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# Carbon reductions and health co-benefits from US residential energy efficiency measures

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## Abstract

The United States (US) Clean Power Plan established state-specific carbon dioxide ($CO_2$) emissions reduction goals for fossil fuel-fired electricity generating units (EGUs). States may achieve these goals through multiple mechanisms, including measures that can achieve equivalent $CO_2$ reductions such as residential energy efficiency, which will have important co-benefits. Here, we develop state-resolution simulations of the economic, health, and climate benefits of increased residential insulation, considering EGUs and residential combustion. Increasing insulation to International Energy Conservation Code 2012 levels for all single-family homes in the US in 2013 would lead to annual reductions of 80 million tons of $CO_2$ from EGUs, with annual co-benefits including 30 million tons of $CO_2$ from residential combustion and 320 premature deaths associated with criteria pollutant emissions from both EGUs and residential combustion sources. Monetized climate and health co-benefits average $49 per ton of $CO_2$ reduced from EGUs (range across states: $12–$390). State-specific co-benefit estimates can inform development of optimal Clean Power Plan implementation strategies.

## Introduction

In August 2015, the United States Environmental Protection Agency (US EPA) issued the Final Rule for the Clean Power Plan [1], which established state-specific carbon dioxide ($CO_2$) emissions reduction goals for fossil fuel-fired electricity generating units (EGUs). States may achieve these goals through multiple mechanisms, including source-specific emissions standards or measures that can achieve equivalent $CO_2$ reductions, such as residential energy efficiency.

Residential energy efficiency is an appealing approach for emissions reductions, given evidence of greater cost-effectiveness relative to other strategies [2]. While studies have identified some of the economic benefits of energy efficiency as a $CO_2$ emissions reduction strategy, important co-benefits are often not considered in policy development. Such co-benefits include the influence of other air pollutants from EGUs on public health. Studies have shown that the air

pollution-related public health benefits of EGU control strategies can be appreciable, with thousands of lives saved per year and an array of morbidity benefits for $CO_2$ control strategies that include energy efficiency [3]. The monetary value of air pollution health benefits from EGU emissions reductions has been shown to be comparable in magnitude to the social cost of carbon (SCC) [4, 5]. In addition, energy efficiency measures that influence heating and cooling (e.g., increased residential insulation or air sealing) would not only reduce emissions from EGUs, but would also reduce emissions of $CO_2$ and other air pollutants from direct residential combustion.

Although these pathways are well-recognized, models to date have not provided insight at the state level on the multifactorial benefits of specific residential energy efficiency measures. Models of energy savings associated with energy efficiency are readily available [6] but without extension to emissions and health co-benefits. Recent models examining the

commercial sector incorporated social benefits at the state level related to both $CO_2$ emissions and other air pollutants [7], but focused only on electricity and natural gas, calculated health benefits using estimates that relied on an atmospheric dispersion model with limited secondary chemistry, and characterized average rather than marginal emission rates from the power grid. An older study of the residential sector estimated social benefits of increased residential insulation by extrapolating findings from a more complex atmospheric dispersion model and estimating marginal emission rates, but did not model all source locations directly or account for more complex patterns of electricity dispatch [8]. Studies have applied more complex atmospheric models to evaluate air pollution benefits of energy efficiency or other interventions, but generally only at a national scale [3]. To our knowledge, no studies have incorporated all of the elements needed to accurately estimate social benefits of residential energy efficiency measures or to quantify co-benefits of residential energy efficiency measures targeting $CO_2$ at the state level.

In this study, we develop and apply a comprehensive and integrated model of the economic, climate, and public health benefits of increased insulation as an example of a state-level residential energy efficiency measure. We construct detailed simulations of the state-level energy savings associated with increasing residential insulation for all single-family homes in the continental US in 2013 to levels consistent with the 2012 International Energy Conservation Code (IECC). We estimate emissions reductions by state from both EGUs and residential combustion, and we link these emissions reductions with atmospheric chemistry-transport modeling approaches which allow us to isolate the contribution from individual emitted pollutants, source types, and states to ambient air pollution. We estimate the resulting public health benefits of reductions in ozone and fine particulate matter ($PM_{2.5}$) concentrations and we monetize both health benefits and $CO_2$ emission reductions. We present our central estimates and characterize uncertainty across multiple model components. These outputs allow us to quantify the co-benefits of state-level energy efficiency strategies targeting $CO_2$ emissions from EGUs, and to compare the health and climate benefits with the economic benefits associated with residential energy efficiency.

## Methods

Our simulation model consists of five primary components (figure 1). We describe each of these model components in the sections that follow, with more detail about our energy simulation modeling and atmospheric modeling in supplementary data.

### Energy simulation modeling

We simulated building-wide energy consumption using high-performance computing techniques with an energy simulation program (EnergyPlus) which has been extensively applied and validated in the peer-reviewed literature [9–12]. We began with EnergyPlus building prototypes developed by Pacific Northwest National Laboratory (PNNL) and made available through the Building Energy Codes Program of the US Department of Energy [13]. We then modified these prototypes to correspond with single-family detached homes representative of the US housing stock, using microdata from the 2009 Residential Energy Consumption Survey (RECS; see supplementary data).

We ran EnergyPlus for each home with current insulation and with increased insulation in the wall, ceiling, and floor consistent with the state-specific 2012 IECC. To calculate the benefits of increased residential insulation by state, we selected the RECS templates assigned to each state and calculated the differences in hourly energy consumption between the existing home and post-retrofit home. We then estimated the state-level benefits by using the RECS sample weight for each home but rescaling to represent the total number of single-family homes in each state, as derived from 2009 to 2013 American Community Survey estimates.

