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Effectiveness of Using Enhanced Filters in Schools and Homes to Reduce Indoor Exposures to $PM_{2.5}$ from Outdoor Sources and Subsequent Health Benefits for Children with Asthma

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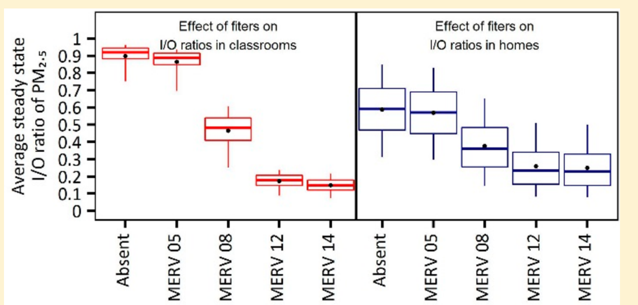
Supporting Information

ABSTRACT: Filters can reduce indoor concentrations of particulate matter ($PM_{2.5}$), but their benefits have not been well-characterized. This study investigates exposure, health, and cost impacts of high efficiency filters in homes and schools, focusing on the asthma-related outcomes. Reductions in indoor exposures to $PM_{2.5}$ from outdoor sources with enhanced filters (e.g., MERV 12) are estimated using probabilistic indoor air quality models, and avoided health impacts are quantified using health impact assessment. These methods are applied using data from Detroit, Michigan, an urban region with elevated asthma rates. Replacing inefficient filters with enhanced filters in schools would reduce the $PM_{2.5}$-attributable asthma burden by 13% annually, with higher benefits for more efficient filters. Marginal costs average \$63 per classroom or \$32 per child with asthma per year. In homes, using efficient furnace filters or air cleaners yields 11 to 16% reductions in the asthma burden with an annualized marginal costs of \$151−494 per household. Additional benefits include reductions in health risk for adults and lower exposures to other contaminants such as PM from indoor sources. On the basis of the included health outcomes, efficient filters in schools in particular is a potentially cost-efficient way to reduce the asthma-related health burden for children.



1. INTRODUCTION

1.1. Background. Children are susceptible to the adverse effects of air pollution,[1−3] and for children with asthma, exposure has been linked to reduced lung function, asthma symptom days, emergency department (ED) visits, and hospitalizations.[4−7] Exposure may contribute to new cases of asthma, especially among children living or attending school near busy roads.[8−11] Children with asthma may be more likely to miss school,[12,13] which may lead to lower academic achievement.[14] The susceptibility of children suggests that interventions that reduce pollutant exposures during childhood could yield large benefits.

Enhanced filtration can reduce $PM_{2.5}$ exposure resulting from indoor and outdoor emission sources.[15−18] Children spend most of their time indoors at home[19] where PM concentrations can greatly exceed outdoor levels due to smoking, cooking, and other activities.[20,21] The next most frequented setting is schools, where $PM_{2.5}$ levels are influenced by indoor and outdoor sources.[22,23] In both settings, the building's envelope, heating, ventilation, and air conditioning (HVAC) system, filters, and other factors affect indoor concentrations.[24]

1.2. Objectives. We estimate exposure, health benefits, and costs of high efficiency filters in homes and schools in Detroit, Michigan, focusing on the asthma-related health burden among school-age children attributable to $PM_{2.5}$ exposure. Prior studies of filters have examined impacts on adults (e.g., hospitalizations and premature mortality);[25−28] benefits to children, a susceptible population, have not been well characterized.

2. METHODS

$PM_{2.5}$ concentrations in classrooms and homes are estimated using indoor air quality (IAQ) models, a range of filter types, and historical ambient $PM_{2.5}$ levels. Then, health impact functions are used to estimate health benefits as the avoided morbidity using "typical" time activity-data. Alternative analyses that consider other time-activity patterns are presented in the Supporting Information. We focus on $PM_{2.5}$ from outdoor sources because the impact functions were

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developed for ambient $PM_{2.5}$; additionally, the variation of indoor $PM_{2.5}$ sources among and within buildings, which may be considerable, is largely unknown. These limitations are discussed later.

2.1. Study Population. The study population is approximately 136000 children ages 6 to 18 years attending 290 schools in Detroit, Michigan, and nearby cities (Figure S1).[29] Of these, an estimated 11000 children ages 6−14 (11.3%) have asthma.[30] We assume children live and go to school in the same ZIP code. Many of the study children are potentially vulnerable given their low socioeconomic status (e.g., 74% of public school students in the area are economically disadvantaged[29]) and high asthma prevalence (11.3% in Detroit vs 9.7% in Michigan).[30] Furthermore, daily attendance at public schools is 89% (versus 93.4% statewide) and only 7% of students score "proficient" on standardized tests (versus 18% statewide).[29] The area has many $PM_{2.5}$ sources, including 38 industrial facilities emitting over 1 ton per year of (primary) $PM_{2.5}$;[31] 4000 miles of truck routes; five commercial ports; and seven rail terminals.[32] Several highways with more than 10000 trucks per day cut through residential areas.[33] Local sources account for one-third to one-half of ambient $PM_{2.5}$ concentrations; the remainder arises from regional sources.[34,35]

2.2. Estimating $PM_{2.5}$ Exposures at Schools and Homes. Indoor $PM_{2.5}$ levels are estimated using steady-state IAQ models that account for building characteristics, ventilation, particle penetration, deposition, and removal by the filter. Monte Carlo (MC) analyses are used to address parameter variability and uncertainty. The models, which express the effect of filters as the change in indoor/outdoor (I/O) concentration ratios, are described below.

