

A simulation model of building intervention impacts on indoor environmental quality, pediatric asthma, and costs

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Background: Although indoor environmental conditions can affect pediatric asthmatic patients, few studies have characterized the effect of building interventions on asthma-related outcomes. Simulation models can evaluate such complex systems but have not been applied in this context.

Objective: We sought to evaluate the impact of building interventions on indoor environmental quality and pediatric asthma health care use, and to conduct cost comparisons between intervention and health care costs and energy savings. **Methods:** We applied our previously developed discrete event simulation model (DEM) to simulate the effect of environmental factors, medication compliance, seasonality, and medical history on (1) pollutant concentrations indoors and (2) asthma outcomes in low-income multifamily housing. We estimated health care use and costs at baseline and subsequent to interventions, and then compared health care costs with energy savings and intervention costs.

Results: Interventions, such as integrated pest management and repairing kitchen exhaust fans, led to 7% to 12% reductions in serious asthma events with 1- to 3-year payback periods. Weatherization efforts targeted solely toward tightening a building envelope led to 20% more serious asthma events, but bundling with repairing kitchen exhaust fans and eliminating indoor sources (eg, gas stoves or smokers) mitigated this effect.

Conclusion: Our pediatric asthma model provides a tool to prioritize individual and bundled building interventions based on their effects on health and costs, highlighting the tradeoffs between weatherization, indoor air quality, and health. Our work bridges the gap between clinical and environmental health sciences by increasing physicians' understanding of the effect that home environmental changes can have on their patients' asthma. (*J Allergy Clin Immunol* 2013;■■■:■■■-■■■.)

Key words: Air pollution, allergen, asthma, discrete event simulation, energy savings, green building, housing, intervention, indoor air, lung function, NO₂, PM_{2.5}

Asthma is a classic example of a dynamic and nonlinear disease, with numerous factors influencing disease course.¹ In the United States asthma is among the most common chronic diseases of childhood across all socioeconomic classes and is the most frequent cause of hospitalization among children after birth.² A number of studies have documented relationships between asthma exacerbation and exposure to indoor environmental stressors found in residential settings, such as allergens (eg, dust mites and cockroach), air pollutants (eg, ozone, nitrogen dioxide [NO₂], and fine particulate matter), and environmental tobacco smoke.^{3,4} Other factors influencing asthma exacerbations include access to health care, medication compliance, and respiratory tract infections, such as rhinovirus.^{5,6}

A recent systematic review by the Centers for Disease Control and Prevention found that multitier, multicomponent, home-based environmental interventions for children were effective at improving asthma quality of life and productivity. However, the report provided little guidance as to the essential elements of such interventions.⁷ Many studies have demonstrated that indoor environmental interventions can lead to significant reductions in contaminants known to influence pediatric asthma. For example, integrated pest management (IPM) can reduce cockroach allergen levels,⁸ replacement mattresses and hypoallergenic pillow covers can reduce dust mite concentrations,⁹ intensive cleaning can reduce levels of multiple allergens and fungi,¹⁰ and air cleaners or source elimination can reduce concentrations of air pollutants.¹¹ Some environmental intervention studies were able to demonstrate statistically significant reductions in asthma symptoms or unscheduled clinic visits,¹¹⁻¹³ but few were able to document significant changes in hospital admissions, emergency department (ED) visits, or other less frequent outcome measures that are key components of asthma-related direct costs.¹⁴ Without evidence of changes in health care use, it is challenging to develop generalizable insights for policy analysis or requisite inputs to compare the benefits and costs of candidate interventions.

Intensive field investigations of indoor environmental interventions face logistic challenges because of small study populations (power constraints), the rareness of many serious asthma outcomes, and potential confounders, particularly in complex populations, such as low-income multifamily residents. These studies are further challenged by the emphasis in many studies on bundled interventions. Even the studies with adequate power to capture some changes in health care use¹¹⁻¹³ could not separate out the influence of various individual components, an important input for policymakers looking to invest in only those components with demonstrated effectiveness. This takes on added importance when some interventions (eg, tightening the building envelope)

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Abbreviations used

DEM:	Discrete event simulation model
ED:	Emergency department
FEV ₁ %:	Percent predicted forced expiratory volume in 1 second
IPM:	Integrated pest management
MEPS:	Medical Expenditure Panel Survey
NO ₂ :	Nitrogen dioxide
PM _{2.5} :	Particulate matter less than 2.5 μ m in diameter

might yield energy savings and reduce outdoor air infiltration but increase the influence of indoor sources, whereas others might influence different indoor contaminants to varying degrees.

Simulation models have been used previously to evaluate complex systems for application to cost-benefit analysis. In this context simulation modeling refers to a systems science approach involving modeling of a complex system that evolves over time given changes in state variables that occur at defined points in time.¹⁵ We previously developed and evaluated a discrete event simulation model (DEM) of pediatric asthma¹⁶ to simulate the effect of indoor environmental factors, medication compliance, seasonality, and medical history on asthma outcomes (symptom days, medication use, hospitalizations, and ED visits) in low-income multifamily housing. The model allows for evaluation of changes in asthma health outcomes and pollutant concentrations caused by changes in building characteristics, as would occur with energy-saving measures and other interventions that alter the indoor residential environment. In this study we apply our model to quantify the effect of multiple building interventions in low-income multifamily dwellings, focusing on health care use in comparison with estimated costs of implementing interventions. For building construction changes meant to be implemented as energy-saving measures, we also consider the economic benefits of the interventions. Results from these analyses can help decision makers prioritize among candidate environmental interventions.

METHODS

Model overview

We used a DEM of pediatric asthma to simulate health outcomes over a range of building interventions (Fig 1). The model begins with a baseline population of high-risk children characterized by demographic, residential, and behavioral factors. We modeled indoor environmental concentrations of 4 contaminants that can potentially affect a child's lung function and asthma status: 2 combustion pollutants (NO₂ and particulate matter <2.5 μ m in diameter [PM_{2.5}]), cockroach allergen (Bla g 1 and Bla g 2), and dampness, which serves as a proxy for mold. Other common pollutants associated with asthma exacerbations, such as ozone, mouse, cat, dog, and dust mite allergen, were not included because we either lacked a critical mass of literature linking the exposure with percent predicted forced expiratory volume in 1 second (FEV₁%) or an ability to readily model indoor concentrations. NO₂ and PM_{2.5} were simulated by using CONTAM (NIST, Gaithersburg, Md; <http://www.bfrl.nist.gov/IAQanalysis/>).¹⁷ Cockroach allergen was probabilistically estimated from prior field studies. Dampness or mold growth was a function of sustained relative humidity over time and was affected by showering, occupant breathing, use of the dishwasher, and cooking. Detailed model inputs and references are provided in Supplement 1 (Tables E1-E4) in this article's Online Repository at www.jacionline.org and described elsewhere.¹⁶

Other time-varying characteristics included age, outdoor temperature, indoor and outdoor relative humidity, daily random variation in baseline FEV₁%, and changes in FEV₁% caused by all risk factors. As previously described¹⁶ and summarized in Supplement 2 (Table E5) in this article's

Online Repository at www.jacionline.org, contaminant concentrations are then used to predict FEV₁%, as done elsewhere in the context of policy models for asthma medication.¹⁸⁻²⁰ The daily value of FEV₁% determined the probability of asthma exacerbations and health care use. Asthma outcomes were computed daily for each child, derived from a prior model of the association between FEV₁% and asthma symptoms or serious asthma events (ED visits, hospitalizations, and clinic visits with prescribed oral steroid bursts).²¹ The model was then used to evaluate changes in exposures and responses resulting from multiple interventions, as described below.

