
	(0.046)	(0.051)	(0.042)	(0.037)
N.Obs	336,720	336,720	336,720	336,720

Notes: The dependent variable is an indicator for student-day absences. We report heterogeneous treatment effect estimates based on the average of outdoor pollen levels. Every row provides a separate regression for each group of pollens indicated. *All pollens* includes: Alternaria, Alnus, Betula, Cladosporium, Ambrosia, Artemisia, Carpinus betulus, Corylus avellana, Cupressaceae and Taxaceae, Fagaceae, Gramineae, Oleaceae, Urticaceae. *Selected Pollens* includes Ambrosia, Grimanae, Cupr-Taxaceae, and Betula. Concentrations are calculated as total pollen per m^3. Data on pollen concentrations comes from weekly pollen bulletins compiled by the Association of Italian Territorial and Hospital Allergists and Immunologists (https://www.pollinieallergia.net/). The model multiplies the treatment indicator (Treat×Post) by three indicator variables equal to one if the pollen in the given row is within the second, third, and fourth concentration quartiles for the 10-day average concentration in the city of Milan. The reference category includes days in the lowest quartile of the given pollen level. All models include student, date, school-by-weekday, and school-by-month fixed effects, and are estimated with a Probit Maximum Likelihood Estimator panel model. Coefficients are effects on log-odds. Marginal effects are reported below each estimate. Standard errors are clustered at the treatment level (classroom). Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Correlation between reported symptoms and absences at baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Symptoms							
	Runny nose	Blocked nose	Sneezing	Cough	Short breath	Tiredness	Headache	Stomach ache
Pre-treat absences	0.309*	0.331*	0.053	0.238	0.250	0.259	0.191	0.035
	(0.186)	(0.183)	(0.177)	(0.185)	(0.164)	(0.182)	(0.188)	(0.184)
N. Obs.	1,451	1,437	1,430	1,433	1,375	1,397	1,405	1,389

Notes: Panel A reports Probit estimates (marginal effects) of the correlation of pre-treatment absences and self-reported health symptoms. The dependent variables equal one if the student reported the symptom at least some time over the previous week and zero otherwise. Models control for gender and foreign nationality and include grade and school fixed effects. Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.

B. Air pollution in the North of Italy

Air pollution levels in Northern Italy consistently exceed WHO guidelines. For instance, in 2021, the average annual concentration of $PM_{2.5}$ in Milan—the region's largest city—was above 20 $\mu g/m^3$, surpassing the WHO recommended limit of 15 $\mu g/m^3$. Figure B.1 shows the share of deaths and years of life lost among children under 16 attributable to air pollution, across selected European countries. In 2019, 4.2% of child fatalities in Italy were linked to air pollution exposure—the highest rate among major Western European nations (Institute for Health Metrics and Evaluation, 2019).