2.2.1. $PM_{2.5}$ Concentrations in Schools. We model indoor concentrations in schools using a fully mixed one compartment model that assumes the classroom uses a unit ventilator (UV), a packaged air handling unit providing ventilation and filtration, which typically serves a single classroom.[36] The indoor $PM_{2.5}$ concentration (C_s) in a classroom using a UV that accommodates a drop-in filter[37] due to outdoor sources at steady-state is

$$C_s = \frac{C_o[Q_{o,s}(1-\varepsilon_s) + Q_{in}P_s]}{Q_r\varepsilon_s + Q_{o,s} + Q_{in} + k_{dep,s}} \tag{1}$$

where C_o = outdoor $PM_{2.5}$ concentration (μg m^{-3}), $Q_{o,s}$ and Q_r = volume-normalized outside air and recirculation air flow rates, respectively, through the filter (h^{-1}), Q_{in} = volume-normalized infiltration air flow rate (h^{-1}), P_s = particle penetration factor for infiltration (dimensionless), $k_{dep,s}$ = particle loss rate from deposition (h^{-1}), and ε_s = particle removal efficiency of the filter (dimensionless). We assume the UVs run continuously while students are in the classroom. Table S1 lists typical values of these parameters. Additional details on parameter selection are in the Supporting Information.

2.2.2. $PM_{2.5}$ Concentrations in Homes with Forced-Air Systems. Approximately 85% of homes in the study area have forced-air systems (whole-house furnaces) that can accommodate a drop-in style filter.[38] In these homes, air tends to be well-mixed when the HVAC system is operating.[39] Indoor concentrations are estimated using a fully mixed one compartment model (Figure S2-A).[37] At steady state, the indoor concentration (C_h) from outdoor $PM_{2.5}$ sources is

$$C_h = \frac{Q_{o,h}C_oP_h}{Q_{h,f}f_r\varepsilon_f + Q_{h,o} + k_{dep,h}} \tag{2}$$

where $Q_{o,h}$, $Q_{h,f}$, and $Q_{h,o}$ = volume-normalized flows from the outside into the house, from the house into the furnace, and from the house to the outside (h^{-1}), respectively, C_o = outdoor concentration (μg m^{-3}), P_h = penetration factor (dimensionless) for homes, $k_{dep,h}$ = deposition loss rate (h^{-1}), f_r = the fraction of time the system is running (dimensionless), and ε_f = filter removal efficiency (dimensionless). For the baseline case, we assume f_r = 0.10 (2.4 h day^{-1}). For the improved filtration cases, we assume the system runs 20 min h^{-1} (7.9 h day^{-1}), which is more consistent with ASHRAE Standard 62.1[40] and thus adjust the filter flow rate $Q_{h,f}$ by f_r = 0.33. Table S1 gives typical values of these parameters, and the Supporting Information also provides details on parameter selection.

Filter efficiency ε_f for MERV ratings of 5, 8, 12, and 14 are derived for representative filters and 196 different outdoor particle size distributions measured in Europe and North America.[41] $PM_{2.5}$ efficiencies were not overly sensitive to particle density or size distribution assumptions.[41] A "no filter" case provides a comparison case.

2.2.3. $PM_{2.5}$ Concentrations in Homes without Forced-Air Systems. Stand-alone or "portable" air cleaners can be used in homes with radiators or baseboard heating.[38] These filters, rated by their "clean air delivery rate," typically service one or several rooms but not the entire building, thus a multizone model is required. We model free-standing HEPA-equipped air cleaners (hereafter called "air cleaners") using a three-compartment model representing a bedroom, living room, and the remainder of the house (Figure S2B). An air cleaner is placed in the bedroom; a second is placed in the living room, the locations where children spend most of their time. $PM_{2.5}$ concentrations in the bedroom (C_i), living room (C_k), and remainder of the house (C_j) are

$$C_i = \frac{C_oP_hQ_{o,i} + C_jQ_{i,j} + C_kQ_{i,k}}{Q_{i,o} + Q_{i,j} + Q_{i,k} + k_{dep,h} + Q_{i,f_1}\varepsilon_1} \tag{3}$$

$$C_j = \frac{C_oP_hQ_{j,o} + C_iQ_{i,j} + C_kQ_{k,j}}{Q_{j,o} + Q_{j,i} + Q_{j,k} + k_{dep,h}} \tag{4}$$

$$C_k = \frac{C_oP_hQ_{o,k} + C_iQ_{i,k} + C_jQ_{j,k}}{Q_{k,o} + Q_{k,i} + Q_{k,j} + k_{dep,h} + Q_{k,f_2}\varepsilon_2} \tag{5}$$

where ε_1 and ε_2 are removal efficiencies of filters in the bedroom and living room (dimensionless), respectively, $Q_{i,f1}$ and $Q_{k,f1}$ are volume-normalized flows through bedroom and living room filters (h^{-1}), respectively, $Q_{o,i}$, $Q_{o,j}$, $Q_{o,k}$, $Q_{i,j}$, $Q_{j,k}$, $Q_{j,I}$, $Q_{j,k}$, $Q_{k,i}$, $Q_{k,j}$, $Q_{i,o}$, $Q_{j,o}$, and $Q_{k,o}$ are volume-normalized flows (h^{-1}) between compartments, subscripts *i*, *j*, *k*, and *o* are bedroom, other spaces, living room, and outside, respectively, and other parameters are as in eq 2; subscripts on flows indicate transfers between compartments. Typical values and distributions of these parameters are shown in Table S1. Additional details on parameter selection are in the Supporting Information. Eqs 3−5 are coupled and were solved algebraically, and the variability of these parameters is addressed using Monte Carlo analysis (see below). The indoor exposure in houses with air cleaners (C_{fil}) is the time-weighted average of exposures in bedrooms, living rooms, and other parts of the

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house. The stand-alone air cleaners are assumed to run continuously when children are home.