The model, which was built in R (R 2.12.1, R Foundation of Statistical Computing), generates an ensemble or cohort of children and their associated households. We simulated one million children to ensure an ability to detect changes in relatively infrequent asthma outcomes associated with changes in each environmental risk factor.

Study population and housing characteristics

The simulated cohort was comprised of children living in low-income multifamily housing consistent with public housing residents, a population known to have increased asthma prevalence and severity.²²⁻²⁴ Inputs describing demographic and housing characteristics were drawn from studies in Boston public housing or other publications related to low-income urban populations. In this population 89% had a gas stove,²⁵ 38% used the oven for supplemental heat in the winter,²² 34% had a current smoker in the house,²³ and 13% had a functioning kitchen exhaust fan.²⁵ Although we lacked sufficient symptom and severity data to apply the National Heart, Lung, and Blood Institute's classification guidelines for managing asthma,⁶ we used the FEV₁% cutoffs that correspond with severity classification for patients with persistent asthma (>80% for mild, 60% to 80% for moderate, and <60% for severe asthma) and used these to determine the prescribed medications. Patients with intermittent asthma were excluded from the simulation because of the limited environmental literature on this severity class.

Asthma medication use and cost data

Our assumptions regarding asthma medication prescriptions, use, and costs are shown in Table 1 stratified by FEV₁% categorization. Although patients with persistent asthma should be prescribed controller medications,⁶ studies have found gaps for a number of reasons.²⁶ Therefore we simulated the probability of using a controller medication as a function of FEV₁% (see Supplement 2 in this article's Online Repository).

Children were evaluated at the end of each simulated year to determine changes in their asthma medication prescriptions, approximating adjustments that would happen during a yearly physical examination. At every year anniversary, we compared each child's average FEV₁% value during the past 365 days with his or her FEV₁% value at the beginning of the year and reclassified the child's asthma severity category, if appropriate. Although severity classification and changes in medication are based on many components beyond FEV₁%, we simplified this step by using the standard ranges of FEV₁% associated with each severity classification.¹⁶ In addition to long-term control and quick-relief asthma medication, children were prescribed an oral steroid burst if they visited the ED or the clinic. The medication cost assigned to the oral steroid burst was \$10 (2010\$) per visit based on prednisone costs.²⁷

Health care use costs

Costs for asthma-related clinic visits (\$156, Current Procedural Terminology code 99244), ED visits (\$638), and hospitalizations (\$10,167) were derived from the 2007/2008 Massachusetts Medicaid Reimbursement Survey,²⁸ the Medical Expenditure Panel Survey (MEPS),²⁹ and the 2006 Agency for Healthcare Research and Quality Healthcare cost and utilization project,³⁰ respectively. For the simulation all costs were adjusted to 2009 dollars based on the Medical Care Consumer Price Index.³¹ Although numerous indirect costs associated with asthma exacerbations have important economic implications,¹⁴ such as lost work days or missed school, we focused on direct health care costs to be aligned with prior cost-benefit analyses of asthma interventions.¹² In addition, we focused on low-income multifamily housing, where

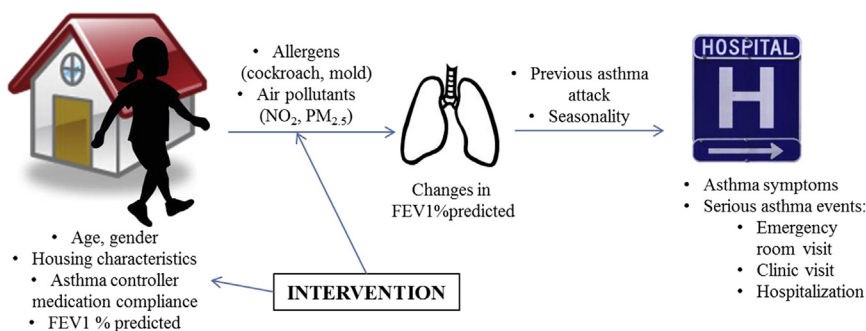


FIG 1. Schematic of the pediatric asthma discrete event simulation model.

TABLE I. Asthma medication prescriptions, use, and cost stratified by asthma severity classification

FEV ₁ % category	Quick-relief medication	Long-term control medication	Frequency	Cost of medicine per day used (2009\$)*
>80%	SABA		2 d/wk 2 puffs/d	\$0.24†
		Low-dose ICS	Daily	\$4.05‡
60% to 80%	SABA	Medium-dose ICS	Daily, 2 puffs/d	\$0.24†
			Daily	\$6.46§
<60%	SABA	Medium-dose ICS + LABA	Daily, 6 puffs/d	\$0.72†
			Daily	\$8.20

ICS, Inhaled corticosteroids; LABA, long-acting β_2 -agonists; SABA, short-acting β_2 -agonists.*Based on values reported in the 2010 Red Book²⁷ adjusted to 2009 dollars based on the Medical Care Consumer Price Index.³¹

†Assumes a cost of \$25 per albuterol canister, with 200 doses per canister.

‡Based on cost of Flovent HFA (GlaxoSmithKline, Research Triangle Park, NC), \$125 per month.

§Based on cost of Advair HFA (GlaxoSmithKline), \$200 per month.

||Based on cost of Flovent HFA plus Singulair, \$256 per month.

health coverage might be through partially or totally government-subsidized health care (eg, Medicaid and Medicare). For this subpopulation, the government (broadly defined) might both be responsible for building repairs/improvements and paying health care costs, and therefore it is valuable to determine the benefit-cost comparisons from a governmental perspective.

Interventions

We evaluated a number of candidate interventions for improving indoor environmental conditions and also considered an intervention aimed at reducing energy costs that could influence the indoor environment. The interventions included (1) fix and/or operate kitchen and bathroom exhaust fans; (2) replace gas stoves with electric stoves; (3) eliminate use of the stove for heating by fixing the heating system; (4) institute a smoke-free housing policy; (5) use high-efficiency particulate air filters; (6) IPM; and (7) weatherization. Supplement 3 in this article's Online Repository at www.jacionline.org presents the intervention list, along with the rationale for each intervention and the changes implemented in the model to simulate each intervention. We also tested bundles of interventions that couple weatherization with interventions that can potentially offset the indoor environmental effects (interventions 8-10, listed at the end of Table E6). Interventions were added in order of ascending cost (fans being the cheapest intervention and a no-smoking policy being more expensive).

