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Integrating Risk Assessment and Life Cycle Assessment: A Case Study of Insulation

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Increasing residential insulation can decrease energy consumption and provide public health benefits, given changes in emissions from fuel combustion, but also has cost implications and ancillary risks and benefits. Risk assessment or life cycle assessment can be used to calculate the net impacts and determine whether more stringent energy codes or other conservation policies would be warranted, but few analyses have combined the critical elements of both methodologies. In this article, we present the first portion of a combined analysis, with the goal of estimating the net public health impacts of increasing residential insulation for new housing from current practice to the latest International Energy Conservation Code (IECC 2000). We model state-by-state residential energy savings and evaluate particulate matter less than 2.5 μm in diameter ($PM_{2.5}$), NOx, and SO_2 emission reductions. We use past dispersion modeling results to estimate reductions in exposure, and we apply concentration-response functions for premature mortality and selected morbidity outcomes using current epidemiological knowledge of effects of $PM_{2.5}$ (primary and secondary). We find that an insulation policy shift would save 3×10^{14} British thermal units or BTU (3×10^{17} J) over a 10-year period, resulting in reduced emissions of 1,000 tons of $PM_{2.5}$, 30,000 tons of NOx, and 40,000 tons of SO_2. These emission reductions yield an estimated 60 fewer fatalities during this period, with the geographic distribution of health benefits differing from the distribution of energy savings because of differences in energy sources, population patterns, and meteorology. We discuss the methodology to be used to integrate life cycle calculations, which can ultimately yield estimates that can be compared with costs to determine the influence of external costs on benefit-cost calculations.

KEY WORDS: Life cycle assessment; insulation; particulate matter; intake fraction; exposure efficiency; energy

1. INTRODUCTION

The residential sector is a significant consumer of total energy in the United States. In 1997, residential end-use consumption was responsible for about 15% of total energy consumed nationwide, of which more than 50% was attributable to space heating.(1,2) Despite some gains in energy efficiency per housing unit in the past 20 years,(3) improvements have slowed given the lower cost of energy since the mid-1980s and the steady increase in the floor area of new homes.(4)

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The residential sector would therefore appear to be a worthwhile target for reducing U.S. energy intensity, which could provide numerous benefits (e.g., reduced greenhouse gas emissions, reduced local and regional air pollution, decreased dependence on foreign oil).

To reduce residential energy consumption, one of the major strategies would be to increase insulation levels. For new construction, adding insulation is a fairly simple process and best practice insulation levels are prescribed in a number of places. For example, insulation can be added according to the International Energy Conservation Code (IECC 2000), which applies to all new residential and commercial buildings and additions to such buildings.(5) In spite of the potential energy savings, most states have not adopted the most stringent code levels. As of the end of 2000, only four states had considered IECC 2000 for mandatory statewide implementation, while 29 states had only limited (or nonexistent) requirements or had recommended energy codes that were equal to or less stringent than the 1995 Model Energy Code.

From a public policy perspective, the critical question is whether this allocation of codes is desirable or whether changes in energy codes in selected states would be beneficial. From the consumer's perspective, additional insulation would likely lead to reduced utility bills and an increased resale value of his or her home, but would have additional up-front costs and could adversely influence the housing market.(6) From a societal perspective, reductions in energy consumption will reduce air pollution and any associated health effects. However, increased insulation manufacturing adds potential risks, including emissions at the manufacturing facility and any occupational hazards due to installation and manufacturing. Because of the multiple pathways and the need to quantify net health impacts, it is apparent that determining the net benefits of insulation policies requires tools from both risk assessment and life cycle assessment (LCA).

Although some past researchers have attempted to quantify the benefits of increased insulation or other demand-side management (DSM) programs, few have provided the necessary combination of LCA and risk assessment. Many studies largely focused on changes in energy consumption or emissions.(7–9) However, energy savings in one location may not result in an air pollution reduction in the immediate area, especially when the energy source is electricity. In that case, the energy savings are more relevant to the concentration reductions of air pollutants downwind of the power plants that are supplying electricity to the area. Furthermore, the concentration reduction of air pollutants is not necessarily proportional to the health benefits. One unit of pollutant concentration reduction is more effective in reducing health effects in areas that are more densely populated than where there is less population density. These factors imply that simply quantifying the emission savings (even from a life cycle perspective) is insufficient to quantify health benefits.

Past studies that addressed impacts of emissions during the production process were generally limited to global pollutants and did not take into account the regional impacts of air pollution. One recent externality study of DSM measures(10) attempted to address these concerns, but had a difficult time grappling with issues of site specificity and appropriately incorporating notions of uncertainty. Damages were calculated only when the site of the emissions could be determined, which led to approximately 40–50% of the SO_2 and NOx emissions (and perhaps more of the health risk) being omitted from the analysis. Although these studies shed some light on the risks and benefits associated with DSM measures (generally finding them favorable from a life cycle perspective), the lack of a comprehensive risk-based perspective makes them difficult to interpret.

To address these issues, we construct a model framework that allows for the evaluation of net benefits combining risk assessment and LCA. In this article, we focus our quantitative analysis on the public health risk reductions associated with particulate matter, NOx, and SO_2 emission reductions from power plants, and residential combustion sources. We present an analytical framework that can incorporate life cycle impacts using a risk assessment framework, and we discuss the necessary steps to create this linkage. In future analyses, the end-use risk calculations will be linked with economic costs/savings and life cycle impacts to provide the information needed for a comprehensive benefit-cost analysis.

2. METHODOLOGY

In the following sections, we detail our methodology to quantify the direct health benefits associated with end-use reductions in energy consumption. The economic consequences of increased insulation and the upstream impacts are not quantified in this article. Thus, our analysis consists of four phases.

1. Determining how much energy would be saved in a 10-year period (2001–2010) if all homes built during this period increased

insulation levels from current practice to IECC 2000 levels.

2. Translating energy savings into emission reductions given residential fuel types and fuels combusted by power plants affected by incremental changes in electricity consumption.
3. Estimating the influence of the emission reductions on human exposure to air pollutants considered to affect human health at current ambient levels.
4. Quantifying the health benefits of pollutant exposure reductions.

Broadly, our approach for each of these four phases involves developing a model that characterizes the general trends, can be applied in a life cycle analysis, and can incorporate quantification of uncertainty. Within each phase, more detailed and complex models are available than the ones we use, but we adopt a hierarchical approach to risk analysis that focuses on the construction of a simpler model and the ultimate determination of which additional analyses would most improve our estimates and reduce the overall uncertainties.

In this spirit, we limit our focus to climate, insulation, foundation types, floor area, heating and cooling systems, and fuel types as the determinants of energy savings by state. We model energy savings by fitting a predictive regression model to outputs from a home energy simulation software package. We determine emission reductions from power plants with some assumptions about the facilities influenced on the margin, and we evaluate residential emission reductions using standard emission factors. We focus only on $PM_{2.5}$ and NOx, and SO_2 as particulate matter precursors. This assumes that $PM_{2.5}$ exposure is likely to contribute a significant fraction of health risks from fuel combustion, although other criteria pollutants and/or air toxics could contribute to the impacts from a life cycle perspective. However, it is worth noting that risk from air toxics is generally found to be much smaller than risk from criteria pollutants. For example, approximately 800 excess annual cancer cases have been estimated for 1990 outdoor concentrations of hazardous air pollutants,(11) while more than 30,000 annual excess deaths have been attributed to fine particulate concentrations associated with power plants alone.(12) Exposure estimation is based on predictions from previous model runs, and standard concentration-response functions from the epidemiological literature are used to quantify mortality and selected morbidity reductions. In all phases, we quantify uncertainty both through objective determination of confidence intervals and through subjective evaluation of the overall model uncertainties. We present deterministic findings in Section 3 using appropriate central estimates, and we evaluate the overall uncertainty and the importance of key assumptions in Section 4.