Because of the need to edit and simulate energy consumption for tens of thousands of templates, we developed code in Python to batch edit, process, and run homes in EnergyPlus. We utilized Eppy [14], a previously developed Python library for processing EnergyPlus inputs and outputs, for the batch file edits. We ran the simulations on the Shared Computing Cluster, a heterogeneous Linux cluster at Boston University.

We conducted two primary sensitivity analyses. First, given the possibility of systematic bias in EnergyPlus, we developed calibration factors by reportable domain (state or state aggregates), fuel type (electricity, natural gas, fuel oil, LPG/propane), and usage category (heating, cooling, all other) by comparing simulated baseline energy consumption with corresponding values from RECS. We used the calibrated values for our primary estimates but tested the sensitivity of our findings to the use of uncalibrated values. Second, because air tightness can greatly influence heating and cooling energy consumption and the estimation of effective leakage area (ELA—see supplementary data) may contain appreciable uncertainties, we calculated the benefits of increased insulation with modeled ELA and with ELA fixed to IECC 2012 levels for all homes.

### Emissions estimation

For EGUs, we applied an electricity dispatch model (the AVoided Emissions and geneRation Tool— AVERT) that uses historical hourly data on electricity

**Figure 1.** Flow diagram depicting all of the components of our simulation model.
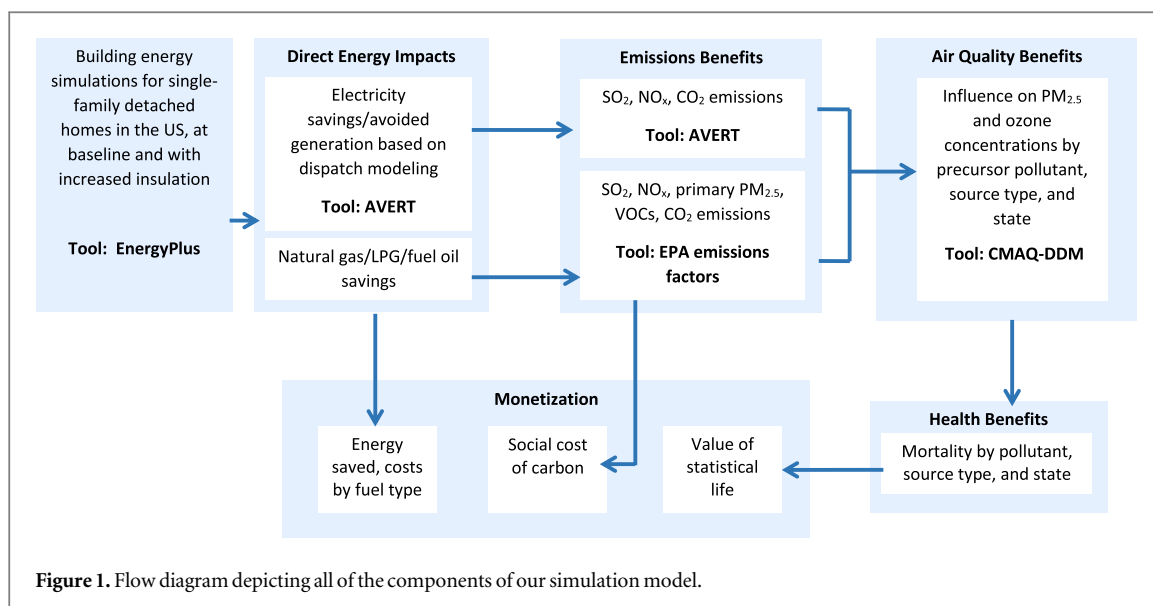
generation and dispatch to determine which EGUs would reduce generation given reductions in hourly demand [15]. We used baseline EGU attributes for 2013 for consistency with the other elements in our modeling platform. As multiple states are divided across electricity dispatch regions in AVERT, we first divided the modeled electricity savings across regions based on the number of single-family homes found in each region. For each state/region combination, we then input the modeled hourly electricity savings from EnergyPlus, assuming a constant 3.167 ratio between source electricity and site electricity [16]. We extracted outputs of $SO_2$, $NO_x$, and $CO_2$ emissions reductions by state and season. We omitted primary $PM_{2.5}$ emissions from EGUs given limitations in available input data consistent with AVERT, but note that about 95% of $PM_{2.5}$-related benefits from EGUs are attributable to secondary $PM_{2.5}$ formation from $SO_2$ and $NO_x$ emissions [17], so this would contribute a modest downward bias. Residential combustion criteria pollutant emissions for each fuel type were estimated from EPA's 2011 National Emissions Inventory [18], including $SO_2$, $NO_x$, VOCs, and primary $PM_{2.5}$ emissions (the sum of filterable and condensable). For $CO_2$ emissions, we derived emission factors by fuel type from EPA's Emission Factors for Greenhouse Gas Inventories [19].

**Atmospheric modeling**

To determine the influence of changes in emissions from EGUs and residential combustion by pollutant and state on concentrations of $PM_{2.5}$ and ozone, we used the Community Multiscale Air Quality (CMAQ) model v. 4.7.1 [20, 21] instrumented with the direct decoupled method (DDM) in three dimensions [22]. CMAQ can simulate both primarily emitted and secondarily formed pollutants at a national scale, and DDM decouples sensitivity equations from model

equations to allow for more stable sensitivity values by pollutant and source.