Data processing

Although our simulation model was constructed and evaluated with reference to the published literature, because of the probabilistic nature of our simulation, some implausibly high values for exposures or outcomes were possible. We established exclusion criteria for outcomes and air pollution exposures using multiple approaches, including investigating surveillance and field measurement data,³²⁻³⁵ consulting with the study pediatrician, and performing a standard review for outliers. Exclusion values were 225 per year

for asthma symptom days, 24 per year for serious asthma events, 3 per year for hospitalizations, 7 per year for ED visits, 24 per year for clinic visits, 200 ppb for NO₂, and 200 $\mu\text{g}/\text{m}^3$ for PM_{2.5}.

RESULTS

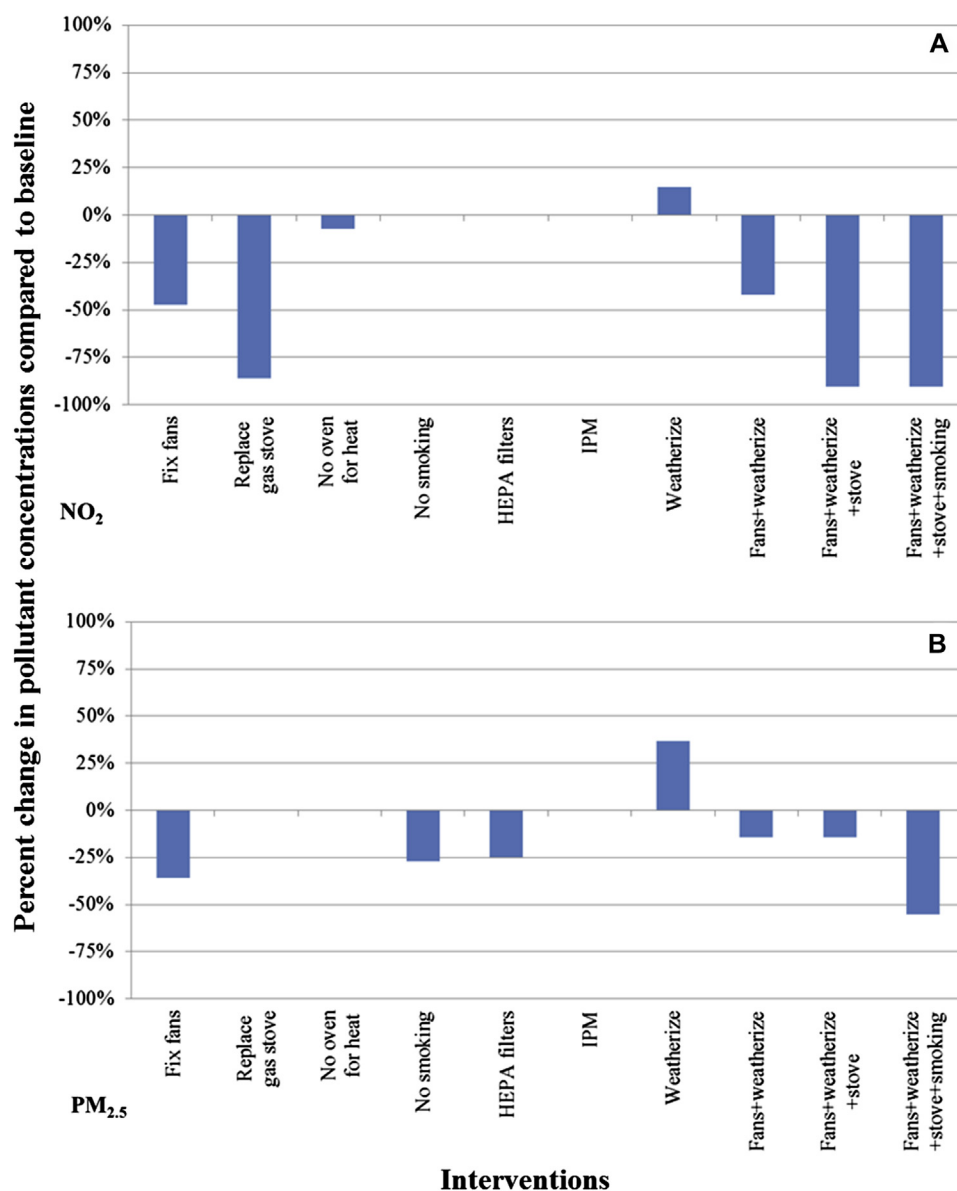
The cohort of one million children was simulated for the baseline scenario and for each intervention over a 10-year horizon. On the basis of the exclusion criteria, 0.83% of simulated children were excluded. In the absence of interventions, baseline average yearly health outcomes stratified by asthma severity classification are presented in Table II. As expected, children with lower FEV₁% values had a higher incidence of asthma symptom days and serious asthma events. We evaluated the stability of the mean estimates by dividing the group of 1 million simulated children into subgroups of 100,000 and calculating SEs for the means of all pollutant and asthma health outcomes. The ratio of SE to mean varied between 0.0002 and 0.003, evidence of the stability of our calculated means across subpopulations.

Fig 2 presents the changes in NO₂ and PM_{2.5} concentrations attributable to each intervention compared with baseline values. Concentrations of Bla g 1 and Bla g 2 are not shown in Fig 2 because they were only affected by IPM, which resulted in concentration decreases of 75% and 89%, respectively. In the baseline scenario 19% of homes were damp at the end of the 10-year simulation. Installation of fans decreased this to 17%, whereas weatherization led to dramatic increases in damp homes (ie, to 67%). The combined intervention of weatherization plus operating kitchen and bathroom exhaust fans increased the percentage of damp homes to 66%.

TABLE II. Baseline health care outcomes from a simulation of asthmatic children over 10 years

FEV ₁ % category	Days with asthma symptoms per year (SD)*	Serious asthma events per year (SD)	ED visits per year (SD)	Hospitalizations per year (SD)	Clinic visits with prescribed oral steroid bursts per year (SD)	No. of children
>80%	140 (11)	0.8 (0.6)	0.09 (0.29)	0.02 (0.08)	0.66 (0.57)	578,155 (58%)
60% to 80%	161 (11)	1.1 (0.7)	0.12 (0.20)	0.03 (0.09)	0.96 (0.64)	385,974 (39%)
<60%	174 (14)	1.8 (1.1)	0.18 (0.22)	0.04 (0.10)	1.6 (1.0)	27,547 (3%)
Across all categories	149 (15)	0.9 (0.7)	0.11 (0.19)	0.03 (0.09)	0.80 (0.65)	991,676

*SD across the million children.

**FIG 2.** Percentage change in pollutant concentrations for each intervention scenario compared with the baseline scenario: **A**, NO₂; **B**, PM_{2.5}. HEPA, High-efficiency particulate air.

