Do Air Filters Improve Student Learning? Experimental Evidence from Colombia*

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Abstract

We conducted a randomized control trial to test whether the placement of portable air filters in schools improves student outcomes in Colombia. Air filters reduced the $PM_{2.5}$ pollution inside classrooms by 0.73 $\mu g/m^3$ (p-value 0.013) from a base of 10.10 $\mu g/m^3$ and by 1.7 $\mu g/m^3$ when pollution was above the World Health Organization's threshold of 5 $\mu g/m^3$ (p-value 0.00). Students in treated schools scored 0.03σ higher (p-value 0.03) on a high-stakes exam taken 3–4 months after filters were installed. We do not find evidence of different effects by socio-economic status, pollution levels, or where classroom construction included vents, allowing air to circulate from outside. Instrument variable estimates suggest that an increase of 1 $\mu g/m^3$ in indoor $PM_{2.5}$ reduces test scores by $.082\sigma$. If filters also influenced test scores by reducing infection risk, this should be considered an upper bound. Despite the modest effect size, air filters are cost-effective at raising learning levels, even without factoring in any potential health benefits and any benefits of avoiding school closures in future pandemics.

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1 Introduction

Globally, air pollution shortens the average person's life by 2.2 years (Greenstone, Hasenkopf, & Lee, 2022). Yet, developing countries do not have ambitious goals to reduce pollution. Placing high-efficiency particulate air (HEPA) filters in schools could help address the adverse effects of high pollution levels, reduce routine infectious disease transmission, and serve as a preparedness measure for pandemics by reducing disease transmission and the risk of school closure.[1] While filters are inexpensive relative to some other investments to mitigate pollution and disease risk at schools, there are also reasons to be skeptical about the potential impact of filters on learning. For example, many classrooms in low- and middle-income countries, including in our context, have vents allowing outside air; teachers or students may turn off filters to reduce noise levels or to use electrical outlets for other purposes; and they may also open windows when it is hot, letting in particulate matter from outside.

We report on an at-scale, light-touch randomized control trial on the impact of placing portable HEPA filters in classrooms in Bogota, Colombia. The study involves 42,389 in 357 public schools. The trial was designed to study the effects of filters in real-world conditions that might attenuate their impact. We can detect relatively small treatment effects due to the large number of schools involved in our trial. Additionally, we use administrative test score data and historical data that helps account for much of the variation in test scores. In this setting, students take the test we use to measure learning outcomes in central locations rather than in their schools, which allows us to isolate the impact of filters on learning as opposed to their effect on performance during the day of the test.

Consistent with the concerns of some in the engineering community, reductions in pollution were relatively modest. However, even these modest improvements in air quality were sufficient to yield measurable benefits on education in the form of higher test scores. Air filters lowered the level of $PM_{2.5}$ in classrooms by 0.73 $\mu g/m^3$ (p-value 0.013) from a base of 10.10 $\mu g/m^3$. The effect of the filter is larger, when the level of outdoor pollution is high.

[1] Multiple quasi-experimental and correlational studies find links between air pollution, including particulate matter, and test scores (e.g., Stafford (2015); Ebenstein, Lavy, and Roth (2016); Zhang, Chen, and Zhang (2018); Persico and Venator (2019); Heissel, Persico, and Simon (2020); Balakrishnan and Tsaneva (2021); Gilraine and Zheng (2024); Aguilar-Gomez, Dwyer, Graff Zivin, and Neidell (2022); Gilraine (2023); Biasi, Lafortune, and Schonholzer (2025)). Related papers estimate how contemporaneous pollution levels affect cognitive performance, see Ebenstein et al. (2016); S. Roth (2020); Künn, Palacios, and Pestel (2023). Routine respiratory diseases cause school absences in normal times (McLean, Peterson, King, Meece, & Belongia, 2017) and lead to learning losses. Further, the annual probability of a pandemic that is at least as severe as COVID-19 is approximately 1% (Glennerster, Snyder, & Tan, 2023), potentially leading to large-scale school shutdowns and large learning losses (Azevedo, Hasan, Goldemberg, Geven, & Iqbal, 2021; Narayan et al., 2022; Azevedo, Cojocaru, Talledo, & Narayan, 2023; Schady, Holla, Sabarwal, Silva, & Chang, 2023).

For example, the effect is -1.7 $\mu g/m^3$ (p-value 0.00) when outdoor pollution is above the World Health Organization (2021) recommended threshold of 5 $\mu g/m^3$.[2]

We find that having air filters while learning, improved test scores. Students exposed to filters scored .03σ (p-value 0.03) higher on the Saber 11 test, which was taken 3–4 months after filter installation. The improvement comes mainly from math, Spanish and social sciences, which exhibited increases of .04σ (p-value 0.02), .03σ (p-value 0.04), and .03σ (p-value 0.02) respectively. These results are robust to including school controls (average lagged scores), pollution measures, and student demographic controls (age, gender, parental education, and socio-economic strata).

We do find higher particulate levels in schools in lower SES neighborhoods, but we see no evidence of differential effects of the filters on learning by SES or particulate levels outside the school. More generally, we do not find heterogeneity in treatment effects by student characteristics (gender, age, and socio-economic strata) or school characteristics (average lagged scores). Perhaps surprisingly, despite 66% of classrooms having vents or slits or vents surrounding windows that enable uncontrolled airflow from outside, we also see no evidence that effects differ in schools that have vents.

Assuming filters only affect test scores through exposure to particulate matter rather than by reducing exposure to viruses or other respiratory diseases, one can construct an instrumental variable estimate of the effect of particulate matter on test scores by instrumenting indoor air quality with the presence of the filter (restricting the data to schools with monitors). These estimates suggest that an increase in particulate matter of 1 $\mu g/m^3$ in indoor $PM_{2.5}$ reduces test scores by .082σ. If there is also a disease reduction channel, this could be considered an upper bound on the LATE of pollution reduction.

Our estimates suggest that in non-pandemic periods, such as the time of this study, the purely educational benefits of installing HEPA filters would make them reasonably cost-effective and that allowing for even minimal reductions in the risk of school closures in future pandemics would make them highly cost-effective. Our estimates suggest an increase of 0.90-1.85standard Learning-Adjusted Years of Schooling per 100 USD invested per student. Air filter ranks comparable to other interventions aiming to improve educational outcomes in low and middle-income countries that were labeled as cost-effective by recent systematic reviews (Angrist, Filmer, Rogers, & Sabarwal, 2025; GEEAP, 2023).[3] Under conservative assumptions, following (Glennerster

[2]These estimates are similar to experimental estimates of portable HEPA filters in Los Angeles, which reduced $PM_{2.5}$ by 0.581$\mu g/m^3$ (Simona, Bartell, & Vieira, 2025).

[3]See also Kremer, Brannen, and Glennerster (2013) and Angrist, Evans, et al. (2025) for summaries of cost-effectiveness measures across interventions and settings.

et al., 2023), if the filters reduce the probability of school closures conditional on a pandemic scenario by 7%, the net benefits would be equivalent to $2.6 million only in Bogota; each additional 1% reduction in the probability of school closures would be equal to $6.6 million, or nearly $18 billion worldwide.

This study contributes to three strands of the literature. First, we advance research on policy alternatives to mitigate the effects of air pollution. While several countries, including Colombia, have pledged to reduce air pollution — such as Sustainable Development Goals 3.9 and 11.6 (United Nations, 2015)[4] —policymakers, including those focusing on education, may wish to consider investing in mitigating the adverse effects of pollution in the meantime. Two studies have found that installing HEPA filters in schools in the US improves learning outcomes (Gilraine, 2023; Biasi et al., 2025). We different in the context and the nature of the intervention. In those cases, dramatic changes were made to the ventilation systems in schools, the HEPA filters were not portable, and the cost was 10 times higher. Further, the pollution levels were much lower. In contrast, we provide experimental evidence on the effects of a lighter touch-at-scale filter program in a middle-income country context with high levels of pollution and demonstrate that they are an effective way to improve learning outcomes in developing settings.

Second, we contribute to the evidence on the effects of school health interventions on learning. Interventions such as deworming (e.g., Miguel and Kremer (2004)), providing eyeglasses (e.g., Glewwe, Park, and Zhao (2016)), nutritional interventions (e.g., Glewwe and Miguel (2007); Field, Robles, and Torero (2009); Luo et al. (2012); Sylvia et al. (2013); Araújo, Carrillo, and Sampaio (2021)), and anti-malarial treatment (e.g., Fernando, De Silva, Carter, Mendis, and Wickremasinghe (2006)) are highly cost-effective ways to improve student outcomes. We complement these findings by establishing that air filters are another cost-effective policy alternative.

Third, if the results are unlikely to be driven mostly by reductions in infectious disease, our results bolster the evidence of the negative effects of air pollution — particularly on cognitive performance and learning.[5] This contribution is fourfold. First, while most papers focus on high pollution the day of the exam, our paper focuses on reducing indoor pollution while students are learning. Second, while previous research in this area is based on quasi-experimental evidence, we complement these results by

[4]Indicators 3.9.1 and 11.6.2

[5]Prior work has documented its impact on health ((Neidell, 2004; Currie & Neidell, 2005; Beatty & Shimshack, 2014; Currie, Neidell, & Schmieder, 2009), human capital accumulation (Currie, Hanushek, Kahn, Neidell, & Rivkin, 2009; Sanders, 2012; Bharadwaj, Gibson, Zivin, & Neilson, 2017),performance on tests (Ebenstein et al., 2016) , migration (S. Chen, Oliva, & Zhang, 2022), labor supply (Hanna & Oliva, 2015) and productivity (Graff Zivin & Neidell, 2012; T. Chang, Graff Zivin, Gross, & Neidell, 2016; T. Y. Chang, Graff Zivin, Gross, & Neidell, 2019).

providing experimental evidence of how pollution affects learning. Third, most of the evidence comes from developed countries; three notable exceptions are Zhang et al. (2018) who study China and Merkus (2024); Villalobos and Blackman (2025) who study Colombia. However, the impact of pollution has been shown to vary across settings Arceo, Hanna, and Oliva (2016). We, therefore, complement these results with further evidence from a middle-income country. Finally, while most prior work analyzes outdoor or ambient air pollution, we focus on indoor air pollution.

2 Context

2.1 Education in Bogotá

Schooling in Colombia is divided into basic primary education (grades 1–5), basic secondary education (grades 6–9), and upper secondary education (grades 10–11). Education is compulsory through grade 9; the final 2 years are not mandatory but are necessary to access university or technical education. Public schools in Colombia run from January through November.[6] In Bogotá, 22.31% of all students and 61.76% of low-income students attend a public school.

In the last year of high school (Grade 11), students must take a nationwide standardized test (Saber 11) to graduate. There are five sections — mathematics, Spanish, natural sciences, social studies, and English — scored from 0 to 100, with a maximum global score of 500. While no minimum score is required to graduate, the results are one of the primary factors that higher education institutions consider in admissions and scholarship decisions. The Instituto Colombiano para la Evaluación de la Educación (ICFES) administers the exam on a Sunday at central locations (e.g., at a local university). Students in our sample sat the exam in August.[7]

2.2 Pollution in Bogotá

Particulate matter pollution consists of airborne particles such as dust, pollen, mold, soot, and smoke. Particulate matter is categorized based on the size of the particles. Fine particulate matter smaller than 2.5 micrometers ($PM_{2.5}$) is of particular concern as it is more easily absorbed deep into the brain (J.-C. Chen et al., 2017), lungs or bloodstream when inhaled compared to larger particles. However, coarser particulate matter, smaller than 10 μm (PM_{10}), is also known to be detrimental (Environmental

[6] Schools in Colombia follow one of two academic calendars: Calendar A runs from January through November, while Calendar B runs from September through June. All public schools in Bogotá and 98.17% of private schools follow Calendar A.

[7] This timing applies to all schools that follow Calendar A, which includes public schools.

Protection Agency, 2023). Exposure to high levels of such pollution can produce immediate respiratory symptoms, such as difficulty breathing and irritation to the eyes, throat, or lungs. Long-term exposure has been linked to chronic respiratory illnesses, cardiovascular disease, and cancer (World Health Organization, 2022).

The average particulate matter concentrations in Bogotá — 20.05 $\mu g/m^3$ for $PM_{2.5}$ and 55.64 $\mu g/m^3$ for PM_{10} — exceed the World Health Organization (2021)'s guidelines of 5 $\mu g/m^3$ for $PM_{2.5}$ and 25 $\mu g/m^3$ for PM_{10}. Although Bogota's pollution levels are consistently above the recommended limits of the World Health Organization (WHO), they are modest compared to those of other cities. For example, the 2023 World Air Quality Report ranked it 67 among 115 capital cities (IQAir, 2023) —- Delhi, Hanoi, Jakarta, Beijing, Accra, and Lahore (among many others) have pollution levels that are 3–7 times those of Bogotá.[8]

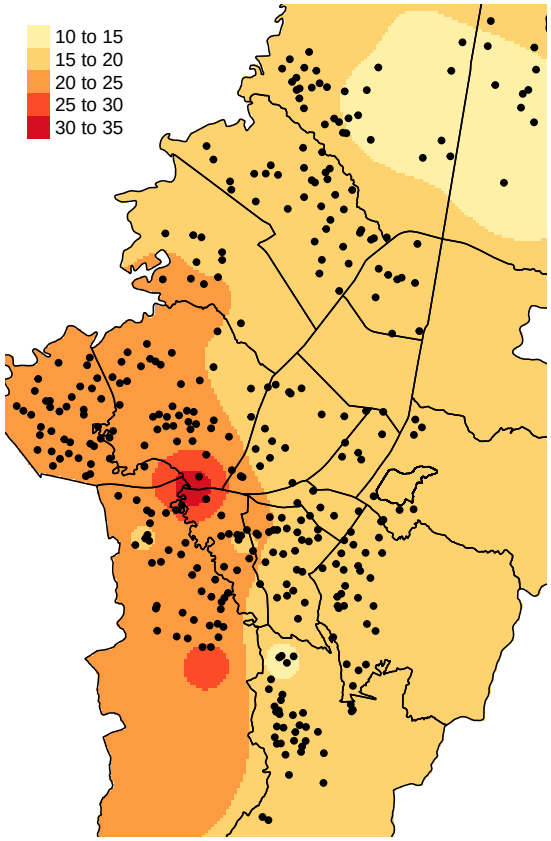
Particulate matter in Bogotá tends to be highest from January to March due to the atmospheric conditions present early in the year (Mura et al., 2020). Data from monitors we installed inside classrooms suggests students are exposed to $\sim$11 $\mu g/m^3$ of $PM_{2.5}$ on average during school hours. In 2021, re-suspended particulates, including from building and road construction, were the largest sources of particulate matter pollution in Bogotá, followed by road transit (Durán, Ramírez, Fajardo, Gómez, & Parra, 2022). Trucking was the largest primary source of $PM_{2.5}$, accounting for 11.6% of $PM_{2.5}$ emissions that year (Durán et al., 2022).

