

ENVIRONMENTAL STUDIES

The climate and health benefits from intensive building energy efficiency improvements

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Intensive building energy efficiency improvements can reduce emissions from energy use, improving outdoor air quality and human health, but may also affect ventilation and indoor air quality. This study examines the effects of highly ambitious, yet feasible, building energy efficiency upgrades in the United States. Our energy efficiency scenarios, derived from the literature, lead to a 6 to 11% reduction in carbon dioxide emissions and 18 to 25% reductions in particulate matter (PM_{2.5}) emissions in 2050. These reductions are complementary with a carbon pricing policy on electricity. However, our results also point to the importance of mitigating indoor PM_{2.5} emissions, improving PM_{2.5} filtration, and evaluating ventilation-related policies. Even with no further ventilation improvements, we estimate that intensive energy efficiency scenarios could prevent 1800 to 3600 premature deaths per year across the United States in 2050. With further investments in indoor air quality, this can rise to 2900 to 5100.

INTRODUCTION

Global energy consumption is expected to rise by 27% by 2040 (1), which underscores serious challenges for mitigating climate change. In the United States, building energy use alone accounts for 40% of total energy demand (2). Investments in building energy efficiency hold promise to reduce energy demand (3) and thus curb emissions from fossil fuel combustion, including emissions of both greenhouse gases and non-greenhouse gas pollutants, the latter of which are hereafter referred to as “local” air pollutants (4, 5). These reductions in local air pollutant emissions would improve outdoor air quality, potentially providing substantial benefits to human health. However, people in the United States spend 87% of their time indoors (6). This raises a potential concern of increased exposure to indoor pollutants for some homes due to decreased air exchange rates via infiltration that result from the tightening of the building shell for energy efficiency improvements (7). Thus, some intensive energy efficiency measures could also negatively affect human health, potentially offsetting the gains from improved outdoor air quality, unless additional measures are taken, including reductions in indoor emissions and/or investments in indoor air recirculation with pollutant filtration or increased outdoor air ventilation, such as those available as part of heating, ventilation, and air conditioning (HVAC) systems (8).

This study examines the long-run impacts of intensive energy efficiency improvements in buildings that go far beyond the current utility energy efficiency programs but align with calls for concentrated efforts to deeply improve energy efficiency (3). We explore the impacts on energy consumption and emissions, outdoor air quality health impacts, and indoor air quality effects (both with and without improvements in recirculation with filtration or emission reductions). To examine a range of potential impacts, we develop two scenarios of energy efficiency improvements in a comprehensive set of building services, such as space heating, space cooling, water

heating, and lighting. These carefully designed scenarios are more ambitious than those in previous work and deeply grounded in the literature on potential energy efficiency improvements. We also implement an example carbon pricing scenario to better understand the effects of intensive energy efficiency in a world with carbon pricing on electricity generation.

To our knowledge, we are the first to explore the impacts of intensive building energy efficiency improvements on emissions, indoor air quality, and human health across the entire United States. A rich body of research has studied energy efficiency (9–14). In a related study, Buonocore *et al.* (15) examined the health and climate benefits of a set of energy efficiency and renewable energy scenarios in the U.S. Mid-Atlantic and Lower Great Lakes regions using an electricity system simulation model calibrated to 2012. Buonocore *et al.* provided deep insights into short-run decarbonization strategies and the effect of (more modest) energy efficiency scenarios on outdoor air quality but did not examine long-run effects or indoor air quality implications. In another related study, Brown and Li (16) explored the long-run effects of energy efficiency policies on emissions in the commercial, residential, and industrial sectors when there is a carbon tax on electricity generation. Our study examines much more intensive energy efficiency improvements and quantifies the human health impacts resulting from changes in outdoor and residential indoor air quality (see the Supplementary Materials for a review of several less directly related studies).

Our analysis is based, in part, on scenarios implemented in the National Energy Modeling System (NEMS) run on a Yale server (and thus described henceforth as Yale-NEMS). NEMS is a well-known large-scale energy-economic equilibrium model of the U.S. energy system that includes all major sectors and runs from the present to 2050. While no model can perfectly project the future, NEMS has been described as the “gold standard” for long-run energy modeling in the United States (17). Researchers have used versions of NEMS to examine many questions relating to U.S. energy markets and environmental policies (18–20), including the effect of energy efficiency policies (16, 21–23). This work represents the first combination of a large-scale energy-economic model of the U.S. economy with extensive modeling of indoor air quality across the U.S. housing stock to examine the outdoor and indoor impacts of large-scale energy

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efficiency. By examining more intensive energy efficiency improvements and quantifying the long-run impacts on human health (inclusive of potential indoor air quality effects), our study sheds new light on how energy efficiency can contribute to deeper decarbonization and improved human health.

RESULTS

Energy efficiency and carbon pricing scenarios

The starting point for our analysis is the U.S. Energy Information Administration's (EIA) Annual Energy Outlook 2017 (AEO2017) reference case (24). AEO2017 projects U.S. energy market outcomes (e.g., equilibrium prices and quantities of various energy fuels) and the associated emissions out to 2050. It incorporates nearly all existing national and state-level policies until their sunset dates. No projection of the future is ever perfectly accurate, and EIA projections are no different (25), but researchers in the private sector, academia, and the government widely recognize EIA's projections as plausible baselines. In this study, we use AEO2017 without the Obama Administration's Clean Power Plan as our reference case (26).

We develop two scenarios—"Intermediate EE" and "Optimistic EE"—to represent future paths of energy efficiency improvements. These scenarios are based on feasible potential energy efficiency improvements for building services and shell materials that are not currently widely adopted but have been laid out in the technical literature (27–31). They cover energy services for residential and commercial buildings such as space heating and cooling, water heating, lighting, refrigeration, and cooking. They also cover building shell efficiency improvements for existing and new buildings in the residential, commercial, and industrial sectors. Table 1 shows the assumptions for our two scenarios. In the Intermediate EE scenario, we allow 20% efficiency increases on all building appliances and equipment and 40 to 60% efficiency improvements from better shell materials in new and existing buildings. The Optimistic EE scenario is a more ambitious case, in which we allow 50% efficiency improvements on appliances and equipment and 60 to 90% improvements on building shell materials (see the Supplementary Materials).

To better understand the impacts of energy efficiency when the electricity sector is decarbonizing, which could reduce the benefits of energy efficiency, we also implement a "Carbon Pricing" scenario

both alone and combined with the efficiency scenarios. In this scenario, we assume a time path of carbon prices on electricity generation (either through a carbon tax or tradeable permit system) that gradually increases from \$1/ton CO₂ in 2021 to \$30/ton CO₂ in 2040 and remains constant thereafter. This path is below the central case estimate of the social cost of carbon of the Obama Administration (32) and well below the values in recent work (33–35) or the values needed to reach a 1.5°C temperature rise target, as advocated by the Intergovernmental Panel on Climate Change. This carbon price path was chosen simply to illustrate the dynamics at play when a moderate carbon price path is in place, which is arguably more likely given recent historical experience and if major incentive policies for energy efficiency are already in place.

Energy consumption and associated emissions

Figure 1A presents the projected energy consumption in the residential, commercial, and industrial sectors in the quadrillions of Btus (quads) in the United States from the present to 2050. The effect of improving building energy efficiency on energy consumption is evident: Energy consumption is notably lower in the two energy efficiency scenarios than the reference case. In 2050, the Optimistic EE scenario leads to 16% reduction of energy consumption in the three energy consumption sectors, while the Intermediate EE scenario leads to a 9% reduction. In contrast, the stand-alone Carbon Pricing scenario results in only a 3% reduction in energy consumption in 2050. The combined Optimistic EE and Carbon Pricing scenario achieves a 19% reduction in 2050 relative to the reference case. We present more detailed results, including total economy-wide energy consumption, energy consumption disaggregated by fuel source, and end-use service in figs. S1 to S5.

Figure 1B shows the CO₂ emissions from fossil fuel combustion in the residential, commercial, and industrial sectors, including those associated with electricity used by the building sectors, which is generated at the power sector. In the Intermediate EE scenario, the CO₂ emissions are lower by 9% in 2050. In the Optimistic EE scenario, the emissions are 16% lower in 2050, which is about 600 million metric tons (MMT) of CO₂. The Carbon Pricing scenario achieves a similar level of emissions to the Optimistic EE scenario in 2050. Under the Optimistic EE and Carbon Pricing scenario, CO₂ emissions decline by 1222 MMT in 2050, a 33% reduction. The CO₂ emission

Table 1. Summary of energy efficiency scenarios for key efficiency improvements.

		Intermediate EE	Optimistic EE	
Appliances and equipment*	Residential	20% (28) [†]	50% (28) [†]	
	Commercial	20% (28) [†]	50% (28) [†]	
Building shell [‡]	Residential	Existing	2% per year (27, 30) [§]	
		New	60% (9, 27, 29, 30)	
	Commercial	Existing	40% (27, 30)	
		New	60% (9, 27, 29, 30)	
	Industrial		60% (27, 30)	90% (27, 30)

*The appliances and equipment include those providing space heating, cooling, water heating, lighting, refrigeration, cooking, and numerous other services. [†]The efficiency improvements for appliances and equipment are based on the advanced case of U.S. EIA's building-sector reports (31).