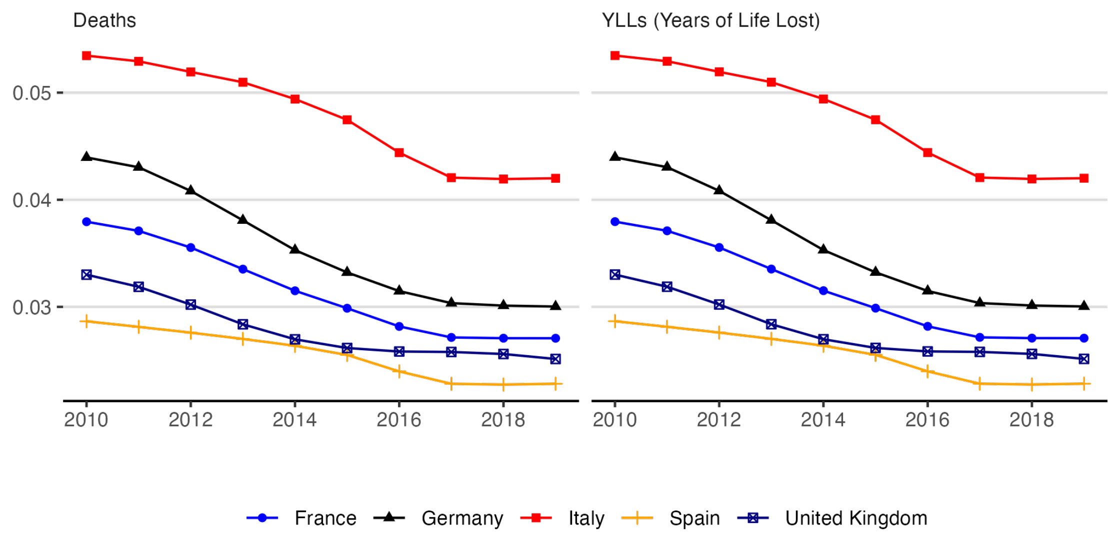

Figure B.1: Proportion of total deaths and years of life lost due to air pollution exposure for children between zero and sixteen years old (2010-2019) *Notes:* Source: IHME (2023)

?? Panel (a) displays the average annual $PM_{2.5}$ concentrations in Milan from 2008 to 2020. While air pollution has declined over this period, levels remain well above the WHO thresholds for good air quality. Moreover, annual averages can mask significant seasonal peaks, as illustrated in Panel (b). Pollution levels are notably higher in winter than in summer, driven by factors such as thermal inversions, increased residential heating, and the reduced efficiency of internal combustion engines at lower temperatures.

To reduce exposure to air pollution, regional and local governments have implemented various measures, including investments in public transportation, upgrades to power plants, promotion of cleaner fuels, improvements in energy efficiency, and public awareness campaigns on air quality (Italian Republic, 2010; Lombardy Region, 2006, 2013). In Milan, vehicle traffic is regulated through a congestion charge introduced in 2012 and a Low Emission Zone (LEZ) established in 2022 (Municipality of Milan, 2022a, 2023).[17] The city also continues to invest in public infrastructure to improve the public transport network and promote cycling as part of its broader Air-Climate Plan (Municipality of Milan, 2022b). However, these efforts have produced only marginal improvements, typically appearing over the medium to long term.

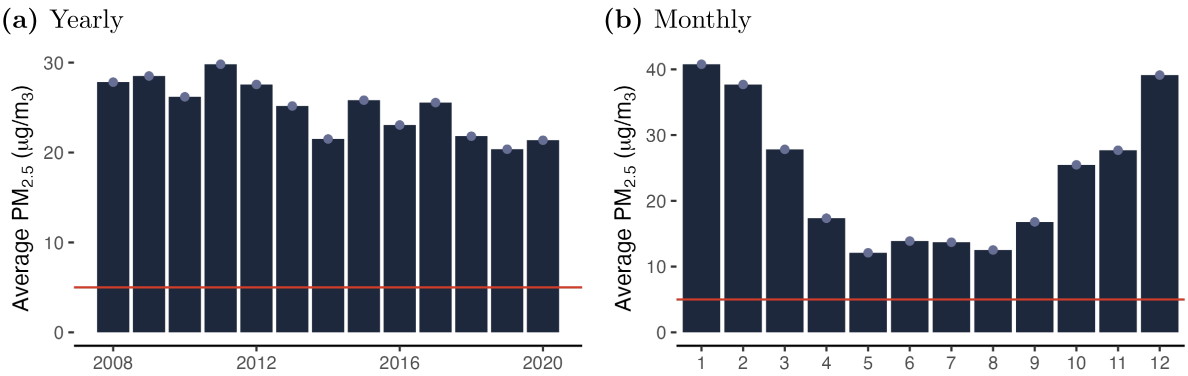

Figure B.2: Yearly and monthly time series of average $PM_{2.5}$ in Milan (2008-2020)
Notes: The values come from yearly and monthly averages of daily air pollution measurements across the 39 stations in the metropolitan city of Milan. The red line marks the yearly guideline values set by the WHO (5 μg/m^3).