Colombia's national air quality surveillance system — Subsistema de Información sobre Calidad del Aire (SISAIRE) — maintains 22 monitoring stations throughout the city that collect hourly pollution measures. Lower-income areas in the south and west of the city tend to experience the highest levels of particulate matter pollution (Mura et al., 2020). As a result, students from lower socio-economic backgrounds are exposed to worse air quality (see Figure 1 and Figure A.1 for graphical correlational evidence).

[8] See https://www.who.int/data/gho/data/themes/air-pollution/who-air-quality-database/2022 and https://www.iqair.com/world-most-polluted-cities for information on pollution in different cities.

Figure 1: Pollution, poverty, and schools' locations

(a) $PM_{2.5}$ pollution in $\mu g/m^3$



(b) Multidimensional poverty index in 2018

Figures/poverty_IPMlowres.png

Notes: The black dots denote the schools in the experimental sample. The shading in Figure 1a reflects average pollution levels in 2022. Raw data on pollution was obtained from SISAIRE, the government's official platform that maintains real-time records of multiple pollution measures http://aircolombia.sisaire.gov.co/portal/index.col. For Bogotá, this information is captured by 22 monitoring stations. Pollution across the city was estimated via a linear interpolation process. The multidimensional poverty in Figure 1b measures deprivation in five categories: housing and access to public utilities, education, health, work, and childhood conditions. The information is based on the 2018 Census and measures the percentage of poor households according to the multidimensional index (see https://geoportal.dane.gov.co/visipm/ for more details). School locations were obtained from the Ministry of Education's publicly available databases https://www.datos.gov.co/Educaci-n/ESTABLECIMIENTOS-EDUCATIVOS-COLOMBIA/upkm-vdjb.

2.3 Respiratory diseases

School absence due to illness is a significant issue. Respiratory diseases cause substantial absenteeism at normal times (Dennis et al., 2012; Hsu, Qin, Beavers, & Mirabelli, 2016) and can lead to large school closures in pandemic circumstances. Air filters may affect test scores by reducing exposure to respiratory infections (Hammond, Khalid, Thornton, Woodall, & Hay, 2021; Curtius, Granzin, & Schrod, 2021; Burgmann & Janoske, 2021) by potentially eliminating harmful viruses and bacteria that cause infectious respiratory diseases.

During pandemics, school closures can cause severe learning losses.[9] In the Colombian case, schools were closed for 25 weeks due to the COVID-19 pandemic (UNESCO, 2020); similar length closures occurred in the region and other countries worldwide, leading to an estimated global cost from learning losses of USD $21 trillion (Schady et al., 2023). The annual probability of a pandemic that is at least as severe as COVID-19 is approximately 2.63% (Marani, Katul, Pan, & Parolari, 2021, 2023) and conservative estimates of the expected present value of learning losses from future pandemics are about USD $1.7 trillion (Glennerster et al., 2023).

3 Experimental design

3.1 Sample

Our sample consists of 357 public high schools located in urban areas of Bogotá with over 120,000 Grade 11 students (see Figure 2).[10] The random allocation is stratified at the locality level and only includes localities with at least four schools.

3.2 Randomization

Schools were randomized into one of four groups: schools that received only filters, schools that received only monitors, schools that received both filters and monitors, and a control group. The allocation was stratified at the locality level. Seventy-five schools were assigned to each treatment group, and the remaining 132 schools were assigned to the control group. Table 1, Panel A presents summary statistics for all eligible schools in 2022 (the year before the treatment). Students are 17.5 years old when they take the exam, on average, and 64% are from the lowest socio-economic strata. Experimental groups balance is held when comparing each treated group to the control group and in pairwise comparisons between different treatment arms (see table A.2). The p-value from a joint significance test, where the null is that all coefficients are equal to zero, using a system of seemingly unrelated equations, is 0.78.

Beyond balance on observable characteristics, there are no concerns of differential attrition (see Table 1, Panel B). The likelihood that we observe a school in the post-treatment years

[9] There is ample evidence of severe learning loses during the COVID-19 pandemic both in high-income (see Patrinos, Vegas, and Carter-Rau (2022); Moscoviz and Evans (2022); Betthäuser, Bach-Mortensen, and Engzell (2023) for reviews) as well as middle- and low-income countries (e.g., see Alasino, Ramírez, Romero, Schady, and Uribe (2024); Guariso and Björkman Nyqvist (2023); Ardington, Wills, and Kotze (2021); Lichand, Doria, Leal-Neto, and Fernandes (2022); Singh, Romero, and Muralidharan (2024)).

[10] Bogotá's administrative boundaries include a large rural area in the south. We exclude schools in this area since they typically have low pollution levels and due to logistical constraints.

is balanced, as is the number of students that take the Saber 11 test.[11] The observable characteristics of students (age, sex, maternal education, and SES strata) are also balanced in the post-treatment years (see Tables 1, A.4, and A.5)). Therefore, we do not believe differential attrition is a first-order issue in our setting.

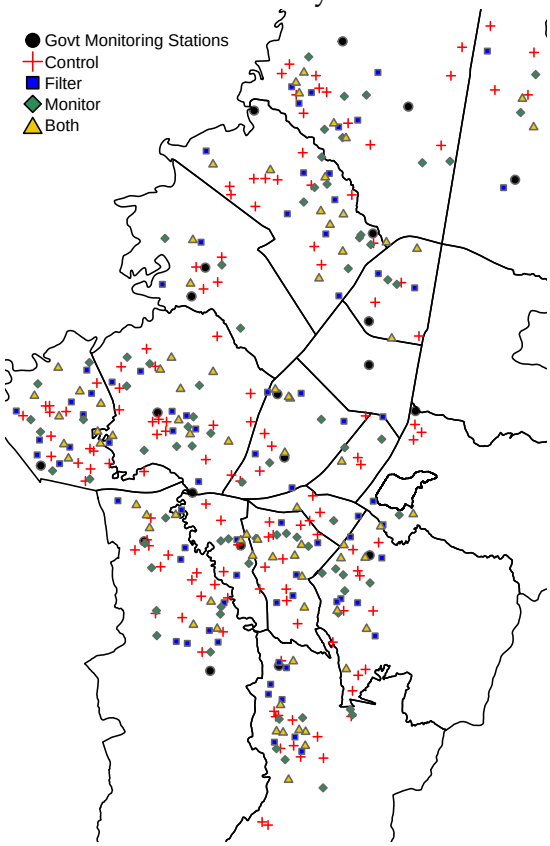
[11]Schools were selected based on 2021 data showing grade 11 students, but 11 schools had no students taking the Saber 11 exam in 2023 (4 control schools, 2 filter only schools, 3 monitor only schools, and 2 filter and monitor schools).

Table 1: Balance across experimental groups (2022)

	Mean (SD) for each group				p-value
	Control	Filter	Monitor	Both	(equality)
	(1)	(2)	(3)	(4)	(5)
Panel A: Pre treatment (2022)					
Global score	0.01	0.01	-0.00	0.01	0.934
	(0.31)	(0.33)	(0.33)	(0.31)	
Reading score	0.01	0.01	0.00	0.01	0.982
	(0.26)	(0.28)	(0.28)	(0.25)	
Math score	0.02	0.01	-0.01	0.02	0.750
	(0.28)	(0.31)	(0.30)	(0.29)	
SES strata 1 or 2	0.67	0.70	0.61	0.66	0.061*
	(0.25)	(0.24)	(0.26)	(0.24)	
Lower SES	0.28	0.26	0.34	0.30	0.067*
	(0.25)	(0.24)	(0.27)	(0.25)	
Female	0.55	0.54	0.56	0.54	0.251
	(0.08)	(0.05)	(0.09)	(0.03)	
Age (exam date)	17.39	17.47	17.49	17.46	0.900
	(1.59)	(0.53)	(0.36)	(0.29)	
Mother some secondary education	0.50	0.50	0.50	0.50	0.770
	(0.06)	(0.05)	(0.06)	(0.04)	
PM2.5	17.54	17.56	17.45	17.53	0.835
	(1.95)	(2.19)	(2.05)	(1.77)	
PM10	36.08	35.94	35.37	35.91	0.192
	(5.49)	(5.72)	(5.81)	(5.52)	
Without Saber 11 data	0.03	0.01	0.03	0.01	0.756
	(0.17)	(0.12)	(0.16)	(0.12)	
Students (Grade 11)	116.08	127.19	103.83	111.81	0.254
	(73.32)	(90.82)	(60.08)	(66.06)	
F-test p-value					0 .783
Panel B: Treatment (2023)					
Without Saber 11 data	0.03	0.03	0.04	0.03	0.958
	(0.17)	(0.16)	(0.20)	(0.16)	
Students (Grade 11)	121.94	132.07	104.01	114.49	0.111
	(79.39)	(93.24)	(63.59)	(69.33)	
	[132]	[75]	[75]	[75]	

Notes: Columns 1–4 show the mean, standard deviation (in parentheses) and number of observations (in square brackets) for each of the following groups: Control, schools where filters were installed, schools where air quality monitors were installed, and schools where both filters and air quality monitors were installed. Column 5 reports the p-value of whether the mean is the same across all groups. The equality test considers the randomization design (i.e., it includes strata fixed effects and clusters standard errors at the school level). All variables except age, number of students, pollution measures, and test scores are % with respect to the number of students in Grade 11. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2: Distribution of study schools across the city



*N*otes: Red crosses indicate control schools; blue squares indicate schools treated only with filters; green rhomboids schools treated with pollution monitors only; and golden triangles schools treated with both filters and pollution monitors. Black dots indicate government pollution monitoring stations.

3.3 Interventions

3.3.1 Filters

Schools were provided Smart Air HEPA Sqair filters, which are recommended for use in rooms up to $40m^3$.[12]These are portable devices that consist of a fan with a HEPA filter attached, have low electricity consumption (6-38 watts), and are relatively quiet (23-52 decibels).[13] The equipment lasts up to 8 years and costs 287.63 USD (including import fees, transportation costs, and installation). However, HEPA filters have a shorter lifespan than the fan and should be replaced roughly every 9 months (if used 6 hours per school day on average) to maintain efficiency; the HEPA replacement pad costs 54 USD (including installation).

[12]See https://smartairfilters.com/en/product/sqair-air-purifier/ for more details.

[13]For comparison, a typical air conditioner consumes between 500-1500 watts and generates noise levels of approximately 50-60 decibels, while an iPhone generates approximately 30 decibels during use.

Air filters were placed in Grade 11 classrooms in treated schools. Teachers and students in schools with filters received training on how to use them. They also received an infographic with key information as well as reminders throughout the school year on the potential benefits of using the equipment. Schools were revisited on July to check its usage and deliver a pamphlet with instructions (see Figure A.2). The mayor's office randomly selected 14 schools for additional in-person training sessions on best practices for filter usage.

While in some schools, students sit in the same classroom all day and the teachers rotate, in others, students rotate across classrooms for different subjects. If students rotated, we attempted to maximize their exposure to the filter during core subjects (Math, Spanish, science, and social sciences) and thus exposure hours.[14] We provided a total of 421 filters to 144 schools.

3.3.2 Monitors

A local NGO, Trebola, installed Plantower PMS7003 monitors in treated schools.[15] The monitors were connected to the school's Wi-Fi when possible (85% of monitors). The rest collected the readings on a microSD card, which a student from Universidad del Rosario retrieved every 3 months. However, we had to exclude the data from these cards since they had the incorrect date and time. During the installation process, teachers and students were told how the monitors work and given a link to access live and historical data collected by the monitor. We produced a pamphlet with information about the monitors and a QR code to access the data (see Figure A.3).

In each school, one monitor was installed outdoors, typically in the school courtyard, and two indoors (in Grade 11 classrooms). In schools with air filters, the two monitors were located randomly in two of the three classrooms with a filter. In schools without filters, we installed the monitors in Grade 11 classrooms that would have received a filter if the school had been assigned to the treatment group. We installed a total of 426 air quality monitors in 146 schools.

3.4 Compliance

Most schools accepted the equipment, so we focus on intent-to-treat effects throughout the paper. Only five schools in the filters-only group, three in the monitor-only group,

[14] When we arrived at the school, we asked if the students rotated classrooms. If possible, we asked for the schedule to select the classrooms that devoted more hours to core subjects. If we were unable to obtain the schedule, we installed them in the classrooms where the school coordinator indicated Grade 11 students spent most of their time.

