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

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Abstract

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

Objective—To evaluate the impacts of building interventions on indoor environmental quality and pediatric asthma healthcare utilization, and to conduct cost comparisons between intervention and healthcare 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 multi-family housing. We estimated healthcare utilization and costs at baseline and subsequent to interventions, and then compared healthcare costs to energy savings and intervention costs.

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

Conclusion—Our pediatric asthma model provides a tool to prioritize individual and bundled building interventions based on their impact on health and cost, and highlighting the tradeoffs between weatherization, indoor air quality, and health. Our work bridges the gap between clinical

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and environmental health sciences by increasing physicians' understanding of the impact that home environmental changes can have on their patients' asthma.

Keywords

air pollution; allergen; asthma; discrete event simulation; energy savings; green building; housing; intervention; indoor air; lung function; NO₂; PM_{2.5}; simulation

Introduction

Asthma is a classic example of a dynamic and non-linear disease with numerous factors influencing disease course (1). In the US, 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 (e.g., dust mites, cockroach allergens), air pollutants (e.g., ozone, nitrogen dioxide, fine particulate matter), and environmental tobacco smoke (ETS) (3, 4). Other factors influencing asthma exacerbations include access to health care, medication compliance, and respiratory infections such as rhinovirus (5, 6).

A recent systematic review by the Centers for Disease Control and Prevention (CDC) found that multi-trigger, multi-component, 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 (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 room (ER) visits, or other less frequent outcome measures that are key components of asthma-related direct costs (14). Without evidence of changes in healthcare utilization, 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 logistical challenges due to small study populations (power constraints), rareness of many serious asthma outcomes, and potential confounders, particularly in complex populations such as low-income multi-family 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 utilization (11–13) 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 (such as tightening the building envelope) may yield energy savings and reduce outdoor air infiltration but increase the influence of indoor sources, while others may 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

validated a discrete event simulation model (DEM) of pediatric asthma (16) to simulate the effect of indoor environmental factors, medication compliance, seasonality, and medical history on asthma outcomes (symptom-days, medication use, hospitalizations, and ER visits) in low-income multi-family housing. The model allows for evaluation of changes in asthma health outcomes and pollutant concentrations due to changes in building characteristics as would occur with energy saving measures and other interventions which alter the indoor residential environment. In this study, we apply our model to quantify the effect of multiple building interventions in low-income multi-family dwellings, focusing on health care utilization 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 (Figure 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 four contaminants that can potentially affect a child's lung function and asthma status: two combustion pollutants (NO_2 and $\text{PM}_{2.5}$), 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 FEV1%, or an ability to readily model indoor concentrations. NO_2 and $\text{PM}_{2.5}$ were simulated using CONTAM (NIST, Gaithersburg, MD, USA) (<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 (RH) 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 and described elsewhere (16).

Other time-varying characteristics included age, outdoor temperature, indoor and outdoor RH, daily random variation in baseline FEV1%, and changes in FEV1% due to all risk factors. As previously described (16) and summarized in Supplement 2, contaminant concentrations are then used to predict the percent predicted forced expiratory volume in one second (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 utilization. Asthma outcomes are computed daily for each child, derived from a prior model of the association between FEV1% and asthma symptoms or serious asthma events (ER 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, built in R (R 2.12.1, The 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 multi-family housing consistent with public housing residents, a population known to have elevated 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). While we lacked sufficient symptom and severity data to apply the National Heart, Lung and Blood Institute (NHLBI) classification guidelines for managing asthma (6), we used the FEV1% cutoffs that correspond with severity classification for persistent asthmatics (> 80% for mild, 60–80% for moderate, and < 60% for severe), and used these to determine the prescribed medications. Intermittent asthmatics were excluded from the simulation because of the limited environmental literature on this severity class.

Asthma medication utilization and cost data

Our assumptions regarding asthma medication prescriptions, usage, and costs are shown in Table I, stratified by FEV1% categorization. Although persistent asthmatics should be prescribed controller medications (6), studies have found gaps for a number of reasons (26). We therefore simulated the probability of using a controller medication as a function of FEV1% (Supplement 2).