Health outcomes decrease under most intervention scenarios but increase with the weatherization efforts, even when coupled with some of the source-reduction measures in the bundled interventions (Fig 3). Interventions such as IPM and repairing

kitchen exhaust fans led to 7% to 12% reductions in serious asthma events. Although repairing exhaust fans reduces indoor concentrations of combustion pollutants, leading to significant outcome improvements for intervention 8 (weatherize plus fix

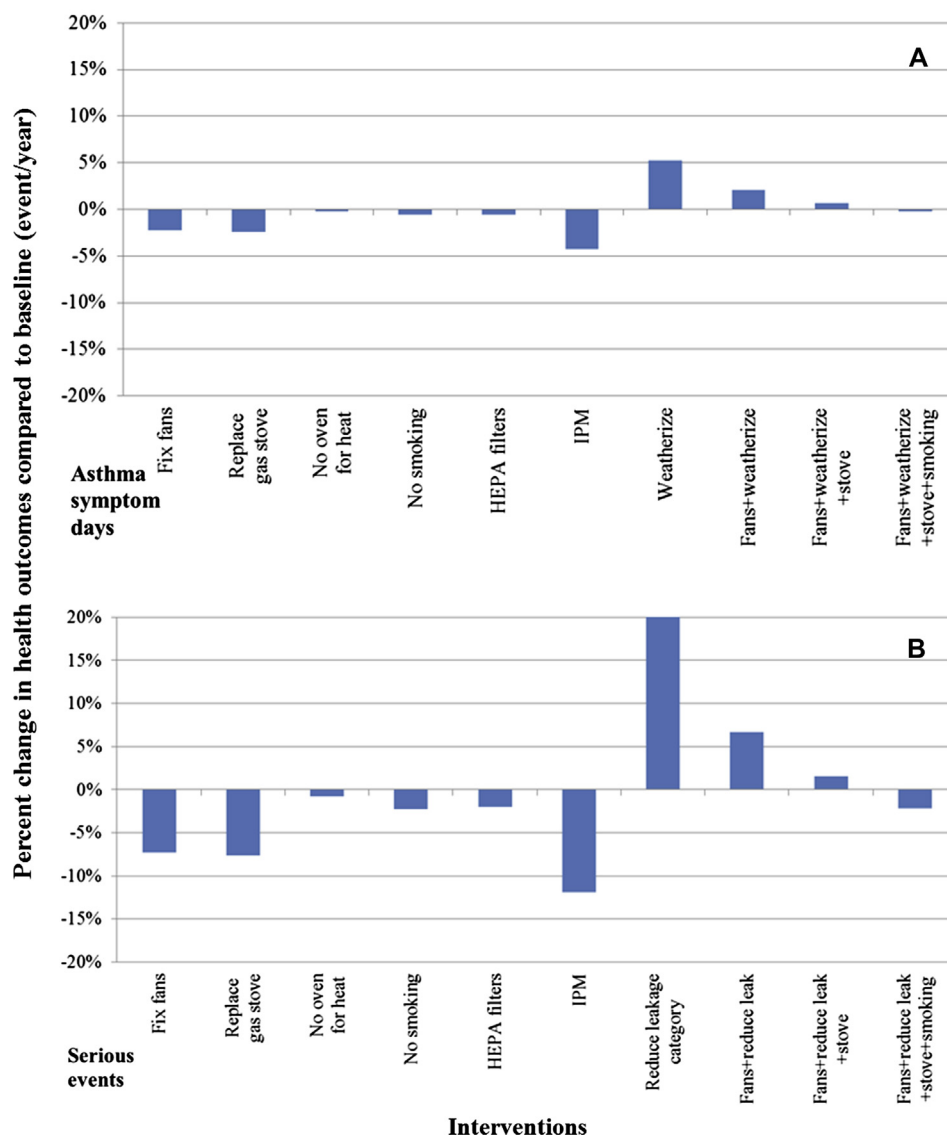


FIG 3. Percentage change in health outcomes for each intervention compared with the baseline scenario. **A,** Asthma symptom days include days with any symptom, including wheeze, cough, and nighttime awakenings. **B,** Serious events include asthma hospitalizations, ED visits, and clinic visits. Asthma outcomes reflect changes in exposure to NO_2 , $\text{PM}_{2.5}$, cockroach allergen, and damp homes. *HEPA*, High-efficiency particulate air.

exhaust fans) relative to weatherization alone, there remains a net increase in symptoms given the limited influence of localized kitchen exhaust fans on reducing apartment humidity. These changes in health outcomes correspond with changes in the yearly cost per asthmatic patient compared with the baseline scenario for each intervention (Fig 4). The highest savings in health care use were associated with IPM, fixing exhaust fans, and replacing the gas stove, and the intervention with the highest cost was weatherization without any other intervention.

DISCUSSION

We demonstrated an application of our DEM of pediatric asthma to estimate differences in health care use costs comparing 7 home-based interventions plus 3 intervention bundles. Our

findings are broadly consistent with the literature. For example, average health outcome rates across all asthma categories (Table II) align closely with our baseline model inputs drawn from the literature: 0.023 (SE, 0.005) hospitalizations per year,^{36,37} 0.1 (SE, 0.02) ED visits per year,³⁸ and 0.78 serious events per year.²¹ Many interventions led to significant reductions in pollutant concentrations, with the magnitude driven by the relatively small apartment size (700 sq ft), the presence of multiple indoor combustion sources, and other assumed building conditions and occupant behaviors. Indoor concentrations were previously shown to agree with the observational literature¹⁶ once the assumed setting was taken into account, and the changes in concentrations in Fig 2 are consistent with these previous comparisons. The weatherization intervention led to a significant increase in the prevalence of damp homes (19% to 67%).