[15] See https://trebola.org/experiencias/ciencia-ciudadana/ for more information about Trebola and its work.

and one in the filters + monitors group declined the equipment (recall 75 schools were assigned to each of the three treatment groups).

3.5 Timeline

A quarter of schools assigned to the filter treatment had a filter by February 23, 50% had one by April 21, 75% by May 11, and 90% by May 23 (see Figure A.4). Filters had been installed in all treatment schools that complied with the treatment by early June. In 2023, Grade 11 students took the Saber 11 exam on August 13. Therefore, by the time of the 2023 exam, filters had been in place for 2 months (one during the school year and one during the holidays) in all schools, and some had had a filter for 3–6 months.

The monitors were installed between June and November 2023. Installation was initially slow due to contracting issues and problems connecting the monitors to the schools' Wi-Fi. Thus, as of July 13, a month before the test, only two schools allocated to receive air quality monitors had them installed. By August 2, 25% of schools assigned to monitors had them; 50% of them did by August 14, 75% by September 1, and all schools that accepted the equipment had it installed by the end of November. (see Figure A.4) Thus, students were barely exposed to the monitors in 2023 but fully exposed in 2024. This timeline will alter our empirical strategy when studying student outcomes in 2023. Figure A.6 provides an overview of the analyzed sample, and the percentages of filter and monitor assignments over time.

3.6 Data

3.6.1 Student learning

ICFES anonymized provides Saber 11 test scores for each student, along with their school, socio-economic strata, whether they work, have access to a computer or internet in their household, and their parent's education level.[16] As mentioned above, the exam takes place in centralized locations (e.g., local universities) and thus, we measure the filters' impact on *learning* rather than the effects of air pollution exposure during the exam.

3.6.2 Air quality and air filter usage

Monitors register air quality readings of $PM_{2.5}$ every 15 minutes. This paper analyzes data from July to December 2023, the academic year for which we have test scores.

[16] In Colombia, households are classified into six socioeconomic strata (estratos) based on their location. This classification, established by Law 142 of 1994, is used to allocate utility subsidies and cross-subsidies. Households in lower strata (1, 2, and 3) receive subsidized utility rates, while those in higher strata (5 and 6) pay surcharges to fund these subsidies. Stratum 4 is considered neutral, paying cost-reflective rates. While the system has been criticized for inefficiencies and potential distortions in targeting, it is widely used as a proxy for socioeconomic status.

In addition to our pollution monitors, we use hourly data on various pollution measures ($PM_{2.5}$, PM_{10}, NO_2, CO, and O_3) from the publicly available SISAIRE databases, which gather air quality data from 22 monitoring stations dispersed across Bogotá (see Figure 2). We use a simple interpolation (based on the quadratic distance to the monitor) to calculate hourly pollution measurements for each school in our sample.

The city pollution monitors are of higher quality and provide more accurate readings than the monitors we installed in schools, but we must interpolate the city monitors' data to infer the pollution near the school. Still, readings from SISAIRE and school monitors are tightly correlated. (see Figure A.7). The outdoor school monitors systematically indicate lower pollution levels than the city monitors, which could be due to their location in courtyards protected from direct traffic pollution.

3.6.3 School and classrooms survey

We collected data on classroom size, number of windows, whether they could be closed, subjects taught, and class frequency when we installed the air quality monitors or placed the portable filters in the schools. 66% of classrooms in the treatment groups had vents around windows, which allow uncontrolled airflow from outside (see Figure A.8). These vents could reduce the air filters' effectiveness.

In 77% of schools with filters, Grade 11 students rotated classrooms, spending only part of their day in treated rooms, with additional time in courtyards or hallways, increasing their exposure to outdoor pollution. We test for heterogeneous effects based on whether the classroom had vents and time spent in treated classrooms (see Section 4).

3.7 Empirical strategy

3.7.1 Main estimation

We estimate the intent-to-treat effect of the three treatments vis-à-vis the control group by ordinary least squares. Our main estimates are based on an ANCOVA-style specification as it is the most efficient estimator in this setting (J. Roth & Sant'Anna, 2023).

We estimate the following equation:

$$\begin{aligned} Y_{isl} \;=\; & \beta_F Filter_s + \beta_M Monitor_s + \beta_B Both_s + \\ & \alpha_1 \overline{Y_{s,-1}} + \alpha_2 \overline{Y_{s,-1}} \times Filter_s + \alpha_3 \overline{Y_{s,-1}} \times Monitor_s + \\ & \alpha_4 \overline{Y_{s,-1}} \times Both_s + \gamma_l + \epsilon_{isl}, \end{aligned} \tag{1}$$

where Y_{isl} is the standardized test score of student i, graduating from school s located in locality l, $Filter_s(=1)$ indicates that school s received only filters, $Monitor_s(=1)$ that

school s received only monitors, and $Both_s(=1)$ that it received both. $\overline{Y_{s,-1}}$ are the demeaned average lagged scores of the school, and γ_l are dummies for localities, the unit of stratification. We cluster standard errors at the school level (the unit of randomization).[17]

We also estimate variations of these models by adding student controls (gender, age, parental education, and socio-economic strata of their household) and other school controls (pollution measured by the SISAIRE network). Our coefficients of interest are β_F, β_M, and β_B, which estimate the effect of supplying filters, monitors, and both. We cannot control for individual student performance on earlier Saber test because we do not have this data.

3.7.2 Saber 2023

When analyzing the 2023 scores, since most of the monitors were installed after the exam, we pool "monitor only" schools with controls and "monitor + filter" schools with "filter only" and estimate the following equation:

$$Y_{isl} = \beta_F Filter_s + \alpha_1 \overline{Y_{s,-1}} + \alpha_2 \overline{Y_{l,-1}} \times Filter_s + \gamma_l + \epsilon_{isl}, \tag{2}$$

where everything is as in Equation 1. In Tables A.6 and A.7, we check that the "controls + monitor only" and "filter + both" groups are generally balanced. Controlling for variables that are unbalanced at baseline does not change the qualitative nature of our results. To test if there are any effects of air quality monitors on student outcomes (i.e., if knowing the pollution concentration in the classrooms leads teachers or students to take additional measures to reduce pollution, such as keeping doors or windows closed), in the future we will compare the monitor only group to the control group.

3.7.3 Effect of air quality on test scores

Since we cannot continuously monitor filter usage, we use the difference between the air quality readings from the indoor and outdoor monitors at schools with and without filters as a proxy for filter use. Restricting the sample to schools that received air quality monitors, we assess the effect of installing filters on indoor air pollution by comparing schools with filters and monitors to those with only monitors using the following equation:

$$P_{slt} = \lambda_F Filter_s + \alpha_2 P^o_{slt} + \gamma_l + \gamma_t + \epsilon_{slt}, \tag{3}$$

[17] As J. Roth and Sant'Anna (2023) highlight, interacting the demeaned lagged scores with the treatment dummies is more efficient than simply controlling for the lagged scores (see Lin (2013)) as McKenzie (2012) proposed in the presence of heterogeneous treatment effects.

where P_{slt} is the air quality (measured by $PM_{2.5}$) inside school s in locality l at time t. $Filter_s(=1)$ indicates whether school s was assigned to receive the filters (in addition to the monitors). P^o_{slt} denotes outdoor pollution near the school, measured by our monitors and the city monitors. γ_l and γ_t are locality and time (e.g., hour and day of the week) fixed effects. As before, standard errors are clustered at the school level (the unit of randomization). The coefficient of interest is λ_F, which measures the effect of assigning a school to receive filters *and* monitors (vis-a-vis receiving only monitors).

Next, we estimate the effect of air pollution on student outcomes via two-stage least squares by instrumenting air pollution with the random assignment of filters. Again, we restrict the sample to schools that received air quality monitors. The first stage is:

$$P_{slt} = \lambda_1 Filter_s + \theta_1 P^o_{slt} + \gamma_l + \gamma_t + \epsilon_{slt} \tag{4}$$

and the second stage is:

$$Y_{isl} = \beta_0 + \beta_{PM_{2.5}} \widehat{P_{slt}} + \alpha_1 \overline{Y_{s,-1}} + \alpha_2 \overline{Y_{s,-1}} \times Filter_s + \gamma_l + \epsilon_{isl} \tag{5}$$

The coefficient of interest is $\beta_{PM_{2.5}}$, which measures the effect of air quality ($PM_{2.5}$) on student outcomes. Under the assumption that filters affected test scores only through particulate matter, this approach estimates the impact of particulate matter on learning. If one believes that filters also raise test scores by reducing infection rates of respiratory diseases, this could be considered an upper bound of the effect of particulate matter on learning. The first stage is estimated with pollution data after the Saber 11 exam, so this empirical exercise assumes the usage of the filters is similar before and after the exam.

4 Results

4.1 Test scores

Students exposed to the filters for 3–4 months before the exam, scored .03σ (p-value 0.03) higher in their overall score. The improvement comes mainly from math, Spanish and social sciences with increments of .04σ (p-value 0.02), .03σ (p-value 0.04), and .03σ (p-value 0.02), respectively. These results are robust to including pollution measures and student demographic controls (age, gender, parental education, and socio-economic strata).

There is no evidence of heterogeneity in treatment effects either by school characteristics (historical performance in the Saber test and pollution levels) or student characteristics (sex, age, and socio-economic strata) (see Table A.9). There is also no evidence of heterogeneous effects by classroom features such as size, number of windows and

vents. (See Table A.10). We also estimate treatment effects using unconditional quantile regressions (Firpo, Fortin, & Lemieux, 2009) with the RIF package in Stata (Rios-Avila, 2020). Overall, the positive effects are accrued throughout the distribution of test scores, with little heterogeneity (see Figure A.9).

Table 2: Effect of filters on test scores

Dep. var.	Math	Spanish	Science	Social Sciences	English	Global
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged scores						
Treatment (filters)	0.040**	0.030**	0.020	0.029**	0.019	0.033**
	(0.0176)	(0.0143)	(0.0155)	(0.0130)	(0.0178)	(0.0154)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.076	0.064	0.073	0.058	0.082	0.087
Panel B: Lagged scores + pollution						
Treatment (filters)	0.039**	0.028**	0.019	0.028**	0.020	0.032**
	(0.0170)	(0.0138)	(0.0150)	(0.0127)	(0.0176)	(0.0149)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.076	0.064	0.073	0.058	0.082	0.087
Panel C: All controls						
Treatment (filters)	0.035**	0.026**	0.015	0.024**	0.019	0.028**
	(0.0153)	(0.0128)	(0.0138)	(0.0122)	(0.0158)	(0.0134)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.16	0.11	0.14	0.095	0.14	0.16

Notes: All regressions consider the randomization design (i.e., include strata fixed effects). Panel A controls for average school-level lagged scores (we do not have individual student-lagged scores). Panel B also controls for the average pollution levels of $PM_{2.5}$, PM_{10}, NO_2, CO, and O_3 during school hours (7 am–4 pm) in the 270 days (roughly the length of the school year) and 90 days (roughly the length of exposure to the filters) preceding the exam. Panel C controls for lagged scores, pollution levels, age, sex, mother's level of education, and socio-economic strata. Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

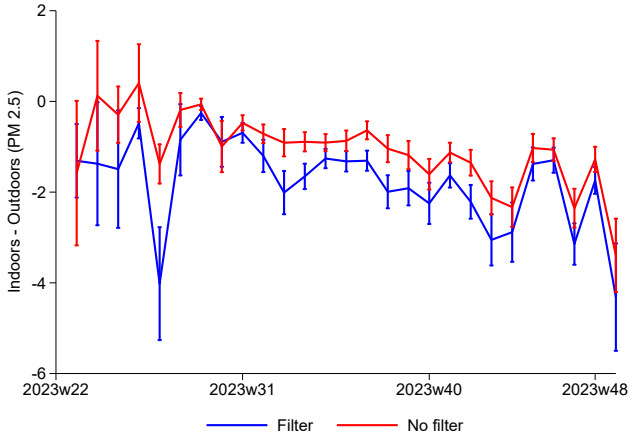
When estimating the treatment effects using the original randomized assignment, global test scores increase by (.04σ, p-value 0.09) for schools that received filters only and by (.03σ, p-value 0.08) for schools that received both filters and monitors. No effect on test scores is found in schools that received monitors only (see Table A.8), as expected given the delayed installation.

4.2 Air quality

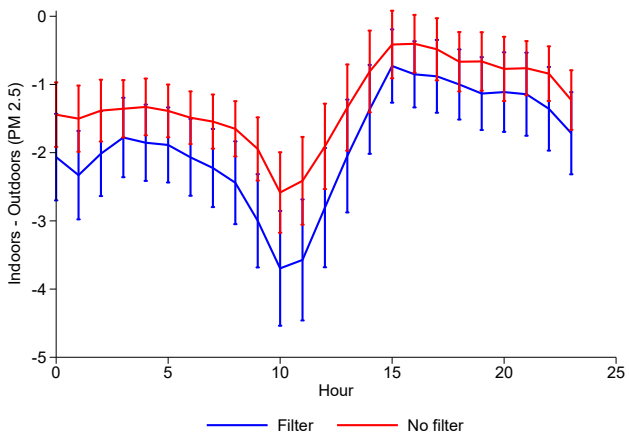
To assess how the filters affected indoor air pollution, we can only use the sample of schools that received monitors (assigned to the monitor only and monitor + filter treatment groups). First, we plot the the gap between indoor and outdoor pollution. Since outdoor pollution is usually higher, the gap is typically negative. The gap between indoor and outdoor readings in schools with filters is consistently wider than in those with only monitors (Figure 3b). This difference widens over time (Figure 3a).[18]

Figure 3: Difference between indoor and outdoor readings in schools with and without filters

(a) Differences by weeks



(b) Differences by time of the day



Notes: These figures display the average difference between indoor and outdoor readings in each school, depending on whether they have filters. Figure 3a averages the data across weeks, while Figure 3b averages the data across hours of the day.