2.1. Energy Savings Estimation

To calculate energy savings in each state, we used a regression-based approach based on model outputs from an energy simulation software package (REM/Design,^{TM} Architectural Energy Corporation, Boulder, CO). REM/Design passed the Home Energy Rating System Building Energy Simulation Test (BESTEST), a method for evaluating the credibility of building energy software.(13) For our analysis, we simulated the heating and cooling energy consumption of a number of prototype homes and developed regression equations to predict REM/Design output based on a limited number of parameters. This allowed us to model the energy savings for a large number of homes without the computational burden associated with constructing profiles for all home types in all new construction settings.

Briefly, our prototype homes reflected combinations of foundation type, heated floor area, number of stories, heating systems, and insulation levels. All house characteristics were derived from past publications,(1,2,14,15) with current-practice insulation levels based on a proprietary survey.(16) The associations between independent variables and heating and cooling loads from REM/Design were assessed using multivariate regressions based on the ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) standard heat loss equations,(17) constructed separately for each combination of foundation type, heating system, and number of stories. The regression models were then linked with the number of new homes constructed in each state and metropolitan statistical area (MSA).(18) To limit possible bias associated with REM/Design, we used data from the 1997 Residential Energy Consumption Survey (RECS) to calibrate the predicted consumption.(1) The ratio between our "current-practice" estimate and actual energy consumption from RECS was applied to both current-practice and IECC 2000 consumption scenarios. Detailed information about our prototype homes and regression models is available from the authors on request.

We assumed that 1.2 million new single-family homes will be built each year from 2001 to 2010,(19) with the same geographic distribution found in 1999 (44% in the south, 24% in the west, 21% in the midwest, 10% in the northeast). We also assumed that the trend of increasing square footage per home from 1987 to 1998 would continue, at a constant rate of 1.4% per year. All other home characteristics, including the distribution of heating fuels and systems, were assumed to be unchanged.

2.2. Emissions Estimation

Given the estimated changes in energy consumption, we quantify the resulting changes in emissions of $PM_{2.5}$, SO_2, and NOx. For residential combustion of natural gas or fuel oil, this is a relatively straightforward calculation, given information about heating systems, fuel types, and typical emission factors. For changes in electricity consumption, the calculation is far more complex, since it requires us to determine which power plants are influenced by incremental changes in electricity consumption in a range of geographic locations.

For residential combustion, we gathered emission factors from the U.S. EPA AP-42 database.(20) Within AP-42, qualitative terms are assigned to the uncertainties in these factors, but no methodology is currently available to quantify these uncertainties. Assuming the energy content of fuel to be known, the only uncertainty we could quantify for residential fuel combustion is related to the sulfur content of oil. For simplicity, we assumed that 0.5% was a representative sulfur content of residential fuel oil, with a standard deviation of 0.15%.(21)

For electricity, we need to identify which power plants are likely to have their generation levels impacted by incremental changes in end-use electricity demand. When the power system experiences a change in load, there is a tiered set of possible responses, which will depend on the magnitude of the load change, its timing, its permanence, and the operating rules of the power controllers in question. A discussion of the complexities of the power system is beyond the scope of this article, but this tiered response has implications for our estimation effort. In determining marginal power plants, we note that the level of incremental demand change in our analysis is small in relation to the capacity of any one power plant and in relation to the forecast hourly changes in load level occurring during a day.

We first consider which plants can be reliably excluded from the pool of potentially impacted plants. Hydroelectric, wind, and solar power have outputs that are governed by supply constraints (e.g., rainfall or sunshine) rather than demand constraints, and would not be affected. In addition, nuclear power operates at full capacity and does not respond to incremental demand changes. To this set of excluded plants, we can also add combined cycle (CC) units, which generally are economical power running at full capacity, and that in any case are not dispatched or adjusted to respond to incremental demand fluctuations. This leaves non-CC fossil-fuel generators (coal, natural gas, oil, and diesel). Finally, we remove all plants above 80% gross capacity factor, assuming that they are operating all or most of the time as base load (with virtually no margin for demand response). According to U.S. EPA's 1997 E-GRID database (the most recent publicly available data at the time of our analysis), 553 power plants remain in this subset with positive net generation.

For our emissions estimation, we must determine which generators among this subset have what likelihood of being impacted by increased residential insulation, an estimate that is highly uncertain with irreducible uncertainties. Within this article, we only quantitatively consider deterministic estimates of electricity-related health benefits due to the difficulties in quantifying uncertainties of marginal power plant emissions. For this deterministic estimate, we assume that all facilities in this derived set of power plants have an equal probability of being affected by incremental demand reductions. One could alternatively assume that the probability that a given plant will be impacted is proportional to the fraction of time it is running during the year (availability). A second alternative would assume that the capacity of a plant influences the probability that its output responds to an incremental demand change (sampling from a population of kWh rather than available demand-minutes). Applying availability-based or generation-based weighting schemes would increase the emission rates from our deterministic level, with generation-based weighting leading to the highest emission rates.

Power plant emissions of NOx and SO_2 were taken from the E-GRID database. Emissions of $PM_{2.5}$ were integrated into the analysis using AP-42 emission factors for PM_{10} and a probabilistic assessment of the $PM_{2.5}/PM_{10}$ ratio in emissions.

2.3. Exposure Estimation

The estimation of exposure to marginal emissions from power plants and residential fuel combustion is complicated by the large number of sources—hundreds of power plants and millions of residential area sources. Constructing detailed atmospheric dispersion models for all these sources is a practical impossibility at this point in time. However, even if this could be done, the relevant questions are whether a simpler approach could adequately represent the risks per unit emissions and whether the degree of uncertainty is sufficient to necessitate more complex modeling. In this article, we adopt a simpler approach, applying a model(22) that predicted the exposure per unit emissions as a function of limited site characteristics.

This study was based on the concept of intake fraction (called exposure efficiency in the cited publications), which can be defined simply as a dimensionless ratio between the amount of pollutant intake and the amount of a pollutant emitted.(23) Intake fraction estimates were taken from a recent analysis, which applied the CALPUFF dispersion model to determine intake fractions for primary $PM_{2.5}$, secondary sulfates, and secondary nitrates for 40 power plants and 40 area sources in the United States.(24) The intake fraction estimates were then regressed against a limited number of simple parameters (e.g., total population within 500 km, annual average temperature at the source).(22) These equations were able to predict intake fractions quite well (R^2 between 0.5 and 0.9). With these equations, we can determine reasonable estimates of annual average exposure from a source.

For our application, we estimated residential combustion intake fraction at the MSA level. Electricity intake fraction was derived at the state level, given information about the pool of power plants providing electricity to the state. Stack heights were collected from Energy Information Administration Form EIA-767, and all meteorological parameters (annual average wind speed, temperature, relative humidity, and afternoon mixing height) were interpolated from National Climatic Data Center or U.S. EPA data. Population data for the United States, Mexico, and Canada were taken from a set of gridded 1995 data (2.5′ by 2.5′ gridblocks), with population within a fixed radius evaluated in SAS.