[‡]Building shell includes the envelope materials for isolating indoors and outdoors of buildings, which primarily preserves heating and cooling inside buildings. [§]The annual efficiency improvement can achieve around 50% cumulative improvements by 2050. ^{||}The annual efficiency improvement can achieve around 60% cumulative improvements by 2050.

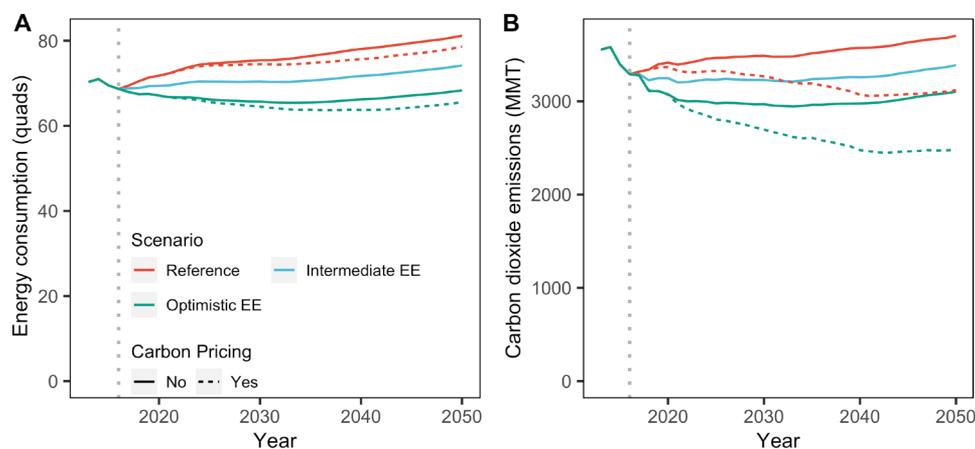


Fig. 1. Projected energy consumption and CO₂ emissions from the residential, commercial, and industrial sectors in the United States. Energy consumption in (A) includes all fossil fuel and electricity consumption in the residential, commercial, and industrial sectors. (B) Energy-related carbon emissions from the residential, commercial, and industrial sectors, including from electricity consumption. The vertical dotted lines separate historical and projected data.

reductions under the Optimistic EE and Carbon Pricing scenario are greater than the sum of the reductions combined from Optimistic EE and Carbon Pricing separately, which is 1183 MMT in 2050. This finding implies that the carbon pricing and energy efficiency policies are complementary on net, a result due to the fact that the two policies together result in more emission reductions in other sectors outside the building sector, which more than offsets the reduced potential emission savings from the building sector when there is cleaner electricity generation. This complementarity result is due to re-equilibration of prices and fuel switching in the industrial sector (see section S4). Figure S6 presents the CO₂ emissions disaggregated by the end-use sector.

Figure 2 illustrates emissions from several non-CO₂ air pollutants associated with fossil fuel combustion across the entire energy system (see Materials and Methods). We observe emission reductions in the energy efficiency scenarios for nearly all non-CO₂ air pollutants that we examine, driven by decreased consumption of fossil fuels (e.g., a 15% decline in coal and a 19% decline in natural gas in the Optimistic EE scenario). For example, sulfur dioxide (SO₂) emissions decline by 4% in the Intermediate EE scenario and 11% in the Optimistic EE scenario in 2050. We also observe a complementary relationship between the energy efficiency scenario (i.e., Optimistic EE) and carbon pricing scenario for all studied non-CO₂ air pollutants except for ammonia (NH₃) and volatile organic compounds (VOCs). We present the detailed air pollutant emissions by sector and Census division in figs. S7 to S12.

Health effects

We estimate the effect of energy efficiency improvements on human health by focusing on changes in premature deaths resulting from reduced outdoor energy-related air pollutant emissions (see Materials and Methods). Table 2 shows the change in premature mortality across the scenarios relative to the reference case in 2050. Our central estimates show that the Intermediate EE scenario leads to 4300 avoided premature deaths annually by 2050, while the Optimistic EE scenario results in 6600 avoided premature deaths per year. The Carbon Pricing scenario results in 3700 avoided deaths per year. The combined Optimistic EE and Carbon Pricing scenario avoids 11,000 premature deaths in 2050.

These considerable reductions in mortality only account for the effects resulting from reductions in outdoor primary pollutant emissions. Improvements to building energy efficiency often involve a variety of factors such as reducing convective losses, improving appliance efficiency, and “tightening” or reducing outdoor air infiltration that occurs through the building shell (i.e., leakage). Aside from occasional natural ventilation (e.g., window opening), most homes in the United States are ventilated solely by infiltration through the building shell; thus, the combination of reduced outdoor air ventilation and substantial indoor emissions may result in a reduction in indoor air quality (7) and the associated negative human health impacts, if no mitigating actions are taken (36). The most common residential conditioning systems in the United States, and those considered in this study, are forced-air recirculation HVAC systems without mechanical ventilation using outdoor air (37, 38), which do not contribute to the overall air exchange rate. However, these recirculation systems typically include varying levels of particle filtration, which can help mitigate indoor air quality. In this analysis, “recirculation with filtration” is used to refer to this common HVAC configuration, where minimum efficiency reporting value 6 (MERV 6)–equivalent and MERV 11–equivalent filters are modeled in existing and new homes, respectively (see section S5 for more details).

We model the changes in indoor air quality associated with the energy efficiency scenarios, focusing on residential buildings because 70% of time is spent indoors at home on average (6). We implement a Monte Carlo simulation using a single-compartment mass-balance box model calibrated to our scenarios (see Materials and Methods) to represent the U.S. housing stock. While spatial gradients in pollutant concentrations are known to occur in homes, this study represents homes with single-compartment box models to allow us to consider the health effects for the entire U.S. housing stock over a long exposure time scale. A promising area for future study would be to combine multicompartment modeling of pollutants and airflow to examine the impact of ventilation scenarios/strategies on those pollutant-specific gradients and their resulting health effects. For tractability, the model focuses on particulate matter (PM_{2.5}), a central indoor air pollutant with well-documented health associations, and we discuss the factors that would influence how our results would apply to other indoor pollutants.

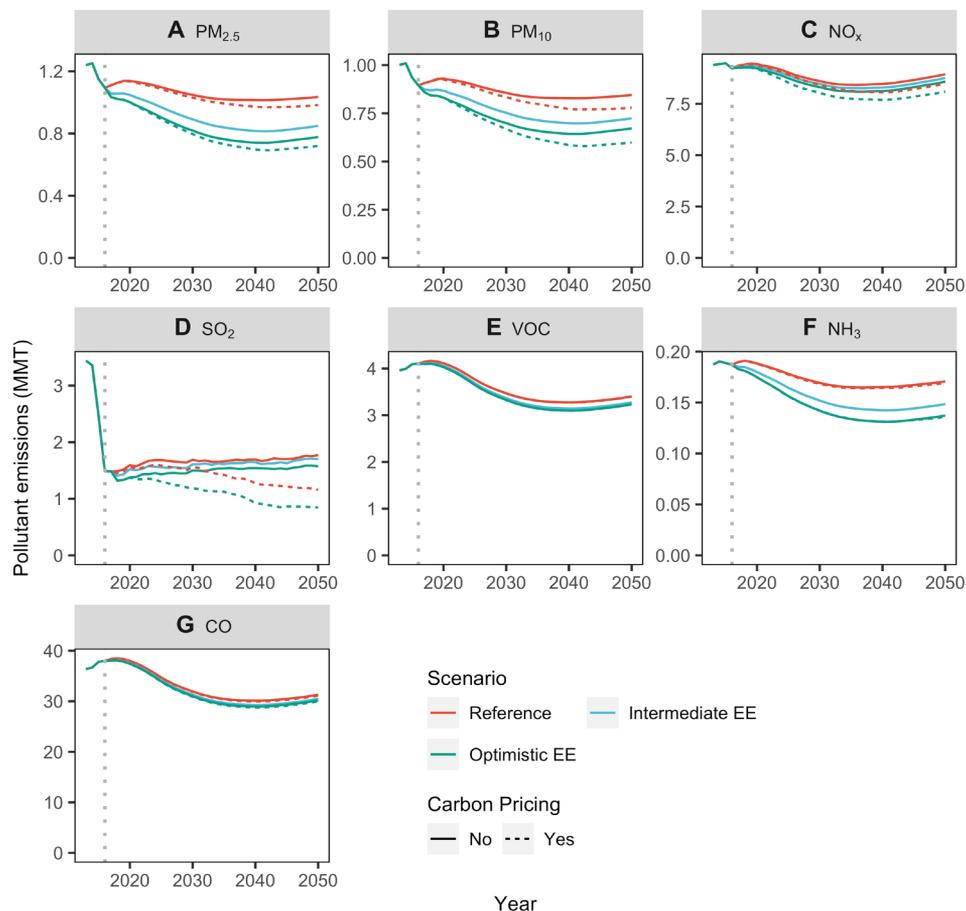


Fig. 2. Projected energy-related local air pollutant emissions in the United States resulting from our scenarios. (A) Projected $PM_{2.5}$ emissions. (B) Projected PM_{10} emissions. (C) Projected NO_x emissions. (D) Projected SO_2 emissions. (E) Projected VOC emissions. (F) Projected NH_3 emissions. (G) Projected CO emissions. The vertical dotted lines separate historical and projected data.