Children were evaluated at the end of each simulated year to determine changes in their asthma medication prescription, approximating adjustments that would happen during a yearly physical exam. At every year anniversary we compared each child's average FEV1% during the past 365 days to his or her FEV1% at the beginning of the year, and reclassified children'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 ER or the clinic. The medication cost assigned to the oral steroid burst was \$10 per visit, based on Prednisone costs (27).

Healthcare utilization costs

Costs for asthma related clinic visits (\$ 156, Current Procedural Terminology/CPT® code 99244), ER 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 (AHRQ) Healthcare cost and utilization project (30), respectively. All costs were adjusted to 2009 dollars based on the Medical Care Consumer Price Index (31). While numerous indirect costs associated with asthma exacerbations have important economic implications (14), such as lost work days or missed school, we focused on direct healthcare costs to be aligned with prior cost-benefit analyses of asthma interventions (12). In addition, we focused on low-income multi-family housing where health coverage may be through partially or totally government-subsidized health care (e.g. Medicaid, Medicare). For this subpopulation, the government (broadly defined) might both be responsible for building repairs/improvements and paying healthcare costs, so 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) smoke-free housing policy, 5) use of

HEPA filters, 6) integrated pest management, 7) weatherization. Supplement 3 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 the table). Interventions were added in order of ascending cost (fans being the cheapest intervention, and a no-smoking policy 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 by multiple approaches including investigating surveillance and field measurement data (32–35), consulting with the study pediatrician, and standard review for outliers. Exclusion values were 225/year for asthma symptom days, 24/year for serious asthma events, 3/year for hospitalizations, 7/year for ER visits, 24/year for clinic visits, 200 ppb for NO₂, and 200 µg/m³ for PM_{2.5}.

Results

The cohort of one million children was simulated for the baseline scenario and for each intervention over a ten year horizon. Based on 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% 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 standard errors for the means of all pollutant and asthma health outcomes. The ratio of standard error to mean varied between 0.0002 and 0.003, evidence of the stability of our calculated means across subpopulations.

Figure 2 presents the changes in NO₂ and PM_{2.5} concentrations attributable to each intervention compared to baseline. Concentrations of Black 1 and Black 2 are not shown in the figure as 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 ten-year simulation. Installation of fans decreased this to 17% while weatherization led to dramatic increases in damp homes, to 67%. The combined intervention of weatherization plus operating kitchen and bathroom exhaust fans resulted in 66% of damp homes.

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 (Figure 3). Interventions such as integrated pest management and repairing kitchen exhaust fans led to 7–12% reductions in serious asthma events. While repairing exhaust fans reduces indoor concentrations of combustion pollutants, leading to significant outcome improvements for intervention 8 (weatherize + fix 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 yearly cost per asthmatic compared to the baseline scenario for each intervention (Figure 4). The highest savings in healthcare utilization 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 healthcare utilization costs comparing seven home-based interventions plus three 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/year (36, 37), 0.1 (SE=0.02) ER visits/year (38), 0.78 serious events/year (21). Many interventions led to significant reductions in pollutant concentrations, with the magnitude driven by the relatively small apartment size (700 square feet), 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 literature (16) once the assumed setting was taken into account, and the changes in concentrations in Figure 2 are consistent with these previous comparisons. The weatherization intervention led to a significant increase in the prevalence of damp homes (19% to 67%). While this prevalence estimate may 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), generally consistent with our findings.

Our estimated costs of healthcare utilization are also consistent with the literature. In the simulated baseline population scenario, the mean yearly asthma-related healthcare expenditure was \$1,306(2009\$), while the 2008 MEPS for children reported total healthcare costs of \$2,503 and \$1,762 (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 medication (40), compared to \$848 (2009\$) in our population.

Our estimated costs for ER 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, 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 healthcare expenditure, clinic visits 10%, ER visits 5%, and hospitalizations 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 \$550 (41), and the healthcare utilization cost savings are \$175/yr/asthmatic (Figure 4), then the payback period is approximately 1.6 to 3 years. Similarly, if the cost of maintaining an IPM program is \$200/year/unit (unpublished data from Boston public housing (13)), and the corresponding healthcare utilization cost savings are \$302/yr/asthmatic (Figure 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 asthmatics, 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 healthcare expenditures.