Because of the good predictive power of the regression equations and the fact that we are applying models derived within the United States to the United States (avoiding questions of generalizability), most of the uncertainty is related to the broader question of whether the underlying model accurately reflects the true intake fractions from the selected sources. The subjective characterizations of model uncertainty are presented in Section 4.

2.4. Concentration-Response Functions

To determine the health benefits associated with the estimated reductions in $PM_{2.5}$ exposure, we rely on a survey of the relevant epidemiological literature. We principally focus on premature mortality, since it has contributed a large portion the total benefits in past studies.(25) In addition, to help communicate the range of health effects, we also apply concentration-response (C-R) functions for asthma attacks and restricted activity days (RAD). Other morbidity outcomes have been associated with $PM_{2.5}$ exposure, but we do not address these in this article.

We assume within this analysis that the slopes of the C-R functions are linear throughout the range of ambient concentrations in the United States, with any population threshold below the lowest ambient concentration. Since ambient $PM_{2.5}$ concentrations vary across the United States, any nonlinearities would imply that different slopes should be applied in different locations. Given the linkage with intake fractions, we assume that there is no dose-rate dependence. For simplicity, we also assume that background disease prevalence and mortality rates are constant across the United States.

Since the independent derivation of C-R functions is not the focus of this analysis, we rely on past literature estimates with some subjective evaluation of uncertainties. More comprehensive information about the evidence for causality, biological plausibility and physiological mechanisms, and issues related to PM exposure can be found elsewhere.(26–28)

For premature mortality, we primarily rely on the cohort mortality literature, taking our central estimate from the American Cancer Society (ACS) study,(29) as has been done in many past regulatory assessments.(25,30) We draw our central estimate from a model in the Health Effects Institute (HEI) reanalysis of this study,(31) in which a 24.5 $\mu g/m^3$ increase in annual mean $PM_{2.5}$ concentrations was associated with a 1.12 relative risk for premature mortality (95% CI: 1.06, 1.19). For small changes in concentrations, this will translate into a 0.5% increase in premature deaths for each $\mu g/m^3$ increase in annual mean $PM_{2.5}$ concentrations, which can be applied to a baseline mortality rate of 0.014 deaths/person/year for individuals 30 years of age or older.(32)

The uncertainty in this estimate is greater than implied by the confidence limits in the HEI reanalysis (0.2%, 0.7%). The Six Cities Cohort Study yields a central estimate of 1.3%,(33) and it is possible that these studies overestimate risk. For simplicity, we assume that the C-R function is a normal distribution with a mean of 0.5% per μg/m^3 increase in $PM_{2.5}$ and standard deviation of 0.2%. This should be considered as a first-order attempt to evaluate the uncertainty in the premature mortality C-R function, rather than a conclusive distribution that reflects expert judgment on the appropriate functional form and magnitude of the uncertainties.

We also evaluate C-R functions for asthma attacks and RAD. For both outcomes, we rely on the studies incorporated into the recent EPA benefit-cost analyses,(25,30) although other studies in the literature are relevant to these endpoints. Asthma attacks are based on a single older study of children and adults in southern California that evaluated the influence of total suspended particulates (TSP) in models including ozone.(34) Using a conventional assumption of a 0.3 $PM_{2.5}$/TSP ratio, a 1 μg/m^3 increase in $PM_{2.5}$ concentrations is associated with a 0.2% increase in the daily incidence of asthma attacks (95% CI: 0.06%, 0.4%). The EPA estimate assumes a daily incidence rate of 0.027 among asthmatics(35) and an asthma prevalence rate of 5.6% for all ages in all settings.(36)

The relationship between RAD and $PM_{2.5}$ exposure was derived from a study of adults age 18 to 65 included in the Health Interview Survey between 1976 and 1981.(37) The EPA determined a pooled estimate from the six year-specific regressions using a weighted average with weights that reflect the inverse of the variance in the reported coefficients.(38) This pooling methodology yielded an estimated 0.47% increase in RAD per μg/m^3 of daily average $PM_{2.5}$ (95% CI: 0.42%, 0.53%), applied to a daily incidence rate of 0.0177 for all adults age 18 to 65.

Although these morbidity estimates are clearly more uncertain than indicated by the reported confidence intervals (particularly for RAD), the uncertainties in these estimates are unlikely to materially affect a benefit-cost analysis of increased insulation given the relative valuation of morbidity and mortality. If either outcome were shown to be a significant contributor to benefits, a subjective assessment of the uncertainties for the morbidity estimates would be warranted.

3. RESULTS

Within this section, we present the deterministic findings of all components of our end-use impact model (energy savings, emission reductions, and risk reductions), using central estimates for all uncertain parameters. We address the overall uncertainties and subcomponent uncertainties within the Uncertainty/Sensitivity analysis.

3.1. Energy Savings

Our regression models to predict REM/Design outputs showed a strong fit for all prototype homes, with R^2 ranging between 0.83 and 0.99. Despite this strong fit, our regression models tended to systematically overestimate RECS-based estimates. For homes using oil or natural gas for space heating, our model overestimated actual consumption by a factor of 1.2 to 1.8 in the midwest, northeast, and west, with an estimate close to actual consumption in the south. Past evaluations of REM/Design(13) have found it to somewhat overestimate energy consumption, so systematic differences of this magnitude might be expected.

For electric-heated homes, the space heating overestimates were greater, on the order of one to five times the actual consumption levels. Possible explanations for this difference include the assumed square footages of the homes, assumed base temperature, and unknown terms related to occupant behaviors or house characteristics. Since it seems unlikely that these factors alone could explain this degree of bias, our benefit estimates for all-electric homes should be considered somewhat uncertain.

For space cooling, our modeled electricity consumption is lower than RECS estimates in the south and west but is higher in the midwest and the northeast, within a factor of 1.5 in all regions. The underestimation may be due to the differences in the assumed cooling degree hours, as RECS used a 65 degree baseline while 74 degrees was assumed in our analysis.

Using the calibrated regression models, we estimate that requiring all new homes built from 2001 to 2010 to use insulation at IECC 2000 levels would save approximately 300 TBTU/year (3×10^{17} J) of primary energy in that 10-year period (Table I). The south and midwest regions have the largest share of the net savings (36% and 31%, respectively), with the northeast contributing the smallest share (14%). Because a relatively small number of new units are built compared with the existing housing stock, these energy savings correspond to only 0.4% of all heating and cooling energy consumption during this period.