2.2.4. Ambient $PM_{2.5}$ Concentrations. Outdoor $PM_{2.5}$ concentrations use 24 h measurements at 12 Detroit area monitoring sites taken every third day from 2011 to 2015.[42] To help account for spatial variability in the region, concentrations are apportioned into the "background" (or regional) component, represented as the second lowest daily measurement across the monitoring network, and the "local increment," defined as the highest measurement (at any monitor) minus the daily background.[43] To account for elevated levels near major roads (from exhaust emissions, entrained dust, tire, and brake wear), the 75 schools within 200 m of a freeway or state highway ("near road" schools) are assigned the local increment; other schools and all homes are assigned half of the increment.[43] This approach is supported by the emissions inventory data showing mobile sources account for approximately 50% of the $PM_{2.5}$ emissions in Wayne County,[44] and receptor modeling results apportioning approximately 50% of $PM_{2.5}$ in the area to regional sources and 15 to 30% from diesel exhaust and other mobile sources.[35]

2.2.5. Parameter Variability and Filter Use Patterns. Effects of parameter variability are evaluated using MC analysis with 10000 simulations (@Risk software, Palisade Corporation). MC analyses are performed for each filter rating and each of the three applications. Distributions of input parameters are shown in Table S1. If a supporting study did not specify a distribution, a triangular distribution is assumed. In all cases, airflow balance is maintained.

For schools, outdoor concentrations are drawn from ambient concentrations on school days (weekdays from September 1 through June 15). Positive correlations between Q_r, Q_{in}, and Q_o are assumed (Spearman $R = 0.3$) since infiltration rates in schools tend to be higher when HVAC systems are operating.[45]

For homes, daily outdoor concentrations are drawn by season. The ACR, which is bounded between 0.1 and 6 h^{-1}, is positively correlated ($R = 0.2$) to the bedroom ACR for the multizone house model (eqs 3–5), ratios of flows between the bedroom and the rest of the house ($\alpha_{b,h}$ and $\alpha_{h,b}$) are positively correlated ($R = 0.2$), and ACRs and ratios of flows between rooms are negatively correlated ($R = -0.3$).[38]

The MC analysis does not address variability in the operating schedule for the UVs, forced-air systems, and air cleaners. Sensitivity analyses are used to evaluate usage from 0 to 100%.

2.3. Health Impact Assessment. Incidences of three asthma-related outcomes (hospitalizations, ED visits, and respiratory symptom days), are estimated using quantitative health impact assessment (HIA) methods.[46] Concentration–response (CR) functions are taken from cited epidemiological studies in U.S. EPA's most recent Regulatory Impact Assessment for $PM_{2.5}$ and BenMAP's User's Manual (Table S3).[47] CR coefficients are pooled using a random effects model according to methods reported by US EPA.[48] These studies were selected for consistency with previous HIAs and because U.S. EPA has determined these studies meet specific inclusion criteria.[48] No effect threshold is assumed, consistent with the current lack of evidence for a population-level exposure threshold.[49] Hospitalization rates are calculated at the ZIP code level using data from the Michigan Inpatient Database and the 2013 American Community Survey.[50] ED visit rates are estimated from Medicaid data at ZIP code level for schools in Detroit and county level for other schools.[30,51] ED visit rates for children on Medicaid are assumed to apply to the entire study population. Respiratory symptom day rates come from an ongoing cohort study in Detroit (Batterman, S.A., unpublished data).

The number of attributable cases is converted to disability-adjusted life years (DALYs) and monetized impacts in 2010 dollars.[48,52–54] A 95% confidence interval (CI) is estimated using the 95% CI of the CR coefficient, which accounts for most of the uncertainty in health impact estimates.[55]

2.4. Health Benefits and Scenarios. Health benefits are estimated for three scenarios: installing efficient filters in all schools; in only "near-road" schools; and in all homes. In each, MERV 8, 12, and 14 filters are compared to a baseline case: schools with UVs and inefficient (MERV 5) filters; homes with a forced air system and the same filter; and no filtration for homes without forced-air systems. Because a minimum MERV 8-rated filter in classrooms is recommended,[56] we also present results using MERV 8 at baseline in the Supporting Information. Effects for the full year are reported [i.e., reductions at schools are scaled by 0.48 to reflect the length of a school year (177 days)].

Using CRs from air pollution epidemiological studies in filter studies involves several challenges. First, filters affect only a portion of total exposure (e.g., people spend an average of 87% of their time indoors).[57] Thus, outdoor concentrations represent a proxy for total exposures. Second, the indoor portion of exposure affected by filters in epidemiological and filter studies can vary. Third, CR relationships are functions of outdoor concentrations not indoor concentrations. For these reasons, we calculate an "equivalent concentration" to account for indoor and outdoor exposures in a manner comparable with the available CR functions. Using a time-weighted average of concentrations over the day, the equivalent concentration, C_{eq}, is

$$C_{eq} = C_{out}\left[\frac{(\sum_m F_{in,m}C_{in,F,m}) + F_{out}C_{out}}{(\sum_m F_{in,m}C_{in,B,m}) + F_{out}C_{out}}\right] = C_{out}\left[\frac{(\sum_m F_{in,m}R_{F,m}C_{out}) + F_{out}C_{out}}{(\sum_m F_{in,m}R_{B,m}C_{out}) + F_{out}C_{out}}\right] \quad (6)$$

where $F_{in,m}$ and F_{out} are fraction of time spent indoors and outdoors, respectively, $C_{in,F,m}$ and $C_{in,B,m}$ are indoor concentrations with enhanced filters and baseline filters, respectively, subscript m refers to the indoor space (e.g., homes or schools), C_{out} is outdoor concentration, and $R_{F,m}$ and $R_{B,m}$ is I/O ratios for space m with enhanced and baseline filters, respectively. Additional details on the use of the C_{eq} are discussed in the Supporting Information.