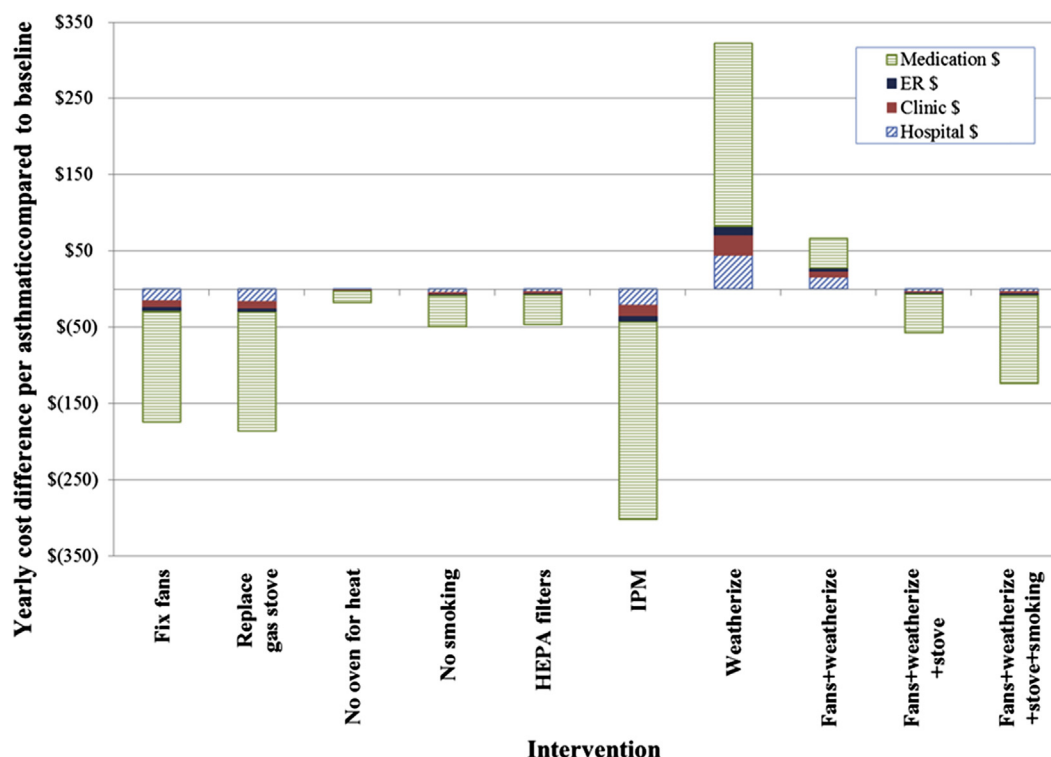


FIG 4. Changes in costs of health care use for each intervention compared with baseline averaged over all asthmatic patients. HEPA, High-efficiency particulate air.

Although this prevalence estimate might appear high, we were simulating small apartments, and previous studies in a Boston public housing development showed 42% of units to have moisture and 43% to have mold,³⁹ which is generally consistent with our findings.

Our estimated costs of health care use are also consistent with the literature. In the simulated baseline population scenario, the mean yearly asthma-related health care expenditure was \$1306 (2009\$), whereas the 2008 MEPS for children reported total health care costs of \$2503 and \$1762 (2008\$) for children with and without asthma treatment, respectively.⁴⁰ The MEPS study reported an average of \$838 (with asthma treatment) and \$192 (without asthma treatment) spent on prescription medication⁴⁰ compared with \$848 (2009\$) in our population. Our estimated costs for ED visits are similar to those in MEPS, which is unsurprising given our use of MEPS to estimate unit costs. In contrast, our estimated expenditures on clinic visits and hospitalizations are less than in MEPS, which is likely related to our use of Medicaid reimbursement codes for clinic visits and an alternative data resource for hospitalizations. In total, in our simulated population asthma medication accounted for 65% of the asthma health care expenditures, clinic visits accounted for 10%, ED visits accounted for 5%, and hospitalizations accounted for 20%.

Given reasonable concordance between our outputs and the literature, we can use some rough approximations of the costs of the interventions to provide insight about the most promising interventions. If the cost of installing a kitchen fan is between \$300 and \$550⁴¹ and the health care use cost savings are \$175/y per asthmatic patient (Fig 4), then the payback period is approximately 1.6 to 3 years. Similarly, if the cost of maintaining an IPM program is \$200/y per unit (unpublished data from Boston public

housing¹³) and the corresponding health care use cost savings are \$302/y per asthmatic patient (Fig 4), the intervention pays for itself every year. This comparison is complicated by the fact that IPM is often implemented on a building-wide basis, with not all units including asthmatic patients, but the study used to derive the reductions in cockroach allergen levels associated with interventions involved unit-specific measures. Thus these would appear to be highly beneficial interventions, especially if the government is paying substantial fractions of both interventions and health care expenditures.

In a comprehensive energy retrofit scenario in which the building is weatherized by sealing cracks, insulating roofs and walls, and replacing windows, the per-unit cost is approximately \$6500.⁴² This increases the cost of health care use by \$322/y per asthmatic patient (Fig 4) but would lead to reduced energy consumption. We can approximate energy savings using the Lawrence Berkeley National Laboratory Home Energy Saver calculator,⁴³ assuming a multifamily building in Boston with 1955 construction, 700 sq ft apartments, and 4 persons living in each apartment. Weatherization was simulated by specifying insulated floor, wall insulation, weather stripping, and roof insulation, as well as replacing single-pane windows with double-pane windows. The resulting energy savings would be \$605 per year. The payback period would therefore be 11 years if only energy savings and intervention costs were considered but 23 years if health care use costs were also included. If, in addition to weatherizing, kitchen exhaust fans are made operable (additional cost \$400), then the payback period is 13 years considering all costs (including health care) and 11.6 years considering only energy savings and weatherization costs. Weatherization can clearly include measures with widely varying intensity, but these

calculations illustrate some of the potential tradeoffs and mitigation measures.

The estimates presented in the previous paragraphs represent payback periods for the average population we simulated. If we restrict the population to the patients with severe asthma, then interventions have a larger effect on health care costs, and those interventions that might not be cost-effective when applied to all units with asthmatic patients might be cost-effective as more targeted measures.

Limitations inherent in the model were discussed previously¹⁶ and include the fact that there was only 1 suitable published study at the time of our analysis of the relationships between lung function and asthma outcomes, limiting the generalizability of our results to other populations. Another limitation is the simplification in classifying patients with persistent asthma for medication assignment solely based on FEV₁% values, although asthma classification is far more complex.^{6,44} In addition, although our model contains numerous parameters and assumptions, we could not characterize CIs for our model outputs, given the use of common random numbers across simulation scenarios to reduce random noise, as well as the model complexity, computational intensity, and lack of evidence beyond parametric uncertainty in reported literature values. One-way (single parameter) sensitivity analyses would have been more computationally viable but would have contributed only limited insight given the complexity of our model, and we addressed sensitivity in part through simulation of numerous children with varying characteristics. Broadly, we view this modeling effort as providing an analytic infrastructure that could be adjusted over time and reparameterized to be applied to specific populations and buildings.

Also, because we constructed a hypothetical population and building with a number of defined characteristics (ie, residents of multifamily low-income housing living in Boston), the cost-benefit comparisons might not generalize to other settings. However, most assumptions were relevant to low-income urban populations living in colder climates, and our model framework could be readily applied to study populations with similar housing characteristics but different demographics or residents living in other types of housing. In addition, our cost-benefit comparisons need to be interpreted with caution in settings in which the entities bearing the costs and benefits of each component are different. For private housing, intervention costs would be a burden on homeowners or landlords (and indirectly on renters), and energy savings would affect homeowners, renters, and/or landlords, whereas changes in health care use would be a combination of societal and individual costs. Finally, although our analysis included multiple environmental exposures and other stressors, there are clearly other exposures that would be influenced by building interventions and influence asthma, which could merit inclusion as the quantitative evidence base evolves. As more information becomes available on other air pollutants and their interactions (eg, ozone, which can interact with NO₂⁴⁵ and is associated with lung function^{4,46}), these can be incorporated into the model. In addition, a comprehensive and decision-relevant model should be expanded to capture the effect on other diseases, such as cardiovascular disease. In spite of these limitations, our DEM offers novel and relevant insight consistent with the small literature database on intervention studies and asthma outcomes.^{11,12,47-49}

Our work bridges the gap between clinical and environmental health sciences by providing physicians with information to increase their understanding of the effect that home

environmental changes can have on their patients' asthma. Physicians can then educate their patients on environmental hazards that contribute to asthma exacerbations and suggest interventions to decrease exposures.