C. Purifiers and monitors' technical features

The study utilizes NETCO NIVEUS NV100 purifiers, shown in the left panel of Appendix Figure C.1. These purifiers feature U15 Ultra Low Particulate Air (ULPA) filters, which capture up to 99.99% of particles larger than 0.026 microns. ULPA filtration is the highest standard of mechanical air purification, certified and recognized internationally. It surpasses the more common HEPA filters, providing 10 to 100 times greater efficiency (see Appendix Figure C.1).

The purifiers are energy-efficient, consuming only 4W per hour at the operating speed used in the study, comparable to a 60-watt incandescent bulb. They also operate quietly, with average acoustic pressure levels ranging from 29 to 45 dB(A). Air enters the device and passes through the ULPA filter, made of layers of ultrafine material, followed by an activated carbon filter, before being recirculated into the environment. The efficiency of the purifiers is measured primarily by the Clean Air Delivery Rate (CADR), expressed in cubic meters per hour (m^3/h), and the Air Exchange Rate, which indicates how many times per hour the purifier can filter all the air in a given room. Following the manufacturer's recommendations, we selected a model suitable for the

[17] While many studies find that LEZs significantly improve environmental outcomes (Klauber et al., 2024; Pestel and Wozny, 2021; Gehrsitz, 2017), the local environmental impact of Milan's congestion charge appears to be limited (Percoco, 2013, 2014).

average classroom volume. The installed units have a CADR of 200 m^3/h, yielding an average Air Exchange Rate of 1.04 across classrooms (ranging from 0.7 to 1.5). To balance effectiveness and noise reduction, purifiers operate at 60% capacity (speed 3 of 5), producing an acoustic pressure of 33.5 dB(A)—below the WHO recommended limit of 35 dB(A) for classrooms.

In addition to the purifiers, we installed 31 ENVIRA Nanoenvi indoor air quality sensors, as shown in the right panel of Figure C.1. These sensors measure concentrations of CO_2 (ppm), $PM_{2.5}$, PM_{10}, and CO (ppm), along with temperature ($°C$), humidity (%), and atmospheric pressure (hPa). Their technical specifications are detailed in Appendix Table C.2. Once powered and connected to the internet, the sensors transmit measurements every 30 seconds to an online data platform. Each device features a small LED display that visually represents indoor air quality using a four-level color-coded scale based on the Indoor Ambient Air Quality Index defined by the manufacturer. To ensure comparability between classrooms with and without sensors—and to minimize the risk of influencing behavior—we covered the LED displays with anti-tampering tape to prevent students and teachers from seeing real-time air quality readings.

Figure C.1: Purifiers and sensors installed
Notes: Left: The NETCO NIVEUS NV100 air purifiers installed in treated classes. The purifiers mount U15 Ultra Low Particulate Air (ULPA) filters and have a CADR of 200 m^3/h. Right: NVIRA Nanoenvi indoor air quality sensors installed in 31 calsses. The LED disaplays have been LED displays with covered with anti-tampering tape.

Table C.1: Efficiency of different mechanical filter technologies.

Filter Group	Class	MPSS INTEGRAL VALUES		MPSS INTEGRAL VALUES	
		Efficiency (%)	Penetration (%)	Efficiency (%)	Penetration (%)
EPA	E10	85	15	-	-
	E11	95	5	-	-
	E12	99.5	0.5	-	-
HEPA	H13	99.95	0.05	99.75	0.25
	H14	99.995	0.005	99.975	0.025
ULPA	U15	99.9995	0.0005	99.9975	0.0025
	U16	99.99995	5E-05	99.99975	0.00025
	U17	99.99995	5E-05	99.9999	0.0001

Notes:

Table C.2: Technical specifications of the low-cost sensors employed.