Filters reduce indoor $PM_{2.5}$ by 0.73 $\mu g/m^3$ (p-value 0.013) during school hours (see Table 3).[19] The reduction including all hours and weekends is similar, .51 $\mu g/m^3$ (p-value 0.02), which may be driven by schools not shutting down the filters when students are not in the classroom.[20] Teachers and students were told it was particularly important to turn the filters on whenever pollution was above the WHO's recommended threshold of 5 $\mu g/m^3$ for $PM_{2.5}$ (World Health Organization, 2021). When outdoor pollution is above the WHO threshold, filters reduce indoor pollution by -1.7 $\mu g/m^3$ (p-value 0.00),

[18]The confidence intervals vary by week since some schools turn off their electricity during school holidays, which shuts down the monitors. Figure A.10 displays the evolution of the readings over time. Table A.11 reports no differential attrition across treatment groups in the pollution monitor data. However, schools with filters and monitors are slightly more likely to have missing data from their outdoor monitors compared to those with only monitors.

[19]Since the standard deviation of indoors $PM_{2.5}$ is 9.1 $\mu g/m^3$, the treatment effect over school hours is equivalent to -.08σ.

[20]Some teachers mentioned they leave the filters on, regardless of whether there is a class, pollution is high, or it is the weekend.

suggesting they are more effective when pollution is high. As expected, filters have no effect on outdoor pollution levels (see Table A.12).

Table 3: Effect of filters on students' exposure to $PM_{2.5}$

Dep. var.	$PM_{2.5}$ Indoors pollution ($\mu g/m^3$)				
	(1)	(2)	(3)	(4)	(5)
Filter and Monitor	-.56**	-.54**	-.51**	-.73**	-1.7***
	(.22)	(.22)	(.22)	(.29)	(.51)
Control mean	9.1	9.1	9.1	9.9	14
N. of obs.	1,178,324	1,178,324	1,178,320	283,450	131,737
Locality FE	X	X			
Hour FE	X				
Date FE	X				
Hour × Date FE		X			
Locality × Date × Hour FE			X	X	X
Hours	All	All	All	7am–4pm	7am–4pm
Days	All	All	All	Mon–Fri	Mon–Fri
Outdoors pollution	All	All	All	All	> 5

Notes: The outcome in all regressions is the indoor readings of $PM_{2.5}$. All regressions control for outdoor readings of $PM_{2.5}$ (demeaned), both as measured by the monitors we installed in schools and the city monitors and their interaction with the treatment dummy (following J. Roth and Sant'Anna (2023); Lin (2013)). Column 5 defines outdoor pollution as measured by our monitors. Column 6 defines outdoor pollution based on the city monitors. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also study heterogeneity by pollution levels, measured by our outdoor monitors and the city's monitors, and find no meaningful heterogeneity (see Table A.13 and Figures A.12, A.11, and A.13).

4.3 Effect of air quality on test scores

We estimate the effect of indoor $PM_{2.5}$ pollution on test scores using the experimental assignment of filters as an instrument for $PM_{2.5}$ levels. Three caveats apply: First, for 2023, we only have $PM_{2.5}$ data from *after* the exam, so we assume pre-exam ussage levels were similar. Second, the instrumental variable approach assumes filters only affect scores via $PM_{2.5}$ (the exclusion restriction), but filters likely reduce exposure to all particulate matter (including PM_{10} and $PM_{0.1}$), so this should be interpreted as an effect of reductions in all types of particulates, not $PM_{2.5}$ specifically. Finally, filters likely affect respiratory infections (Hammond et al., 2021; Curtius et al., 2021; Burgmann & Janoske, 2021). Thus, the estimate may be an upper bound of the effect of particulate matter on learning.

We can only use the sample of 114 schools with both Saber 11 scores and monitors(58 in the filter + monitor group and 56 in the monitor-only group). In these schools, filters reduced indoor $PM_{2.5}$ by 1 $\mu g/m^3$ (p-value $<$ 0.001) from a base of 10.9 (Panel A, Table 4). The reduced form shows a .085σ increase in scores (p-value $<$ 0.001), leading to an instrumental variable estimate that 1 $\mu g/m^3$ increase in indoor $PM_{2.5}$ lowers scores by .082σ (p-value 0.01) (Panel C, Table 4).

Differences from sections 4.1–4.2 arise due to sample variation, the comparison between the filter + monitor and monitor-only groups, and the inclusion of outdoor pollution controls. The Wald estimator from the full sample suggests a 1 $\mu g/m^3$ increase in indoor $PM_{2.5}$ reduces test scores by $\sim$0.045σ.

Table 4: Effect on 2023 Saber tests

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First Stage						
Dep. var.	$PM_{2.5}$					
Treatment (filters)	-1.00***					
	(0.295)					
N. of obs.	12,950					
Only monitors mean	10.9					
N. Schools	114					
R^2	0.49					
Panel B: Reduced Form						
Dep. var.	Math	Spanish	Science	Social Sciences	English	Global
Treatment (filters)	0.080***	0.080***	0.056**	0.082***	0.040	0.082***
	(0.0272)	(0.0272)	(0.0242)	(0.0261)	(0.0298)	(0.0256)
N. of obs.	12,950	12,950	12,950	12,950	12,948	12,950
N. Schools	114	114	114	114	114	114
R^2	0.081	0.064	0.079	0.060	0.073	0.089
Panel C: IV Estimates						
Dep. var.	Math	Spanish	Science	Social Sciences	English	Global
Average PM 2.5 (indoors)	-0.080**	-0.080**	-0.056**	-0.082***	-0.040	-0.082**
	(0.0337)	(0.0363)	(0.0251)	(0.0307)	(0.0320)	(0.0322)
N. of obs.	12,950	12,950	12,950	12,950	12,948	12,950
N. Schools	114	114	114	114	114	114
R^2	0.078	0.060	0.079	0.057	0.071	0.086

Notes: All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. The p-value of joint F-test for the first stage is 11.441. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Cost effectiveness

The estimated learning effects in this study imply that filters would be reasonably cost-effective based on their learning impact in non-pandemic periods and are highly cost-effective even under relatively conservative assumptions about reductions in the risk of future school closures due to pandemics. We compute the effects per $100 USD by considering the following four key parameters: (i) the treatment effect per student of having filters in the school, (ii) the number of Grade 11 students exposed per school, (iii) the cost of the filters, and (iv) how long the filters last.

Air filters improve test scores by .03σ (see Table 2, column 6). Each school in our sample has, on average, 123 students in grade 11 and received 3 filters. Each filter costs 288 USD (including all the associated costs of placing the filter in the school), and the yearly replacement filter pad costs 54 USD.[21] According to the manufacturer, each filter equipment lasts at least 8 years (only 1 out of 421 broke in the first year of the experiment). These numbers give an improvement in test scores of 0.72–1.50σ per 100 USD invested, depending on whether we assume the filter lasts 2 or 8 years. We also estimate the gains in Learning-Adjusted Years of Schooling (LAYS) per 100 USD invested. Air filters increase learning outcomes by 0.90–1.85LAYS per 100 USD comparable to other cost-effective educational interventions highlighted in the 2023 Smart Buys report (GEEAP, 2023; Angrist, Filmer, et al., 2025) such as reducing travel times to schools and giving merit-based scholarships to disadvantaged children and youth (See Figure A.11).[22] They also yield higher LAYS per 100 USD than the median of other types of school-based mass health treatment interventions such as deworming and malaria.

To estimate the expected value of filters as an investment in preparedness for reducing the costs of future pandemics, we calculate the net present value of installing and maintaining air filters in Bogota's public schools over the next century. Bogota has over 1.2 million pupils enrolled in public institutions throughout all grades (including pre-kindergarten, kindergarten, primary, and secondary school); 63%. attend public schools (roughly 750,000). Assuming the same number of filters per student as in the study (3 filters for 123 students, or 1 per 41 students), the government would need to buy and maintain 18,577 air filters. Assuming that filter pads are replaced annually and filters last 8 years, the total net present value is $44 million. [23]

On the other hand, following Glennerster et al. (2023), we calculate Bogota's predicted pandemic learning loss stream for the next century as more than $1 billion. If we divide this loss proportionally between private and public schools, we can estimate that the educational loss from public education is $667 million. Thus, filters would pay for themselves if they reduce the probability of school closures conditional on a pandemic by at least 6.6%. If filters reduced the likelihood of school closures in a pandemic scenario by 7%, the net benefits would be $2.6 million; each further one percentage point decrease in pandemic school closures would be worth $6.6 million in Bogota alone, or roughly $18 billion globally.

[21] The pads need to be replaced roughly every 9 months, which matches the length of the academic year.

[22] See Kremer et al. (2013); Angrist, Filmer, et al. (2025)) for summaries of cost-effectiveness measures across interventions and settings.

[23] Assuming a discount rate of 4%.

5 Conclusions and discussion

We find evidence that installing high-efficiency particulate (HEPA) air filters in classrooms in Bogota, Colombia increased learning levels even after a short period of exposure. In schools randomly assigned to receive filters 3–4 months before a high-stakes exam—conducted outside school premises—students scored $.03\sigma$ higher. Data from air pollution monitors suggests that students in schools with filters were exposed to lower levels of $PM_{2.5}$ (a reduction of 0.73 $\mu g/m^3$ from a base of 10.10 $\mu g/m^3$). We find that air filters are a more cost-effective intervention than the median of other types of school-based mass interventions. Filters are particularly important given the weak pollution reduction goals in developing countries.

Further tests over longer periods seem warranted. Ideally, these would take place in a range of different environments with varying pollution levels to evaluate their impact. Additionally, it would be ideal also to collect health information to determine if infectious disease transmission is an important mediator or if the primary channel relates to pollution, as well as to assess whether the effects are particularly strong for individuals with pre-existing conditions that make them more vulnerable to air pollution such as asthma.

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A Additional tables and figures

A.1 Tables

Table A.1: Student-level balance (2022)

	Mean/SD for each group				Treatment effect (vs control)			Comparing treatments		
	Control (C)	Filter (F)	Monitor (M)	Both (B)	F vs C (2)vs(1)	M vs C (3)vs(1)	B vs C (4)vs(1)	F vs M (3)vs(2)	F vs B (4)vs(2)	M vs B (4)vs(3)
Global score	-0.01	0.04	-0.02	0.00	0.06	-0.04	-0.00	-0.10**	-0.06	0.04
	(1.01)	(0.99)	(1.00)	(1.00)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
Reading score	-0.01	0.03	-0.02	0.00	0.04	-0.03	-0.00	-0.08*	-0.05	0.03
	(1.01)	(0.99)	(1.00)	(1.00)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
Math score	-0.01	0.05	-0.05	0.00	0.07	-0.07	0.00	-0.13***	-0.06	0.07
	(1.01)	(1.00)	(0.98)	(0.99)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
SES strata 1 or 2	0.63	0.68	0.60	0.64	0.03	-0.01	0.02	-0.05*	-0.02	0.03
	(0.48)	(0.47)	(0.49)	(0.48)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
SES strata 3 or 4	0.30	0.27	0.34	0.30	-0.02	0.02	-0.01	0.04	0.02	-0.03
	(0.46)	(0.44)	(0.47)	(0.46)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
Female	0.55	0.53	0.56	0.53	-0.03*	0.00	-0.02*	0.03*	0.00	-0.03*
	(0.50)	(0.50)	(0.50)	(0.50)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]
Age (exam date)	17.61	17.47	17.61	17.57	-0.14**	0.00	-0.04	0.14*	0.10	-0.04
	(1.55)	(1.26)	(1.46)	(1.36)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	[15,105]	[9,438]	[7,714]	[8,296]	[24,543]	[22,819]	[23,401]	[17,152]	[17,734]	[16,010]
Mother some secondary education	0.48	0.50	0.49	0.49	0.01	0.01	0.01	0.00	0.00	0.00
	(0.50)	(0.50)	(0.50)	(0.50)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[15,323]	[9,539]	[7,787]	[8,386]	[24,862]	[23,110]	[23,709]	[17,326]	[17,925]	[16,173]

Notes: Columns 1–4 show the mean, the standard deviation (in parentheses), and the number of observations (in square brackets) for each of the experimental groups: Control, Filters (F), Monitors (M), and Both (B). Columns 5–7 report the difference between the three treatment groups and the control, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). Columns 8–10 show the difference between treatment groups, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). All the differences between groups (Columns 4–10) consider the randomization design (i.e., include strata fixed effects). Standard errors are clustered at the school level. The p-value from a joint test that all coefficients in Columns 1–4 are zero (from a multinomial logit with the treatment groups on the left-hand side and all the covariates on the right-hand side) is .126. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: School-level balance (2022)

	Mean/SD for each group				Treatment effect (vs control)			Comparing treatments		
	Control (C) (1)	Filter (F) (2)	Monitor (M) (3)	Both (B) (4)	F vs C (2)vs(1) (5)	M vs C (3)vs(1) (6)	B vs C (4)vs(1) (7)	F vs M (3)vs(2) (8)	F vs B (4)vs(2) (9)	M vs B (4)vs(3) (10)
PM2.5	17.54	17.56	17.45	17.53	0.02	-0.06	0.05	-0.08	0.03	0.11
	(1.95)	(2.19)	(2.05)	(1.77)	(0.15)	(0.12)	(0.11)	(0.15)	(0.15)	(0.12)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
PM10	36.08	35.94	35.37	35.91	-0.10	-0.61*	-0.01	-0.51	0.09	0.60*
	(5.49)	(5.72)	(5.81)	(5.52)	(0.34)	(0.32)	(0.33)	(0.35)	(0.36)	(0.34)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
O3	26.90	26.41	27.10	26.81	-0.53	0.12	-0.02	0.65	0.51	-0.13
	(4.51)	(3.93)	(3.93)	(3.88)	(0.36)	(0.38)	(0.39)	(0.40)	(0.41)	(0.42)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
Without Saber 11 data	0.03	0.01	0.03	0.01	-0.02	-0.00	-0.02	0.01	-0.00	-0.01
	(0.17)	(0.12)	(0.16)	(0.12)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
Students (Grade 11)	116.08	127.19	103.83	111.81	12.40	-11.69	-3.09	-24.08*	-15.49	8.60
	(73.32)	(90.82)	(60.08)	(66.06)	(11.84)	(9.27)	(9.53)	(12.28)	(12.43)	(10.14)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]