EGUs were modeled by individual power plants and aggregated to 36 km $\times$ 36 km grid cells by state, subdividing states that cut across multiple dispatch regions to allow for direct connection to AVERT outputs. Residential combustion sources were modeled as ground-level area sources including all residential fuel types and aggregated to county level for apportionment to grid cells by state. The meteorological inputs were from the Weather Research Forecast model and emissions inventories from EPA's National Emissions Inventories for the year 2005 were processed through the Sparse Matrix Operator Kernel Emissions modeling system.

Because CMAQ-DDM is computationally intensive, we selected two months (January and July 2005) to provide bi-seasonal representation. Modeling a subset of sources for the full year found differences of ~10% on an annual average basis, confirming the validity of this approach. To provide initial background conditions, a spin-up period of 11 days just prior to each month was simulated. The computational intensity of CMAQ-DDM also led us to incorporate multiple states in a single run, grouping states that were expected to have minimal concentration overlap based on results from pilot analyses. We developed and applied an image segmentation technique to separate concentration surfaces from one another, described in supplementary data.

We focused on contributions of primary $PM_{2.5}$ (elemental carbon, organic carbon, and primary sulfate), $NO_x$, $SO_2$, and VOCs to ambient $PM_{2.5}$; and on contributions of $NO_x$ and VOCs to ozone. For consistency with health impact modeling approaches, $PM_{2.5}$ constituents were estimated as 24 h averages and ozone was estimated as daily 8 h maximum values.

## Health damage function modeling

We calculated mortality risks using the following equation:

$$\Delta y = \sum_{i=1}^{N} \sum_{j=1}^{M} (y_{0ij}(e^{\beta \cdot \Delta x_{ij}} - 1) \cdot \text{Pop}_{ij}),$$

where $i$ is row number and $j$ is column number, $N$ is total number of rows and $M$ is total number of columns in the CMAQ grid. $\Delta y$ is the change in mortality across the continental US, $y_0$ is the baseline mortality incidence rate at location $ij$, $\beta$ is the concentration-response function (CRF), $\Delta x$ is the change in air quality for a given precursor at location $ij$, and Pop is the population of interest at location $ij$.

For $PM_{2.5}$, we applied a central estimate of a 1% increase in mortality for every $1 \mu g\, m^{-3}$ increase in annual ambient $PM_{2.5}$ concentrations, consistent with an expert elicitation study [23] and in between the central estimates from two major cohort studies [24, 25]. As done previously [26], we used 0.3% as a lower-bound estimate and 2.0% as an upper-bound estimate, consistent with the median values across experts for the 5th and 95th percentiles of the uncertainty distributions as well as the uncertainty bounds for the two major cohort studies. For ozone, we applied a central estimate of a 0.4% increase in daily mortality per 10 ppb increase in daily 8 h maximum concentrations, based on major multi-city and meta-analysis studies [27–32], with 0.2% as a lower-bound estimate and 0.6% as an upper-bound estimate (representing the 5th and 95th percentiles of an equally-weighted pooling of the six major studies).

To estimate population and mortality, values for individuals aged 25 and over from 2001 to 2010 were obtained from CDC WONDER [33] and averaged for stability of values. County-wide values were projected as Lambert conformal conic in ArcMap v. 10.1 and intersected with CMAQ grid cells, assuming uniform population density and mortality rates within counties. Health damages per unit emissions were then estimated for each emitted precursor/ambient pollutant combination, by state and source sector, assuming that January represents October–March and that July represents April–September.

## Economic modeling

We estimated the economic benefits of increased residential insulation using 2013 fuel costs by state, applying regional values for states with missing information or national average values for regions with missing information [34]. To monetize the public health benefits, we applied a value of statistical life (VSL) commonly used in US EPA regulatory impact analyses [35], which corresponds to $9.7 million in 2013 dollars and 2013 income levels given recommended conversions for inflation and real income growth, with corresponding lower-bound and upper-bound values of $2 million and $20 million. We discount future $PM_{2.5}$-related deaths as done in EPA