Pollutant/Parameter	**Precision**	**Measuring range**
Carbon monoxide (CO)	±5%	0 - 5000 ppm
Particulate matter ($PM_{2.5}$)	±10 μg/m^3	0 - 1000 μg/m^3
Carbon dioxide (CO_2)	±30 ppm	0 - 40000 ppm
Temperature	±0.02 ºC	0 - 65 ºC
Relative humidity	±2%	10 - 95%
Atmospheric pressure	±10 hPa	500 - 1150 hPa

Notes: This table presents the precision and measuring range of low-cost sensors by measured pollutant (CO, CO_2, $PM_{2.5}$) and environmental parameter (temperature, relative humidity, atmospheric pressure). *Source:* (ENVIRA, 2024a,b).

D. Indoor sensors' intercomparison

We conducted a sensor-to-sensor intercomparison study to evaluate the performance and consistency of the ENVIRA Nanoenvi low-cost sensors. To ensure comparability, we co-located all sensors in an indoor, non-laboratory environment and operated them continuously for four days under nearly identical conditions. We positioned the sensors at a uniform height, spaced approximately 30 cm apart, to minimize differences in exposure to air volume and environmental factors. We computed hourly averages for all monitored variables. Table D.1 presents summary statistics, including sample size, mean, standard deviation, minimum, maximum, and quartiles. We identified one monitor as an outlier due to its low variation and extremely low pollutant readings. We excluded this monitor from all analyses.

To assess whether imprecise measurements bias our main impact estimates, we calculated the absolute hourly deviation from the overall mean monitor reading for each sensor, using the average across all sensors. We then regressed these absolute deviations on a treatment indicator and hour fixed effects. Results presented in Table D.2 indicate no statistically significant differences in measurement accuracy between sensors installed in treatment and control classrooms.

Table D.1: Hourly-level sensor-to-sensor intercomparison summary statistics

Parameter	N	Mean	Sd	Min	25th	50th	75th	Max
$PM_{2.5}$	2418	13.78	6.81	5.49	10.09	12.27	14.79	84.34
PM_{10}	2418	13.85	7.04	5.49	10.10	12.29	14.81	96.69
CO	2418	1.23	0.83	0.00	0.41	1.34	1.96	3.57
CO_2	2331	853.40	179.36	380.68	751.45	847.91	936.66	1864.11
Temperature	2418	21.16	0.41	20.05	20.85	21.16	21.45	22.42
Humidity	2418	65.96	2.26	58.00	64.49	66.03	67.60	71.38
Atmospheric pressure	2418	1010.09	1.29	1006.57	1009.17	1010.02	1010.92	1014.07

Notes: The sample size for CO_2 is lower due to missing data in two sensors.

Table D.2: Average treatment effects on the absolute deviations of indoor air quality and environmental variables in the sensor-to-sensor intercomparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Absolute deviation from hourly mean						
	Indoor air quality			Other environmental variables			
	$PM_{2.5}$	PM_{10}	CO	CO_2	Temp.	Humidity	Pressure
Estimate	0.106	0.111	-0.147	5.61	0.016	-0.083	0.020
	(0.084)	(0.093)	(0.136)	(4.73)	(0.058)	(0.179)	(0.196)
N.Obs	2,418	2,418	2,418	2,331	2,418	2,418	2,418
Control Mean	3.900	3.980	0.803	106.492	0.323	1.714	0.857

Notes: The table reports the average treatment effects (ATE) on indoor air quality ($PM_{2.5}$, PM_{10}, CO) and other environmental variables (CO_2 and temperature, humidity, and atmospheric pressure) absolute deviations from the hourly means. The sample is restricted to sensor-to-sensor intercomparison days. All models include hour fixed effects. Standard errors are clustered at the sensor level. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.

E. Detecting ventilation episodes

Natural ventilation through open windows and doors alters the air exchange rate between indoor and outdoor environments, which can impact the effectiveness of air purifiers. We investigate how air purifiers affect ventilation behavior in treatment and control classrooms. The installation of purifiers can lead to conflicting outcomes: teachers in treated classrooms may reduce ventilation to optimize purifier performance and limit the infiltration of outdoor pollutants. Conversely, the protection offered by purifiers might encourage more frequent ventilation, even during high pollution periods, based on the assumption that the device lessens associated risks. To identify ventilation events, we leverage the characteristic sharp declines in indoor CO_2 concentrations that typically occur during air exchange with the external environment. These events may also accompany temperature drops when outdoor temperatures fall below indoor levels.