On a per unit basis, the regional story differs somewhat, demonstrating that the aggregate trends are somewhat a function of where new homes are being built. Although the northeast represents the least total benefits, the per-unit benefits are the second greatest in the northeast at 5.6×10^6 BTU/household/

Table I. Cumulative Heating and Cooling Energy Savings by Region Associated with Increasing Insulation in New Homes, Both Aggregate Savings and Per House Average Savings Per Year Over a 10-Year Period

	Natural Gas Savings (MMBTU)	Oil Savings (MMBTU)	Net Electricity (Primary Energy) Savings (MMBTU)	Total (MMBTU)
Aggregate				
Midwest	7.7E+07	0.0E+00	9.0E+06	8.6E+07
West	4.2E+07	0.0E+00	8.7E+06	5.1E+07
South	4.4E+07	0.0E+00	5.4E+07	9.9E+07
Northeast	2.4E+07	1.0E+07	3.3E+06	3.8E+07
Total	1.9E+08	1.0E+07	7.6E+07	2.7E+08
Per Unit	Fuel Savings for Heating (MMBTU/Year)[1]	Electricity Savings (Primary Energy) for Heating (MMBTU/Year)[2]	Electricity Savings (Primary Energy) for Cooling (MMBTU/Year)[3]	Average Per Unit Savings (MMBTU/Year)[4]
Midwest	5.9	5.6	0.2	6.1
West	2.9	3.3	0.3	3.1
South	2.9	3.3	0.2	3.3
Northeast	5.6	4.0	0.2	5.6

Note: MMBTU = 10^6 BTU. The ratio of primary energy BTUs/site BTUs for electricity was assumed to be 3.391.

[1] For homes using natural gas or heating oil for heating.

[2] For homes using electricity for heating.

[3] For homes using air conditioning for cooling.

[4] Simple average of heating and cooling energy per unit.

year (6×10^9 J/household/year) (Table I). The per-unit benefits are substantially lower in the south and west than in the colder northeast and midwest.

We can also evaluate the energy savings on a state-by-state basis, a necessary analysis for policy evaluation. The five states with the greatest total energy savings are (in order) Michigan, Texas, Nevada, Virginia, and Illinois. In total, these states account for 32% of the net total primary energy saved throughout the country, with the top half of the states accounting for 82% of the total energy savings potential. On a per-unit basis, energy savings potential is greatest in Nevada, followed by New Mexico, West Virginia, North Dakota, and Missouri. As in the regional analysis, this clearly demonstrates that the states with greatest per-unit energy savings are not necessarily the states with the highest rates of new construction.

3.2. Emission Reductions

First focusing on the aggregate emission reductions, the 300 TBTU (3×10^{17} J) energy savings is associated with reduced emissions of approximately 1,000 tons of $PM_{2.5}$, 40,000 tons of SO_2, and 30,000 tons of NOx during the 10-year period (Table II). However, these emissions are not spread uniformly across source types or regions. Almost all the SO_2 emissions are related to electricity savings in the south (73%, associated with the relatively high prevalence of electric-heated homes). For NOx, electricity savings in the south again have a substantial contribution (50%), followed by residential and power plant fuel combustion savings in the midwest. Primary $PM_{2.5}$ follows similar patterns as NOx, based on similarities in relative emission rates. In total, 94% of the SO_2 savings are from power plants, compared with 56% of primary $PM_{2.5}$ and 67% of NOx. Given differences in exposure patterns, this will have implications for the distribution of risk by pollutant.

On a per-unit basis, the emission reductions $PM_{2.5}$ are fairly similar across regions (ranging between 0.02 kg/year in the midwest and 0.01 kg/year in other regions). Patterns are similar for NOx, with the south and the midwest having the greatest per-unit emission reductions. Units in the south have the greatest SO_2 emission reduction per unit, with much lower values in the west. Although these emission reduction calculations illustrate that simply looking at energy savings is insufficient from an environmental perspective, they are difficult to interpret without an understanding of pollutant dispersion and resulting health effects.

At the state level, Texas had the greatest reduction of $PM_{2.5}$, and Virginia had the greatest reductions

Table II. Cumulative Emission Reductions Associated with Increasing Insulation in New Homes, Both Aggregate Savings and Per House Average Savings Per Year Over a 10-Year Period (Presented to Two Significant Figures)

	Electricity			Residential (Natural Gas + Oil)			Total		
	$PM_{2.5}$	SO_2	NOx	$PM_{2.5}$	SO_2	NOx	$PM_{2.5}$	SO_2	NOx
Aggregate (tons)									
Midwest	65	5,100	2,300	160	20	3,200	220	5,200	5,500
West	39	1,600	1,400	85	11	1,800	125	1,600	3,200
South	360	30,000	13,000	90	12	1,800	450	30,000	15,000
Northeast	16	1,800	580	57	2,400	1,600	74	4,200	2,200
Total	480	39,000	17,000	390	2,500	8,400	870	41,000	26,000
Per unit (kg/year)									
Midwest	4.5E−03	3.6E−01	1.6E−01	1.1E−02	1.4E−03	2.2E−01	1.5E−02	3.6E−01	3.8E−01
West	2.4E−03	9.4E−02	8.5E−02	5.1E−03	6.8E−04	1.1E−01	7.5E−03	9.5E−02	1.9E−01
South	1.2E−02	9.9E−01	4.3E−01	3.0E−03	3.9E−04	6.1E−02	1.5E−02	9.9E−01	4.9E−01
Northeast	2.3E−03	2.6E−01	8.3E−02	8.2E−03	3.5E−01	2.3E−01	1.1E−02	6.1E−01	3.2E−01

of NOx and SO_2, all of which were largely related to substantial electric space heating. Other states provide significant emission reductions that are largely related to reductions in residential heating fuel combustion. Michigan (ranked third for $PM_{2.5}$ and fourth for NOx) provides $PM_{2.5}$ and NOx reductions that have minimal contributions from electricity, whereas Pennsylvania (ranked 11th for SO_2 reductions) provides SO_2 reductions largely from residential fuel oil combustion. On a per-unit basis, $PM_{2.5}$, NOx, and SO_2 are most substantially reduced in new homes in West Virginia and Kentucky, because of a high prevalence of homes using electric space heating with electricity provided by higher-emitting power plants.

3.3. Risk Reductions

Because of our intake fraction approach, we consider exposure and risk simultaneously in this section. Averaging the state-level intake fraction estimates, the northeast has the highest intake fractions for all pollutants for both power plants and residential combustion sources (Table III). This is likely a function of the higher population density in the northeast. For both area sources and power plants, $PM_{2.5}$ has the highest intake fractions, followed by SO_2/sulfate and NOx/nitrate. Primary $PM_{2.5}$ intake fraction is somewhat more variable by region than secondary particulate intake fraction.

We calculate health benefits using the derived C-R functions, along with a standard estimate for breathing rate (20 m^3/day), the size of the at-risk population, and the prevalence of the health outcomes. In total, the mortality risk reduction associated with the reduced emissions of $PM_{2.5}$, NOx, and SO_2 is approximately 60 deaths, with the south (57%) making the largest contribution (Table IV). Of this total mortality risk reduction, 36% was related to residential fuel combustion, with 64% from electricity savings (even though only 28% of total energy savings were from power plants). More than one-third of the total risk reduction was related to reduced SO_2 emissions from electricity savings in the south.