In conclusion, we applied a validated DEM to evaluate the implications of home-based interventions on indoor environmental quality and pediatric asthma. Results from the model highlight the short payback periods for key interventions, such as IPM and repairing exhaust fans, and emphasize the importance of responsibly implementing energy-saving interventions with a focus on indoor environmental quality and health. Bundling of interventions, such as installing point-source exhaust fans and removing indoor combustion sources, can largely offset the increase in indoor air pollution resulting from weatherization and still maintain energy savings. Our work highlights the effect that environmental exposures have on asthma symptoms, increases awareness of a multi-intervention approach to control asthma that includes both medication and environmental components, and highlights the cost-benefits of environmental home interventions.

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Key messages

- Environmental changes in the homes of asthmatic patients can affect their asthma symptoms because of changes in exposure to indoor environmental pollutants.
- Clinicians should take a multi-intervention approach to asthma control, which includes both medication and environmental interventions, to reduce asthma-associated pollutant exposures.
- Results emphasize the importance of responsibly implementing energy-saving interventions with a focus on indoor environmental quality and health and highlight the short payback periods for key interventions, such as IPM, repair or installation of exhaust fans, and indoor source elimination.

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Supplement 1. Exposure-related input distributions and equations for discrete event simulation model

Table E1 presents the distributions, values and references for indoor and outdoor pollutant sources used in discrete event simulation model

Supplement 1 equations

24-hour indoor NO_2 and $\text{PM}_{2.5}$ concentration equations

For NO_2 and $\text{PM}_{2.5}$, daily 24-hour average exposures were estimated with regression models developed using the multi-zone simulation software output from CONTAM2.4c (NIST, Gaithersburg, MD, <http://www.bfrl.nist.gov/IAQanalysis>), an approach described in more detail elsewhere (1). Briefly, within CONTAM, we selected the building most typical of Boston public housing and other low-income multi-family dwellings in Boston –a building 4 stories, 1940-1969 construction, and naturally ventilated (2). A family of 2 adults and 2 children were simulated living in each 703 square foot apartment, which included a bedroom, bathroom, living room, and kitchen. Sources of NO_2 included the gas stove used for cooking, the gas oven used for supplemental heat in the winter, and outdoors. Sources of $\text{PM}_{2.5}$ included environmental tobacco smoke, cooking, and outdoors. Based on the regression models developed, the 24-hour concentration of each pollutant was updated daily in the simulation model. Tables E2 and E3 show the regression equations, copied from (3).

Mold growth model equations

Mold growth was calculated using a set of differential equations developed to model mold growth on wooden material (4) which estimate a daily mold index (M) (Table E4).

Mold growth was associated with relative humidity with the following equations, taken from (4):

where:

dM/dt = change in mold index (day^{-1})

M = mold index (unitless)

t = time (days)

t_{m1} = time (weeks) at which mold growth will initiate at constant RH and temp, i.e. $M=1$

k_1, k_2 = correction coefficients (unitless), where

if $M < 1$ then

$k_1 = 1$

$k_2 = 1$

if $M \geq 1$ then

where

t_v = time (weeks) at which there will be visible mold, ie $M=3$

$M_{\max}$ = largest possible value of the mold index at a given
relative humidity and temperature

Supplement 2. Health outcome-related input distributions and equations for discrete event simulation model

Table E5 presents distributions, values and references describing lung function parameters, relationships between indoor pollutants and lung function, and lung function and healthcare utilization

Supplement 2 equations

Probability of being prescribed and adhering to taking prescribed asthma medication (i.e. “compliant”)

We used data from HPHI to estimate the relationship between FEV1% and the probability of being prescribed a controller medication. We used SAS (Proc Logit, version 9.1, SAS Institute Inc., Cary, NC) to calculate the odds of being prescribed asthma medication, and converted the odds ratio to a probability estimate. The resulting probability equation was:

where: P_{med} is the probability of reporting a controller medication
FEV1% is the baseline lung function value.

The assigned probability was then used in a binomial distribution to transform into a “Yes/No” variable.

Cockroach allergen equations

We selected an individual study with all relevant attributes but conducted in adults (asthmatics and non-asthmatics). In this study, Weiss et al. found that log-transformed dust concentrations of Bla g 1 and Bla g 2 were both significantly associated with longitudinal FEV1 decline (Δ FEV1), with multiple linear regression coefficients of -194.14 mL/year and -94.83 mL/year respectively (5). The study did not report functions for asthmatics only, so we used values for the entire population, noting that the relationship between dust concentrations and FEV1 was not appreciably different for the non-asthmatic population than the population as a whole. We converted change in FEV1 (Δ FEV1) to change in FEV1% by dividing Δ FEV1 by FEV1 predicted, where FEV1 predicted was calculated using the NHANES equation below (6), using the average age and height reported in Table 1 of the Weiss study.

where:

age = 57.5 years (5)

height = 174.42 cm (5).

where FEV1predicted = 3.52 L (calculated with previous equation)

Δ FEV1 = -194.14 mL/year for Bla g 1, and -94.83 mL/year for Bla g 2, respectively

Probability of asthma symptom days

The frequency of asthma symptoms was characterized in Fuhlbrigge et al (7) (listed in that article’s Figure 1), which shows the number of episode-free days per 4-month period across four categories of

FEV1% (<60%, 60-79%, 80-99%, ≥ 100%). An episode-free day was defined as “a day with an asthma diary asthma score of 0, and no report of night awakening, morning and evening peak flow >80% personal best, no albuterol use for symptoms or prednisone use, absence from school as a result of asthma, or physician contact as a result of asthma”. We focused on the number of days with symptoms to be better aligned with our model structure. To convert this into a continuous function of FEV1%, we used the estimated midpoint of each FEV1% (50%, 70%, 90%, and 110%) category and fit the following polynomial expression:

$$P_{\text{symptom_day}} = 2.95 \text{ FEV1\%}^3 - 6.93 \text{ FEV1\%}^2 + 4.68 \text{ FEV1\%} - 0.27$$

where

$P_{\text{symptom_day}}$ = daily probability of having a day with asthma symptoms as defined above.

FEV1% = forced expiratory volume 1 percent predicted

The equation is valid for values of FEV1% between 0.5 and 1.2.

The assigned probability was then used in a binomial distribution to transform into a “Yes/No” variable.