We focus our analysis on school hours and exclude the last 90 minutes before student dismissal to prevent capturing air quality changes linked to end-of-day routines. To reduce measurement noise, we apply a five-minute rolling average to the temperature time series. We define "ventilation episodes" based on specific thresholds for the magnitude and duration of decreases in indoor CO_2 concentrations and, when applicable, temperature. It is important to note that a single instance of window or door opening may result in the detection of multiple ventilation episodes. Figure E.1 illustrates the distribution of detected ventilation episodes under various threshold definitions.

To examine whether air purifiers influenced ventilation behavior, we estimate model 1 using the daily number of ventilation episodes as the dependent variable. Table E.1 reports average treatment effects based on different threshold definitions. For instance, Column 1 shows the treatment effect on the number of episodes per day where CO_2 concentrations decrease by at least 25 ppm per minute and temperature drops by at least 0.005°C per minute for at least a minute. Columns 7 to 12 define ventilation episodes based solely on CO_2 drops, noting that during spring and fall, outdoor temperatures may exceed indoor temperatures, potentially leading to an increase in indoor temperature during ventilation.

Across all specifications, we find no statistically significant differences between the treatment and control groups. This indicates that installing air purifiers did not change ventilation behavior. Since ventilation patterns may vary seasonally with outdoor temperatures, we further split the sample into winter and spring months (Tables E.2 and E.3). Even when disaggregated by season, we find no significant differences in ventilation behavior between treated and control classrooms.

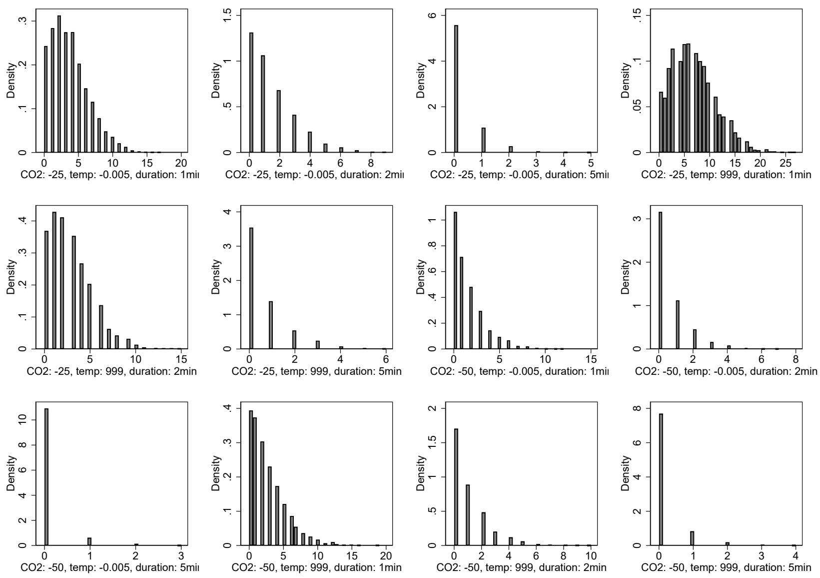

Figure E.1: Distribution of detected ventilation episodes for different thresholds.