For the two morbidity outcomes evaluated, the total risk reductions were approximately 2,000 fewer asthma attacks and 30,000 fewer RAD. Given the assumption of uniform disease prevalence and identical C-R functions in all settings, the geographic distribution of these morbidity outcomes is identical to the distribution for premature mortality. To provide some

Table III. Mean Intake Fraction by Region, Derived from Intake Fraction Regression Model[22] and Site/Source Characteristics

	Area Sources			Power Plants		
	$PM_{2.5}$	SO_2/sulfate	NOx/nitrate	$PM_{2.5}$	SO_2/sulfate	NOx/nitrate
Midwest	7.2×10^{-6}	1.4×10^{-7}	2.7×10^{-8}	2.3×10^{-6}	1.4×10^{-7}	2.4×10^{-8}
West	3.3×10^{-6}	7.1×10^{-8}	2.8×10^{-8}	1.5×10^{-6}	9.0×10^{-8}	4.5×10^{-8}
South	9.9×10^{-6}	1.3×10^{-7}	2.1×10^{-8}	2.9×10^{-6}	1.5×10^{-7}	2.3×10^{-8}
Northeast	1.3×10^{-5}	1.6×10^{-7}	3.2×10^{-8}	6.1×10^{-6}	1.5×10^{-7}	3.2×10^{-8}

Table IV. Cumulative Premature Mortality Reduction Associated with Increasing Insulation in New Homes, Both Aggregate Reduction and Per House Average Reduction Per Year Over a 10-Year Period (Presented to Two Significant Figures)

	Residential Combustion			Power Plants			Total			
	$PM_{2.5}$	SO_2	NOx	$PM_{2.5}$	SO_2	NOx	$PM_{2.5}$	SO_2	NOx	Total
Aggregate										
Midwest	7.9	0.0	0.5	0.9	4.5	0.3	9	4.5	0.8	14
West	1.8	0.0	0.3	0.3	0.8	0.4	2.1	0.8	0.6	3.6
South	4.5	0.0	0.2	5	25	2	10	25	2	37
Northeast	5.1	2.2	0.3	0.5	1.5	0.1	5.6	3.7	0.4	10
Total	19	2.2	1.3	7	32	2	27	34	4	64
Per unit (incidence/year)										
Midwest	5.5E−07	1.3E−09	3.6E−08	6.3E−08	3.1E−07	2.2E−08	6.1E−07	3.1E−07	5.7E−08	9.8E−07
West	1.1E−07	2.6E−10	1.8E−08	2.0E−08	4.7E−08	2.1E−08	1.3E−07	4.8E−08	3.9E−08	2.1E−07
South	1.5E−07	2.8E−10	7.3E−09	1.8E−07	8.2E−07	5.2E−08	3.3E−07	8.2E−07	5.9E−08	1.2E−06
Northeast	7.3E−07	3.1E−07	4.1E−08	6.7E−08	2.2E−07	1.4E−08	7.9E−07	5.3E−07	5.5E−08	1.4E−06

context for these mortality and morbidity estimates, it should be noted that the population influenced is approximately 250 million people (the population of the continental United States).

At the state level, Virginia (the fourth-ranked state in total energy savings) ranks first in mortality risk reduction, followed by Michigan, Kentucky, North Carolina, and Texas (first, eleventh, ninth, and second in total energy savings, respectively). These five states represent about 37% of national mortality risk reduction. In general, the ranking of states by risk reduction bears little resemblance to the ranking of states by total energy savings.

4. UNCERTAINTY/SENSITIVITY ANALYSIS

Our analysis has incorporated information from a number of domains, including building energy simulation, air emissions estimation, dispersion modeling, exposure estimation, and concentration-response modeling. In this section, we attempt to quantify major components of uncertainty associated with all phases of our analysis. This can help guide model refinement and determine the applicability of our model to the life cycle portion of our analysis. Since detailed quantification of all uncertainties is beyond the scope of this article, we focus on the results of uncertainty propagation and importance analysis for premature mortality from residential combustion sources. This analysis was conducted using Analytica (Lumina Decision Systems, Los Altos, CA), assuming statistical independence among all input uncertainties.

One issue deserves careful mention at the outset of this section. In a few important cases, we make simple subjective "factor of x" assessments of the underlying uncertainty in these estimates. However, underlying these simple factors are assumptions regarding the symmetry/skewness and spread/central tendencies of these uncertainties. These assumptions, along with the functions chosen to model them, have a strong influence on the results of both the uncertainty analysis and the uncertainty importance analysis. While we have used our best judgment to arrive at the present results, it would be valuable to formally characterize the uncertainties and carefully test the sensitivity of conclusions about uncertainty to reasonable choices that could be made in uncertainty modeling.

4.1. Energy Modeling and Emissions Uncertainty

In our analysis, we have limited information about uncertainties for energy modeling and emissions estimation. Our regression equation to predict energy savings per house provides multiple estimates of parameter uncertainties. However, the application of calibration factors to correct for deviations from reported energy consumption data indicates that overall model uncertainty is likely to contribute far more substantially to the aggregate energy modeling uncertainty than subcomponents of the regression models. For simplicity, we assume that the calibration factor provides an estimate of energy savings that is correct within a factor of two, fitted with a triangular distribution. If this initial round of uncertainty analysis indicates that uncertainties in the energy demand savings estimates make a major contribution to the total uncertainty, this will warrant a future "bottom-up," factor-by-factor quantification and assessment of the uncertainties in the energy model.

For emissions, the lack of quantitative uncertainty estimates for AP-42 makes it impossible to include these terms in the analysis. For area sources, the only term that contributes uncertainty is the sulfur content of fuel oil. We do not quantify power plant emissions uncertainties in this report, but it is clear that substantial uncertainties are associated with our assumptions of which sources are affected and to what degree.

4.2. Exposure Uncertainty

The standard errors from the intake fraction regression equations$^{(20)}$ and the residual variance from the model fit clearly underestimate the uncertainties. As for the energy model, we adopt a "top-down" approach to quantify the pollutant-specific uncertainties related to the ability of CALPUFF to accurately predict atmospheric dispersion and from the specific application of CALPUFF used to derive intake fractions.$^{(23)}$

Some uncertainties are associated with the meteorological data used by the model. Since CALPUFF incorporates three-dimensional windfields, the number and spatial distribution of weather stations used to construct these windfields affects the accuracy and precision of the meteorological field predictions. The Wolff application$^{(23)}$ used 10 meteorological stations across the United States, which provides significantly less resolution than in typical (shorter-range) CALPUFF applications. Verification studies comparing actual meteorological fields with those predicted by Wolff have not been conducted, making these data somewhat uncertain.

Concerning the formation and fate of pollutants, CALPUFF uses first-order transformation approaches allowing for the conversion of SO_2 to sulfate and NOx to nitrate aerosol. Because of the complexity of the sulfate-nitrate-ammonia-water system, which can include significant nonlinearities in formation rates,$^{(39)}$ this simplified approach may not accurately capture secondary particle intake fractions. Another element adding to nitrate uncertainties is the fact that nitrate particles generally tend to form at colder temperatures. In the Wolff publication, the annual average ambient secondary nitrate concentrations from CALPUFF were reduced by a factor of four,$^{(22)}$ intended to ensure that only particle-phase nitrate was counted. Since seasonal patterns in nitrate formation vary substantially across the United States, this simplified adjustment leads to substantial uncertainties, both in the overall magnitude of nitrate intake fraction and in the geographic patterns (since temperature patterns differ regionally). We maintain the use of Wolff's original estimates for consistency, but acknowledge that this may underestimate NOx-related benefits, particularly for heating.

Finally, atmospheric transport uncertainty can be related to the size of the grid and the spacing between receptors. Puff splitting issues could imply that long-run concentrations in CALPUFF are overestimated.$^{(40)}$ The Wolff application used somewhat coarse grid spacing (100 km by 100 km), but it is unclear whether this would bias intake fraction calculations. However, it would seem more likely that errors would be induced for ground-level sources (whose intake fractions will more significantly depend upon local population) than for sources with taller stacks.