Notes: Columns 1–4 show the mean, the standard deviation (in parentheses), and the number of observations (in square brackets) for each of the experimental groups: Control, Filters (F), Monitors (M), and Both (B). Columns 5–7 report the difference between the three treatment groups and the control, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). Columns 8–10 show the difference between treatment groups, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). All the differences between groups (Columns 4–10) consider the randomization design (i.e., include strata fixed effects). Standard errors are clustered at the school level. The p-value from a joint test that all coefficients in Columns 1–4 are zero (from a multinomial logit with the treatment groups on the left-hand side and all the covariates on the right-hand side) is .376. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Balance across experimental groups (2023)

	Mean/SD for each group				p-value
	Control	Filter	Monitor	Both	(equality)
	(1)	(2)	(3)	(4)	(5)
Panel A: Student level (2023)					
SES strata 1 or 2	0.60	0.63	0.57	0.60	0.432
	(0.49)	(0.48)	(0.50)	(0.49)	
	[16,096]	[9,905]	[7,801]	[8,587]	
SES strata 3 or 4	0.30	0.29	0.35	0.31	0.643
	(0.46)	(0.45)	(0.48)	(0.46)	
	[16,096]	[9,905]	[7,801]	[8,587]	
Female	0.54	0.52	0.57	0.54	0.033**
	(0.50)	(0.50)	(0.50)	(0.50)	
	[16,096]	[9,905]	[7,801]	[8,587]	
Age (exam date)	17.55	17.39	17.48	17.47	0.263
	(1.69)	(1.28)	(1.38)	(1.39)	
	[15,737]	[9,782]	[7,703]	[8,466]	
Mother some secondary education	0.48	0.48	0.47	0.49	0.202
	(0.50)	(0.50)	(0.50)	(0.50)	
	[16,096]	[9,905]	[7,801]	[8,587]	
Panel B: School level (2023)					
PM2.5	15.78	15.68	15.67	15.77	0.569
	(2.04)	(2.06)	(2.09)	(2.00)	
	[132]	[75]	[75]	[75]	
PM10	31.80	31.71	31.25	31.76	0.199
	(4.87)	(5.00)	(4.99)	(4.96)	
	[132]	[75]	[75]	[75]	
O3	27.16	26.69	27.49	26.93	0.269
	(4.73)	(4.69)	(4.57)	(4.72)	
	[132]	[75]	[75]	[75]	
Without Saber 11 data	0.03	0.03	0.04	0.03	0.958
	(0.17)	(0.16)	(0.20)	(0.16)	
	[132]	[75]	[75]	[75]	
Students (Grade 11)	121.94	132.07	104.01	114.49	0.111
	(79.39)	(93.24)	(63.59)	(69.33)	
	[132]	[75]	[75]	[75]	

Notes: Columns 1-4 show the mean, standard deviation (in parentheses) and the number of observations (in square brackets) for each of the following groups: Control, schools where filters were installed, schools where air quality monitors were installed, and schools where both filters and air quality monitors were installed. Column 5 reports the p-value of whether the mean is the same across all groups. The equality test considers the randomization design (i.e., it includes strata fixed effects and clusters standard errors at the school level). All variables except age, number of students, pollution measures, and test scores are % with respect to the number of students in Grade 11. The p-value from a joint test that all coefficients are zero (from a multinomial logit with the treatment groups on the left-hand side and all the covariates on the right-hand side) is .354 for Panel A and .426 for Panel B. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: Student-level balance (2023)

	Mean/SD for each group				Treatment effect (vs control)			Comparing treatments		
	Control (C) (1)	Filter (F) (2)	Monitor (M) (3)	Both (B) (4)	F vs C (2)vs(1) (5)	M vs C (3)vs(1) (6)	B vs C (4)vs(1) (7)	F vs M (3)vs(2) (8)	F vs B (4)vs(2) (9)	M vs B (4)vs(3) (10)
SES strata 1 or 2	0.60	0.63	0.57	0.60	0.02	-0.02	0.01	-0.04	-0.01	0.03
	(0.49)	(0.48)	(0.50)	(0.49)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
	[16,096]	[9,905]	[7,801]	[8,587]	[26,001]	[23,897]	[24,683]	[17,706]	[18,492]	[16,388]
SES strata 3 or 4	0.30	0.29	0.35	0.31	-0.01	0.02	-0.01	0.03	0.00	-0.03
	(0.46)	(0.45)	(0.48)	(0.46)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
	[16,096]	[9,905]	[7,801]	[8,587]	[26,001]	[23,897]	[24,683]	[17,706]	[18,492]	[16,388]
Female	0.54	0.52	0.57	0.54	-0.02	0.02	-0.01	0.04***	0.01	-0.03*
	(0.50)	(0.50)	(0.50)	(0.50)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
	[16,096]	[9,905]	[7,801]	[8,587]	[26,001]	[23,897]	[24,683]	[17,706]	[18,492]	[16,388]
Age (exam date)	17.55	17.39	17.48	17.47	-0.15*	-0.06	-0.07	0.10	0.08	-0.02
	(1.69)	(1.28)	(1.38)	(1.39)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)
	[15,737]	[9,782]	[7,703]	[8,466]	[25,519]	[23,440]	[24,203]	[17,485]	[18,248]	[16,169]
Mother some secondary education	0.48	0.48	0.47	0.49	0.01	-0.00	0.02*	-0.01	0.01	0.02*
	(0.50)	(0.50)	(0.50)	(0.50)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[16,096]	[9,905]	[7,801]	[8,587]	[26,001]	[23,897]	[24,683]	[17,706]	[18,492]	[16,388]

Notes: Columns 1–4 show the mean, the standard deviation (in parenthesis), and the number of observations (in square brackets) for each of the experimental groups: Control, Filters (F), Monitors (M), and Both (B). Columns 5–7 report the difference between the three treatment groups and the control, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). Columns 8–10 show the difference between treatment groups, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). All the differences between groups (Columns 4–10) consider the randomization design (i.e., include strata fixed effects). Standard errors are clustered at the school level. The p-value from a joint test that all coefficients in Columns 1–4 are zero (from a multinomial logit with the treatment groups on the left-hand side and all the covariates on the right-hand side) is .354. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: School-level balance (2023)

	Mean/SD for each group				Treatment effect (vs control)			Comparing treatments		
	Control (C) (1)	Filter (F) (2)	Monitor (M) (3)	Both (B) (4)	F vs C (2)vs(1) (5)	M vs C (3)vs(1) (6)	B vs C (4)vs(1) (7)	F vs M (3)vs(2) (8)	F vs B (4)vs(2) (9)	M vs B (4)vs(3) (10)
PM2.5	15.78	15.68	15.67	15.77	-0.09	-0.07	0.05	0.02	0.14	0.12
	(2.04)	(2.06)	(2.09)	(2.00)	(0.11)	(0.10)	(0.11)	(0.11)	(0.12)	(0.10)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
PM10	31.80	31.71	31.25	31.76	-0.04	-0.49*	0.14	-0.44	0.18	0.62*
	(4.87)	(5.00)	(4.99)	(4.96)	(0.30)	(0.29)	(0.32)	(0.30)	(0.33)	(0.32)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
O3	27.16	26.69	27.49	26.93	-0.50	0.14	-0.16	0.64*	0.34	-0.30
	(4.73)	(4.69)	(4.57)	(4.72)	(0.32)	(0.29)	(0.34)	(0.34)	(0.38)	(0.36)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
Without Saber 11 data	0.03	0.03	0.04	0.03	-0.00	0.01	-0.00	0.01	0.00	-0.01
	(0.17)	(0.16)	(0.20)	(0.16)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]
Students (Grade 11)	121.94	132.07	104.01	114.49	11.15	-17.34*	-6.32	-28.49**	-17.47	11.02
	(79.39)	(93.24)	(63.59)	(69.33)	(12.38)	(9.71)	(10.22)	(12.59)	(12.97)	(10.58)
	[132]	[75]	[75]	[75]	[207]	[207]	[207]	[150]	[150]	[150]

Notes: Columns 1–4 show the mean, the standard deviation (in parenthesis), and the number of observations (in square brackets) for each of the experimental groups: Control, Filters (F), Monitors (M), and Both (B). Columns 5–7 report the difference between the three treatment groups and the control, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). Columns 8–10 show the difference between treatment groups, the standard error of the difference (in parentheses), and the number of observations used for the estimation (in square brackets). All the differences between groups (Columns 4–10) consider the randomization design (i.e., include strata fixed effects). Standard errors are clustered at the school level. The p-value from a joint test that all coefficients in Columns 1–4 are zero (from a multinomial logit with the treatment groups on the left-hand side and all the covariates on the right-hand side) is .426. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Balance across experimental groups (2022)

	Control (1)	Filter (2)
Panel A: Student level (2022)		
SES strata 1 or 2	0.62	0.03*
	(0.48)	(0.02)
	[23,110]	[41,035]
SES strata 3 or 4	0.31	-0.02
	(0.46)	(0.02)
	[23,110]	[41,035]
Female	0.55	-0.03**
	(0.50)	(0.01)
	[23,110]	[41,035]
Age (exam date)	17.61	-0.09*
	(1.52)	(0.05)
	[22,819]	[40,553]
Mother some secondary education	0.49	0.01
	(0.50)	(0.01)
	[23,110]	[41,035]
Global score	-0.02	0.05
	(1.00)	(0.03)
	[23,110]	[41,035]
Reading score	-0.01	0.03
	(1.01)	(0.03)
	[23,110]	[41,035]
Math score	-0.02	0.06*
	(1.00)	(0.03)
	[23,110]	[41,035]
Panel B: School level (2022)		
PM2.5	17.50	0.06
	(1.98)	(0.09)
	[207]	[357]
PM10	35.82	0.17
	(5.61)	(0.25)
	[207]	[357]
O3	26.97	-0.31
	(4.30)	(0.28)
	[207]	[357]
Without Saber 11 data	0.03	-0.02
	(0.17)	(0.02)
	[207]	[357]
Students (Grade 11)	111.64	8.88
	(68.92)	(7.83)
	[207]	[357]

Notes: Column 1 reports the mean, standard deviation (in parentheses), and number of observations (in square brackets) of the control group. Column 2 shows the difference between the treatment and control groups, accounting for the randomization design (i.e., it includes strata fixed effects), the standard errors of the difference (clustered at the school level, in parentheses), and the number of observations (in square brackets). The p-value from a joint test that all coefficients are zero (from a regression with the treatment dummy on the left-hand side and all the covariates on the right-hand side) is .094 for Panel A and .718 for Panel B. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7: Balance across experimental groups (2023)

	Control (1)	Filter (2)
Panel A: Student level (2023)		
SES strata 1 or 2	0.59	0.02
	(0.49)	(0.02)
	[23,897]	[42,389]
SES strata 3 or 4	0.32	-0.01
	(0.47)	(0.02)
	[23,897]	[42,389]
Female	0.55	-0.02**
	(0.50)	(0.01)
	[23,897]	[42,389]
Age (exam date)	17.52	-0.10*
	(1.59)	(0.06)
	[23,440]	[41,688]
Mother some secondary education	0.47	0.01*
	(0.50)	(0.01)
	[23,897]	[42,389]
Panel B: School level (2023)		
PM2.5	15.74	0.00
	(2.06)	(0.08)
	[207]	[357]
PM10	31.60	0.22
	(4.91)	(0.22)
	[207]	[357]
O3	27.28	-0.38
	(4.66)	(0.24)
	[207]	[357]
Without Saber 11 data	0.03	-0.01
	(0.18)	(0.02)
	[207]	[357]
Students (Grade 11)	115.44	8.69
	(74.40)	(8.24)
	[207]	[357]

Notes: Column 1 reports the mean, standard deviation (in parentheses), and number of observations (in square brackets) of the control group. Column 2 shows the difference between the treatment and control groups, accounting for the randomization design (i.e., it includes strata fixed effects), the standard errors of the difference (clustered at the school level, in parentheses), and the number of observations (in square brackets). The p-value from a joint test that all coefficients are zero (from a regression with the treatment dummy on the left-hand side and all the covariates on the right-hand side) is .126 for Panel A and .39 for Panel B. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.8: Effect on 2023 Saber tests for all treatment groups