Table E.1: Average treatment effect on the number of ventilation episodes

Daily ventilation episodes	(1)	(2)	(3)	(4)	(5)	(6)
	<-25ppm	<-25ppm	<-25ppm	<-50ppm	<-50ppm	<-50ppm
	<-0.005°	<-0.005°	<-0.005°	<-0.005°	<-0.005°	<-0.005°
	>1'	>2'	>5'	>1'	>2'	>5'
Estimate	0.250	0.148	0.035	-0.032	0.012	-0.002
	(0.42)	(0.24)	(0.08)	(0.31)	(0.16)	(0.04)
Control Mean	3.5	1.4	0.2	1.5	0.6	0.1
Observations	3422	3422	3422	3422	3422	3422
	(7)	(8)	(9)	(10)	(11)	(12)
	<-25ppm	<-25ppm	<-25ppm	<-50ppm	<-50ppm	<-50ppm
	>1'	>2'	>5'	>1'	>2'	>5'
Estimate	0.311	0.251	0.130	-0.029	0.012	0.001
	(0.63)	(0.38)	(0.17)	(0.47)	(0.26)	(0.08)
Control Mean	6.6	2.7	0.6	2.6	1.0	0.2
Observations	3422	3422	3422	3422	3422	3422

Notes: The dependent variable is the number of ventilation episodes per day, identified by prolonged variations (in minutes) in indoor concentrations of CO_2 (ppm) and temperature (°C) (Columns (1)- (6)) or CO_2 alone (Columns (7)- (12)). All regressions include fixed effects for grade, calendar day, school-by-weekday, and school-by-month. The sample is restricted to school days. Standard errors are clustered at the treatment level (classroom). *** significance at the 1% level, ** at the 5% level, * at the 10% level.

Table E.2: Average treatment effect on the number of ventilation episodes from November to March

Daily ventilation episodes, November to March	(1) <-25ppm <-0.005° >1'	(2) <-25ppm <-0.005° >2'	(3) <-25ppm <-0.005° >5'	(4) <-50ppm <-0.005° >1'	(5) <-50ppm <-0.005° >2'	(6) <-50ppm <-0.005° >5'
Estimate	0.172	0.098	0.036	-0.083	0.004	0.005
	(0.44)	(0.25)	(0.09)	(0.32)	(0.17)	(0.05)
Control Mean	3.6	1.5	0.3	1.5	0.6	0.1
Observations	2226	2226	2226	2226	2226	2226
	(7) <-25ppm >1'	(8) <-25ppm >2'	(9) <-25ppm >5'	(10) <-50ppm >1'	(11) <-50ppm >2'	(12) <-50ppm >5'
Estimate	0.412	0.249	0.130	0.002	0.028	0.003
	(0.68)	(0.41)	(0.19)	(0.50)	(0.28)	(0.09)
Control Mean	6.3	2.8	0.6	2.5	1.0	0.2
Observations	2226	2226	2226	2226	2226	2226
R-squared	0.31	0.30	0.26	0.29	0.25	0.20

Notes: Sample restricted to November, December, January, February, and March. The dependent variable is the number of ventilation episodes per day identified by prolonged variations (in minutes) in indoor concentrations of CO2 (ppm) and temperature (°C) (Columns (1)- (6)) or CO2 alone (Columns (7)- (12)). All regressions include fixed effects for grade, calendar day, school-by-weekday, and school-by-month. The sample is restricted to school days. Standard errors are clustered at the treatment level (classroom). *** significance at the 1% level, ** at the 5% level, * at the 10% level.

Table E.3: Average treatment effect on the number of ventilation episodes from April to June

Daily ventilation episodes, April to June	(1) <-25ppm <-0.005° >1'	(2) <-25ppm <-0.005° >2'	(3) <-25ppm <-0.005° >5'	(4) <-50ppm <-0.005° >1'	(5) <-50ppm <-0.005° >2'	(6) <-50ppm <-0.005° >5'
Estimate	0.419	0.259	0.037	0.063	0.031	-0.014
	(0.43)	(0.24)	(0.08)	(0.31)	(0.16)	(0.05)
Control Mean	3.3	1.1	0.2	1.5	0.5	0.1
Observations	1196	1196	1196	1196	1196	1196
	(7) <-25ppm >1'	(8) <-25ppm >2'	(9) <-25ppm >5'	(10) <-50ppm >1'	(11) <-50ppm >2'	(12) <-50ppm >5'
Estimate	0.133	0.284	0.141	-0.083	-0.013	-0.003
	(0.63)	(0.37)	(0.16)	(0.46)	(0.24)	(0.08)
Control Mean	7.2	2.5	0.4	2.9	1.0	0.1
Observations	1196	1196	1196	1196	1196	1196