C_{eq} is estimated separately for schools and homes with the assumption that filters are used in schools or homes, but not both. Time allocations used to calculate C_{eq}, based on nationally representative average values, are 7.0, 1.9, 14.4, and 0.7 h day^{-1} in schools, outdoors, home, and elsewhere, respectively, during school days, and 0, 1.9, 14.4, and 7.7 h day^{-1}, respectively, on nonschool days.[19,58] For the multizone model, the time spent in bedrooms, living rooms, and other spaces is 10.5, 2.6, and 1.3 h day^{-1}, respectively.[19] For homes and schools without improved filters, the average I/O ratios calculated using eq 2 are 0.58 and 0.64, respectively. Concentrations in the "other spaces," which are unknown, are assumed equal to those at unfiltered homes during the school year analysis and to those at unfiltered schools during

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the full year analysis. These assumptions are based on seasonal time-activity data that show time spent by children at home is fairly consistent across seasons and that time spent in school is replaced by time spent in other homes and other spaces which may have indoor environments more similar to schools than homes.[19]

The MC analysis generates 10000 iterations of outdoor and indoor concentrations in school and homes. We estimate C_{eq} for each iteration, fit a distribution to the resulting concentrations, and then randomly draw from this distribution to create representative years (177 days for school exposures; 365 days for home exposures).

Because the health benefits of filters depend on the amount of time children spend in filtered indoor environments, the sensitivity of health benefits is demonstrated using two bounding scenarios: no time outdoors and 6 h day^{-1} outdoors. Results of this sensitivity analysis are in the Supporting Information.

The health benefits scenarios are summarized in Table S5.

2.5. Cost Analysis. Costs of more efficient filters for schools and homes with forced air systems are referenced to MERV 5 filters. Filter costs are based on quotes from Hometown Filter, an Indiana-based company supplying filters to Midwestern schools. Costs reflect a "bulk" discount that might be available to school districts. The quoted cost of a more efficient filter ($10.56 per filter) is similar to that of a MERV 13 filter from a hardware store (e.g., Home Depot; homedepot.com). Air cleaners include a one-time cost for the purchase of the unit, and annualized costs assume a lifetime of 8 years and discount rate of 7% per year. Increased electricity consumption from running UVs, furnace fans, or air cleaners assumes, at baseline, system run times of 1.68, 2.40, and 0 h day^{-1}, respectively (Table S4); marginal consumption is estimated for a range of increased run times. Maintenance, retrofits and any additional heating and cooling costs are excluded. The cost-relevant factors are summarized in Table S4.

3. RESULTS AND DISCUSSION

3.1. Outdoor $PM_{2.5}$ Concentrations. Daily ambient $PM_{2.5}$ concentrations during 2011−2015 average 9.8 μg m^{-3} (range: 0.7 to 34.2 μg m^{-3}; Table S6). The "local increment" averages approximately 50% of the mean "background" concentration. $PM_{2.5}$ levels vary by season (e.g., near-road concentrations during the spring, summer, fall, and winter average 11.3, 13.4, 11.6, and 14.1 μg m^{-3}, respectively) (Kruskal−Wallis K = 18.03, p < 0.001); the non-near road $PM_{2.5}$ concentrations average 9.3, 11.4, 9.6, and 12.0 μg m^{-3}, respectively (K = 23.7, p < 0.001). Concentrations during the school year are slightly lower than those for the full year.

Ambient $PM_{2.5}$ concentrations in Detroit tend to be lower than other metropolitan areas, and the Detroit region is considered in attainment of the $PM_{2.5}$ National Ambient Air Quality Standard.[59] However, $PM_{2.5}$ is still an important pollutant from a health effects perspective for several reasons, including that monitors may miss intraurban gradients that may result in higher exposures for some populations (e.g., those living near roads),[60,61] and that there are no recognized thresholds for exposure below which health effects do not occur.[49]

3.2. Indoor/Outdoor Ratios. *3.2.1. Classrooms.* I/O ratios fall as filter efficiency increases (Figure 1, Table S7). In schools, I/O ratios are lowered from MERV 5 levels by 46, 80, and 83% using MERV 8, 12, and 14 filters, respectively. Schools show greater reductions in I/O ratios than homes, a result of lower ACRs (Table S1) and higher initial (baseline) I/O ratios.