As changes to infiltration, natural ventilation, and HVAC recirculation adoption are all central to changes to indoor air quality (IAQ), we first summarize modeled differences in these parameters by year and scenario. In 2016, the distribution of infiltration air exchange rates in the entire U.S. housing stock (which are based on literature values) is estimated as $0.69 \pm 0.22 \text{ hour}^{-1}$. The literature has shown that newer homes, on average, tend to have lower infiltration rates (39), which, in this study, is taken as post-2009 construction. Only 3% of homes were considered to be post-2009 construction in 2016. In 2050, the distribution of infiltration air exchange rates changes to 0.44 ± 0.17 , 0.23 ± 0.10 , and $0.18 \pm 0.08 \text{ hour}^{-1}$ for the reference, Intermediate EE, and Optimistic EE scenarios (fig. S22), respectively. Natural ventilation rates remain constant throughout each scenario. Across this period, the share of homes with HVAC recirculation systems increased from 53% in 2016 to 63% in 2050.

Figure 3A shows the relative changes in indoor $PM_{2.5}$ concentrations from 2016 to 2050 as a function of the magnitude of indoor emissions across the U.S. housing stock (shown by emission percentile on the x axis) to demonstrate the nonlinear effect resulting from variations in indoor emissions (e.g., cooking activity and frequency, electric versus natural gas stovetops/ovens, appliance usage, and cleaning activity). Building energy efficiency measures result in reduced $PM_{2.5}$ concentrations in homes with lower indoor emissions

versus increased concentrations in homes with higher indoor emissions. Aside from differences in indoor emissions, another key difference between homes is the presence of indoor air recirculation systems that include adequate $PM_{2.5}$ filtration. Thus, we plot the change in concentrations both with and without these measures (Fig. 3A). Figure 3B shows the relative changes in response time, specifically the ability of homes to dissipate a pollution event, modeled as 1 hour of elevated emissions during stovetop cooking. This response time increases with greater building energy efficiency measures, largely because of reduced infiltration of outdoor air, and is further increased in the absence of recirculation systems with filtration.

Indoor air quality is not independent of outdoor air quality. Figure 3C demonstrates the combined effect of indoor emissions and outdoor concentrations on indoor $PM_{2.5}$ concentrations for the Optimistic EE scenario relative to the reference in 2050. Ratios less than 1 (blue shading) represent situations where higher EE scenarios lead to a net benefit for indoor air quality by reducing occupant exposure to elevated levels of outdoor air pollution, especially with additional mitigation measures such as recirculation with filtration. The opposite is true for ratios greater than 1 (red shading), where the decreased air exchange rate due to the tightening of the building shell leads to increased exposure to indoor emissions. To further illustrate the interplay of outdoor and indoor air, Fig. 3D displays

Table 2. Avoided premature mortality per year (shown for 2050) across the scenarios relative to the reference case in the United States. “Investment” refers to investments in recirculation systems with filtration. The “current patterns” row assumes that 62% of homes in 2050 have recirculation with filtration investments and thus can be thought of as a baseline. The numbers in parentheses provide bounds on the health effects of indoor air quality changes. The numbers in parentheses represent the lower and upper bounds of the health effects. For health effects associated with outdoor emissions, we estimate the lower and upper bounds based on three integrated assessment models [IAMs; i.e., Air Pollution Emission Experiments and Policy (AP3), Estimating Air pollution Social Impact Using Regression (EASIUR), and Intervention Model for Air Pollution (InMAP)]. For indoor air quality, we estimate the ranges of health outcomes based on the 95% confidence interval of the concentration-response function coefficient from the epidemiology literature. The ranges of net health effects are combinations of the above two.

	Intermediate EE	Optimistic EE	Carbon Pricing	Optimistic EE and Carbon Pricing
Avoided premature deaths resulting from reductions in outdoor pollutant emissions				
Estimated value	4300	6600	3700	11,000
	(3700, 5000)	(5700, 7800)	(2900, 5100)	(9000, 13,000)
Avoided premature deaths resulting from differences in PM_{2.5} exposure occurring indoors				
Current patterns of investment	–2500	–3000	0	–3000
	(–4500, –850)	(–5400, –1000)	0	(–5400, –1000)
No investment	–4400	–5500	0	–5500
	(–7900, –1500)	(–9900, –1900)	0	(–9900, –1900)
Investment in all homes	–1400	–1500	0	–1500
	(–2500, –460)	(–2700, –490)	0	(–2700, –490)
Net changes in avoided premature deaths				
Current patterns of investment	1800	3600	3700	8000
	(–820, 4200)	(260, 6800)	(2900, 5100)	(3600, 12,000)
No investment	–79	1100	3700	5500
	(–4200, 3500)	(–4200, 5900)	(2900, 5100)	(–920, 11,000)
Investment in all homes	2900	5100	3700	9500
	(1200, 4500)	(3000, 7300)	(2900, 5100)	(6300, 13,000)

the modeled ratio of indoor to outdoor PM_{2.5} concentrations and estimates that PM_{2.5} concentrations are often greater outdoors for the majority of U.S. homes, with the exception of homes with the largest indoor emissions and in locations with low outdoor concentrations.

The main takeaway of Fig. 3 is that building shell efficiency improvements can affect indoor air quality, and the magnitude and direction of the effect vary depending on the magnitude of indoor pollutant emissions, implementing HVAC systems with pollutant filtration, and ambient outdoor concentrations. We use the results from Fig. 3 to estimate indoor PM_{2.5} concentrations over time in our scenarios and the net negative health effects from reduced indoor air quality (over all households) relative to the reference in 2050 (see Materials and Methods and the Supplementary Materials). We perform this calculation in three ways in a bounding exercise: one assuming no additional HVAC system investments, one assuming all homes invest in HVAC systems with particle filtration, and one assuming that HVAC investments follow current patterns.

Table 2 also presents the net health effects associated with these changes in indoor air quality across the scenarios compared to the reference case in 2050. On the basis of the 2050 estimates of homes using recirculation systems with filtration (i.e., 62%), worsened indoor air quality in the Intermediate EE scenario results in 2500 premature deaths in 2050. The Optimistic EE scenario leads to 3000 premature deaths. In a lower bound scenario where no homes have recirculation with filtration, the Intermediate EE and Optimistic EE scenarios lead

to 4400 and 5500 premature deaths, respectively. In contrast, when the investments in recirculation with filtration are made in all homes, the Intermediate EE scenario results in only 1400 premature deaths and the Optimistic EE scenario results in 1500 premature deaths.

For net health impacts of our scenarios, the central estimates suggest that all scenarios reduce premature mortality on net, with the Intermediate EE scenario reducing premature mortality by 1800 and the Optimistic EE scenario reducing it by 3600 (if investments in recirculation/filtration follow the patterns currently in the data). Figure S13 shows the net human health results for other years.

Figure 4 presents the results of net changes in avoided premature deaths from Table 2 (assuming 62% of homes have recirculation with filtration in 2050) disaggregated to the U.S. Census division level put in terms of avoided premature mortality per hundred thousand residents, illustrating that the magnitude of changes in avoided premature mortality is not evenly distributed across the regions. We apply the impacts from our national-level indoor air quality analysis to regions based on population but acknowledge that there may be geographical and seasonal variations in ventilation changes and housing characteristics. The avoided premature deaths are primarily concentrated in the East and Midwest (i.e., Upper Midwest and Middle Atlantic). For example, the Optimistic EE and Carbon Pricing scenario results in six avoided premature deaths per 100,000 residents in the Upper Midwest region and five avoided deaths per 100,000 residents in the Middle Atlantic regions. This spatial pattern is