Probability of “serious asthma events”

A similar process was used to fit an equation predicting “serious asthma events”, defined in Fuhlbrigge et al. as oral steroid use, hospitalization, or emergency room visit (7). Table 3 of Fuhlbrigge et al. provides a multivariate regression model including the influence of FEV1% (again in four categories) as well as night awakenings and previous hospitalizations. To convert the reported odds ratios into a probability of a serious asthma event based on a continuous FEV1% scale, we first determined the baseline rate of serious asthma events and converted it to a probability of a serious asthma event. Fuhlbrigge et al reported that their study population had a baseline rate of 0.26 serious asthma events per 4 month period, or approximately 0.0022 events per day (probability of 0.0022). Distributing this rate on a population-weighted basis following odds ratios and population numbers in Table 1 of Fuhlbrigge et al. yields daily event probabilities of 0.0068, 0.0032, 0.0022, and 0.0017 in the four FEV1% categories of decreasing severity. Fitting a polynomial expression to these values leads to a resulting equation of:

$$P_{\text{serious event}} = -0.045 \text{ FEV1\%}^3 + 0.1277 \text{ FEV1\%}^2 - 0.1224 \text{ FEV1\%} + 0.0417$$

where:

$P_{\text{serious event}}$ = daily probability of having a serious asthma event

FEV1% = forced expiratory volume 1 percent predicted

The equation is valid for values of FEV1% between 0.5 and 1.2. $P_{\text{serious event}}$ was multiplied by a seasonality factor.

The assigned probability was then used in a binomial distribution to transform into a “Yes/No” variable.

Probability of asthma hospitalization

We constructed a polynomial equation to predict the daily probability of hospitalization based on FEV1% using the approach described above, with the resulting equation:

$$P_{\text{hosp}} = -0.0013 \text{ FEV1\%}^3 + 0.0037 \text{ FEV1\%}^2 - 0.0036 \text{ FEV1\%} + 0.0012$$

where P_{hosp} includes direct hospitalizations and transfers from the ER to the hospital.

The assigned probability was then used in a binomial distribution to transform into a “Yes/No” variable.

Based on data published in the Fuhlbrigge study, if a child had a hospitalization due to asthma in the previous 12 months, their probability of having a serious asthma event increased (Table 3, (7)). We calculated this multiplicative factor following the same process described above, with the resulting polynomial equation:

$$O_{\text{hospit}} = -45.7\text{FEV1}\%^3 + 129.7\text{FEV1}\%^2 - 124.4\text{FEV1}\% + 42.4$$

where:

O_{hospit} = increased odds of having a serious asthma event given an asthma hospitalization in the last 12 months, and was equal to 1 if no hospitalization had occurred.

Probability of ER visits and oral steroid bursts

For ER visits, we built a similar equation, where the daily probability of going to the ER is:

$$P_{\text{ER}} = -0.0057 \text{FEV1}\%^3 + 0.0162 \text{FEV1}\%^2 - 0.0155 \text{FEV1}\% + 0.0053$$

Because 8% of ER visits result in hospitalization and are already accounted for in P_{hosp} , we multiplied P_{ER} by 0.92 so as not to overestimate ER visits (8).

Oral steroid bursts were estimated by subtracting P_{hosp} and P_{ER} from $P_{\text{serious event}}$.

The assigned probability was then used in a binomial distribution to transform into a “Yes/No” variable.

Supplement 3.

Table E6 presents the simulated interventions targeting the indoor environment or energy savings. See Supplement 1 for pollutant source details.

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Table E1. Distributions, values and references for indoor and outdoor pollutant sources used in discrete event simulation model

Indoor pollutant concentrations				
PM _{2.5} and NO ₂	Estimated using regression models, see Supplement 1			
Damp house	Dichotomous variable indicating house was “damp”, estimated based on mold index, calculated with differential equations, see section Supplement 1			
Cockroach allergen	<i>Geometric mean</i>	<i>Geometric standard deviation</i>	<i>Distribution</i>	<i>Reference</i>
Bla g 1 in houses...				
a) with holes in walls and below average housekeeping	143.5 U/g	3.6	lognormal	raw data from (9)
b) with holes in walls and average or >average housekeeping	42.7 U/g	6.2	lognormal	raw data from (9)
c) without holes and average or >average housekeeping	8.2 U/g	14.6	lognormal	raw data from (9)
Bla g 2 in houses...				
a) with holes in walls and below average housekeeping	691.4 U/g	8.6	lognormal	raw data from (9)
b) without holes in walls and average or >average housekeeping	117.3 U/g	9.0	lognormal	raw data from (9)
c) without holes and average or >average housekeeping	21.9 U/g	12.5	lognormal	raw data from (9)
Other factors				
Indoor multiplication factor (time spent indoors)			0.7	Table 15-3 of (10)
Seasonality factor for “serious” asthma health outcomes			(11)	
Spring	1.11			
Summer	0.60			
Fall	1.23			
Winter	1.05			
NO ₂ indoor/outdoor infiltration	0.58	Average of infiltration rates reported by (12-15)		
PM _{2.5} indoor/outdoor infiltration	0.72	Average of infiltration rates reported by (15-17)		

Table E2. Regression models predicting indoor NO₂ concentrations from cooking, heating the house with the oven, and outdoors, from a set of apartments in a multi-family building simulated with CONTAM.

Dependent variable: log (NO₂ from cooking (µg/m³))				Model R²=0.89		
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	3.03	0.03	93.5	<.0001	-	-
Fan off	0.98	0.01	68.8	<.0001	0.60	0.60
Box model term 1 ^a	0.47	0.02	28.0	<.0001	0.29	0.86
AER ^b	-0.06	0.01	-9.9	<.0001	0.20	0.87
Lower level	-0.23	0.02	-14.3	<.0001	0.01	0.89
Dependent variable: log (NO₂ from heating in winter(µg/m³))				Model R²= 0.98		
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	3.56	0.03	106.6	<.0001	-	-
Box model term 2 ^c	1.91	0.05	38.1	<.0001	0.92	0.92
AER ^b	-0.11	0.01	-22.2	<.0001	0.82	0.96
Lower level	-0.16	0.01	-11.1	<.0001	0.13	0.98
Fan off	0.05	0.01	4.1	<.0001	0.004	0.98
Dependent variable: log (NO₂ from outdoors(µg/m³))				Model R²=0.90		
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	0.83	0.03	25.3	<.0001	-	-
Infiltration term ^d *NO ₂ out	141.71	2.58	54.9	<.0001	0.86	0.86
AER ^b	-0.02	0.01	-3.7	0.0002	0.50	0.87
Season: Fall	0.16	0.02	8.7	<.0001	0.13	0.87
Season: Spring	0.08	0.02	4.6	<.0001	-	-
Season: Summer	0.14	0.02	7.1	<.0001	-	-
Lower level	0.21	0.01	15.2	<.0001	0.06	0.90

^a Box model term 1=stoveuse/(aer+kNO₂)

^b AER= air exchange rate or air change rate

^c Box model term 2= 1/(aer+kNO₂)

^d Infiltration term= p*aer/(aer+kNO₂)

Table E3. Regression models predicting indoor PM_{2.5} concentrations from cooking, environmental tobacco smoke (ETS), and outdoors, from a database of apartments in a multi-family building simulated with CONTAM.