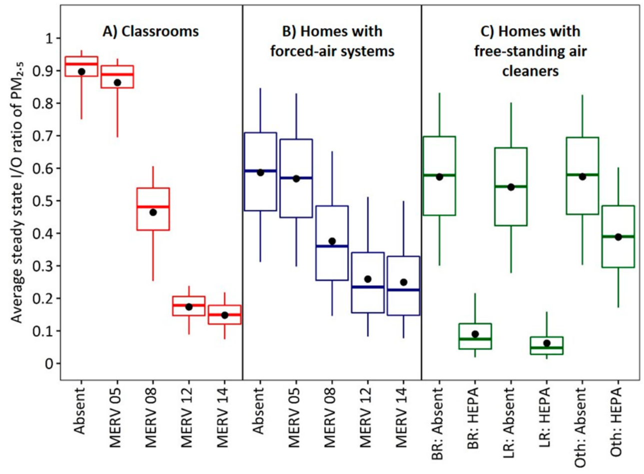

Figure 1. Boxplots showing I/O ratios of $PM_{2.5}$ concentrations contrasting absent, low, medium, and high efficiency filters. (A) Classrooms with unit ventilators, (B) homes with forced-air systems, and (C) homes with free-standing HEPA air cleaners in bedrooms and living rooms. Plots show 5th, 25th, median (bar), mean (dot) 75th, and 95th percentiles.

I/O ratios of $PM_{2.5}$ in schools have been reported in several studies. I/O ratios for black carbon (BC), which has few if any indoor sources, ranged from 0.24 to 0.59 for classrooms using MERV 6 filters.[17] Our estimates are comparable: 0.86 and 0.46 for MERV 5 and 8 filters, respectively. I/O ratios of 0.03−0.26 have been estimated for MERV 15 filters,[17] similar to our estimate of 0.15 for MERV 14 filters. Higher I/O ratios (0.48−0.51) for BC have been measured in a classroom with a MERV 14 filter, but high infiltration rates may have affected these results.[62] Our results may vary from the literature due to differences in building characteristics, run times, particle size distributions,[63,64] and other factors.

In classrooms, I/O ratios decrease as the run time increases, with the exception of classrooms equipped with MERV 5 filters (Figure 2A). In mechanically ventilated classrooms, increasing the UV run time introduces additional outside air, which increases $PM_{2.5}$ levels when inefficient filters are used. In contrast, in naturally ventilated homes, increasing the fan run time does not alter outside air flows, thus, increased filter use only reduces I/O ratios.

I/O ratios increase as the run time increases for classroom UVs equipped with inefficient filters (Figure 2A), indicating the potential for higher $PM_{2.5}$ levels from outdoor sources at higher ventilation rates. Often, classrooms need additional ventilation to lower levels of indoor contaminants, improve student and teacher health, and comply with ventilation requirements.[65−67] However, outside air must be appropriately filtered to avoid increasing $PM_{2.5}$ levels; levels of other pollutants like ozone also may increase at high ventilation rates. While the ventilation-energy trade-off is well-recognized, the ventilation-$PM_{2.5}$ trade-off is not. Fortunately, this can be largely eliminated by more efficient filters. Often, however, no specification is provided for filters, or only intermediate efficiency filters are recommended. For example, U.S. EPA's *Tools for Schools* calls for MERV 8 to 13 filters.[56]

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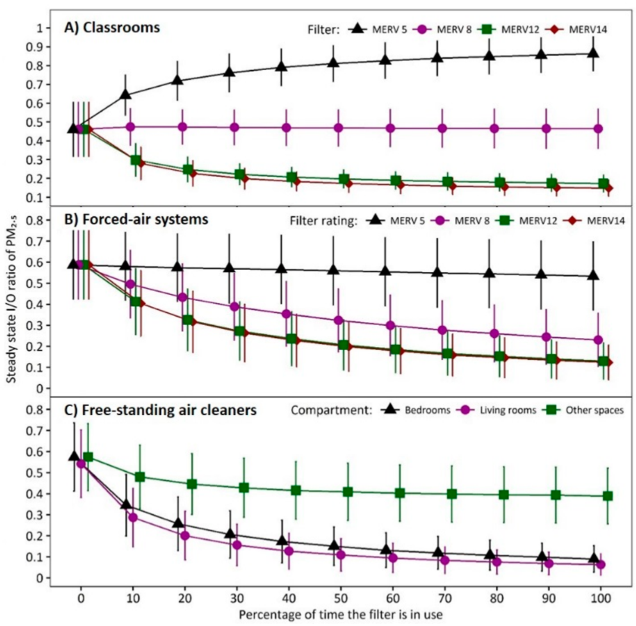

Figure 2. Sensitivity analysis of system run time on $PM_{2.5}$ I/O ratios for (A) classrooms, (B) homes with forced-air systems, and (C) bedrooms, living rooms, and other rooms in houses using free-standing HEPA air cleaners. Error bars show standard deviation of the mean estimates.

Our results for schools apply to classrooms using UVs, which are widely used. However, schools also use other types of mechanical ventilation systems (e.g., central air handling units with variable air volume system). While assessment of such systems is beyond our scope, the use of more efficient filters in other types of ventilation systems that condition and filter comparable air flows is expected to yield benefits and costs fairly similar to those estimated for UVs. Dedicated outside air systems (DOAS), a relatively new type of ventilation system beginning to be seen in schools, might attain comparable benefits at lower cost by equipping only the DOAS system with enhanced filters. We note that a sizable fraction of classrooms do not appear to meet ventilation requirements,[65] and thus both ventilation and filtration must be addressed to meet air quality goals.

3.2.2. Homes. Trends of I/O ratios in homes are comparable to those seen for schools, with 34, 54, and 56% reductions using MERV 8, 12, and 14 filters, respectively. Installing air cleaners in homes without forced-air systems reduced I/O ratios by 84 and 88% in bedrooms and living rooms, respectively, from the baseline case (no filter; Figure 1, Table S7). Modest reductions (32%) are attained elsewhere in the home due to flows between compartments (Figure S2). Seasonal variability of the I/O ratios is limited, in part due to the overlap between seasonal ACRs (Table S1).