To quantify the intake fraction uncertainties requires a subjective assessment of the magnitude of the above effects. Qualitatively, issues with the atmospheric chemistry will imply that secondary particle intake fraction would be more uncertain than primary particle intake fraction, with nitrates more uncertain than sulfates because of issues with the atmospheric chemistry.

Focusing on residential combustion, we consider the primary $PM_{2.5}$ intake fraction estimates to be accurate within a factor of two. This was chosen to be greater than the anticipated power plant uncertainty due to coarse grid spacing, which we estimate as a factor of 1.5 (consistent with the magnitude of uncertainty often associated with Gaussian dispersion models). For sulfates, we consider the intake fraction estimates to be accurate only within a factor of three, and we use a factor of five for nitrates. We acknowledge that these model uncertainty estimates are quite crude, represent the subjective judgments of the authors, and would strongly influence the uncertainty analysis. It should be noted that others$^{(41)}$ have evaluated the same study and assigned somewhat smaller uncertainties. Further research on the magnitude of uncertainties associated with national-level CALPUFF applications would be warranted.

4.3. Concentration-Response Uncertainty

For the C-R functions, the overall uncertainties can be greater than the calculated confidence intervals reported in the individual studies or derived from meta-analyses. For premature mortality, since we considered alternative studies and scenarios to provide broad confidence intervals, it is our judgment that we have captured the appropriate uncertainties. Additional uncertainties are associated with the translation between $PM_{2.5}$, PM_{10}, and TSP; the possibility of differential health effects associated with sulfates, nitrates, and other forms of particulate matter; and the possibility of thresholds or nonlinearities that would imply different C-R functions in different regions. While we feel that our broad uncertainty bounds are reasonable, many uncertainties are difficult to quantify and additional scientific evidence (such as for the existence of a population threshold) could significantly alter our estimates.

4.4. Uncertainty/Sensitivity Analysis Results—Residential Fuel Combustion

When we combine the above uncertainties, our median estimate is that the reductions in residential fuel combustion would result in approximately 110 fewer premature deaths during a 10-year period (90% CI: 40, 1200). In contrast, our deterministic estimate was 20. The generally higher values from the uncertainty analysis are largely due to the assumed distributions for individual factors (often triangular distributions derived from multiplicative factors).

In Fig. 1, we show the estimated confidence intervals for mortality risk reductions by fuel type and pollutant, aggregated across geographic regions. These figures emphasize a few major points. First, as indicated in the deterministic analysis, primary $PM_{2.5}$ and NOx contribute most of the impacts from natural-gas-heated homes, while SO_2 contributes the largest share of median impacts from oil-heated homes. However, the large uncertainty in NOx-related impacts allows for the possibility of relatively high impacts from that pollutant for both fuels. This uncertainty can be related to the large uncertainty bounds assumed for the

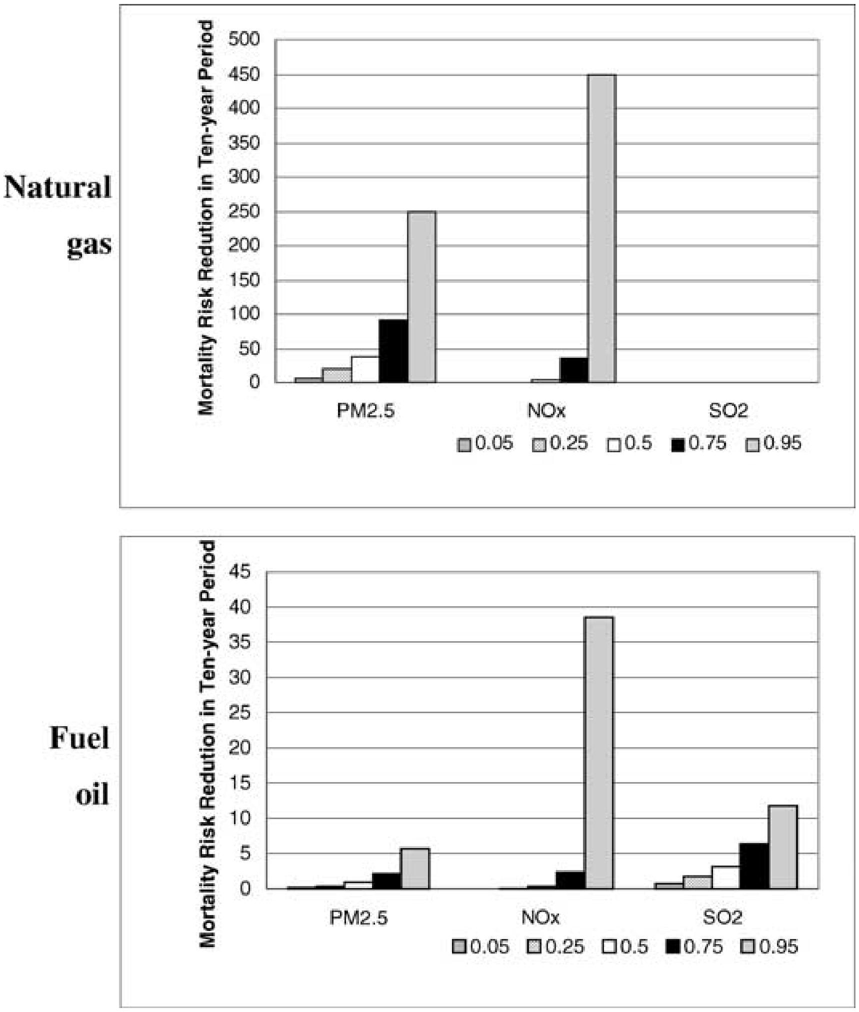

Fig. 1. Confidence intervals for total premature mortality impacts avoided (residential combustion only, by fuel type and pollutant).

exposure estimation for secondary nitrate particles, along with the fact that the secondary sulfate term (which itself is somewhat uncertain) is embedded in the predictive regression equation for secondary nitrates.

To help in the prioritization of future research, we investigate the relative influence of the various input uncertainties on the total uncertainty in the final results. To accomplish this, we examine the rank-order correlations between each of the uncertain inputs and total impacts by region, pollutant, and heating fuel. A consistent result is that the single most influential uncertainty is the uncertainty in the C-R function for premature mortality, regardless of pollutant or region. Second in importance is generally the total uncertainty in estimates of avoided exposures, with uncertainties in energy savings estimates less influential than either C-R or exposure uncertainties. This ranking is entirely a function of our subjective uncertainties.

The relative importance of C-R functions over intake fraction is perhaps unintuitive, given the seemingly large uncertainties attributed to exposure models (e.g., a "factor of five" for secondary nitrates). However, with the application of a triangular distribution to represent this factor of five (mode of 1, minimum/maximum values of 0.2 and 5), the coefficient of variation is approximately 50%, similar to the coefficient of variation for the C-R function. This demonstrates that careful expert elicitation of uncertainties, including estimation at multiple percentiles to establish the functional form, would be crucial in evaluating the most important next steps.