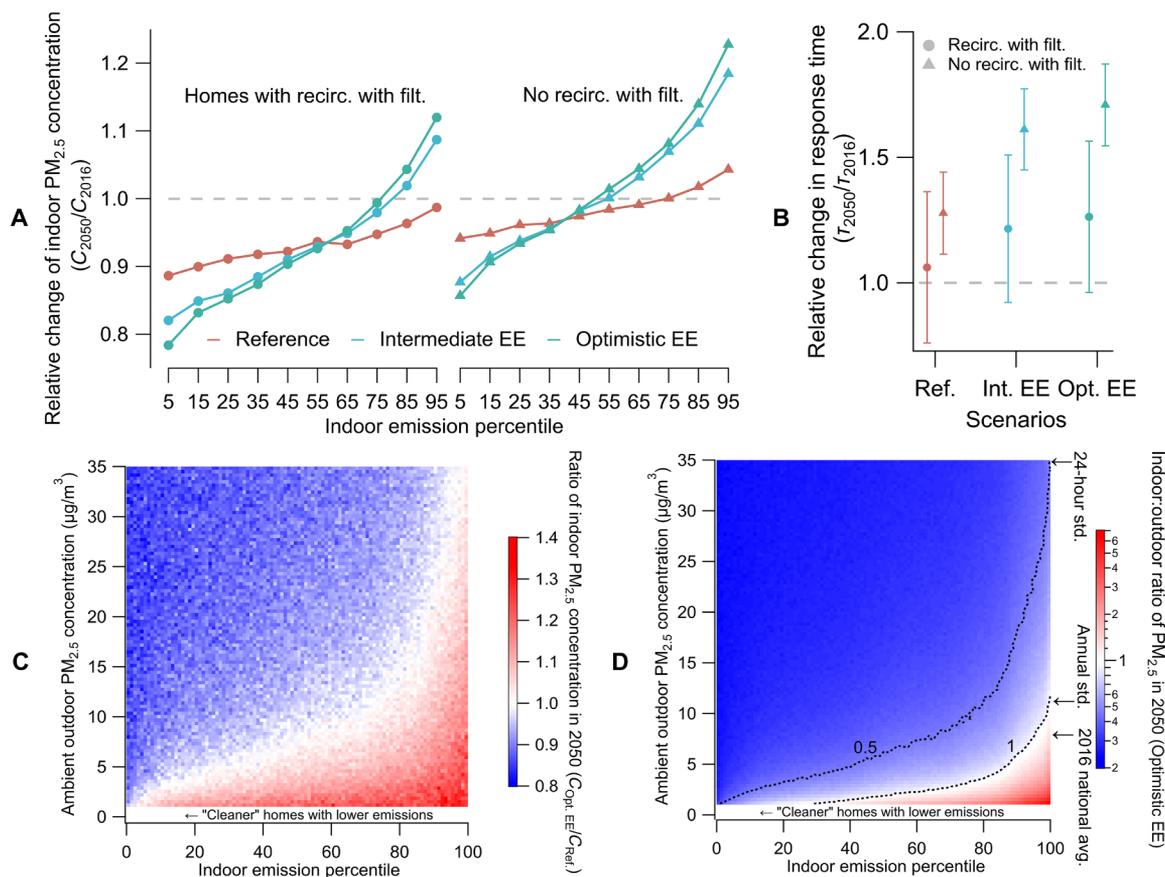


Fig. 3. Impact of projected energy efficiency scenarios on residential indoor air quality. (A) Relative change of residential indoor $PM_{2.5}$ concentration from 2016 to 2050 for homes with and without HVAC recirculation systems with particle filtration for each EE scenario as a function of indoor emission percentile (a lower value means a “cleaner” home). (B) Relative change of the response time from 2016 to 2050 of homes to an indoor emission event for each EE scenario (simulated as 1 hour of stovetop cooking). Error bars indicate SDs. (C) Color map of the change of indoor $PM_{2.5}$ concentration for 2050 from the optimistic EE scenario relative to the reference case as a function of indoor emissions and outdoor $PM_{2.5}$ concentrations. (D) Logarithmic color map of the indoor:outdoor (I/O) ratio of $PM_{2.5}$ for the optimistic EE scenario in 2050 (contour lines show the 0.5 and 1 curve). Note that outdoor concentrations in (A) and (B) use the 2016 national average, while in (C) and (D), the outdoor concentration is shown up to $35 \mu g/m^3$ to include the 24-hour standard [shown in (D) alongside annual primary standard and 2016 average].

primarily driven by greater marginal damages of non- CO_2 air pollutant emissions in these regions.

Sensitivity analysis

We examine multiple sensitivity cases related to energy system modeling and health effects estimation. The sensitivity analyses for energy system modeling focus on the Optimistic EE scenario. The results do not appear to be sensitive to varying penetration levels of renewables in the energy system, which is useful to know because AEO2017 underprojects renewable growth relative to the trends that we have seen in the past 2 years (see fig. S27). In addition, the emission results do not vary substantially using the U.S. Environmental Protection Agency (EPA) National Emissions Inventory (NEI) 2017 data and 2017 as the base year for outdoor emission projections (see fig. S28). However, the results appear to be dominantly driven by the projections of the emission factors of fossil fuel consumption (see figs. S29 and S30).

The health effects due to changes in outdoor pollutant emissions are influenced by the assumptions about the marginal damages from air pollutant emissions, which are drawn from the literature (40–42). We also conduct a sensitivity analysis for estimating the health effects owing to changes in $PM_{2.5}$ exposure occurring indoors using

an alternative concentration-response (C-R) function. The results are consistent with the primary results (see table S3). The full set of sensitivity analyses is presented in the Supplementary Materials.

DISCUSSION

This paper analyzes the effects of intensive improvements in building energy efficiency that go substantially beyond current policies on outdoor emissions, indoor air quality, and human health. We use a large-scale energy-economic model, Yale-NEMS, and combine it with a detailed indoor air quality analysis. We implement two detailed energy efficiency scenarios and a carbon pricing scenario to depict an evolving energy system. Our results suggest that intensive efficiency scenarios lead to a 6 to 11% decrease in energy-related CO_2 emissions, a 4 to 11% decrease in SO_2 emissions, and an 18 to 25% decrease in primary $PM_{2.5}$ emissions in 2050. These outdoor emission reductions can bring about considerable health benefits, which can reduce premature mortality by 3700 to 7800 lives in the United States annually in 2050.

While intensive energy efficiency improvements may lead to worsened indoor air quality for some homes, we show that premature deaths are avoided on net (i.e., up to 6800 avoided deaths annually

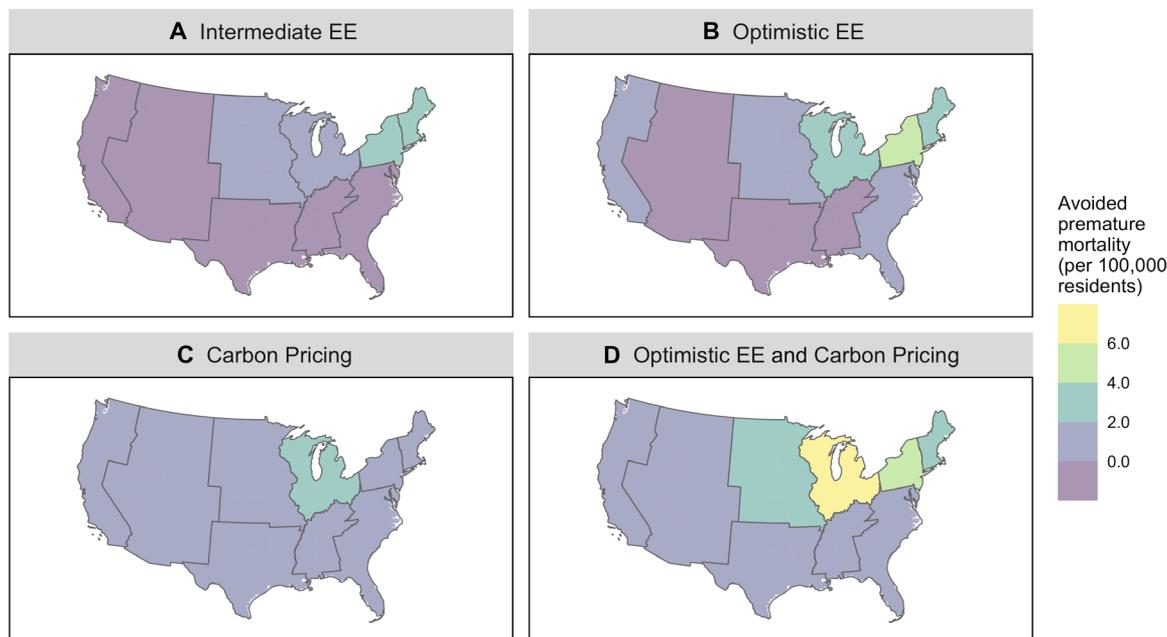


Fig. 4. Net benefits of avoided premature mortality per 100,000 residents per year in the U.S. Census divisions. (A) Net benefits of avoided premature mortality per year for the Intermediate EE scenario. (B) Net benefits of avoided premature mortality per year for the Optimistic EE scenario. (C) Net benefits of avoided premature mortality per year for the Carbon Pricing scenario. (D) Net benefits of avoided premature mortality per year for the Optimistic EE and Carbon Pricing scenario. The results are the net mean effects of changes in outdoor and indoor air quality (assuming current patterns of investment in indoor air recirculation systems with filtration) relative to the reference case in 2050. We use the nationwide indoor air quality results and divide by the population of each of the regions.

in 2050) even after accounting for changes in indoor air quality (assuming that investments in recirculation with filtration follow current patterns), a new and important result. From a policy perspective, it is also important to note that attention to ventilation practices, indoor emissions, and investments in indoor air recirculation systems with filtration, including upgrading to better-performing filters, could mitigate the detriments to indoor air quality. This could even improve indoor air quality further, avoiding many additional premature deaths. Our result of a complementarity between intensive energy efficiency and carbon pricing is also highly policy relevant, as it suggests that the two policies could be combined to achieve greater emission reductions.

There are some limitations to our analysis worth mentioning. While we address the potential social benefits from building energy efficiency improvements, we do not examine the costs associated with improving energy efficiency or the costs of additional investments in indoor air recirculation systems (with filtration) beyond those already in place. Thus, similar to Buonocore *et al.* (15), this study does not perform a cost-benefit analysis but rather is an exploration into the climate and health benefits of energy efficiency investments. Since intensive energy efficiency improvements may require substantial cost outlays, future work is warranted to explore those outlays, as well as the future fuel savings that the recipients of the energy efficiency improvements would benefit from. Similarly, we focus our indoor health effects calculations only on $PM_{2.5}$ and do not include any non-air quality-related benefits (e.g., from reductions in cold-related mortality, especially for populations struggling with winter fuel poverty, that result from improved building thermal efficiency).