In a comprehensive energy retrofit scenario, where the building is weatherized by sealing cracks, insulating roofs and walls, and replacing windows, the per unit cost is approximately \$6,500 (42). This increases the cost of healthcare utilization by \$322/yr/asthmatic (Figure 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

multi-family building in Boston with 1955 construction, 700 sq ft apartments, and four people 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 are considered, but 23 years if healthcare utilization costs are 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 healthcare), 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 severe asthmatics, then interventions have a larger impact in healthcare costs, and those interventions that may not be cost-effective when applied to all units with asthmatics may be cost-effective as more targeted measures.

Limitations inherent in the model were discussed previously (16), and include the fact that there was only one 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 persistent asthmatics for medication assignment solely based on FEV1%, although asthma classification is far more complex (6, 44). In addition, although our model contains numerous parameters and assumptions, we could not characterize confidence intervals 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 the 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 analytical infrastructure that could be adjusted over time and reparameterized to be applied to specific populations and buildings.

Also, as we constructed a hypothetical population and building with a number of defined characteristics (i.e., residents of multi-family low-income housing living in Boston), the cost-benefit comparisons may 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 where 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 impact homeowners, renters, and/or landlords, while changes in healthcare utilization would be a combination of societal and individual costs. Finally, while 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 (for example, ozone, which can interact with NO₂ (45) 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 impacts 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 impact 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.

Conclusions

We applied a validated discrete event simulation model to evaluate the implications of home-based interventions on indoor environmental quality and pediatric asthma. Results from the model highlight the short pay-back periods for key interventions such as integrated pest management and repairing exhaust fans, and emphasize the importance of responsibly implementing energy savings 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 impact that environmental exposures have on asthma symptoms, increases awareness of a multi-intervention approach to control asthma which includes both medication and environmental components, and highlights the cost-benefits of environmental home interventions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations

AHRQ	Agency for Healthcare Research and Quality
CDC	Centers for Disease Control and Prevention
CI	confidence interval
CPT®	Current Procedural Terminology
DEM	discrete event simulation model
ER	emergency room
FEV1%	percent predicted forced expiratory volume in one second
ETS	environmental tobacco smoke

HEPA	High-Efficiency Particulate Air
ICS	inhaled corticosteroids
IPM	integrated pest management
LABA	long-acting beta2-agonists
MEPS	Medical Expenditure Panel Survey
NHLBI	National Heart, Lung and Blood Institute
NO₂	nitrogen dioxide
PM_{2.5}	particulate matter smaller than 2.5 µm in diameter
RH	relative humidity
SABA	short-acting beta2-agonists
SD	standard deviation
SE	standard error
US	United States

References

1. Frey U. Predicting asthma control and exacerbations: chronic asthma as a complex dynamic model. *Curr Opin Allergy Clin Immunol*. 2007 Jun; 7(3):223–230. [PubMed: 17489039]
2. Merrill, CT.; Elixhauser, A. Hospitalization in the United States, 2002: HCUP Fact Book No. 6. Rockville, MD: Agency for Healthcare Research and Quality; 2005.
3. Medicine, Io, editor. IOM. Clearing the air: asthma and indoor exposures. Washington DC: National Academy Press; 2000.
4. Sharma HP, Hansel NN, Matsui E, Diette GB, Eggleston P, Breyse P. Indoor environmental influences on children's asthma. *Pediatr Clin North Am*. 2007 Feb; 54(1):103–120. ix. [PubMed: 17306686]
5. Johnston NW, Sears MR. Asthma exacerbations. 1: epidemiology. *Thorax*. 2006 Aug; 61(8):722–728. [PubMed: 16877691]
6. NHLBI. National Asthma Education and Prevention Program Expert Panel Report 3: Guidelines for the diagnosis and management of asthma. Bethesda, MD: National Heart Lung and Blood Institute, National Institutes of Health; 2007.
7. Crocker DD, Kinyota S, Dumitru GG, Ligon CB, Herman EJ, Ferdinands JM, et al. Effectiveness of home-based, multi-trigger, multicomponent interventions with an environmental focus for reducing asthma morbidity a community guide systematic review. *Am J Prev Med*. 2011 Aug; 41(2 Suppl 1):S5–S32. [PubMed: 21767736]
8. Peters JL, Levy JI, Muilenberg ML, Coull BA, Spengler JD. Efficacy of integrated pest management in reducing cockroach allergen concentrations in urban public housing. *J Asthma*. 2007 Jul-Aug; 44(6):455–460. [PubMed: 17654132]
9. Brugge D, Rioux C, Groover T, Peters J, Kosheleva A, Levy JI. Dust mites: using data from an intervention study to suggest future research needs and directions. *Rev Environ Health*. 2007 Jul-Sep; 22(3):245–254. [PubMed: 18078006]
10. Adgate JL, Ramachandran G, Cho SJ, Ryan AD, Grengs J. Allergen levels in inner city homes: baseline concentrations and evaluation of intervention effectiveness. *Journal of exposure science & environmental epidemiology*. 2008 Jul; 18(4):430–440. [PubMed: 18059423]
11. Lanphear BP, Hornung RW, Khoury J, Yolton K, Lierl M, Kalkbrenner A. Effects of HEPA air cleaners on unscheduled asthma visits and asthma symptoms for children exposed to secondhand tobacco smoke. *Pediatrics*. 2011 Jan; 127(1):93–101. [PubMed: 21149427]