5. DISCUSSION

Our analysis demonstrates that despite numerous complexities in structuring a model to evaluate the public health benefits of energy conservation on a national scale, a risk-based approach is feasible and can ultimately help in the determination of optimal code levels. As illustrated by the changes in state rankings when proceeding from energy savings to emission reductions to health benefits, an analysis that tries to infer environmental health benefits directly from energy savings is likely to draw erroneous conclusions. Predictably, the states for which environmental health benefits were proportionately greater were states with greater regional population densities, higher-emitting electricity sources, and residential combustion of fuel oil.

To make our model applicable for policy decisions, further analyses are required. This would involve both expanding and refining our current analysis (the public health benefits of end-use energy reductions) and adding the cost and life cycle components.

On the first point, we have narrowly focused on a 10-year period, considering only the insulation benefits of the conservation code. Code changes would influence homes throughout their lifetimes and would presumably be in place for a number of years, indicating that the total impacts would be orders of magnitude greater than our estimate. If we considered non-residential sectors or the existing residential housing market, the potential energy savings and associated public health benefits would be considerable.

In addition, we relied on somewhat simplified models in all phases of our analysis. The uncertainty analysis showed that our aggregate impact estimates are quite uncertain and that this uncertainty is driven in large part by underlying uncertainties that we estimated somewhat simplistically and subjectively. Furthermore, if our analysis has any regional biases (i.e., energy models that perform better in some climates than others, dispersion models that are based on background concentrations and temperature/humidity conditions), then the rankings by region may be misstated. Our findings could also be affected by elements beyond the scope of our analysis, such as the potential for induced energy demand due to lower marginal heating costs or the long-term emissions profile of the electricity sector.

Another limitation of our analysis (and of any similar large-scale analysis) is the difficulty of validating the findings. The concentration changes and incremental risk reductions are too small to be observed, and even the per-unit energy benefits are difficult to isolate in a context with changing energy prices, home appliances, and housing market characteristics. We can validate components of the analysis through comparisons with other studies. For example, a recent study(12) estimated that "current" power plant emissions (year 2007 baseline) were responsible for approximately 30,000 premature deaths per year in the United States based on net generation of approximately 4,000 TWh. Simply scaling this estimate to our electricity reduction of 22 TBTU at end-use (approximately 6 TWh) yields an estimate of 45 premature deaths/year, which is almost identical to our electricity-related mortality reduction. While this does not validate our entire model, it demonstrates that our aggregate findings are supported by other studies with similar approaches.

In future studies, we will incorporate life-cycle-based information into our model framework while dealing with some of the limitations inherent in an LCA approach. Traditional LCA findings can be difficult to interpret in a benefit-cost analysis, given diverse indicators such as global warming, eutrophication, acidification, human toxicity, and habitat loss. Although these categories have merits when comparing products on the basis of their functional units, the lack of uncertainty analysis and bases for integration across impact categories cause difficulties in interpretation. Our proposed future work would use risk concepts in an LCA framework, considering three impact pathways.

1. Population and occupational exposure to air pollutants associated with the upstream process chains for fossil-fuel cycles.
2. Population and occupational exposure to air pollutants associated with the upstream process chains for insulation manufacturing.
3. Changes in indoor air quality associated with increased residential insulation, leading to changes in exposure of occupants to indoor pollutants.

For the first two pathways, although many analyses of DSM programs assume that the upstream impacts are dominated by the benefits of energy savings over the lifetime of the home, this must be quantitatively evaluated from a risk perspective (particularly when regional differences are important for policy decisions). For the analysis of population risks associated with upstream impact pathways, we will combine economic input/output LCA with intake fraction concepts and concentration-response functions. Economic input/output analysis utilizes national economic accounting tables to capture the emissions from all the upstream sectors in the supply chain of insulation and fuel sources, allowing us to avoid the system boundary issues inherent in process-based LCA. The emissions per dollar of output by sector can be applied within the input/output analysis to estimate the changes in upstream emissions. To refine this analysis and provide some estimates of uncertainty, economic input/output LCA will be complemented by information from process-based LCA, which focuses on specific commodities rather than sectors.

Connecting these emissions with risks contains numerous methodological issues, including determining the sites of emissions to account for site-dependent characteristics. This information is especially important for those sectors that are concentrated in a few regions rather than scattered evenly throughout the country. We can simplify the analysis by categorizing upstream sectors into two groups: those that require regional analysis (i.e., short-range pollutants emitted from localized emission sources) and those that can be approximated by national average exposure patterns (i.e., long-range pollutants emitted from sources scattered evenly across the country). The analysis can be further simplified by estimating risk only for those upstream industries that contribute a significant portion of total emissions, with risk-based adjustments using intake fraction concepts. Thus, although a site-dependent LCA theoretically involves numerous sites, the burden of analysis can be reduced with risk-based screening. Further screening can be based on the economic or health-based valuation of endpoints, which can allow the number of sites to be limited by identifying the sectors that are significant contributors to the total health burden in terms of the aggregate metric.

To calculate occupational health effects, we will use industrial injury and fatality statistics within the input/output LCA, along with evidence from epidemiological studies. Indoor air quality will be incorporated by considering the potential change in air exchange rates and the resulting implications for concentrations of pollutants generated both indoors and outdoors.

This analytical framework will allow for a better understanding of which LCA components matter from a risk perspective. The net health benefits will be integrated with the net economic implications of increased code stringency by state and region. Combining this information will allow us to determine in which settings information about risks would alter the policy decision that would be made based strictly on the economic implications.

6. CONCLUSIONS

We have proposed a methodological framework to combine risk assessment and life cycle assessment concepts, using simple models of exposure and concentration-response functions to prioritize among sources and outcomes. We applied these models to end-use emissions to preliminarily determine the magnitude and distribution of health benefits associated with increased residential insulation in new housing. We estimated benefits over a 10-year period of 60 fewer premature deaths, 2,000 fewer asthma attacks, and 30,000 fewer restricted activity days. Differences between the states and regions contributing energy savings and those contributing public health benefits illustrate that incorporating environmental externalities could affect the prioritization among states. Future analyses incorporating upstream emissions and economic endpoints would be necessary to comprehensively compare the benefits and costs of increased code stringency by state, but this study demonstrates an approach to quantifying a key component of the analysis.