regulatory impact analyses, applying a discount rate of 3% and assuming a mortality lag structure of 30% reductions in the first year, 50% reductions over years 2–5, and 20% over years 6–20 subsequent to the exposure reduction. As ozone-related deaths are based on short-term exposure studies, no discounting is necessary.
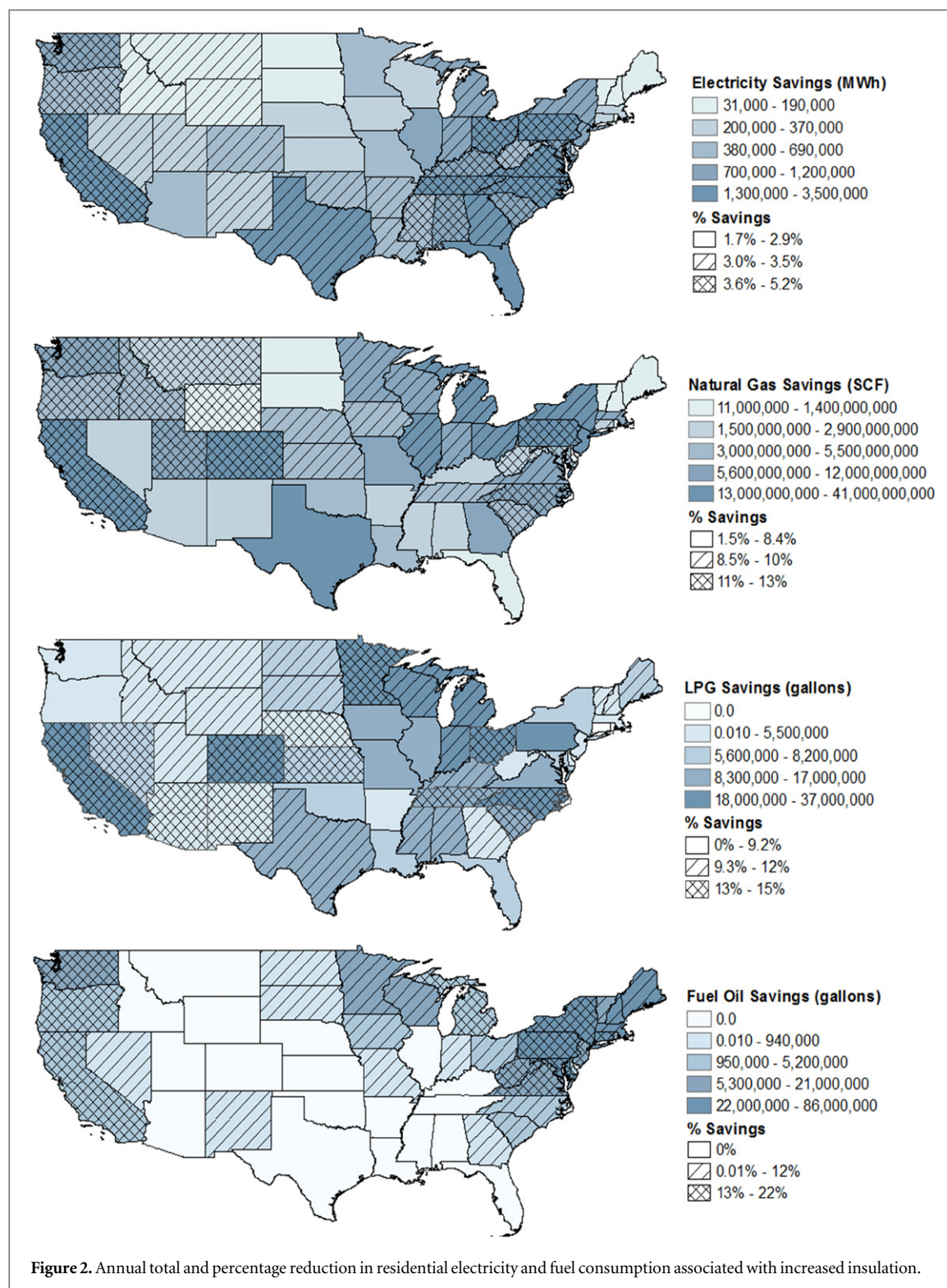
For $CO_2$ emissions, EPA has developed four alternative estimates of the SCC, reflecting different discount rates (5%, 3%, and 2.5%) applied to model average values as well as a 3% discount rate applied to the 95th percentile model value [36]. For a 2013 discount rate year and adjusted to 2013 dollars, the four reported values correspond to $11, $35, $55, and $99 per short ton of $CO_2$. We use the $35 value (corresponding to a 3% discount rate) for our central estimates and test the sensitivity of our findings to the three alternative values.

## Results

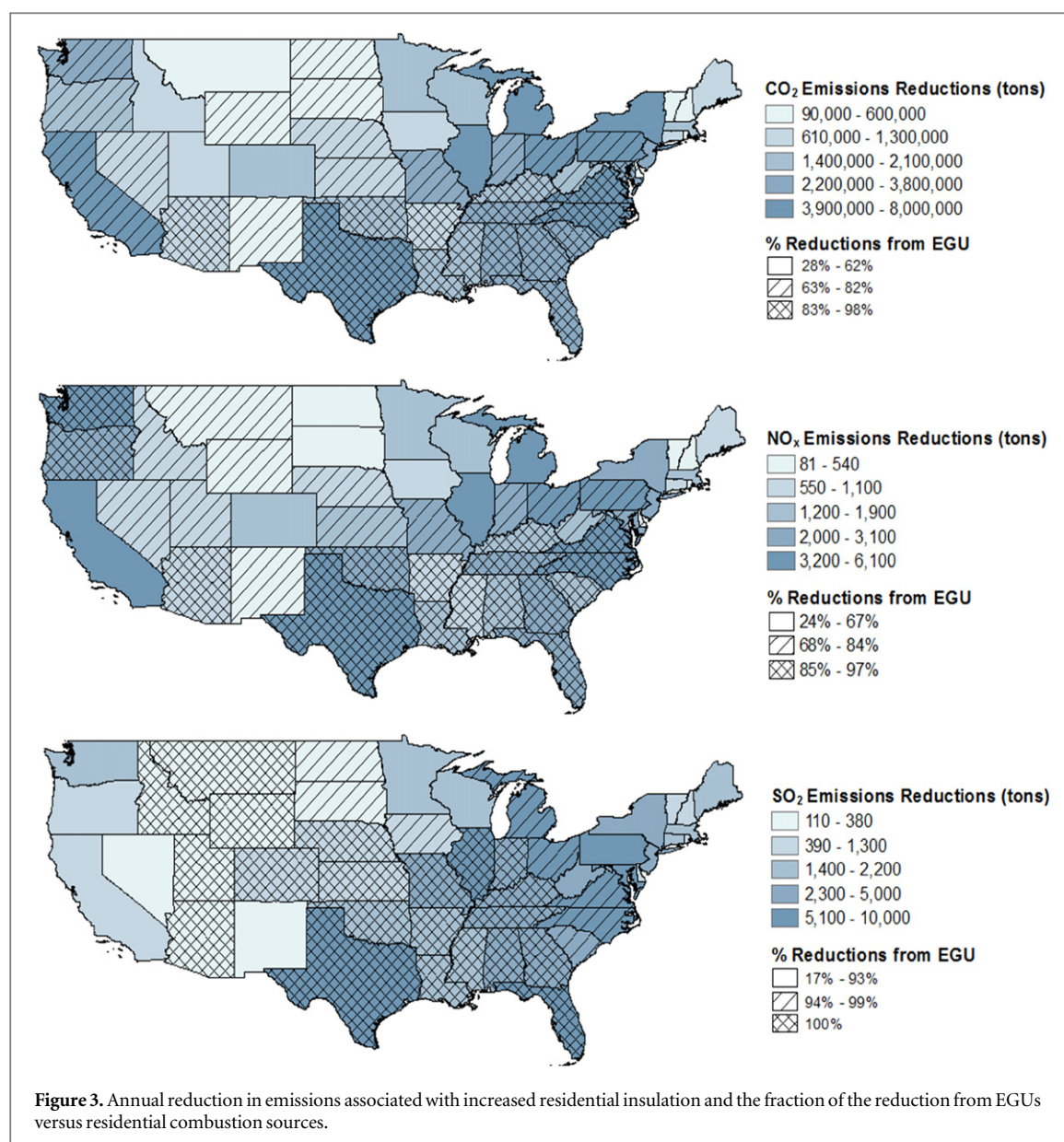### Modeled benefits of residential energy efficiency