Our estimated health benefits naturally depend on the central estimates of marginal damages of emissions and the magnitude of the C-R functions. While the methodologies in this study are widely

used for policy evaluation, there are uncertainties in these values that would further broaden our ranges (see the Supplementary Materials). In addition, our indoor air and health results are focused on $PM_{2.5}$ given its outside impact on premature mortality, but there are other indoor air pollutants. The outcomes and framework of this study may be relevant to the analysis of several of these other pollutants in the context of ventilation scenarios. Key considerations when applying our results to other pollutants include pollutant-dependent differences in the magnitude of indoor emissions, deposition to indoor surfaces, filtration efficiency, chemical reactions/losses, and location- and time-dependent outdoor concentrations that affect indoor-outdoor pollutant gradients. Gas-phase pollutants have compound-dependent deposition rates, potential repartitioning to the gas phase for VOCs, and chemical sinks from reactions, and most will have limited filtration efficiency by traditional filter media in HVAC systems.

Pollutants with a mix of indoor and outdoor sources (e.g., NO_x and VOCs) may exhibit a range of outcomes across the housing stock similar to our observations for $PM_{2.5}$. There may be higher indoor concentrations of gases and particles with major indoor sources (e.g., radon, some VOCs, and biological aerosols) due to decreased ventilation with outdoor air (43), while the indoor concentrations of those of outdoor origin (e.g., ozone and wildfire smoke) may be reduced, especially during peak outdoor periods. Mold exposure, and the underlying issue of dampness, is another important indoor air issue, and one that will respond in a complex way to changes in infiltration and ventilation practices. A recent review of a diverse range of home retrofit studies (43), and the resulting changes in gas-phase pollutants, points to this complexity in the coupled indoor-outdoor system, which emphasizes the importance of building design to mitigate exposure to both outdoor and indoor air pollution.

The presence of a forced-air recirculation HVAC system was found to be a key differentiating factor for indoor air quality, and additional policy measures addressing particle filtration standards or strategic retrofitting incentives could improve health benefits substantially. As building envelopes continue to tighten for energy efficiency purposes, home ventilation could cease their reliance on infiltration and be built or retrofitted with energy-efficient mechanical ventilation systems with outdoor air intake, which are not prevalent in the current housing stock or considered in our analysis. More broadly, our methodology is a scenario analysis designed to illustrate the potential benefits of intensive energy efficiency relative to a reasonable baseline, but the exact paths of future developments in technology, population, economic growth, policy, etc., are unknown. In this sense, we are modeling for quantitative insight, rather than exact estimates of any of our outcome variables. Furthermore, an uncertainty in the indoor air study is the exact relationship of future changes in ventilation rates (i.e., infiltration reduction) to building shell efficiency index (BSEI)-related improvements compared to other efficiency measures (e.g., insulation) (see section S5.1). To examine this, a sensitivity analysis (section S5.5) shows indoor air quality effects with varying degrees of emphasis on building tightening (figs. S25 and S26). In all, the indoor air exposure results emphasize careful consideration of ventilation practices and policies with respect to building efficiency as the indoor air effects are sensitive to the level of prioritization on building tightness, which may also vary as a function of home type, geometry, or location.

The geographic scope of our analysis is restricted to the United States. There are substantial differences between the United States and many other countries in the housing stock, electric grid, indoor pollutant sources (which are sometimes energy-related and connected to relevant policies), and demographics. Intensive energy efficiency achieved by tightening the building shell along with investments in recirculation systems with filtration may have even more substantial benefits from improved indoor air quality in locations with poorer outdoor air quality as long as there is sufficient mitigation of indoor emissions. In addition, widespread bans on natural gas, as are occurring in some U.S. municipalities, would affect building-related greenhouse gas emissions and could mitigate some sources of indoor PM_{2.5} emissions (e.g., table S2). Despite the limitations, the results reported in this study can shed light on how intensive building energy efficiency can be a part of a broader decarbonization strategy and how they can bring about substantial health benefits.

MATERIALS AND METHODS

The methodology used in this study includes a series of model runs and postprocessing estimations. We first run the scenarios in Yale-NEMS to project energy consumptions, CO₂ emissions, and local air pollutant emissions from the present to 2050. On basis of the modeling results from Yale-NEMS, we then extrapolate the emissions associated with fossil fuel combustion for a more extensive set of air pollutants (e.g., PM_{2.5} and VOCs). Next, we analyze the changes in indoor air quality. Last, we quantify the health impacts associated with outdoor and indoor changes to PM_{2.5} exposure across the scenarios.

Yale-NEMS

NEMS is a large-scale energy-economy equilibrium model for the United States, incorporating current policies, resource availability, and technologies. Yale-NEMS is the NEMS modeling framework

run on a server at Yale (the EIA requests all outside users of NEMS to add their name with a hyphen in front of NEMS). This modeling framework is appropriate for our research goals because of its spatial granularity, detailed modeling of the energy markets, and, most importantly, a comprehensive representation of building energy end-use services. The model consists of 13 interconnected modules, including all principal U.S. energy supply and demand sectors at the U.S. Census division level. Yale-NEMS solves energy equilibrium prices and quantities out to 2050, as it equilibrates energy supply and demand. Since we are interested in the effects of building energy efficiency improvements, the following description of Yale-NEMS will focus on the modeling of building energy consumption in the residential, commercial, and industrial sectors.

The modeling of energy demand for the residential sector is in the Residential Demand Module (RDM). The RDM is an integrated dynamic modeling system accounting for residential consumer economic behaviors (44). The module projects residential appliance stocks and market shares of technologies and the associated energy demand starting from EIA's most recent Residential Energy Consumption Survey (i.e., the base year of the module) out to 2050. Specifically, the RDM models residential energy demand with six sequential steps: (i) projecting the stocks of newly built and existing (carried forward or removed) houses based on the results from the Macroeconomic Activity Module (e.g., gross domestic product and population projections); (ii) projecting market shares for each available equipment type; (iii) projecting end-use appliance stock within houses; (iv) projecting building shell technology for space heating and cooling; (v) projecting distributed electricity generation in residential houses from solar, fuel cells, and small wind turbine systems; and (vi) calculating end-use consumption for each residential building service and fuel type. These sequential projections are based on energy prices and macroeconomics factors endogenously determined in Yale-NEMS and other exogenous data sources.

Similarly, the modeling of energy demand for commercial sectors is depicted in the Commercial Demand Module (CDM) (45). The CDM is a dynamic simulation modeling tool that is used to project long-run commercial energy demand from EIA's most recent Commercial Building Energy Consumption Survey to 2050. The module consists of five steps: (i) projecting commercial building floorspace, (ii) projecting energy-consuming services demand, (iii) forecasting electricity generation by distributed generation technologies, (iv) determining equipment choices to meet the service demands, and (v) calculating energy consumption by fuel type.

The equipment and shell efficiency data in AEO2017 are from Navigant Consulting Inc. In our energy efficiency scenarios, we mainly alter the baseline equipment and shell efficiency coefficients. Yale-NEMS models rebound effects for building services in the residential and commercial sectors that lead improved energy efficiency to increase usage. For example, in CDM and RDM, space heating and cooling energy demand associated with increasing equipment efficiency is rebound-adjusted, where the elasticity of energy consumption with respect to the energy efficiency (described as the "rebound elasticity" in the NEMS documentation) is assumed to be -0.15 .

Yale-NEMS models industrial energy consumption in the Industrial Demand Module (46). Unlike the residential and commercial sectors, energy use in industrial buildings only accounts for a small proportion of the total energy consumption in the industrial sector. The majority of energy is allocated to manufacturing processes, which is beyond the scope of this analysis. Here, we change

the baseline energy efficiency coefficients, including lighting and HVAC, which primarily provide services for workers working indoors. Note that Yale-NEMS accounts for increased average temperatures out to 2050, with fewer heating degree days and more cooling degree days.

Air pollutant emissions estimation

For each model run, Yale-NEMS outputs a rich set of results at the Census division level, including energy quantities and prices by fuel type and sector, as well as emissions. For emissions, Yale-NEMS reports economy-wide energy-related CO₂ emissions and SO₂ and nitrogen oxides (NO_x) emissions from the electricity-generating sector from the present to 2050. To obtain broader insights into emissions, we use a postprocessing approach to estimate the emissions of additional local air pollutants from burning fossil fuels in all energy-related sectors, such as NH₃, carbon monoxide (CO), PM_{2.5}, PM₁₀, and VOCs.

For each projected year, we first compute the percentage changes in energy consumption by fuel type in that year compared to the consumption in the year 2014. We then apply the computed percentage changes to the EPA 2014 NEI to extrapolate air pollutant emissions over the projected years. Note that the calculated air pollutant emissions are only associated with fuel combustion. While this approach assumes constant emission factors over time, we conduct a sensitivity analysis for changing emission factors. We also conduct an additional sensitivity analysis using the EPA 2017 NEI data and the year 2017 as the base year for emission projections (see section S6.1).

Indoor air quality analysis

One contribution of this paper is that we develop a model to estimate the effects of our scenarios on home indoor air quality. We analyze how changes in ventilation due to our scenarios influence indoor exposures to PM_{2.5} from indoor sources. We also account for changes in the infiltration of outdoor PM_{2.5} into homes due to our scenarios. The model uses Yale-NEMS output (e.g., BSEI, the number of HVAC systems, and heating and cooling degree days) and factors from existing literature (e.g., air exchange rates, housing stock variables, and PM_{2.5} emission rates). See section S5 for details on the methodology.