Notes: Sample restricted to April, May, and June. The dependent variable is the number of ventilation episodes per day, identified by prolonged variations (in minutes) in indoor concentrations of CO2 (ppm) and temperature (°C) (Columns (1)- (6)) or CO2 alone (Columns (7)- (12)). All regressions include fixed effects for grade, calendar day, school-by-weekday, and school-by-month. The sample is restricted to school days. Standard errors are clustered at the treatment level (classroom). *** significance at the 1% level, ** at the 5% level, * at the 10% level.

F. Pre-specified analysis and deviations from the pre-analysis plan

The current study presents deviations from the pre-analysis plan (PAP) uploaded to the Registry of the American Economic Association.[18] We document and explain the choices made in this paper and provide evidence for the commitments outlined in the PAP that were not implemented in the final version.

Main outcomes: In the PAP, the main outcomes were: $PM_{2.5}$, absences, cognitive skills, achievement, mood, and aggressive episodes. The manuscript presents evidence only on $PM_{2.5}$ and absences.

We chose not to request achievement data from the Italian National Institute of Evaluation of the Education System (INVALSI) and, as a result, omitted the analysis of achievement for the following reasons. First, national tests are available for only 40% of students, as they are administered only in the second and fifth grades. Second, a recent change in the Institute's data protection protocols restricts tracking of individual students, even with fully anonymized data. Score data is accessible only for groups of three students. These factors significantly reduce statistical power and compromise the reliability of our estimates.

For cognitive skills, mood, and aggressive episodes, we used the PAP for their operationalization based on student surveys. The cognitive skill assessment is a Raven test. It consists of a series of visual patterns with a missing piece, where test-takers must choose the correct piece from multiple options. We selected the suitable version for children aged 5 to 12 years from the first wave of the Mexican Family Life Survey (Rubalcava and Teruel, 2006). We summed all correct answers to create a score ranging from 0 to 18 and standardized this score to have a mean of zero and a variance of one for each school-grade combination, using the mean and standard deviation from the control group.

We assess students' mood over the previous week using a survey question based on a Likert scale (very positive, positive, negative, very negative) which we convert into a 1-4 index. To proxy aggressive episodes, we create a dummy variable that equals one if students report arguing or quarreling with any classmate during the past week (sometimes, often, very often) and zero otherwise (never).

Appendix Table F.1 presents the results of the pre-specified main outcomes with the multiple hypothesis correction described in the PAP, specifically FDR-adjusted q-values (Benjamini et al.,

[18] It is available at https://www.socialscienceregistry.org/trials/11960.

2006). The treatment does not significantly impact cognitive skills, mood, or aggressive episodes. Only the effect on indoor air quality remains significant after the multiple hypothesis correction.

Table F.1: Average treatment effect on primary pre-specified outcomes

	(1) $PM_{2.5}$	(2) Daily Absence	(3) Standardized Raven Score	(4) Mood	(5) Aggressive Episodes
Estimate	-4.489***	-0.0641*	-0.033	0.076	0.077
	(0.521)	(0.0381)	(0.050)	(0.071)	(0.090)
	[0.001]	[0.227]	[0.44]	[0.397]	[0.417]
N.Obs	336,716	336,716	1,815	1,651	1,770
Control Mean	11.80	0.056	0	3.424	0.395

Notes: Standard errors clustered at the treatment level (classroom). *** Significance at the 1% level, ** at the 5% level, * at the 10% level. FDR adjusted q-values Benjamini et al. (2006) are reported in brackets.