Our calibrated energy model outputs estimate that, in total, increasing residential insulation to IECC 2012 levels for all single-family homes across the continental US in 2013 would save about 37 TWh of electricity consumption per year, or a 3.4% reduction in residential electricity consumption (range across states: 1.7%–5.2%; figure 2). This is driven by variations in the percent savings for electric space heating and space cooling, and the usage of electric space heating and air conditioning by state. We estimate that annual residential natural gas consumption would be reduced by 360 billion standard cubic feet (9% reduction), LPG/propane consumption by 490 million gallons (10% reduction), and fuel oil consumption by 480 million gallons (12% reduction). Both the absolute and percentage changes vary significantly across states (figure 2).

In total, reductions in electricity generation would be associated with annual reductions of 80 million tons of $CO_2$, 68 000 tons of $NO_x$ and 120 000 tons of $SO_2$. Reductions in direct residential combustion would be associated with annual reductions of 30 million tons of $CO_2$, 25 000 tons of $NO_x$, 10 000 tons of $SO_2$, 1300 tons of VOCs, and 600 tons of primary $PM_{2.5}$ (figure 3, supplementary table 1, and supplementary figure 1). The relative significance of EGUs and residential combustion varies across states and pollutants. For example, only in the Northeast is a significant fraction of $SO_2$ emitted by residential combustion, given fewer coal-fired EGUs and more residential fuel oil. For $CO_2$, states in the Northeast and Midwest tend to have greater contributions from residential combustion given less frequent use of electric space heating. Of note, for electricity, state values reflect the impact of demand reductions in the listed state, though EGUs across multiple states are affected.

**Figure 2.** Annual total and percentage reduction in residential electricity and fuel consumption associated with increased insulation.

Using central estimates for CRFs and calibrated energy model outputs, the criteria pollutant emissions reductions would be associated with 320 fewer premature deaths per year, 130 from residential combustion and 190 from EGUs (figure 4 and supplementary table 1). The states contributing most to EGU benefits are large states with significant coal combustion and large downwind populations (e.g., Pennsylvania, Ohio, Maryland, North Carolina). $NO_x$ contributes