Dep. var.	Math	Spanish	Science	Social Sciences	English	Global
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged scores						
Only Filter	0.057**	0.026	0.022	0.029*	0.012	0.037*
	(0.025)	(0.020)	(0.023)	(0.017)	(0.024)	(0.022)
Only Monitor	-0.00086	-0.0064	-0.0055	-0.010	-0.022	-0.0081
	(0.023)	(0.019)	(0.020)	(0.018)	(0.021)	(0.020)
Filter and Monitor	0.034	0.036*	0.024	0.027	0.027	0.035*
	(0.021)	(0.019)	(0.019)	(0.019)	(0.024)	(0.020)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.077	0.064	0.074	0.058	0.083	0.087
Panel B: Lagged scores + pollution						
Only Filter	0.061**	0.028	0.022	0.031*	0.015	0.039*
	(0.024)	(0.019)	(0.022)	(0.016)	(0.024)	(0.021)
Only Monitor	0.0019	-0.00098	-0.0039	-0.0044	-0.025	-0.0043
	(0.023)	(0.020)	(0.020)	(0.018)	(0.021)	(0.020)
Filter and Monitor	0.033	0.036*	0.024	0.027	0.026	0.034*
	(0.022)	(0.019)	(0.019)	(0.019)	(0.024)	(0.020)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.078	0.065	0.074	0.058	0.083	0.088
Panel C: All controls						
Only Filter	0.040*	0.013	0.0025	0.016	0.0014	0.020
	(0.021)	(0.017)	(0.020)	(0.016)	(0.021)	(0.019)
Only Monitor	-0.0054	-0.0084	-0.011	-0.0090	-0.032*	-0.012
	(0.020)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)
Filter and Monitor	0.039**	0.041**	0.029*	0.031*	0.031	0.040**
	(0.020)	(0.017)	(0.017)	(0.018)	(0.022)	(0.018)
N. of obs.	42,389	42,389	42,389	42,389	42,381	42,389
N. Schools	346	346	346	346	346	346
R^2	0.16	0.11	0.14	0.095	0.14	0.16

Notes: All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Heterogeneity in treatment effects on the 2023 global score

Covariate	High performing (1)	High pollution (2)	Female (3)	Age (4)	Low strata (5)
Treatment (filters)	0.068*	0.038**	0.026	0.034**	0.018
	(0.0383)	(0.0192)	(0.0197)	(0.0140)	(0.0241)
Treatment (filters) × Covariate	-0.039	-0.0077	0.011	-0.021	0.016
	(0.0524)	(0.0321)	(0.0246)	(0.0170)	(0.0305)
Covariate	0.42***	0.039	-0.28***	-0.11***	0.15***
	(0.0379)	(0.0465)	(0.0183)	(0.0105)	(0.0214)
N. of obs.	42,389	42,389	42,389	42,389	42,389
N. Schools	346	346	346	346	346
R^2	0.055	0.087	0.10	0.11	0.092

Notes: The outcome is the global score in all regressions. The covariate in Columns 1 and 2 is defined at the school level. In Column 1, the covariate is a dummy that equals 1 if the school's average score between 2019 and 2022 is above the median average score of schools in the sample. Likewise, in Column 2, the covariate is a dummy that equals 1 if the average $PM_{2.5}$ during school hours (8 am to 4 pm) in the 270 days before the exam is above the median for all schools. In Columns 3–5, the covariates are defined at the student level. We use sex, age (demeaned, so the interaction coefficient is interpreted as the marginal effect at the mean age), and whether the student lives in a household entitled to public utility subsidies. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Heterogeneity in treatment effects on the 2023 global score by school physical features

Covariate	Vents	Rotative	Filter Exposure	Classroom Volume	Proxy Usage	Math Classroom
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0020	-0.010	0.011	-0.011	-0.037	-0.12
	(0.0880)	(0.0926)	(0.0838)	(0.0841)	(0.0526)	(0.107)
Treatment x Covariate	-0.056	0.014	-0.00049	0.00015	0.00034	0.059
	(0.0473)	(0.0545)	(0.00213)	(0.000114)	(0.000590)	(0.0454)
Covariate	0.0030	-0.0034	0.00062	-0.00024**	-0.00072	-0.032
	(0.0396)	(0.0497)	(0.00177)	(0.000107)	(0.000845)	(0.0389)
N. of obs.	42389	42389	42389	42389	42389	42389
N. Schools	346	346	346	346	346	346
R^2	.088	.087	.087	.088	.087	.077
Mean of Covariate	.39	.46	8.2	150	45	.31

Notes: The outcome is the global score in all regressions. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11: Attrition in the pollution monitor data

	Sensor-level panel				Location-level panel			School-level panel	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Filter and Monitor	-.022	-.022	-.021	-.052*	.003	.003	-.033	.0023	.0023
	(.027)	(.027)	(.027)	(.029)	(.028)	(.028)	(.034)	(.031)	(.031)
Outside				-.0062			-.1***		
				(.025)			(.027)		
Filter & Monitor × Outside				.087**			.068		
				(.04)			(.04)		
Control mean	.44	.44	.44	.44	.49	.49	.49	.55	.55
N. of obs.	65,156	65,156	65,156	65,156	44,408	44,408	44,408	22,750	22,750

Notes: The outcome in all columns is whether the air pollution monitor data is missing. In Columns 1–4, the dataset is a monitor-level panel at the day level. In Columns 5–7, the data is a daily school-location-level panel: each school has two observations per day, one outdoors and one indoors. In Columns 8–9, the data is a school-level panel at the day level. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: Effect of filters on students' exposure to $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
Panel A: Outdoor $PM_{2.5}$					
Filter and Monitor	.53*	.51	.49	.48	.54
	(.32)	(.32)	(.33)	(.39)	(.42)
Control mean	11	11	11	12	17
N. of obs.	677,916	677,913	677,833	162,118	100,825
Panel B: Indoor $PM_{2.5}$					
Filter and Monitor	-.48*	-.5**	-.51**	-.66**	-1.2***
	(.25)	(.25)	(.24)	(.31)	(.45)
Control mean	9.1	9.1	9.1	9.9	14
N. of obs.	1,178,324	1,178,324	1,178,320	283,450	131,737
Panel C: Δ Indoor–Outdoor $PM_{2.5}$					
Inside	-1.1***	-1.2***	-1.2***	-1.4***	-2.5***
	(.23)	(.22)	(.22)	(.26)	(.32)
Filter & Monitors × Indoors	-.83**	-.81**	-.72**	-.78*	-1.2**
	(.35)	(.35)	(.36)	(.4)	(.47)
Control mean	11	11	11	12	17
N. of obs.	1,856,240	1,856,240	1,855,777	445,468	232,937
Locality FE	X	X			
Hour FE	X				
Date FE	X				
Hour × Date FE		X			
Locality × Date × Hour FE			X	X	X
Hours	All	All	All	7am–4pm	7am–4pm
Days	All	All	All	Mon–Fri	Mon–Fri
Outdoors pollution	All	All	All	All	> 5

Notes: The outcome in all regressions is the indoor readings of $PM_{2.5}$. In all regressions, we control for the outdoor readings of $PM_{2.5}$ (demeaned), both as measured by the monitors we installed in schools and by the city's monitors (SISAIRE) and their interaction with the treatment dummy (following J. Roth and Sant'Anna (2023); Lin (2013)). Column 5 defines outdoor pollution based on the monitors we installed. Column 6 defines outdoor pollution based on the city's monitors. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.13: Effects of filters on students' exposure to $PM_{2.5}$ by schools' pollution levels

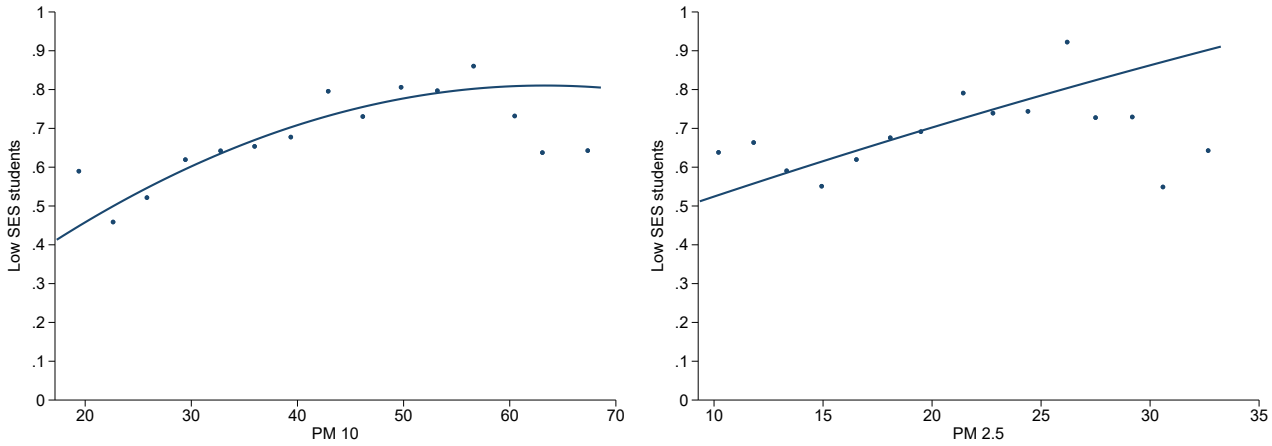
	$PM_{2.5}$	
	(1)	(2)
Filter and Monitor	-.49	-.58*
	(.34)	(.34)
PM25_ext_demean_NM × Dummy_NM	.083	
	(.052)	
PM25_ext_demean_NM × Filter and Monitor × Dummy_NM	.013	
	(.04)	
PM 2.5 (city sensors)		.046*
		(.026)
PM 2.5 (city sensors) × Filter and Monitor		-.05*
		(.027)
N. of obs.	69,739	69,739
Locality × Date × Hour FE	X	X
Hours	7am–4pm	7am–4pm
Days	Mon–Fri	Mon–Fri
Outdoor pollution	All	All

Notes: The outcome in all regressions is the indoor readings of $PM_{2.5}$. In all regressions, we control for the outdoor readings of $PM_{2.5}$ (demeaned), both as measured by the monitors we installed in schools and by the city's monitors (SISAIRE) and their interaction with the treatment dummy (following J. Roth and Sant'Anna (2023); Lin (2013)). Column 1 defines outdoor pollution based on the monitors we installed. Column 2 defines outdoor pollution based on the city's monitors. All regressions consider the randomization design (i.e., include strata fixed effects). Standard errors, clustered at the school level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Figures

Figure A.1: Pollution and SES across years

(a) PM_{10} and proportion of low SES students (b) $PM_{2.5}$ and proportion of low SES students



*N*otes: These figures show the correlation between the average pollution and the likelihood a student comes from a low SES background (measured by whether they live in a household entitled to subsidies for public utilities). The figures represent binscatter least squares estimations — following Cattaneo, Crump, Farrell, and Feng (2024) — using data from all students graduating from all schools in our experimental sample from 2015 to 2023.