In homes, our estimates of I/O ratios with forced-air systems largely agree with the literature. For example, Azimi et al. estimated I/O ratios for older homes of 0.40, 0.32, 0.25, and 0.25 for MERV 5, 8, 12, and 14 filters, respectively,[68] similar to our estimates (0.56, 0.37, 0.25, and 0.24 for MERV 5, 8, 12, and 14, respectively; Table S7). Measured I/O ratios of $PM_{2.5}$ in homes may vary geographically (e.g., between 0.47 to 0.82 for homes across the U.S.),[69] due to differences in building characteristics, meteorology, air conditioning use, and window opening.[24]

A Detroit field study showed that air cleaners placed in bedrooms reduced PM levels by 50−77%; fine fraction PM (0.3−1 μm dia) had higher removals.[70] Other studies using air cleaners have measured $PM_{2.5}$ reductions between 37 and 43%.[71−73] Using the three-compartment model, we estimate that two air cleaners would remove 84% of outdoor $PM_{2.5}$ in bedrooms when run continuously and 77% when run 60% of the time (Figure 2C). The higher reductions in the present analysis likely result from four factors: we assume units are used continuously (compared to 63−83% in the field studies); we ran both units at their maximum speed; each home was assumed to have two air cleaners (bedroom and living room); and field study measurements included PM from both indoor and outdoor sources. When the air cleaner in the living room was removed and filter in bedrooms run at half speed for 60% of the time (similar to reported use patterns[74]), the bedroom I/O ratio was reduced by an average of 55%. This suggests that our estimates of PM reductions and health benefits for the 15% of homes without forced-air systems may be overestimated.

3.3. Health Impacts. Health impact estimates due to $PM_{2.5}$ exposure are shown in Table 1, along with the estimated incidence of asthma-related impacts for the study population. For example, $PM_{2.5}$ exposures cause 33000 asthma symptom

Table 1. Current (Baseline) Asthma-Related Impacts[a] for School-Aged Children in the Study Area, Including Total Impacts and Impacts Attributable to $PM_{2.5}$ Exposures during the School Year (September 1 to June 15) and Calendar Year

	estimated incidence (per year)	impacts attributable to $PM_{2.5}$ exposure[b,c] (per school year)	impacts attributable to $PM_{2.5}$ exposure[c] (per calendar year)
hospitalization (6−18)	480	8 (3−13)	16 (6−25)
emergency department visits (6−18)	5300	130 (49−200)	250 (98−390)
exacerbation (cough, 6−14)	1400000	33000 (0−100000)	66000 (− 210000)
exacerbation (wheeze, 6−14)	860000	6600 (1300−12000)	13000 (2500−24000)
exacerbation (shortness of breath, 6−14)	820000	8700 (160−17000)	17000 (330−34000)
DALYS (years)	3400	53 (0−150)	110 (0−290)
monetized impacts (2010 $million)	190	3 (0−8)	6 (0−16.1)
attributable fraction (%)[d]		1.6	3.2

[a]Estimates are rounded to two significant figures. 95% Confidence limits (in parentheses) are left-truncated at 0. [b]Considers only 177 days during the school year. [c]Assumes UVs with MERV 5 filters run continuously while children are in classrooms, homes with forced air systems have MERV 5 filters and run 20 min/hour, and homes without forced air systems do not use free-standing HEPA air cleaners. [d]Percent of total DALYs due to DALYs attributable to indoor $PM_{2.5}$ exposures.

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days (defined as having cough) during the school year and 66000 days with cough during the full year. In contrast, an estimated 1400000 days with cough occur due to all causes. In total, $PM_{2.5}$ exposures cause an estimated 110 DALYs and \$6 million in monetized impacts per year (Table 1).

3.4. Benefits of Filters. More efficient filters in classrooms reduce the asthma-related health burden, mostly due to avoided asthma symptom-days (Table 2). Avoided health impacts were reported for the absolute change in indoor $PM_{2.5}$ from outdoor sources due to increased filtration. Replacing MERV 5 filters with MERV 8, 12, or 14 filters in schools reduces the annual $PM_{2.5}$-related asthma burden by 8, 13, and 14%, respectively (17, 28 and 30%, respectively, during the school year), which represents \$0.5−0.9 million year^{-1} in avoided health impacts. The marginal benefit of MERV 14 compared to MERV 12 filters is small (16 vs 15 DALYs avoided year^{-1}, respectively). Benefits increase at near-road schools where annual DALYs are reduced by 10−17%, a result of these schools' greater exposure (18% higher).

At homes, filters avoid 12 to 18 DALYs per year, with monetized benefits from \$0.7 to \$1.0 million per year. This exceeds benefits at schools because children spend more time at home. Replacing MERV 5 filters with MERV 8, 12, or 14 filters in homes reduces the $PM_{2.5}$-related asthma burden by 11, 16, and 17%, respectively (Table 2). As at schools, MERV 14 filters provide only minimal improvement over MERV 12 filters.

Few studies have examined the health benefits of increasing filter efficiency in any building type.[16] Upgrading from MERV 7 to MERV 15 filters in U.S. schools has been estimated to reduce attributable cases of mortality, chronic bronchitis, and stroke risks by 33%.[75] We found a similar decrease (28−30%; 13−14% over the full year) for asthma-related outcomes for upgrading from MERV 5 to MERV 12/14 filters in Detroit schools. Unfortunately, under half of U.S. school districts have an IAQ policy in place,[76] and most schools seem to be using low efficiency filters. Our findings suggest that upgrading filters in schools would confer health benefits to school occupants, including students, teachers, and staff.