51% and $SO_2$ 49% of the EGU benefits, with $NO_x$ making more substantial contributions in the Midwest and Mid-Atlantic. The states contributing most to residential combustion benefits are large states with appreciable use of higher-emitting combustion fuels (e.g., Ohio, New York, Maryland). Primary $PM_{2.5}$ emissions contribute 33% of the total residential combustion health benefits and are typically the greatest contributor in highly populated states in the East and
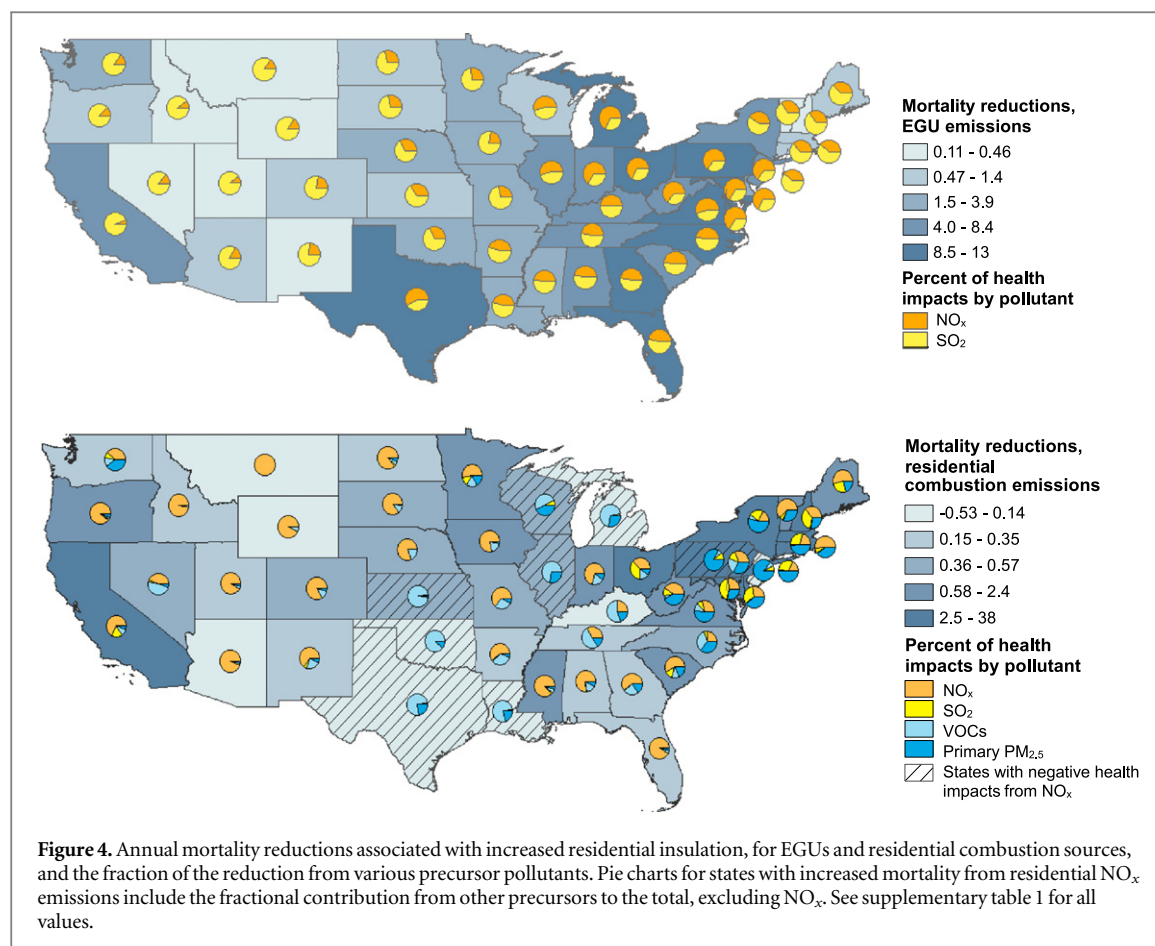
**Figure 3.** Annual reduction in emissions associated with increased residential insulation and the fraction of the reduction from EGUs versus residential combustion sources.

Midwest that have high wintertime health damage functions. $NO_x$ contributes 28% of the total residential combustion health benefits but is the dominant contributor in many states in the West, related in part to substantial wintertime ozone scavenging in the East. $SO_2$ contributes 29% of the total residential combustion health benefits, isolated to a limited number of states with appreciable use of LPG and fuel oil (e.g., Ohio, Maryland, New York, Connecticut).

When monetized using our base case assumptions, the annual health benefits are valued at $2.9 billion, as compared with the SCC of $3.8 billion and the direct economic savings of $11 billion from reduced energy consumption. Across states, the relative contributions of health to monetized social benefits varies from 11% to 80% (figure 5 and supplementary table 2), with health contributing more than climate in states across the Mid-Atlantic and Northeast, while climate is the dominant contributor in much of the West. Similarly,

the monetized social benefits vary significantly across states in comparison with the direct economic benefits, with the states exhibiting large social benefits typically having substantial residential combustion for space heating, a high density of coal-fired EGUs with significant space cooling requirements, and lower than average electricity prices (figure 5 and supplementary table 2).

We can estimate the co-benefits associated with state-level efforts to use residential insulation as a mechanism to reduce $CO_2$ emissions from EGUs. For every ton of $CO_2$ reduced from EGUs, there would be an additional 0.38 tons reduced from residential combustion sources (range across states: 0.02–2.6), an air quality-related mortality reduction of 2.4 per million population per year from EGUs (range across states: 0.58–4.7), and an air quality-related mortality reduction of 1.6 per million population per year from residential combustion sources (range across states:

**Figure 4.** Annual mortality reductions associated with increased residential insulation, for EGUs and residential combustion sources, and the fraction of the reduction from various precursor pollutants. Pie charts for states with increased mortality from residential NO$_x$ emissions include the fractional contribution from other precursors to the total, excluding NO$_x$. See supplementary table 1 for all values.

−0.21–34) (figure 6). If we monetize both health benefits and residential CO$_2$ emissions, the ancillary benefit per ton of EGU CO$_2$ reduction amounts to $49 (range across states: $12–$390). Ancillary benefits are greatest in the Northeast given fuel usage and emissions patterns.

**Uncertainty and sensitivity analysis**

Our energy savings and emissions estimates are insensitive to assumptions about ELA (3%–4% difference across all fuel types and pollutants). Energy model calibration has a greater effect on our estimates, with evidence of a systematic upward bias in EnergyPlus outputs in the absence of calibration to RECS. Using uncalibrated values, our electricity savings are 96% higher, driven by a substantial bias in electricity for space heating (283% higher) and a modest bias for electricity for space cooling (40% higher). Combustion fuel savings are also about a factor of 2 higher when using uncalibrated models. While this degree of bias is concerning, these differentials are not unexpected and calibration to observed baseline data can lead to accurate estimates of marginal benefits [37]. Nevertheless, when combining the alternative CRFs with the calibrated and uncalibrated outputs, our estimates of annual health benefits could be a factor of 3 lower (calibrated outputs, 5th percentile CRF) or a

factor of 4 higher (uncalibrated outputs, 95th percentile CRF) than our central estimates.