We first identify the relationship between energy efficiency improvements and home ventilation. Yale-NEMS projects BSEI out to 2050, which is a key variable linking building EE improvements and indoor air quality. The BSEI expresses the relative amount of energy required to heat or cool the same space over time compared to the base year 2009. In this study, we assume that each factor contributing to BSEI (energy use due to air leakage, convective losses, appliances, etc.) decreases by the same relative amount (see section S5.1 for additional information). Coupling changes in the BSEI, heating and cooling appliance efficiencies, average home size, and heating and cooling degree days allows for the calculation of relative outdoor air infiltration and the resulting air exchange rates compared to a base year (e.g., 2016) across the scenarios. See section S5.5 for a sensitivity analysis exploring the importance of linking changes to energy efficiency with changes to home building tightness and the effect of varying the relationship between BSEI and infiltration-related energy use.

We then calculate absolute air exchange rates from infiltration for 2016 based on the Yale-NEMS output (e.g., the housing stock

and the number of HVAC systems) and various residential home factors from the literature (e.g., the distribution of air exchange rates from infiltration) (37, 39, 47). Using distributions from the literature on key home factors allows for a variety of home types to be represented under a single distribution rather than from being modeled individually. Homes with HVAC systems are assumed to consist of forced-air recirculation with no additional outside intake, which is the most common configuration for North American homes (37, 38). These systems are also assumed to have particle filtration based on house age (MERV 6 equivalent for pre-2009 homes and MERV 11 for post-2009 homes), although there is no known comprehensive survey of HVAC filter adoption (39). HVAC runtimes are taken from the literature and based on current levels of use, but changes in HVAC runtimes could accompany future building ventilation scenarios and lead to different levels of PM_{2.5} filtration (37, 39).

The calculated air exchange rates for infiltration are used in a well-mixed single-compartment box model to estimate indoor PM_{2.5} concentrations. Although each home consists of several compartments with distinct geometry that will affect pollutant exposure, a single-compartment box model was chosen to reduce computational complexity and model overall U.S. housing stock effects. Note that the modeling framework can be applied to other pollutants, but we focus on PM_{2.5} because of its well-known association with health impacts (48). Our indoor air quality model takes into account a wide variety of indoor particle sources (e.g., stovetops, ovens, microwaves, toasters, washing machines, showering, and vacuuming), outdoor PM_{2.5} penetrating through building cracks, and building air recirculation systems with filtration. Note that candles, incense, smoking, or other similar sources are not included and would represent additional PM_{2.5} emissions. We then implement a Monte Carlo simulation using the Yale-NEMS output distributions for the U.S. housing stock, and indoor air quality model parameters to simulate absolute indoor PM_{2.5} concentrations by EE scenario and year.

Because of the nonlinear distribution of indoor emission rates (see section S5.3) and the exponential relationship between PM_{2.5} and premature mortality, PM_{2.5} concentration estimates are grouped by emissions deciles, each of which are assumed to represent $1/10$ of the population. The change in indoor air quality for each decile is then used to estimate health effects. Generally, reductions in air exchange rates due to infiltration, among other factors, provide positive health effects to lower deciles and negative health effects to higher deciles. These effects are subsequently summed over all bins to determine the net effect. The indoor air quality concentration data used for estimating the health effects are presented in fig. S24.

Outdoor health effects estimation

We calculate the effect of outdoor air pollutant emissions on human health using the estimates of marginal damages of air pollutant emissions from three integrated assessment models (IAMs): the Air Pollution Emission Experiments and Policy (AP3) model, the Estimating Air pollution Social Impact Using Regression (EASIUR) model, and the Intervention Model for Air Pollution (InMAP) (40–42). These models examine the health effects of pollution exposure that inherently includes the time spent both indoors and outdoors, as well as pollutant intrusion indoors.

On the basis of historical spatially distributed emissions data (e.g., EPA's NEI), these models first estimate baseline atmospheric concentrations of particulate matter for each location (e.g., county or grid). The models then compute changes in ambient

PM_{2.5} concentrations from the baseline across locations with a one-unit perturbation in pollutant emissions. Following the changes in PM_{2.5} concentrations, the IAMs estimate the number of premature mortality occurrences caused by the changes in emissions using certain C-R functions from the epidemiology literature. Last, assuming a value of statistical life (VSL), the number of premature mortality occurrences is converted to dollar values. The outputs from these models include location-specific marginal damages per unit of NH₃, NO_x, primary PM_{2.5}, SO₂, and VOCs emissions in dollar values for the United States. However, the effect of these emission reductions on secondary PM_{2.5} formation was not modeled as part of this study and may lead to changes in ambient secondary organic and inorganic PM_{2.5} concentrations due to reductions in reactive precursors or changes in chemical processes. We obtain the marginal damages data for AP3 from the website <https://public.tepper.cmu.edu/nmuller/APModel.aspx> and the data for EASIUR and InMAP from the Center for Air, Climate, and Energy Solutions website (www.caces.us).

The three IAMs have been used in various studies concurrently as an approach to shed light on uncertainty (49, 50). Specifically, here, we first calculate the county-level number of premature mortality cases per metric ton of emissions by dividing the reported dollar value marginal damages by the assumed VSL (\$9,186,210 in AP3 and \$6,299,143 in EASIUR and InMAP) for each of the IAMs. We then aggregate marginal damages to the U.S. Census division level weighted by county-level emissions. Next, we calculate the total damages of premature mortality by multiplying marginal damages and projected emissions by pollutant and summing over the products across NH₃, NO_x, primary PM_{2.5}, SO₂, and VOCs. We take the averages of the estimates across the three models as our central estimates and the ranges of these estimates across the models as the lower and upper bounds to provide the reader a sense of the uncertainty in the outdoor health effects calculations. Unfortunately, the IAMs themselves do not provide SEs, so it is not possible to estimate within-model uncertainty currently, but this is a prime area for future research.

Indoor health effects estimation

The effect of changes in indoor PM_{2.5} concentrations on changes in premature mortality is estimated on the basis of an epidemiology-based C-R function adjusted for time spent indoors in Logue *et al.* (51). Following Azimi and Stephens (52), we further modify the C-R function to account for microenvironmental PM_{2.5} concentrations and exposures. While the evidence on the variable effects of indoor versus outdoor air quality on human health is still emerging, here, we apply the best evidence available.

The log-linear C-R function is shown as

$$\Delta Y_{t,s,d} = \gamma_0 (\exp(\beta_{t,s,d}^{\text{OG}} \times \theta^{\text{home}} \times \Delta C_{t,s,d}^{\text{OG}} + \beta_{t,s,d}^{\text{IG}} \times \theta^{\text{home}} \times \Delta C_{t,s,d}^{\text{IG}}) - 1) \times \text{Pop}_{t,s,d} \quad (1)$$

where $\Delta Y_{t,s,d}$ indicates the changes in premature deaths in year t associated with the type of building stock s , $s \in \{\text{homes with recirculation, homes without recirculation}\}$, and emissions decile d that defines the magnitude of indoor emissions in homes. γ_0 is the baseline mortality rate per person per year, assumed to be 0.0074 (51), and θ^{home} represents the average fraction of time that people spend inside residence, which is assumed to be 0.69 (6). $\Delta C_{t,s,d}^{\text{OG}}$ represents the changes in indoor PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$) that result from sources of outdoor origin, and similarly, $\Delta C_{t,s,d}^{\text{IG}}$ represents the changes in indoor PM_{2.5} concentrations that result from indoor-generated sources.

Both $\Delta C_{t,s,d}^{\text{OG}}$ and $\Delta C_{t,s,d}^{\text{IG}}$ are projected from our indoor air quality model and are relative to a baseline value of $0 \mu\text{g}/\text{m}^3$, which is consistent with other recent studies (52, 53). $\text{Pop}_{t,s,d}$ represents the total population. We take the total U.S. population forecasted in Yale-NEMS and disaggregate it into homes with and without recirculation/filtration (based on the number of central air conditioning and home heating units compared to the total number of homes) and indoor emissions decile (assumed to be uniformly distributed).

The parameter $\beta_{t,s,d}^{\text{OG}}$ is the modified PM_{2.5} C-R coefficient for outdoor-generated sources, which is calculated as

$$\beta_{t,s,d}^{\text{OG}} = \beta_0 / \bar{F}_{t,s,d} \quad (2)$$

where β_0 is the PM_{2.5} C-R coefficient from the epidemiological literature, assumed to be 0.0058 (95% confidence interval: 0.0020 to 0.0104) (48). $\bar{F}_{t,s,d}$ is an average of infiltration factors weighted by time fractions spent in four microenvironments (i.e., home, outdoor, vehicle, and other indoors), which is specified as

$$\bar{F}_{t,s,d} = F_{t,s,d}^{\text{home}} \theta^{\text{home}} + F_{t,s,d}^{\text{outdoor}} \theta^{\text{outdoor}} + F_{t,s,d}^{\text{vehicle}} \theta^{\text{vehicle}} + F_{t,s,d}^{\text{other}} \theta^{\text{other}} \quad (3)$$

$F_{t,s,d}^{\text{home}}$ is the infiltration factor for home, which is simulated from the indoor air quality model. The rest of the infiltration factor and time fraction parameters are obtained from Azimi and Stephens (52). The intuition for adjusting the C-R coefficient β_0 from epidemiological studies is that the coefficient β_0 is calculated from ambient PM_{2.5} concentrations as a proxy for overall personal exposure, which includes time spent in various environments (e.g., in a home or vehicle) where concentrations may not be equal to that outdoors (53–55). Following Azimi and Stephens, we assume that the C-R effects for indoor ($\beta_{t,s,d}^{\text{IG}}$) and outdoor ($\beta_{t,s,d}^{\text{OG}}$) generated PM_{2.5} concentrations were equal.