Secondary outcomes: Most secondary outcomes outlined in the PAP are included in the manuscript, except for data on non-standardized student grades calculated at the end of each semester. After extensive discussions with the directors, we concluded that these evaluations are highly subjective and specific to individual teachers and their classes. Since this dataset aimed to support the evidence from national standardized tests, we decided not to proceed with the request in their absence.

Data: In the PAP, we committed to using absence data from two school years: 2022-23 and 2023-24. However, the manuscript only uses data from the latter year. This decision arises from a change in the absence digitization system at one school, which limited access to the 2022-23 data. Consequently, we faced a significant reduction in sample size, worsened by the natural sample loss of 20% among first graders in 2023-24 who were not part of the 2022-23 data. Therefore, we chose to use only the 2023-24 data to maintain adequate statistical power.

Models: The specification in Section 4.3 for survey outcomes differs from that in the PAP. In this specification, we regress endline outcomes on a treatment dummy, individual characteristics, grade, and school fixed effects. In the PAP, we committed to a two-way fixed effects model that included student and survey wave fixed effects. The reasons for these changes are: i. We conducted only two survey waves instead of the planned three due to budget constraints and the inability to conduct a midline survey in some schools. ii. We did not anticipate attrition rates of 11% and 12% in the first and second waves, respectively, or the missing value patterns affecting certain variables (see Appendix Tables A.1 and A.2). Combining both waves in the same model (panel or ANOVA) would result in a sample reduction of 33% to 45% (depending on the variable considered), leading to a loss of statistical power.

Heterogeneity: In the PAP, we committed to examining heterogeneous treatment effects on absences based on pre-treatment absence levels, seasonality (winter vs. spring and fall), and outdoor air pollution values from the previous week. The main text presents these analyses with slight modifications to our operationalization of the heterogeneity dimensions. First, pre-treatment absences refer to the months before treatment deployment, rather than the previous school year. We present the quartile split in the main text and the continuous variable in the appendix instead of the pre-registered median split. This change is based on evidence showing that high values significantly influence heterogeneous effects. Second, we present seasonal effects using monthly data (Figure 1), which provide more precise evidence of treatment dynamics. Third, we utilize the 10-day rolling outdoor $PM_{2.5}$ concentration, constructing quartiles and the continuous variable as interaction terms. This approach highlights the role of extremes and calculates the turning point when purifiers cease to be effective. Results, available upon request, remain consistent whether we use 7, 5, or 3-day rolling averages.

The manuscript introduces additional dimensions of heterogeneity that were not pre-registered: students' gender, nationality, and grade. These factors seek to address readers' interest in exploring aspects of heterogeneity that we did not expect schools would provide.

Robustness checks: As promised in the PAP, we include indoor temperature and humidity in our analysis of air purifiers' impact on indoor pollution. Appendix Table F.2 replicates the results from Panel A of Table 2 (Columns 1-4). Results are consistent. We exclude class characteristics (floor and orientation) because these data are unavailable. We do not repeat this exercise for absences because of sample size limitations and statistical power issues, as the sample is restricted to classes equipped with sensors.

Table F.2: Average treatment effects on indoor air pollution, robustness

	(1)	(2)	(3)
	Indoor Air Quality		
	$PM_{2.5}$	PM_{10}	CO
Estimate	-4.219***	-4.338***	-0.153
	(0.419)	(0.429)	(0.299)
Temperature	-0.557***	-0.488***	0.057
	(0.151)	(0.170)	(0.066)
Rel. Humidity	0.030	0.0967	-0.025
	(0.087)	(0.100)	(0.034)
N.Obs	5,447	5,447	5,447
Control Mean	12.679	13.147	1.291

Notes: This table reports the average treatment effects (ATE) on indoor air quality measures ($PM_{2.5}$, PM_{10}, and CO). All models include calendar date, day of the week, school-by-weekday, school-by-month, and grade fixed effects. Different from the preferred specification, we include indoor air temperature and relative humidity as additional controls. Standard errors are clustered at the treatment (classroom) level. Significance levels: *** p<0.01, ** p<0.05, and * p<0.1.