Considering the range of estimates for VSL and SCC, the relative contribution of air pollution health benefits versus climate benefits to monetized social benefits varies widely. Applying four alternative values for the SCC to calibrated energy model values yields monetized climate benefits between $1.2 billion and $11 billion per year, while applying three alternative values for the VSL yields monetized health benefits between $0.59 billion and $5.9 billion per year using our central health estimates. That said, the health and climate benefits are of a comparable order of magnitude as one another and add appreciably to the $11 billion in direct economic benefits under most assumptions.

# Discussion and conclusions

Our simulation model provides quantitative insight about the extent of co-benefits associated with residential energy efficiency as a strategy to reduce CO$_2$ emissions from EGUs. Previous studies have demonstrated that CO$_2$ emissions can be reduced through 'inside the fenceline' operational changes to EGUs, but that this leads to minimal influence on other air pollutants [3]. Other strategies for CO$_2$ emissions reductions, such as substituting or co-firing with lower
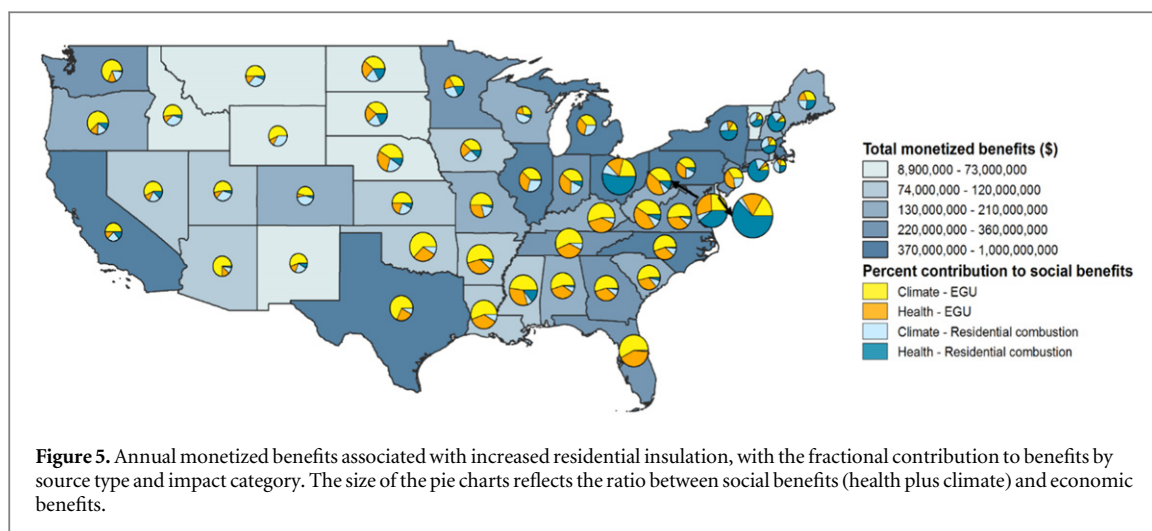
**Figure 5.** Annual monetized benefits associated with increased residential insulation, with the fractional contribution to benefits by source type and impact category. The size of the pie charts reflects the ratio between social benefits (health plus climate) and economic benefits.
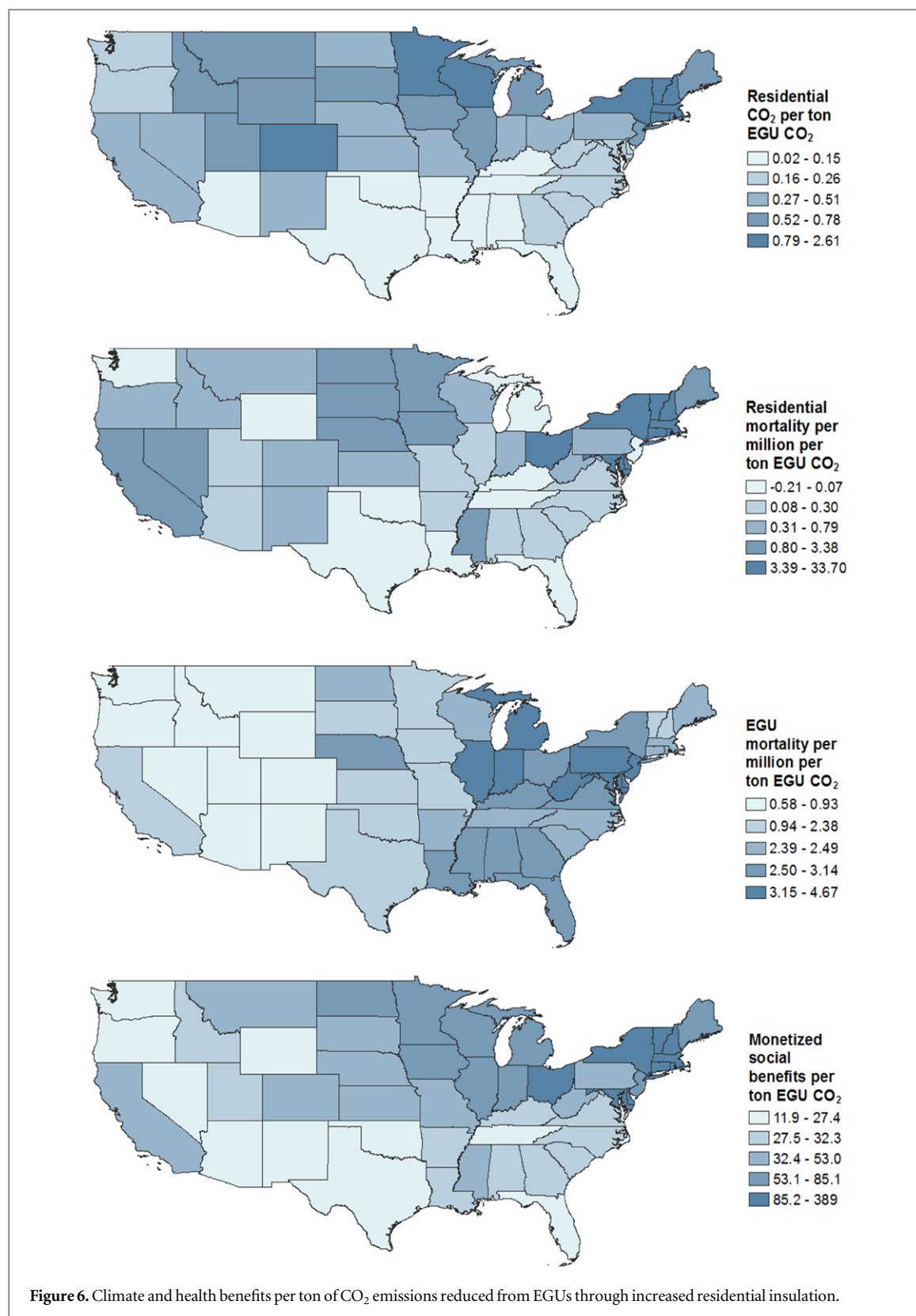
emitting sources, can provide co-benefits from EGU emissions but not residential combustion sources. Residential energy efficiency measures targeting space heating and cooling, such as increased insulation or air sealing, yield both types of co-benefits as well as a potential economic return on investment.