We estimate an 11−16% reduction in the annual $PM_{2.5}$-related asthma burden if every home with a child with asthma in Detroit used better filters (Table 2). A 7.4% reduction was estimated for childhood asthma exacerbations with high-efficiency electrostatic cleaners in home forced-air systems.[27] Similarly, an intervention study found that, although there was little change in asthma symptoms when air cleaners were used in bedrooms, health care utilization (e.g., clinic, ED, and hospital visits) decreased by 19% when the filters were used continuously.[77]

We did not estimate the benefits of simultaneously using filters in schools and homes. Data on individual students, which would have facilitated such an analysis by linking students to specific homes and schools, was unavailable. The total benefits of using filters in both spaces would be slightly less than the sum of the separate estimates due to the (weak) nonlinear concentration−response relationships.

3.5. Costs of More Efficient Filter Use. Marginal costs depend on the filter rating and run time. Here we discuss the costs associated with the scenarios reported in Table 2. In schools, replacing MERV 5 filters using a run time of 3.3 h day^{-1} during the school year (177 school days per year) with more efficient filters and using a run time of 10 h day^{-1} imposes marginal costs of \$40−63 per classroom per year,

Table 2. Asthma-Related Health Benefits Per Year among Children from Replacing MERV 5 Filters with More Efficient Filters in Schools or Homes[a]

	avoided impacts due to filters in all schools			avoided impacts due to filters at near-road schools			avoided impacts due to filters in homes[b]		
	MERV rating								
outcome (cases)	8	12	14	8	12	14	8	12	14
asthma hospitalization	1 (1−2)	2 (1−4)	2 (1−4)	0 (0−1)	1 (0−1)	1 (0−1)	2 (1−3)	3 (1−4)	3 (1−4)
asthma ED visit	22 (9−34)	36 (15−57)	39 (15−60)	6 (2−9)	10 (4−16)	11 (4−16)	29 (11−44)	41 (16−63)	42 (17−65)
cough	6000 (0−17000)	10000 (0−29000)	10000 (0−31000)	1200 (0−3500)	2100 (0−6200)	2100 (0−6400)	8000 (0−23000)	11000 (0−33000)	11000 (0−34000)
wheeze	1200 (220−2100)	1900 (370−3500)	2100 (390−3700)	240 (47−440)	420 (81−750)	440 (84−780)	1600 (300−2800)	2200 (430−4000)	2300 (440−4100)
shortness of breath	1500 (30−2900)	2500 (50−4900)	2700 (50−5200)	320 (6−600)	550 (10−1100)	570 (11−1100)	2000 (40−4000)	2900 (60−5600)	3000 (60−5800)
DALYs (years)	9 (0−24)	15 (0−41)	16 (0−44)	2 (0−5)	3 (0−9)	3 (0−9)	12 (0−33)	18 (0−47)	18 (0−48)
monetized benefit (\$)[c]	0.5 (0−1.3)	0.9 (0−2.3)	0.9 (0−2.4)	0.1 (0−0.3)	0.2 (0−0.5)	0.2 (0−0.5)	0.7 (0−1.8)	1 (0−2.6)	1 (0−2.6)
reduction in DALYs (%)[d]	8	13	14	10	17	17	11	16	17

[a]Health benefits are estimated based on the change in "equivalent exposure concentration" (C_{eq}) and presented as the number of avoided health outcomes per year.

[b]For homes, we assume that houses without forced-air systems use free-standing HEPA air cleaners in children's bedrooms and living rooms. [c]Reported in millions. [d]Calculated as the reduction in DALYs compared to baseline impacts (108 DALYs per year for school, 19 DALYs for year for near-road schools, and 224 DALYs per year for homes). For schools, the percent reduction is scaled by 0.48 to reflect that students are only in school 177 days per year.

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depending on filter rating. Assuming 20 students in a classroom (and 2 students with asthma per classroom), the marginal cost is \$2−3 per student per year or \$20 to \$32 per student with asthma per year. This is well-below the benefits of avoided asthma exacerbations (\$0.5−0.9 million per year or \$49−79 per child with asthma per year). Costs for other run time increases are found in Table S8.

In a home with a forced air system running 2.4 h day^{-1}, replacing MERV 5 filters with more efficient filters and boosting the run time to 7.9 h day^{-1} costs \$151−175 per year, including increased energy costs of \$142 per year. A home with two air cleaners running 14.4 h day^{-1} incurs costs of \$877 for the first year and \$417 for subsequent years, or annualized costs of \$494 per year. Run times over 12 h day^{-1} provide only incremental benefits (Figure 2C). Thus, lower run times can obtain similar benefits at lower cost. The total cost of more efficient filters in homes of children with asthma (assuming one child with asthma in each home) is \$2.2−\$2.4 million per year (\$1.4−\$1.6 million per year for the estimated 9350 homes with forced air systems and \$800000 per year for 1650 homes using air cleaners). Overall, filter costs in homes exceed the monetized benefits of avoided asthma impacts resulting from lower exposures for particles of outdoor origin (\$0.6−1.0 million per year or \$63−93 per child with asthma per year).