Figure A.2: Infographic about the filter



Figure A.3: Infographic about the air quality monitor



Figure A.4: Filter installations and exam date

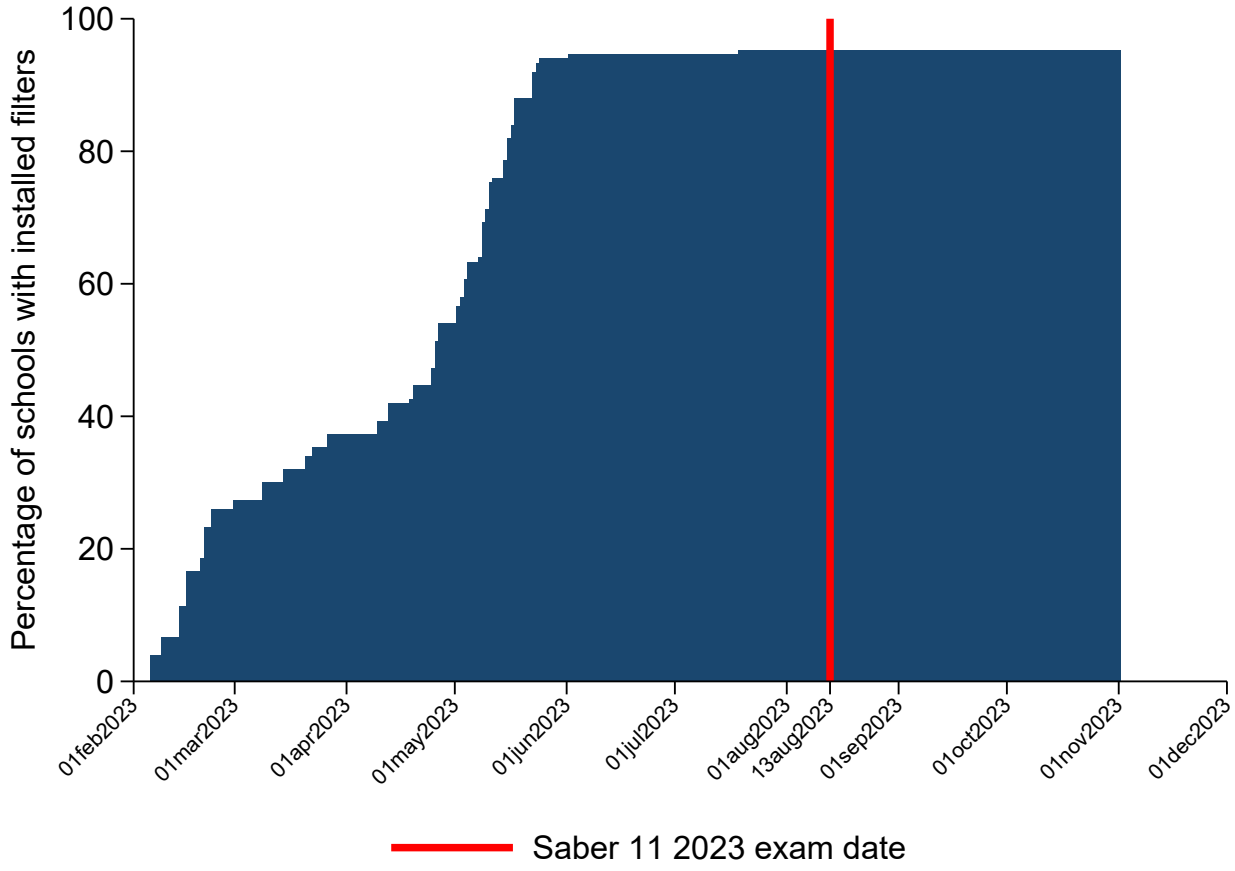


Figure A.5: Monitor installations and exam date

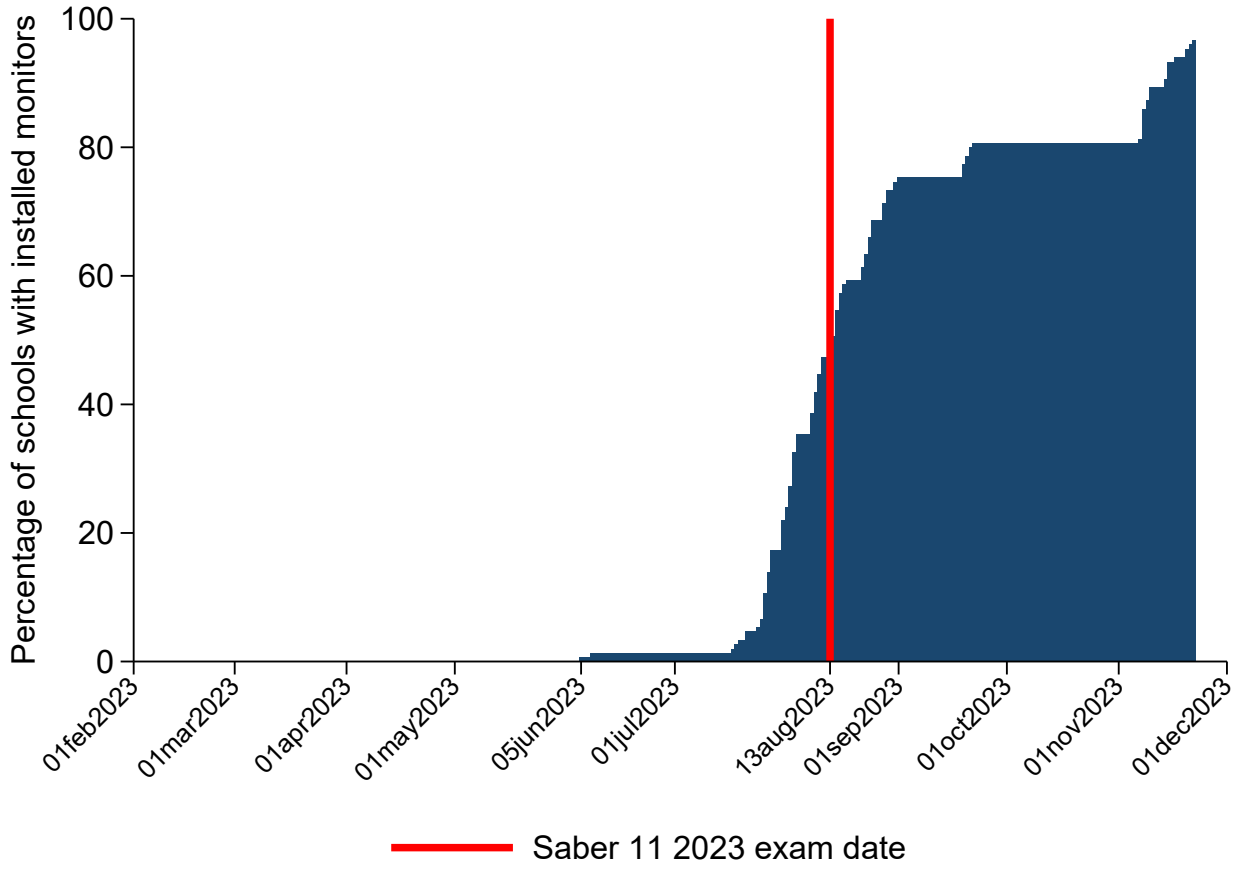


Figure A.6: Consort diagram

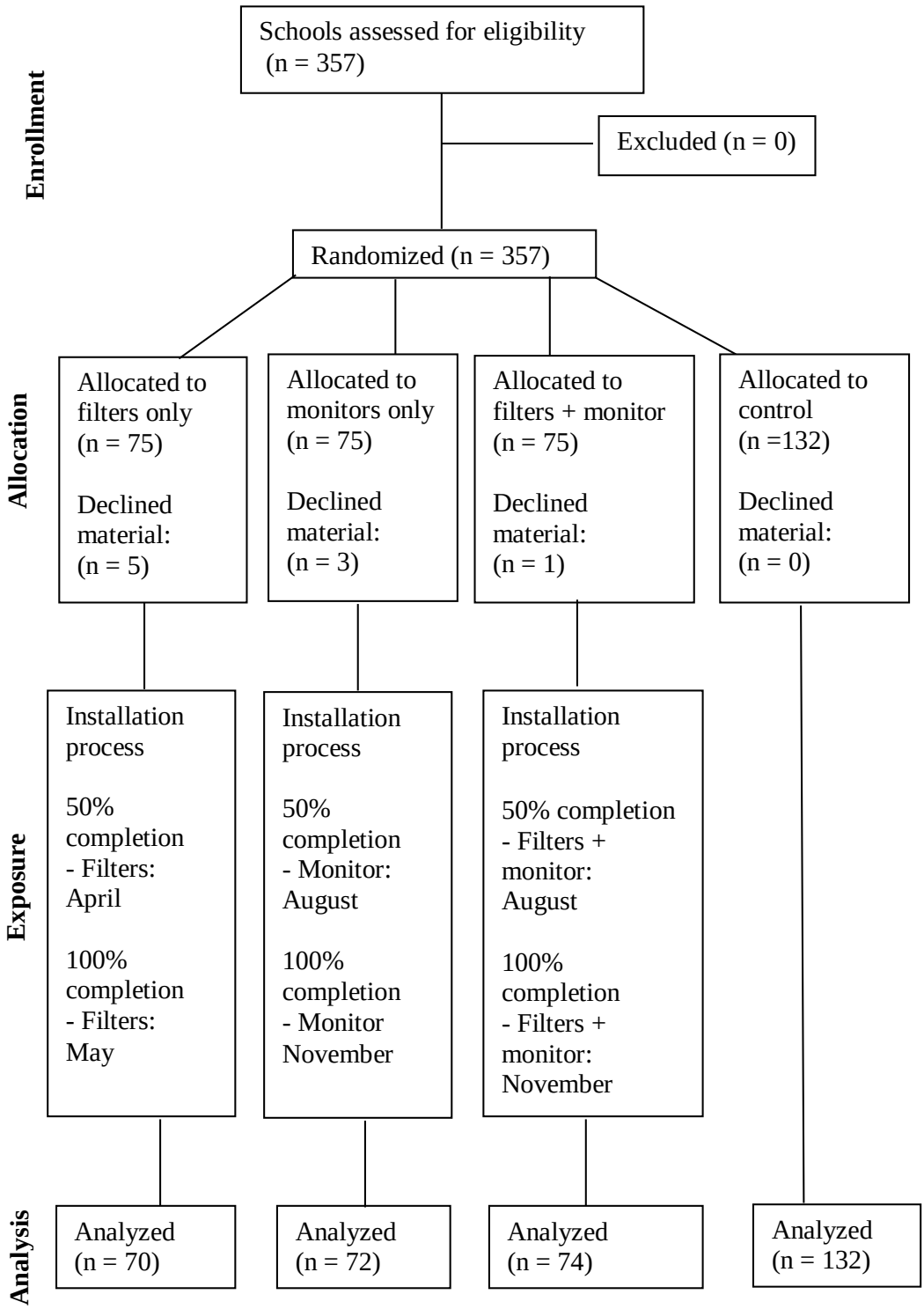
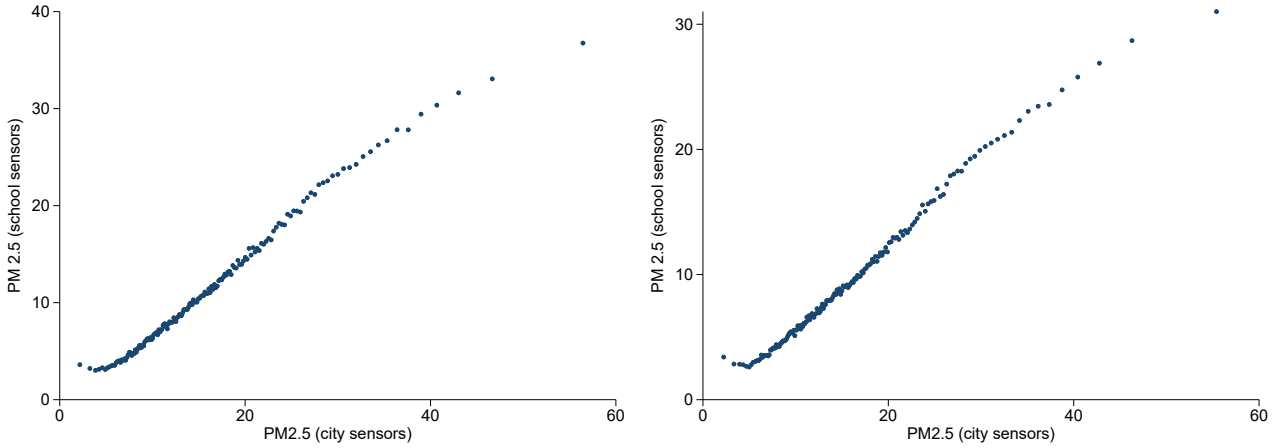


Figure A.7: Pollution readings: SISAIRE vs. school monitors

(a) Outdoor school monitors vs. city monitors (b) Indoor school monitors vs. city monitors

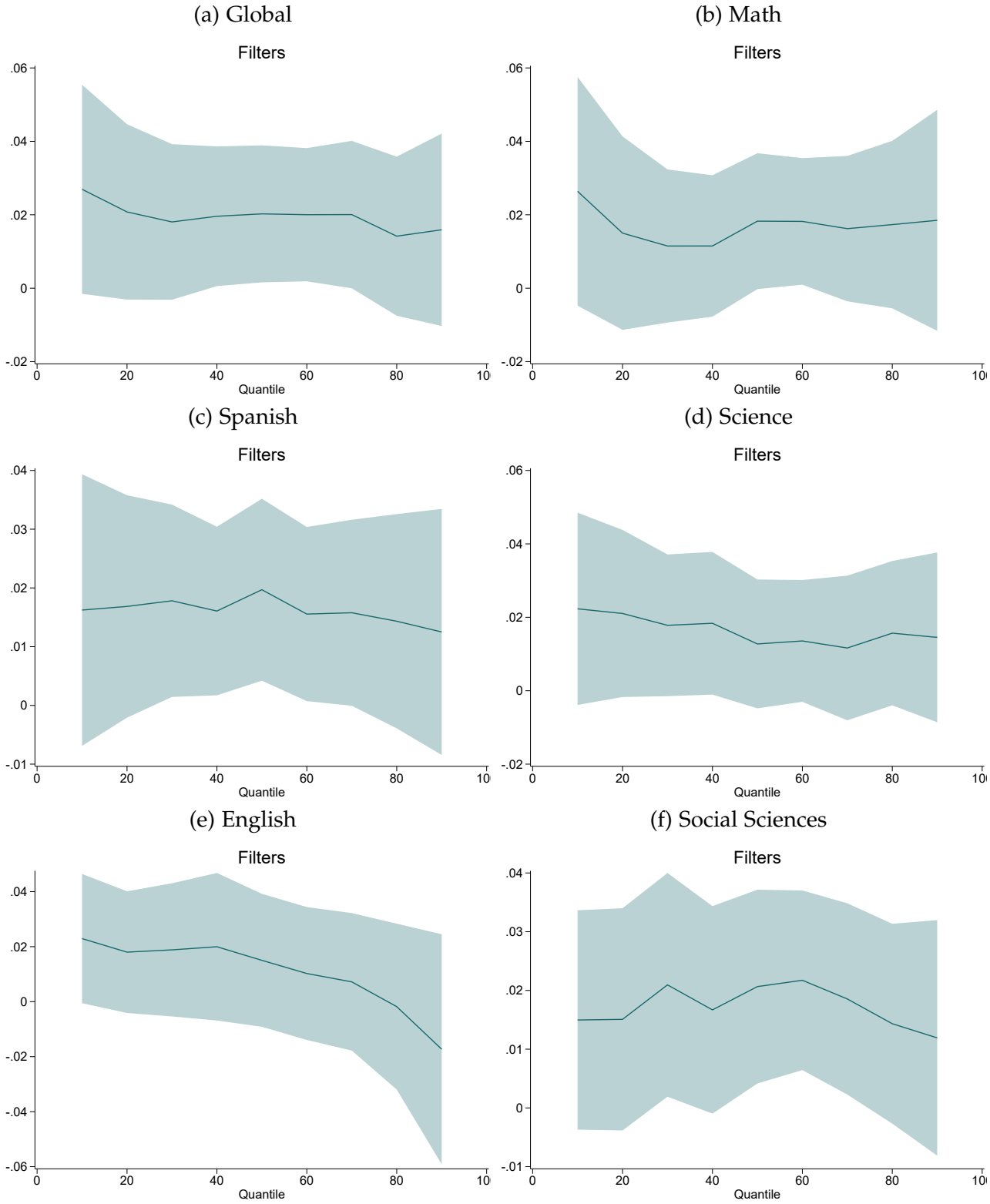


*N*otes: These figures represent binscatter least squares estimations—following Cattaneo et al. (2024)—using hourly data from the pollution monitors we installed in schools, as well as the network of 22 monitors managed by the government, known as SISAIRE. We use a simple interpolation (based on the quadratic distance to the monitor to obtain hourly pollution measurements for each school in the sample.