12. Kattan M, Stearns SC, Crain EF, Stout JW, Gergen PJ, Evans R 3rd, et al. Cost-effectiveness of a home-based environmental intervention for inner-city children with asthma. *J Allergy Clin Immunol*. 2005 Nov; 116(5):1058–1063. [PubMed: 16275376]
13. Levy JI, Brugge D, Peters JL, Clougherty JE, Saddler SS. A community-based participatory research study of multifaceted in-home environmental interventions for pediatric asthmatics in public housing. *Soc Sci Med*. 2006 Oct; 63(8):2191–2203. [PubMed: 16781807]
14. Weiss KB, Sullivan SD. The health economics of asthma and rhinitis. I. Assessing the economic impact. *J Allergy Clin Immunol*. 2001 Jan; 107(1):3–8. [PubMed: 11149982]
15. Law, AM.; Kelton, WD. Simulation modeling and analysis. Boston, MA: McGraw-Hill Higher Education; 2000.
16. Fabian MP, Stout NK, Adamkiewicz G, Geggel A, Ren C, Sandel M, et al. The effects of indoor environmental exposures on pediatric asthma: a discrete event simulation model. *Environ Health*. 2012; 11(66)
17. Fabian MP, Adamkiewicz G, Levy JI. Simulating indoor concentrations of NO₂ and PM_{2.5} in multi-family housing for use in health-based intervention modeling. *Indoor Air*. 2011 Sep 13.
18. Fuhlbrigge AL, Bae SJ, Weiss ST, Kuntz KM, Paltiel AD. Cost-effectiveness of inhaled steroids in asthma: impact of effect on bone mineral density. *J Allergy Clin Immunol*. 2006 Feb; 117(2):359–366. [PubMed: 16461137]
19. Paltiel AD, Fuhlbrigge AL, Kitch BT, Liljas B, Weiss ST, Neumann PJ, et al. Cost-effectiveness of inhaled corticosteroids in adults with mild-to-moderate asthma: results from the asthma policy model. *J Allergy Clin Immunol*. 2001 Jul; 108(1):39–46. [PubMed: 11447380]
20. Wu AC, Paltiel AD, Kuntz KM, Weiss ST, Fuhlbrigge AL. Cost-effectiveness of omalizumab in adults with severe asthma: results from the Asthma Policy Model. *J Allergy Clin Immunol*. 2007 Nov; 120(5):1146–1152. [PubMed: 17904628]
21. Fuhlbrigge AL, Weiss ST, Kuntz KM, Paltiel AD. Forced expiratory volume in 1 second percentage improves the classification of severity among children with asthma. *Pediatrics*. 2006 Aug; 118(2):e347–e355. [PubMed: 16864642]
22. Brugge D, Rice PW, Terry P, Howard L, Best J. Housing conditions and respiratory health in a Boston public housing community. *New Solut*. 2001; 11(2):149–164. [PubMed: 17208906]
23. Digenis-Bury EC, Brooks DR, Chen L, Ostrem M, Horsburgh CR. Use of a population-based survey to describe the health of Boston public housing residents. *Am J Public Health*. 2008 Jan; 98(1):85–91. [PubMed: 18048798]
24. Hynes H, Brugge D, Watts J, Lally J. Public health and the physical environment in Boston Public Housing: a community-based survey and action agenda. *Planning Practice & Research*. 2000; 15(1/2):21–49.
25. Kattan M, Mitchell H, Eggleston P, Gergen P, Crain E, Redline S, et al. Characteristics of inner-city children with asthma: the National Cooperative Inner-City Asthma Study. *Pediatr Pulmonol*. 1997 Oct; 24(4):253–262. [PubMed: 9368259]
26. Levy JI, Welker-Hood LK, Clougherty JE, Dodson RE, Steinbach S, Hynes HP. Lung function, asthma symptoms, and quality of life for children in public housing in Boston: a case-series analysis. *Environ Health*. 2004; 3(1):13. [PubMed: 15585065]
27. PDR. Red Book: Pharmacy's Fundamental Reference: PDR Network. 2010
28. AAP. 2007/08 AAP Medicaid Reimbursement Survey. Elk Grove Village, Illinois: American Academy of Pediatrics;
29. Barnett SB, Nurmagambetov TA. Costs of asthma in the United States: 2002–2007. *The Journal of allergy and clinical immunology*. 2011 Jan; 127(1):145–152. [PubMed: 21211649]
30. Stranges, E.; Merrill, CT.; Steiner, CA. Hospital stays related to asthma in children, 2006. Rockville, MD: Agency for Healthcare Research and Quality; 2008.
31. USDL. Medical care consumer price index and the consumer price index. Washington DC: US Department of Labor; 2013.
32. Burke JM, Zufall MJ, Ozkaynak H. A population exposure model for particulate matter: case study results for PM_{2.5} in Philadelphia, PA. *J Expo Anal Environ Epidemiol*. 2001 Nov-Dec; 11(6): 470–489. [PubMed: 11791164]