Dependent variable: log (PM_{2.5} from cooking (µg/m³))					Model R²=0.91	
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	2.95	0.03	111.3	<.0001	-	-
Fan off	1.02	0.02	62.9	<.0001	0.43	0.43
Box model term 1 ^a	0.24	0.01	38.5	<.0001	0.43	0.83
AER ^b	-0.15	0.01	-23.1	<.0001	0.32	0.87
Lower level	-0.38	0.02	-21.0	<.0001	0.01	0.91
Dependent variable: log (PM_{2.5} from ETS (µg/m³))					Model R²=0.93	
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	3.64	0.02	149.0	<.0001	-	-
AER ^b	-0.31	0.01	-55.9	<.0001	0.75	0.75
Box model term 2 ^c	0.48	0.01	44.4	<.0001	0.66	0.86
Lower level	-0.48	0.02	-31.1	<.0001	0.04	0.92
Season: Fall	-0.04	0.02	-2.3	0.0218	0.04	0.93
Season: Spring	0.04	0.02	2.0	0.0458	-	-
Season: Summer	-0.17	0.02	-8.3	<.0001	-	-
Dependent variable: log (PM_{2.5} from outdoors (µg/m³))					Model R²=0.91	
	Estimate (β)	Standard Error	t value	P value	Univariate R ²	Partial R ²
Intercept	0.80	0.02	35.6	<.0001	-	-
Infiltration term ^d *PM _{2.5} out	0.13	0.002	53.3	<.0001	0.59	0.59
Season: Fall	-0.03	0.01	-2.9	0.0045	0.39	0.76
Season: Spring	-0.21	0.01	-21.3	<.0001	-	-
Season: Summer	-0.42	0.01	-30.8	<.0001	-	-
AER ^b	0.04	0.003	14.7	<.0001	0.14	0.76
Lower level	0.28	0.01	36.4	<.0001	0.01	0.91

^a Box model term 1= stoveuse/(aer+kPM_{2.5})

^c Box model term 2= 1/(aer+kETS)

^b AER= air exchange rate

^d Infiltration term= p*aer/(aer+kPM_{2.5})

Table E4. Description of mold index developed to describe mold growth in wood

mold index (M)	mold growth description
0	No growth
1	Some growth detected only with microscopy
2	Moderate growth detected with microscopy (coverage more than 10%)
3	Some growth detected visually
4	Visually detected coverage more than 10%
5	Visually detected coverage more than 50%
6	Visually detected coverage 100%

Table E5. Distributions, values and references describing lung function parameters, relationships between indoor pollutants and lung function, and lung function and healthcare utilization.

FEV1% distribution & daily variation				
	Mean	Standard deviation	Distribution	Reference
Baseline FEV1%	88.4%	11.6	normal	raw data from HPHI study (n=48)
FEV1% daily difference	5%	raw data from HPHI study (n = 110 individual week long spirometry sessions, with an average 10 observations/session). Total variability (random + environmental effects) was 10%, we assumed 5% was random variability		
Long term changes in FEV1%				
Yearly ΔFEV1% for 5-10 year old asthmatics			(18)	
Without SARE ^a in last 3 years, compliant and non-compliant	-0.8%			
With SARE ^a in last 3 years, compliant	-0.8%			
With SARE ^a in last 3 years, noncompliant	-2.1%			
Yearly ΔFEV1% for 11-17 year old asthmatics			(18)	
Without SARE ^a in last 3 years, compliant and non-compliant	0%			
With SARE ^a in last 3 years, compliant	-0.3%			
With SARE ^a in last 3 years, noncompliant	-1%			
Asthma medication compliance		See Supplement 2		
Coefficients for association between FEV1% and pollutants				
	Mean	Standard error	Distribution	Reference
ΔFEV1% per unit increase in NO ₂ (ppb)	-0.093 %	0.030	normal	(19)
ΔFEV1% per unit increase in PM _{2.5} (ug/m ³)	-0.077%	0.032	normal	(19)
ΔFEV1% when house classified as “damp”	-10.6%	4.95	normal	(20)
ΔFEV1% per unit increase in log transformed Bla g 1 concentration (U/g)	-0.055%	0.013	normal	(5), see Supplement 2
ΔFEV1% per unit increase in log transformed Bla g 2 concentration (U/g)	-0.027%	0.007	normal	(5), see Supplement 2
Baseline rates of asthma health outcomes				

Serious asthma events	0.26 events/4 month period	(7)
Hospitalizations	0.023 per year per asthmatic child	(21, 22)
Emergency room (ER) visits	0.1 per year per asthmatic child	(23)
Associations between FEV1% and asthma health outcomes		
Probability of having an asthma symptom day		See Supplement 2
Probability of having a “serious” asthma event		See Supplement 2
Probability of asthma hospitalization		See Supplement 2
Probability of ER visits		See Supplement 2

^aSARE = severe asthma-related event, defined in our model as a hospitalization or ER visit

Table E6. Simulated interventions targeting the indoor environment or energy savings. See Supplement 1 for pollutant source details.

Intervention	Rationale	Modeling
Individual interventions		
0. Baseline scenario		
1. Fix kitchen and bathroom fans	Proper spot ventilation will reduce exposure to pollutants associated with cooking and control moisture buildup	Assumed kitchen fan was operated 100% of time during cooking events (100 cfm); turned bathroom fan 'on' during shower events (50 cfm)
2. Replace gas with electric stove	Gas stoves are a source of NO ₂ from cooking and supplemental heating; replacement with electric stoves will reduce exposure	Removed NO ₂ stove source, simulating the replacement of gas stoves with electric stoves
3. Fix heating system (eliminate inconsistent heating)	Functional heating will eliminate the need to heat with stove, and thus reduce pollutant exposures	Eliminated NO ₂ source associated with the use of gas stove for supplemental heating
4. Smoke-free housing policy	Cigarettes are major source of indoor PM _{2.5} ; removal of this source will lower exposures	Removed smoking sources
5. Use High-Efficiency Particulate Air (HEPA) filter	Will reduce exposure to particles from smoking and other sources	Reduced PM _{2.5} by 25%
Intervention	Rationale	Modeling
6. Integrated Pest Management	Elimination of pest pathways will reduce allergen levels	Eliminated number of homes with holes in wall
7. Weatherize (air sealing, window replacement)	Elimination of air pathways will conserve energy	Moved households in the highest categories of wall infiltration rates (category 2 and 3) down by one category. Category 1, equivalent to an efficient level of air exchange, remains

Intervention	Rationale	Modeling
		the same
Bundled interventions		
8. Weatherize (#7) + fix exhaust fans (#1)		
9. Weatherize (#7) + fix exhaust fans (#1) + replace gas stove (#2)		
10. Weatherize (#7) + fix exhaust fans (#1) + replace gas stove (#2) + non-smoking policy (#4)		