Figure A.8: Classroom with slits



Figure A.9: Quantile treatment effects (2023)



Notes: These figures present unconditional quantile treatment effects (Firpo et al., 2009) and their 95% confidence intervals estimated using the RIF package in Stata (Rios-Avila, 2020).

Figure A.10: $PM_{2.5}$ readings from the monitors we installed in schools over time

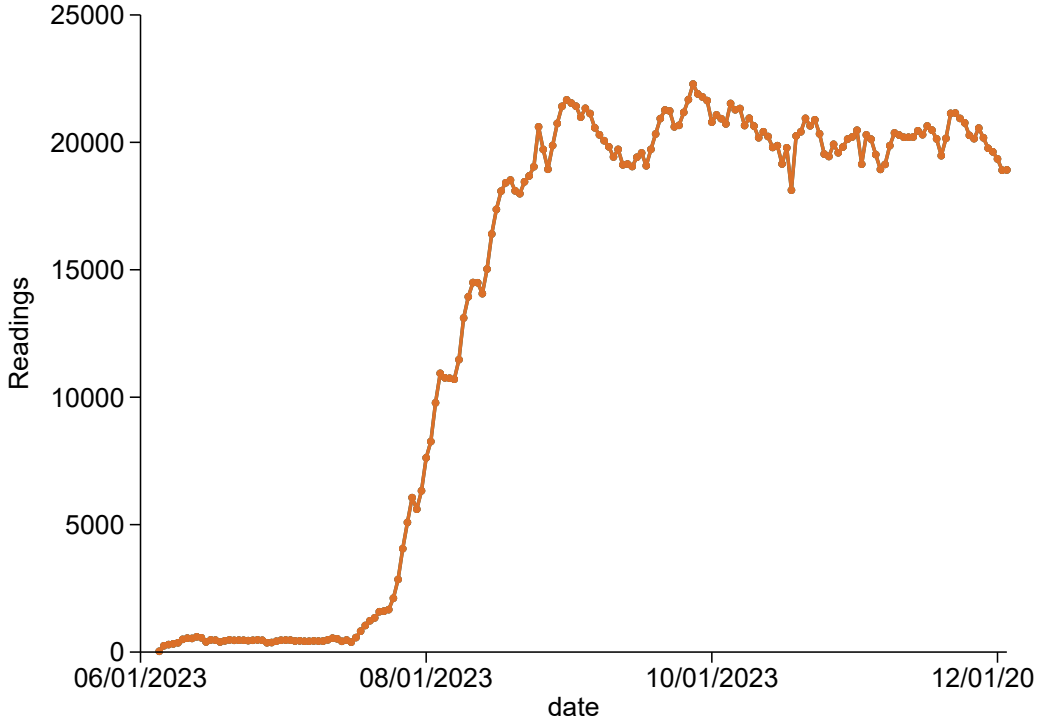
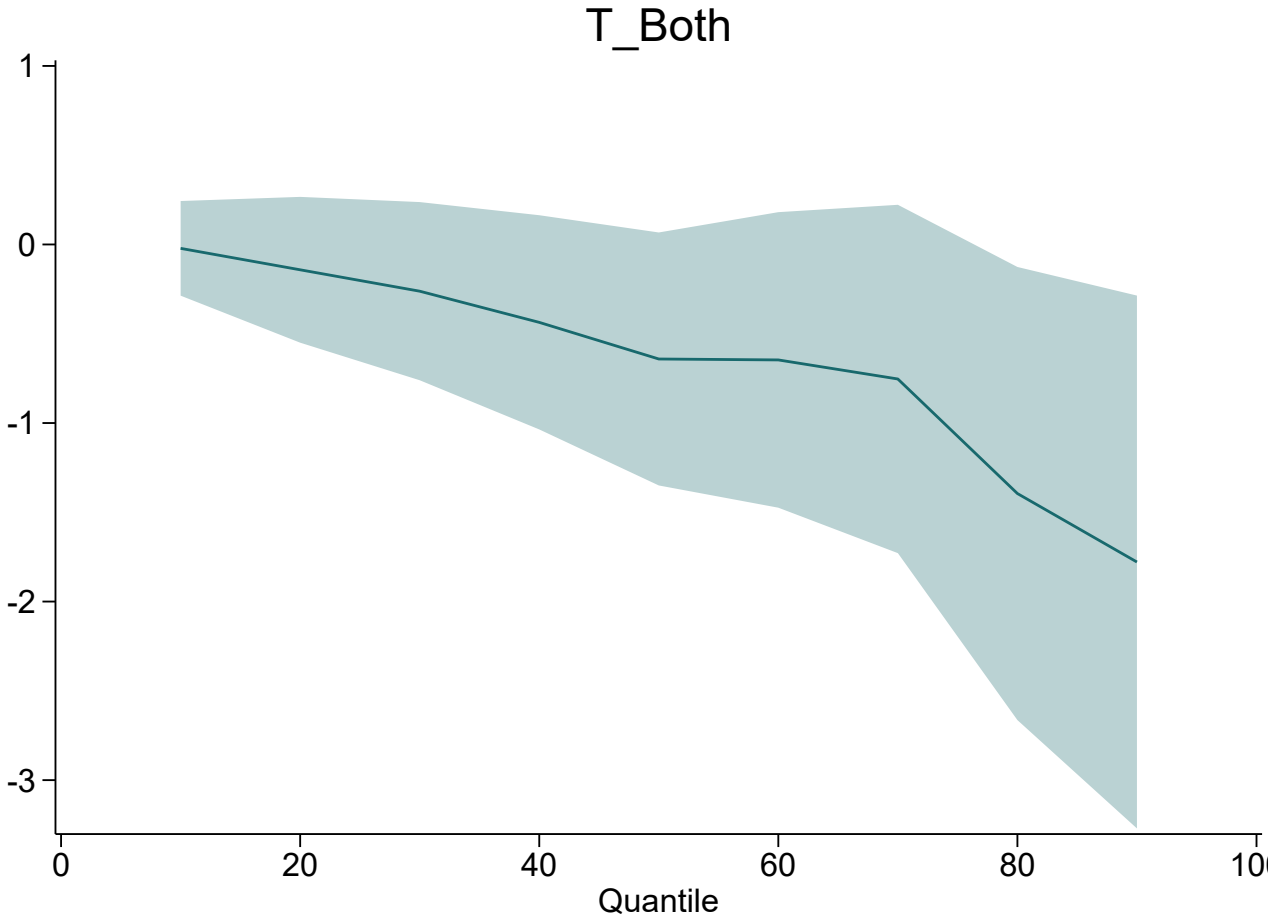
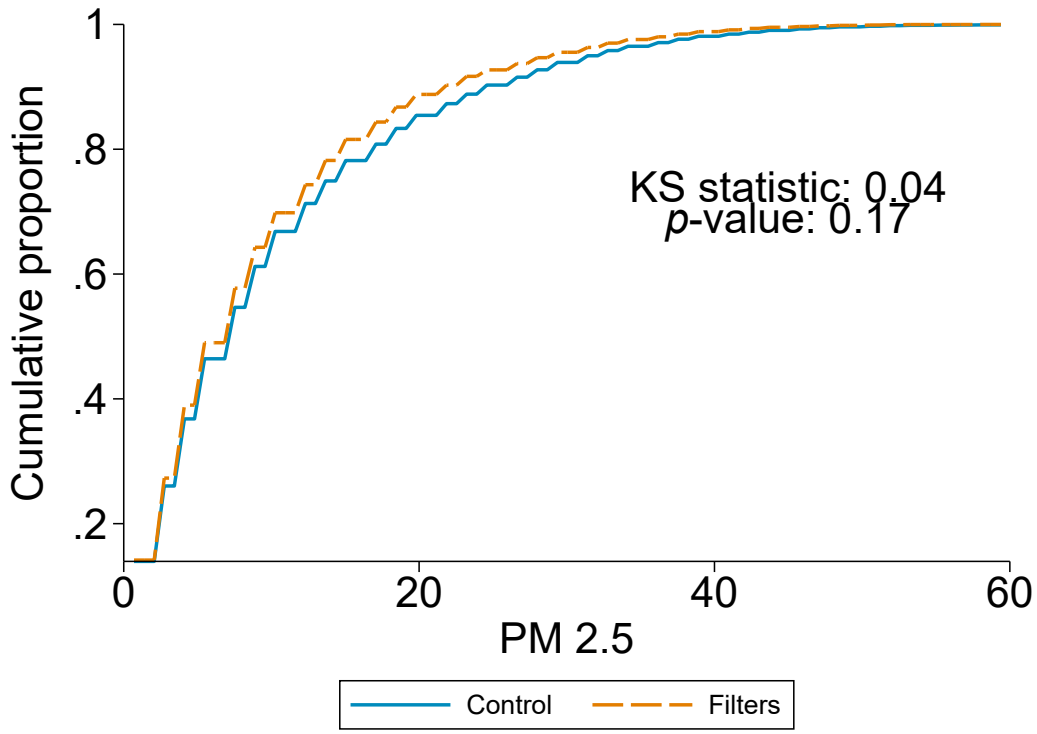


Figure A.11: Quantile treatment effects on $PM_{2.5}$ levels



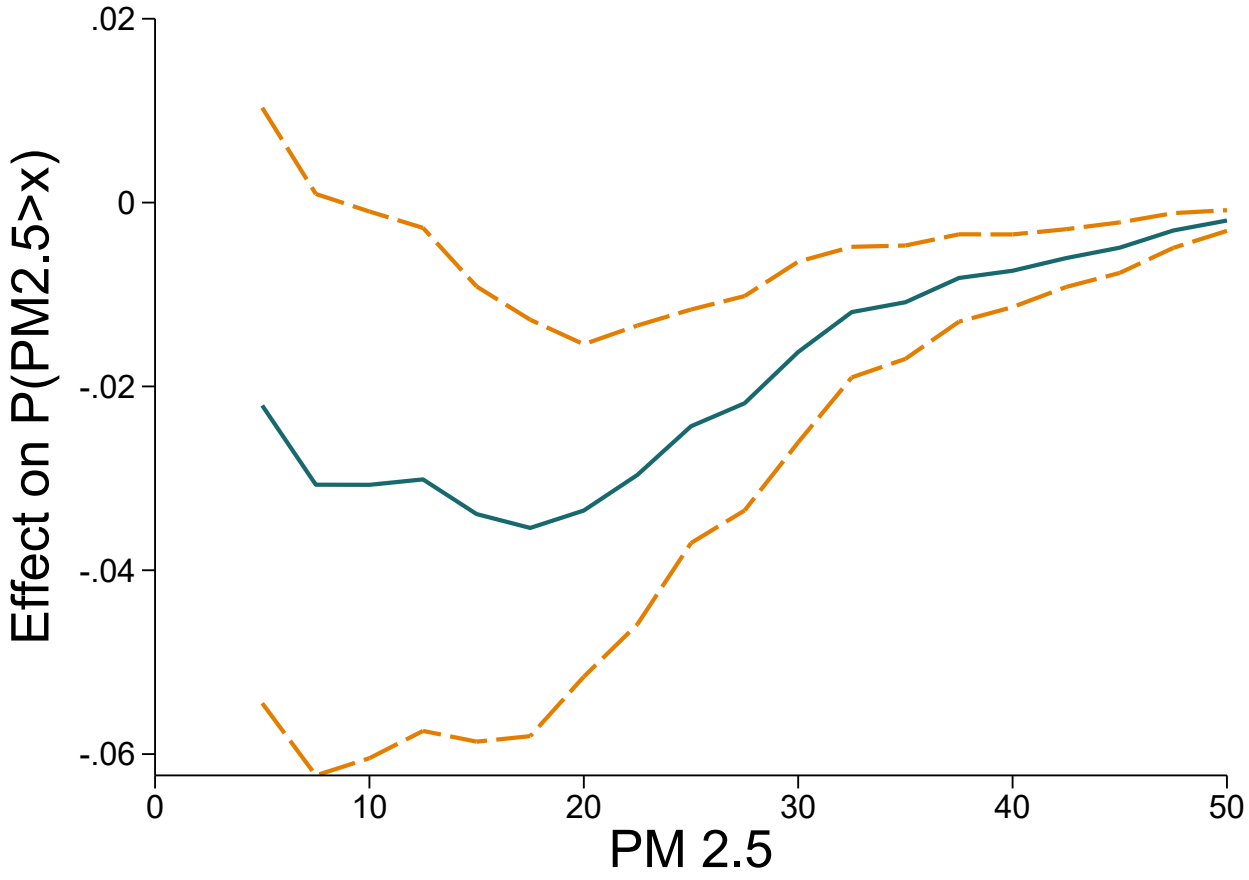
*N*otes: These figures present unconditional quantile treatment effects (Firpo et al., 2009) on indoor $PM_{2.5}$ levels and their 95% confidence intervals estimated using the RIF package in Stata (Rios-Avila, 2020).

Figure A.12: Indoor $PM_{2.5}$ distribution across schools with and without filters



Note: This figure presents the cumulative distribution of $PM_{2.5}$ by treatment status (with or without filters, among schools with monitors) (Abadie, 2002) (and the implementation of Abdulkadiroğlu, Pathak, and Walters (2018)). All estimates control for outdoor pollution readings, hour, day, and locality fixed effects. This figure only includes data for school hours (weekdays, 7 am–4 pm). All models use a Gaussian kernel and Silverman (2018)'s rule of thumb bandwidth. KS statistics are the maximum differences in CDFs. p-values are estimated via bootstrap.

Figure A.13: Distribution regression for indoor $PM_{2.5}$ levels



Notes: This figure presents distribution regression estimators. For each value of $PM_{2.5}$, it displays the effect on the probability that the indoor pollution level is above this value.