33. Lee K, Levy JI, Yanagisawa Y, Spengler JD, Billick IH. The Boston residential nitrogen dioxide characterization study: classification and prediction of indoor NO₂ exposure. *J Air Waste Manag Assoc.* 1998 Aug; 48(8):736–742. [PubMed: 9739626]
34. Levy JI, Lee K, Spengler JD, Yanagisawa Y. Impact of residential nitrogen dioxide exposure on personal exposure: an international study. *J Air Waste Manag Assoc.* 1998 Jun; 48(6):553–560. [PubMed: 9949739]
35. Long CM, Suh HH, Catalano PJ, Koutrakis P. Using time- and size-resolved particulate data to quantify indoor penetration and deposition behavior. *Environ Sci Technol.* 2001 May 15; 35(10):2089–2099. [PubMed: 11393992]
36. CDC. National Hospital Discharge Survey: 2007 Summary. Atlanta: Centers for Disease Control; 2010. Report No.: <http://www.cdc.gov/nchs/data/nhsr/nhsr029.pdf>
37. CDC. Summary Health Statistics for US Children, National Health Interview Survey 2009. Atlanta: Centers for Disease Control; 2010. Report No.: http://www.cdc.gov/nchs/data/series/sr_10/sr10_247.pdf
38. CDC. Ambulatory Medical Care Utilization Estimates for 2007. Atlanta: Centers for Disease Control; 2011. Report No.: http://www.cdc.gov/nchs/data/series/sr_13/sr13_169.pdf Contract No.: 169
39. Hynes HP, Brugge D, Osgood ND, Snell J, Vallarino J, Spengler J. "Where does the damp come from?" Investigations into the indoor environment and respiratory health in Boston public housing. *J Public Health Policy.* 2003; 24(3–4):401–426. [PubMed: 15015872]
40. Sarpong, EM. Health expenditures among children with reported treatment for asthma, United States, 1997–1998 and 2007–2008. Rockville, MD: Agency for Healthcare Research and Quality; 2011. [cited 2012 March 20]; Statistical brief #332]. Available from: http://www.meps.ahrq.gov/mepsweb/data_files/publications/st332/stat332.pdf
41. Homewyse. Cost of kitchen exhaust fans. 2012. [cited 2012 September 25]; Available from: http://www.homewyse.com/costs/cost_of_kitchen_exhaust_fans.html
42. CAPSC. Weatherization. Dover, NH: Community Access Partnership of Stafford County; 2011. [cited 2012 March 16]; Available from: <http://www.staffordcap.org/programs/weatherization>
43. LBL. Home Energy Saver. Berkeley, CA 2012 [cited 2012 Feb 29]; Available from: <http://hes.lbl.gov/consumer/>
44. Spahn JD, Cherniack R, Paull K, Gelfand EW. Is forced expiratory volume in one second the best measure of severity in childhood asthma? *Am J Respir Crit Care Med.* 2004 Apr 1; 169(7):784–786. [PubMed: 14754761]
45. Zhang J, Liou PJ. Ozone in residential air: concentrations, I/O ratios, indoor chemistry, and exposures. *Indoor Air.* 1994; 4(2):95–105.
46. EPA. US Environmental Protection Agency air quality criteria for ozone and related photochemical oxidants Research Triangle Park, NC: US EPA Office of Research and Development. 2006 Report No.: EPA 600/R-05/004aF.
47. Howden-Chapman P, Pierse N, Nicholls S, Gillespie-Bennett J, Viggers H, Cunningham M, et al. Effects of improved home heating on asthma in community dwelling children: randomised controlled trial. *BMJ.* 2008; 337:a1411. (Clinical research ed. [PubMed: 18812366]
48. Morgan WJ, Crain EF, Gruchalla RS, O'Connor GT, Kattan M, Evans R 3rd, et al. Results of a home-based environmental intervention among urban children with asthma. *N Engl J Med.* 2004 Sep 9; 351(11):1068–1080. [PubMed: 15356304]
49. Takaro TK, Krieger J, Song L, Sharify D, Beaudet N. The Breathe-Easy Home: the impact of asthma-friendly home construction on clinical outcomes and trigger exposure. *Am J Public Health.* 2011 Jan; 101(1):55–62. [PubMed: 21148715]