We calculate the central estimates of indoor health effects based on the mean values of the parameters discussed above. To illustrate the uncertainty in these estimates, we also estimate lower and upper bounds using the 95% confidence interval for the PM_{2.5} C-R coefficient β_0 .

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at <http://advances.sciencemag.org/cgi/content/full/7/34/eabg0947/DC1>

REFERENCES AND NOTES

1. International Energy Agency, *World Energy Outlook 2018* (2018); <https://webstore.iea.org/world-energy-outlook-2018>.
2. Energy Information Administration, *Annual Energy Outlook 2019* (Energy Information Administration, 2019); www.eia.gov/outlooks/aeo/.
3. A. Grubler, C. Wilson, N. Bento, B. Boza-Kiss, V. Krey, D. L. McCollum, N. D. Rao, K. Riahi, J. Rogelj, S. De Stercke, J. M. Cullen, S. Frank, O. Fricko, F. Guo, M. Gidden, P. Havlik, D. Huppmann, G. Kiesewetter, P. Rafaj, W. Schoepp, H. Valin, A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. *Nat. Energy* **3**, 515–527 (2018).
4. C. Wilson, A. Grubler, K. S. Gallagher, G. F. Nemet, Marginalization of end-use technologies in energy innovation for climate protection. *Nat. Clim. Chang.* **2**, 780–788 (2012).
5. F. Creutzig, J. Roy, W. F. Lamb, I. M. L. Azevedo, W. Bruine De Bruin, H. Dalkmann, O. Y. Edelenbosch, F. W. Geels, A. Grubler, C. Hepburn, E. G. Hertwich, R. Khosla, L. Mattauch, J. C. Minx, A. Ramakrishnan, N. D. Rao, J. K. Steinberger, M. Tavoni, D. Urge-Vorsatz, E. U. Weber, Towards demand-side solutions for mitigating climate change. *Nat. Clim. Chang.* **8**, 268–271 (2018).
6. N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, W. H. Engelmann, The National Human Activity Pattern Survey (NHAPS):

- A resource for assessing exposure to environmental pollutants. *J. Expo. Anal. Environ. Epidemiol.* **11**, 231–252 (2001).
7. S. E. Frey, H. Destailats, S. Cohn, S. Ahrentzen, M. P. Fraser, The effects of an energy efficiency retrofit on indoor air quality. *Indoor Air* **25**, 210–219 (2015).
 8. J. Sundell, H. Levin, W. W. Nazaroff, W. S. Cain, W. J. Fisk, D. T. Grimsrud, F. Gyntelberg, Y. Li, A. K. Persily, A. C. Pickering, J. M. Samet, J. D. Spengler, S. T. Taylor, C. J. Weschler, Ventilation rates and health: Multidisciplinary review of the scientific literature. *Indoor Air* **21**, 191–204 (2011).
 9. T. Li, Y. Zhai, S. He, W. Gan, Z. Wei, M. Heidarinejad, D. Dalgo, R. Mi, X. Zhao, J. Song, J. Dai, C. Chen, A. Aili, A. Vellore, A. Martini, R. Yang, J. Srebric, X. Yin, L. Hu, A radiative cooling structural material. *Science* **364**, 760–763 (2019).
 10. J. Zhao, Y. Li, G. Yang, K. Jiang, H. Lin, H. Ade, W. Ma, H. Yan, Efficient organic solar cells processed from hydrocarbon solvents. *Nat. Energy* **1**, 15027 (2016).
 11. L. Zhu, A. P. Raman, S. Fan, Radiative cooling of solar absorbers using a visibly transparent photonic crystal thermal blackbody. *Proc. Natl. Acad. Sci. U.S.A.* **112**, 12282–12287 (2015).
 12. A. Levinson, How much energy do building energy codes save? Evidence from California houses. *Am. Econ. Rev.* **106**, 2867–2894 (2016).
 13. M. Walls, Energy efficiency: Building labels lead to savings. *Nat. Energy* **2**, 17055 (2017).
 14. O. I. Asensio, M. A. Delmas, The effectiveness of US energy efficiency building labels. *Nat. Energy* **2**, 17033 (2017).
 15. J. J. Buonocore, P. Luckow, G. Norris, J. D. Spengler, B. Biewald, J. Fisher, J. I. Levy, Health and climate benefits of different energy-efficiency and renewable energy choices. *Nat. Clim. Chang.* **6**, 100–105 (2016).
 16. M. A. Brown, Y. Li, Carbon pricing and energy efficiency: Pathways to deep decarbonization of the US electric sector. *Energ. Effic.* **12**, 463–481 (2019).
 17. J. J. Winebrake, D. Sakva, An evaluation of errors in US energy forecasts: 1982–2003. *Energy Policy* **34**, 3475–3483 (2006).
 18. K. L. Palmer, R. Sweeney, M. Allaire, *Modeling Policies to Promote Renewable and Low-Carbon Sources of Electricity* (Resources for the Future, 2010); www.rff.org/research/publications/modeling-policies-promote-renewable-and-low-carbon-sources-electricity.
 19. M. Cox, M. A. Brown, X. Sun, Energy benchmarking of commercial buildings: A low-cost pathway toward urban sustainability. *Environ. Res. Lett.* **8**, 035018 (2013).
 20. K. Gillingham, P. Huang, Is abundant natural gas a bridge to a low-carbon future or a dead-end? *Energy J.* **40**, 1–26 (2019).
 21. J. T. Wilkerson, D. Cullenward, D. Davidian, J. P. Weyant, End use technology choice in the National Energy Modeling System (NEMS): An analysis of the residential and commercial building sectors. *Energy Econ.* **40**, 773–784 (2013).
 22. Y. Wang, M. A. Brown, Policy drivers for improving electricity end-use efficiency in the USA: An economic–engineering analysis. *Energ. Effic.* **7**, 517–546 (2014).
 23. M. A. Brown, G. Kim, A. M. Smith, K. Southworth, Exploring the impact of energy efficiency as a carbon mitigation strategy in the U.S. *Energy Policy* **109**, 249–259 (2017).
 24. Energy Information Administration, *Annual Energy Outlook 2017* (Energy Information Administration, 2017); www.eia.gov/aeo.
 25. M. Auffhammer, The rationality of EIA forecasts under symmetric and asymmetric loss. *Resour. Energy Econ.* **29**, 102–121 (2007).
 26. Environmental Protection Agency, *Overview of the Clean Power Plan: Cutting Carbon Pollution from Power Plants* (Environmental Protection Agency, 2015); <https://archive.epa.gov/epa/cleanpowerplan/fact-sheet-overview-clean-power-plan.html>.
 27. J. A. A. Laitner, S. Nadel, N. Elliott, H. Sachs, A. S. S. Khan, *The Long-Term Energy Efficiency Potential: What the Evidence Suggests* (American Council for an Energy-Efficient Economy, 2012); <https://aceee.org/sites/default/files/publications/researchreports/e121.pdf>.
 28. J. L. Reyna, M. V. Chester, Energy efficiency to reduce residential electricity and natural gas use under climate change. *Nat. Commun.* **8**, 14916 (2017).
 29. Department of Energy, *Windows and Building Envelope Research and Development: Roadmap for Emerging Technologies* (Department of Energy, 2014); www.energy.gov/sites/prod/files/2014/02/f8/BTO_windows_and_envelope_report_3.pdf.
 30. B. Güneralp, Y. Zhou, D. Ürgü-Vorsatz, M. Gupta, S. Yu, P. L. Patel, M. Fragkias, X. Li, K. C. Seto, Global scenarios of urban density and its impacts on building energy use through 2050. *Proc. Natl. Acad. Sci.* **114**, 8945–8950 (2017).
 31. Energy Information Administration, *Updated Buildings Sector Appliance and Equipment Costs and Efficiency* (Energy Information Administration, 2016); www.eia.gov/analysis/studies/buildings/equipcosts/archive/2016.
 32. Interagency Working Group, *Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866* (Environmental Protection Agency, 2016); www.epa.gov/sites/production/files/2016-12/documents/sc_co2_tsd_august_2016.pdf.
 33. S. Dietz, A. Bowen, B. Doda, A. Gambhir, R. Warren, The economics of 1.5°C climate change. *Annu. Rev. Env. Resour.* **43**, 455–480 (2018).
 34. F. C. Moore, D. B. Diaz, Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Chang.* **5**, 127–131 (2015).
 35. R. S. J. Tol, The economic impacts of climate change. *Rev. Environ. Econ. Policy.* **12**, 4–25 (2018).
 36. A. Bone, V. Murray, I. Myers, A. Dengel, D. Crump, Will drivers for home energy efficiency harm occupant health? *Perspect. Public Health* **130**, 233–238 (2010).
 37. T. Li, M. Alavy, J. A. Siegel, Measurement of residential HVAC system runtime. *Build. Environ.* **150**, 99–107 (2019).
 38. S. Max, Infiltration in ASHRAE's residential ventilation standards. *ASHRAE Trans.* **2**, 887–896 (2009).
 39. T. Fazli, B. Stephens, Development of a nationally representative set of combined building energy and indoor air quality models for U.S. residences. *Build. Environ.* **136**, 198–212 (2018).
 40. K. Clay, A. Jha, N. Z. Muller, R. P. Walsh, External costs of transporting petroleum products: Evidence from shipments of crude oil from North Dakota by pipelines and rail. *Energy J.* **40**, 55–72 (2019).
 41. J. Heo, P. J. Adams, H. O. Gao, Reduced-form modeling of public health impacts of inorganic PM_{2.5} and precursor emissions. *Atmos. Environ.* **137**, 80–89 (2016).
 42. C. W. Tessum, J. D. Hill, J. D. Marshall, InMAP: A model for air pollution interventions. *PLOS ONE* **12**, e0176131 (2017).
 43. W. J. Fisk, B. C. Singer, W. R. Chan, Association of residential energy efficiency retrofits with indoor environmental quality, comfort, and health: A review of empirical data. *Build. Environ.* **180**, 107067 (2020).
 44. Energy Information Administration, *Residential Demand Module of the National Energy Modeling System: Model Documentation* (Energy Information Administration, 2017); www.eia.gov.
 45. Energy Information Administration, *Commercial Demand Module of the National Energy Modeling System: Model Documentation* (Energy Information Administration, 2017); www.eia.gov.
 46. Energy Information Administration, *Model Documentation Report: Industrial Demand Module of the National Energy Modeling System* (Energy Information Administration, 2018); [www.eia.gov/outlooks/aeo/nems/documentation/archive/pdf/m064\(2016\).pdf](http://www.eia.gov/outlooks/aeo/nems/documentation/archive/pdf/m064(2016).pdf).
 47. M. S. Waring, J. A. Siegel, Particle loading rates for HVAC filters, heat exchangers, and ducts. *Indoor Air* **18**, 209–224 (2008).
 48. C. A. Pope III, R. T. Burnett, M. J. Thun, E. E. Calle, D. Krewski, K. Ito, G. D. Thurston, Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* **287**, 1132–1141 (2002).
 49. P. Tschofen, I. M. L. Azevedo, N. Z. Muller, Fine particulate matter damages and value added in the US economy. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 19857–19862 (2019).
 50. B. J. Sergi, P. J. Adams, N. Z. Muller, A. L. Robinson, S. J. Davis, J. D. Marshall, I. M. L. Azevedo, Optimizing emissions reductions from the U.S. power sector for climate and health benefits. *Environ. Sci. Technol.* **54**, 7513–7523 (2020).
 51. J. M. Logue, P. N. Price, M. H. Sherman, B. C. Singer, A method to estimate the chronic health impact of air pollutants in U.S. residences. *Environ. Health Perspect.* **120**, 216–222 (2012).
 52. P. Azimi, B. Stephens, A framework for estimating the US mortality burden of fine particulate matter exposure attributable to indoor and outdoor microenvironments. *J. Expo. Sci. Environ. Epidemiol.* **30**, 271–284 (2020).
 53. A. Rackes, T. Ben-David, M. S. Waring, Outcome-based ventilation: A framework for assessing performance, health, and energy impacts to inform office building ventilation decisions. *Indoor Air* **28**, 585–603 (2018).
 54. C. L. Avery, K. T. Mills, R. Williams, K. A. McGraw, C. Poole, R. L. Smith, E. A. Whitsel, Estimating error in using residential outdoor PM_{2.5} concentrations as proxies for personal exposures: A meta-analysis. *Environ. Health Perspect.* **118**, 673–678 (2010).
 55. D. Zhao, P. Azimi, B. Stephens, Evaluating the long-term health and economic impacts of central residential air filtration for reducing premature mortality associated with indoor fine particulate matter (PM_{2.5}) of outdoor origin. *Int. J. Environ. Res. Public Health* **12**, 8448–8479 (2015).
 56. Energy Information Administration, *The National Energy Modeling System: An Overview 2009* (Energy Information Administration, 2009); www.eia.gov/outlooks/aeo/nems/overview/index.html.
 57. J. Langevin, C. B. Harris, J. L. Reyna, Assessing the potential to reduce U.S. building CO₂ emissions 80% by 2050. *Joule* **3**, 2403–2424 (2019).
 58. Department of Energy, *Solid-State Lighting R&D Plan* (Department of Energy, 2016).
 59. Department of Energy, *Research and Development Roadmap for Emerging Water Heating Technologies* (Department of Energy, 2014); www.osti.gov/home/.
 60. Appliance Standards Awareness Project, *Refrigerators and Freezers* (2014); <https://appliance-standards.org/product/refrigerators-and-freezers>.
 61. Department of Energy, *New Energy Efficiency Standards for Microwave Ovens to Save Consumers on Energy Bills* (Department of Energy, 2013); www.energy.gov/articles/new-energy-efficiency-standards-microwave-ovens-save-consumers-energy-bills.
 62. J. H. Williams, B. Haley, F. Kahrl, J. Moore, A. D. Jones, M. S. Torn, H. McJeon, *Pathways to Deep Decarbonization in the United States* (2014); <http://usddpp.org/>.
 63. Department of Energy, *Energy CO₂ Emissions Impacts of Clean Energy Technology Innovation and Policy* (2017).