An important finding is the substantial geographic heterogeneity in co-benefits per ton of EGU $CO_2$ reduced (more than a factor of 30 across states), which provides insight about the states for which residential energy efficiency could be a more cost-effective approach from a societal perspective in meeting targets under the Clean Power Plan. States in the northern US with greater space heating requirements typically yield greater residential $CO_2$ and public health co-benefits, while states in the industrial Midwest and Southeast typically yield greater EGU public health co-benefits. When monetized, co-benefits per ton of $CO_2$ reduction from EGUs are greatest in the Northeast and Midwest. Numerous factors could influence the compliance strategies for individual states, and complexities of emissions reductions in states where the demand reduction did not occur would need to be addressed, but our findings and related analyses can be an input to the decision process.

Although we have quantified the most substantial uncertainties, additional factors contribute to uncertainty in our outputs. For example, our estimates of health damages per unit emissions are more uncertain for low-emitting states; while this uncertainty would minimally influence national-scale benefits, it should be acknowledged for state-specific applications. Our atmospheric modeling isolates the contributions of all existing sources within a state, but if the subset of sources affected by energy efficiency measures have a differing spatiotemporal pattern from the existing sources, the health damage estimates may differ. In addition, we have modeled a single year (2013), but multiple factors would evolve over time, including emissions characteristics of the power sector given regulatory requirements and technological shifts,

population patterns, and energy costs. While our modeling platform characterizes emissions reductions beyond the influence of existing regulations, the presence of these other regulations will influence the power sector in future years and therefore marginal emissions patterns. Formal application of our model to policy decision-making would benefit from analyses of health benefits over the lifetime of the energy efficiency measure. Our estimates do not incorporate increased emissions related to insulation manufacturing or decreased emissions from upstream energy processes, though earlier studies suggest an emissions payback period for insulation manufacturing on the order of a year for both $CO_2$ and $PM_{2.5}$ [38] with upstream energy processes contributing only about 10% to total impacts [39]. Our modeled energy efficiency measure is a stylized example that does not account for the variable cost-effectiveness across homes and locations, the possibility that increased insulation may only be warranted for parts of the home for some homes, the rebound effect in which lower costs of heating or cooling lead to changes in temperature setpoints or system utilization, or ongoing evolution of code requirements. In general, insulation retrofits for individual homes are economic decisions that depend on an array of factors (e.g., payback period, liquidity, financing, anticipated time in home), and our estimates should be interpreted as the state and national capacity for energy savings rather than the quantified benefits of a specific policy measure.

In general, in spite of multiple uncertainties, our estimates are well aligned with previously published values. For example, a study of the benefits of IECC 2000 insulation levels relative to existing home conditions in 1999 estimated 240 fewer deaths/year [8] (versus our current estimate of 320). Similarly, a study estimated a reduction of approximately 1 ton of $CO_2$ per home per year for insulation retrofits to 60% new and 40% existing homes [38], versus our estimate of 1.4 for existing homes. Our central estimates imply

**Figure 6.** Climate and health benefits per ton of $CO_2$ emissions reduced from EGUs through increased residential insulation.

monetized health impacts comparable in magnitude to monetized climate impacts, as shown elsewhere [5].

Although additional information would be required before determining whether residential energy efficiency would be the most socially cost-effective approach for $CO_2$ emissions reductions, the magnitude of the co-benefits coupled with prior evidence on cost-effectiveness of energy efficiency suggests that states should formally evaluate energy efficiency as part of Clean Power Plan compliance or as a general strategy to improve air quality and reduce $CO_2$ emissions. Our modeling platform has been designed to allow for rapid

future analyses, allowing for the benefits of alternative state-level residential energy efficiency measures to be quantified and used to inform cost-effective and health-protective public policies.

## Acknowledgments

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