Key Messages

- Environmental changes in the homes of asthmatic patients can impact their asthma symptoms due to 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 savings interventions with a focus on indoor environmental quality and health, and highlight the short pay-back periods for key interventions such as integrated pest management, repair or installation of exhaust fans, and indoor source elimination.

Figure 1.
Schematic of pediatric asthma simulation model

Figure 2. Percent change in pollutant concentrations (A. NO₂ and B. PM_{2.5}) for each intervention scenario compared to baseline scenario.

Figure 3. Percent change in health outcomes for each intervention compared to the baseline scenario. A) asthma symptom days include days with any symptom, including wheeze, cough, night awakenings; B) serious events include asthma hospitalizations, emergency room visits and clinic visits. Asthma outcomes reflect changes in exposure to NO₂, PM_{2.5}, cockroach allergen and damp homes.

Figure 4.
Changes in costs of healthcare utilization for each intervention compared to baseline averaged over all asthmatics

Table I

Asthma medication prescriptions, usage and cost, stratified by asthma severity classification

FEV1% category	Quick relief medication	Long term control medication	Frequency	Cost of medicine per day used (2009\$) ^a
>80%	SABA ¹		2 days/week 2 puffs/day	\$0.24 ^b
		Low dose ICS ²	Daily	\$4.05 ^c
60–80%	SABA		Daily, 2 puffs/day	\$0.24 ^b
		Medium dose ICS	Daily	\$6.46 ^d
<60%	SABA		Daily, 6 puffs/day	\$0.72 ^b
		Medium dose ICS + LABA ³	Daily	\$8.20 ^e

^aBased on values reported in the 2010 Red Book (27), adjusted to 2009 dollars based on the Medical Care Consumer Price Index (31)^bAssumes a cost of \$25/albuterol canister with 200 doses per canister^cBased on cost of Flovent HFA, \$125 per month^dBased on cost of Advair HFA, \$200 per month^eBased on cost of Flovent HFA + Singulair, \$256 per month¹SABA = short-acting beta2-agonists²ICS = inhaled corticosteroids³LABA = long-acting beta2-agonists

Table II

Baseline healthcare outcomes from a simulation of asthmatic children over 10 years

FEV1% category	Days with asthma symptoms per year (SD) ^a	Serious asthma events per year (SD)	ER visits per year (SD)	Hospitalizations per year (SD)	Clinic visits w/prescribed oral steroid bursts per year (SD)	Number of children
> 80%	140 (11)	0.8 (0.6)	0.09 (0.29)	0.02 (0.08)	0.66 (0.57)	578,155 (58%)
60–80%	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

^aSD= standard deviation across the one million children