Overall filtration costs include the filter media itself, labor for filter change-out, and electricity for fan operation. Costs increase with filter efficiency and use (Table S8). Because the highest-rated filters achieved only slightly higher performance than slightly lower-rated filters,[68] less expensive intermediate-to-high rated filters could still be beneficial. Filter costs fall on school districts, homeowners, landlords, and tenants, many of whom may be sensitive to costs. We also recognize that filter change-out is likely less frequent than recommended, that high efficiency filters require regular replacement, that some HVAC systems operate without any filters or with inadequate seals around filters, and that costs depend on the HVAC configuration. Finally, our estimates are referenced to low-efficiency filters (MERV-5 or equivalent), and marginal benefits will be lower for homes and schools already using intermediate-to-high efficiency filters (see the Supporting Information).

Costs also will vary by region due to differences in climate, electricity price, baseline system run time, and building configuration. For example, for Detroit homes with forced-air systems running 2.4 h day^{-1} at baseline, increasing the run time to 4.8 h day^{-1} imposes an annual marginal cost of \$71−103 (Table S8). There may be considerable variability in the baseline run times; for example, Azimi et al. (2016) used run times between 16 and 19%, depending on the age of the housing stock.[68] Our estimate of 10% at baseline to 20% under a filtration scenario should be considered conservative; marginal costs would be lower if baseline run times are longer. In comparison, Texas homes have a baseline run time of 4.8 h day^{-1} due to heavy air conditioning use[78] and lower electricity costs (\$0.11 per kWh[79]), thus, the marginal cost for a 4.8 h day^{-1} run time is only \$9−32 per year, essentially just the cost of the better filter. Marginal costs can be higher in states like California due to the low baseline run time (fewer heating and cooling days[80] and high electricity cost) (\$0.19 per kWh); moving from a run time from 1.2 to 4.8 h day^{-1} incurs marginal costs of \$132−165 annually. Still, in homes with children with asthma, filtration costs appear modest relative to asthma-related costs (e.g., hospital visits, lost wages from missing work to care for a sick child)[81] and inhaler costs. Though costs for filters in homes would mostly fall on residents, it is likely many would opt to pay for filters to reduce the asthma-related costs of poorer indoor air quality.

We excluded the potential energy penalty caused by increased pressure drop across the filters. Higher resistance in the system due to more efficient filters or dirty filters causes a greater pressure drop compared to low-efficiency filters, and in systems with constant air flow rates, this pressure drop results in increased fan use.[82−84] Increased filter efficiency can also affect duct leakage on the supply and return sides of the system, which also imposes an energy penalty. Generally, high efficiency filters require only small increases in fan power (5 to 13%), depending on the system and climate,[83,85] and the energy penalty for Detroit is expected to be small.[15,86]

Cost-effectiveness depends on the benefits included. We considered only reductions in $PM_{2.5}$ from ambient sources and only the confirmed $PM_{2.5}$-associated asthma impacts on children. Asthma has other significant impacts (e.g., increased school absenteeism), which will result for a fraction of asthma symptom-days. Unfortunately, this fraction cannot be estimated from the literature. On the basis of a monetized value of \$98 per school absence,[87] filters upgrades would be cost-effective if as few as one in six asthma symptom days led to a school absence (Supporting Information). Filters also reduce PM generated from indoor sources (e.g., pet dander and allergens), several of which can exacerbate asthma.[88] Filters also benefit adults, who can be susceptible to severe health outcomes associated with $PM_{2.5}$ (e.g., premature mortality), that have large monetized values.[49] Filtration in office buildings has been shown to be cost-effective, driven by reductions in PM-related mortality among adults;[89,90] similar findings appear likely for homes.[37] For example, using an improved filter (MERV 9) and increasing a home's force-air system run time or using HEPA air cleaners in homes could lead to 1 to 2 fewer deaths per 10000 each year.[28] Possible but currently speculative effects of PM on school attendance and academic performance are not considered. Given these and potentially other exclusions, the true health benefits of filtration might far exceed our estimates.

3.6. Limitations. Concentrations predictions using "box" models require a number of assumptions and parameters, and the models simplify the true spatial and temporal variability resulting from HVAC operation, time and weather influences, particle composition and size, and other factors.[24,91,92] Not all sources of variability are accounted for in the Monte Carlo analysis (e.g., seasonal data for schools were unavailable). In homes, we assume forced air systems and air cleaners are used 20 min h^{-1} and continuously, respectively. In reality, only the newest thermostats allow cycling or reduced fan speed when operated in "fan" mode. Lastly, air cleaner use patterns vary for comfort, cost, and noise reasons.[74,77] The Supporting Information extends the discussion of uncertainty.

We note other sources of uncertainty. $PM_{2.5}$ exposures use outdoor concentrations averaged across monitors, with "near-road" schools adjusted to account for increased concentrations due to mobile source emissions. This does not capture further spatial (and temporal) variation in exposure (e.g., near idling buses).[93,94] The HIA methods require additional assumptions (e.g., that CR coefficients drawn from studies elsewhere are applicable): that there is no threshold below which $PM_{2.5}$ exposures do not cause adverse health impacts and that baseline health rates at coarse spatial resolution (e.g., ZIP

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codes) apply to individual children. In our estimates of cost, we did not consider variability in the size of blower motors used in homes with forced-air systems. Our assumption was based on a unit that would meet the needs of the average home in the study area (Table S4); larger or smaller systems would likely incur greater or smaller increases in electricity use. Despite these uncertainties, our results suggest that enhanced filters can provide health benefits to children living and attending school in Detroit.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.8b02053.

> Additional details and results pertaining to parameter selection, exposure assessment, and sensitivity analyses (PDF)

A version of the worksheet used to estimate the benefits of filters in homes and schools will be made available upon request to the corresponding author.

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■ ABBREVIATIONS

DALY disability-adjusted life year
ED emergency department
MERV minimum efficiency reporting value

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