64. B. Goldstein, D. Gounaridis, J. P. Newell, The carbon footprint of household energy use in the United States. *Proc. Natl. Acad. Sci. U.S.A.* **117**, 19122–19130 (2020).
65. S. Dominguez-Amarillo, J. Fernández-Agüera, M. Á. Campano, I. Acosta, Effect of airtightness on thermal loads in legacy low-income housing. *Energies* **12**, 1677 (2019).
66. J. Joo, Q. Zheng, G. Lee, J. T. Kim, S. Kim, in *Energy and Buildings* (Elsevier, 2012), vol. 46, pp. 62–67.
67. W. R. Chan, W. W. Nazaroff, P. N. Price, M. D. Sohn, A. J. Gadgil, Analyzing a database of residential air leakage in the United States. *Atmos. Environ.* **39**, 3445–3455 (2005).
68. P. Azimi, D. Zhao, B. Stephens, Modeling the impact of residential HVAC filtration on indoor particles of outdoor origin (RP-1691). *Sci. Technol. Built Environ.* **22**, 431–462 (2016).
69. D. L. Liu, W. W. Nazaroff, Particle penetration through building cracks. *Aerosol Sci. Technol.* **37**, 565–573 (2003).
70. W. W. Nazaroff, Indoor particle dynamics. *Indoor Air* **14**, 175–183 (2004).
71. Environmental Protection Agency, Particulate matter (PM_{2.5}) trends (2021); <https://www.epa.gov/air-trends/particulate-matter-pm25-trends>.
72. US Energy Information Administration, Residential Energy Consumption Survey (RECS): 2015 RECS survey data (2018); <https://www.eia.gov/consumption/residential/data/2015/>.
73. C. He, L. Morawska, J. Hitchins, D. Gilbert, Contribution from indoor sources to particle number and mass concentrations in residential houses. *Atmos. Environ.* **38**, 3405–3415 (2004).
74. T. Hu, B. C. C. Singer, J. M. M. Logue, *Compilation of Published PM_{2.5} Emission Rates for Cooking, Candles and Incense for Use in Modeling of Exposures in Residences* (LBNL-5890E, Lawrence Berkeley National Lab, 2012).
75. G. Shen, M. D. Hays, K. R. Smith, C. Williams, J. W. Faircloth, J. J. Jetter, Evaluating the performance of household liquefied petroleum gas cookstoves. *Environ. Sci. Technol.* **52**, 904–915 (2018).
76. J. Qian, A. R. Ferro, K. R. Fowler, Estimating the resuspension rate and residence time of indoor particles. *J. Air Waste Manag. Assoc.* **58**, 502–516 (2008).
77. L. J. J. Underhill, W. S. S. Dols, S. K. K. Lee, M. P. P. Fabian, J. I. I. Levy, Quantifying the impact of housing interventions on indoor air quality and energy consumption using coupled simulation models. *J. Expo. Sci. Environ. Epidemiol.* **30**, 436–447 (2020).
78. C. Chen, B. Zhao, Review of relationship between indoor and outdoor particles: I/O ratio, infiltration factor and penetration factor. *Atmos. Environ.* **45**, 275–288 (2011).

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contributions: K.T.G., D.R.G., and J.P. conceived the study, and all authors participated in study design. P.H. and K.T.G. carried out the energy modeling, with P.H. conducting the Yale-NEMS analysis. C.B., D.R.G., and J.P. carried out the indoor air quality analysis, with C.B. developing the box modeling code and BSEI translation from Yale-NEMS for the Monte Carlo analysis described above. P.H. carried out outdoor health effects calculations, and P.H. and C.B. carried out indoor health effects calculations. All authors worked on the examination and interpretation of the data and results. K.T.G. led the writing with contributions from all authors on the relevant sections of the manuscript and the Supplementary Materials. All authors reviewed and revised the manuscript, including revisions based on the reviewer comments.

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