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REFERENCES

1. U.S. Department of Energy, Energy Information Administration (EIA). (1999). *A look at residential energy consumption in 1997*. DOE/EIA-0632-97. Washington, DC: EIA.
2. U.S. Department of Energy (DOE). (1997). *Insulation fact sheet*. DOE/CE-0180. Washington, DC: DOE.
3. U.S. Department of Energy, Energy Information Administration (EIA). (1997). *Two decades of RECS: Changes in energy usage in residential housing units*. Available at http://www.eia.doe.gov/emeu/recs/recs97/decade.html.
4. U.S. Bureau of the Census. (2000). *Characteristics of new single-family homes: 1975–1997*. Compiled by National Association of Home Builders Economics Department. Available at http://www.nahb.org/facts/forcast/sf.html.
5. Building Codes Assistance Project. (2000). *Status of state energy codes: Nov/Dec 2000*. Available at http://www.energycodes.org.
6. Hammitt, J. K., Belsky, E., Levy, J., & Graham, J. D. (1999). Residential building codes, affordability, and health protection: A risk-tradeoff approach. *Risk Analysis*, *19*, 1037–1058.
7. Jones, T., Norland, D., & Prindle, B. (1998). *Opportunity lost: A national and state analysis of the 1993 Model Energy Code*. Washington, DC: Alliance to Save Energy.
8. Bernow, S., Ackerman, F., Biewald, B., Fulmer, M., Shapiro, K., & Wulfsberg, K. (1992). Direct environmental impacts of demand-side management. *1992 ACEEE Summer Study on Energy Efficiency in Buildings Proceedings*, *9*, 19–31.
9. Reddy, B. S., & Parikh, J. K. (1997). Economic and environmental impacts of demand side management programmes. *Energy Policy*, *25*, 349–356.
10. Hohmeyer, O., & Brauer, W. (1995). Rational use of energy. In *Insulation of houses energy efficient lighting and frequency converters—Implementation externalities of fuel cycles*. ExternE—Externalities of Energy Project. Germany: European Commission.
11. Woodruff, T. J., Caldwell, J., Cogliano, V. J., & Axelrad, D. A. (2000). Estimating cancer risk from outdoor concentrations of hazardous air pollutants in 1990. *Environmental Research Section A 82,* 194–206.
12. Abt Associates, ICF Consulting, & E.H. Pechan Associates. (2000). *The particulate-related health benefits of reducing power plant emissions*. Prepared for the Clean Air Task Force. Available at http://www.cleartheair.org/fact/mortality/mortalityabt.pdf.
13. Architectural Energy Corporation (AEC). (2000). *BESTEST results*. Provided by Dave Roberts, AEC.
14. U.S. Census Bureau (1998). *New housing characteristics July 1999*. Available at http://www.census.gov.
15. Wenzel, T. P., Koomey, J G., Rosenquist, G. J., Sanchez, M., & Hanford, J. W. (1997). *Energy data sourcebook for the U.S. residential sector*. LBL-4027/UC-1600. Berkeley, CA: Lawrence Berkeley National Laboratory.
16. Norland, D. (2000). Director of Research and Industrial Programs, Alliance to Save Energy. Personal communication.
17. American Society of Heating, Refrigerating and Air-Conditioning. (1997). *ASHRAE Handbook of Fundamentals*. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
18. U.S. Census Bureau. (2000). *New privately owned housing units authorized. Unadjusted units for regions, divisions, and states*. Available at http://www.census.gov/const/C40/Table2/tb2u1999.txt.
19. National Association of Home Bunders. (2001). *The next decade for housing.* Available at http://www.nahb.com.facts/nextdecadeforecast.pdf.
20. U.S. Environmental Protection Agency (EPA). (1995). *Compilation of air pollutant emission factors. AP-42, Fifth edition, volume I: Stationary point and area sources*. Research Triangle Park, NC: EPA.
21. U.S. Department of Energy. (2000). *Technical support document: Energy efficiency standards for consumer products. Appendix K-2: Emissions factors for fuel combustion from natural gas, LPG, and oil-fired residential water heaters.* Washington, DC: Building Research and Standards Office.
22. Levy, J. I., Wolff, S., & Evans, J. S. (2002). A regression-based approach for estimating primary and secondary particulate matter exposure efficiency. *Risk Analysis*, *22*, 893–902.
23. Evans, J. S., Wolff, S., Phonboon, K., Levy, J. I., & Smith, K. (In press). Exposure efficiency: An idea whose time has come? *Chemosphere*.
24. Wolff, S. (2000). Evaluation of fine particle exposures, health risks, and control options. Doctoral thesis. Boston, MA: Department of Environmental Health, Harvard School of Public Health.
25. U.S. Environmental Protection Agency (EPA). (1999). *The benefits and costs of the Clean Air Act: 1990 to 2010*. EPA-410-R99-001. Washington, DC: EPA Office of Air and Radiation.
26. U.S. Environmental Protection Agency. (1997). National ambient air quality standards for particulate matter; Final rule. 40 CFR part 50. *Federal Register*, *62*(138), 38651–38701.
27. Bates, D. V. (2000). Lines that connect: Assessing the causality inference in the case of particulate pollution. *Environmental Health Perspectives*, *108*, 91–92.
28. Pope III, C. A. (2000). Epidemiology of fine particulate air pollution and human health: Biologic mechanisms and who's at risk? *Environmental Health Perspectives*, *108*(4), 713–723.
29. Pope III, C. A., Thun, M. J., Namboodiri, M. M., Dockery, D. W., Evans, J. S., Speizer, F. E., & Heath Jr., C. W. (1995). Particulate air pollution as a predictor of mortality in a prospective study of U.S. adults. *American Journal of Respiratory and Critical Care Medicine*, *151*, 669–674.
30. U.S. Environmental Protection Agency (EPA). (1999). *Regulatory impact analysis—Control of air pollution from new motor vehicles: Tier 2 motor vehicle emissions standards and gasoline sulfur control requirements*. EPA420-R-99-023. Washington, DC: EPA Office of Air and Radiation.

31. Krewski, D., Burnett, R. T., Goldberg, M. S., Hoover, K., Siemiatycki, J., Jarrett, M., Abrahamowicz, M., White, W. H., (2000). *Particle epidemiology reanalysis project. Part II: Sensitivity analyses.* Cambridge, MA: Health Effects Institute.
32. Murphy, S. L. (2000). Deaths: Final data for 1998. *National Vital Statistics Report*, *48*(11).
33. Dockery, D. W., Pope III, C. A., Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris Jr., B. G., & Speizer, F. E. (1993). An association between air pollution and mortality in six US cities. *New England Journal of Medicine*, *329*, 1753–1759.
34. Whittemore, A. S., & Korn, E. L. (1980). Asthma and air pollution in the Los Angeles area. *American Journal of Public Health*, *70*, 687–696.
35. Krupnick, A. J. (1988). *An analysis of selected health benefits from reductions in photochemical oxidants in the northeastern United States: Final report*. Prepared for U.S. Environmental Protection Agency, Office of Air Quality Planning and Standards, EPA Contract No. 68-02-4323. Washington, DC: EPA.
36. Adams, P. F., & Marano, M. A. (1995). *Current estimates from the National Health Interview Survey, 1994*. Vital Health Statistics, Series 10 No. 193. Hyattsville, MD: National Center for Health Statistics.
37. Ostro, B. D. (1987). Air pollution and morbidity revisited: A specification test. *Journal of Environmental Economics and Management*, *14*, 87–98.
38. Abt Associates. (1999). *Final tier 2 rule: Air quality estimation, selected health and welfare benefits methods, and benefit analysis results*. EPA420-R-99-032. Washington, DC: U.S. EPA Office of Air Quality Planning and Standards.
39. West, J. J., Ansari, A. S., & Pandis, S. N. (1999). Marginal $PM_{2.5}$: Nonlinear aerosol mass response to sulfate reductions in the eastern United States. *Journal of the Air and Waste Management Association*, *49*, 1415–1424.
40. U.S. Environmental Protection Agency (EPA). (1999). *Interagency Workgroup on Air Quality Modeling (IWAQM) Phase 2 summary report and recommendations for modeling long range transport impacts*. EPA-454-R-98-019. Available at http://www.epa.gov/scram001 (under 7th Modeling Conference).
41. Carrothers, T. J., Wolff, S. K., Tuomisto, J., Wilson, A., Levy, J. I., Graham, J. D., & Evans, J. S. (2001). Assessing the economic value of further research for fine particle air pollution: Model framework and preliminary findings. Unpublished manuscript.