The Climate and Health Benefits from Intensive Building Energy Efficiency Improvements

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Abstract

Intensive building energy efficiency improvements can reduce emissions from energy use, improving outdoor air quality and human health, but may also affect indoor air quality through changes in ventilation. This study examines the effects of highly ambitious, yet feasible, building energy efficiency upgrades in the United States through 2050. Our energy efficiency scenarios—derived from the literature—lead to a 6-11% reduction in carbon dioxide emissions and 18-25% reductions in particulate matter ($PM_{2.5}$) emissions in 2050. These reductions are complementary with a carbon pricing policy on electricity. However, indoor air quality may be impacted, pointing to the importance of mitigating indoor $PM_{2.5}$ emissions, implementing improved $PM_{2.5}$ filtration, and evaluating ventilation policies. However, even with no further ventilation improvements, we estimate that intensive energy efficiency scenarios could prevent 1,800-3,600 premature deaths per year across the United States in 2050. With further investments in indoor air quality, this can rise to 2,900-5,100.

Keywords: Energy efficiency, carbon emissions, local air pollution, indoor air quality, health effects

Introduction

Global energy consumption is expected to rise 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 impact 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, 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 related work, Buonocore et al. examine 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 (*15*). Buonocore et al. provide deep insights on 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 other related work, Brown and Li explore 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 (*16*). 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 United States 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 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 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 40-60% 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 60-90% improvements on building shell materials (see 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 CO_2 in 2021 to \$30/ton CO_2 in 2040 and stays constant thereafter. This path is below the central case estimate of the social cost of carbon (SCC) 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 polices for energy efficiency are already in place.

Energy consumption and associated emissions

Fig. 1A presents the projected energy consumption in the residential, commercial, and industrial sectors in the quadrillions of Btus (quads) in the United States from 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 & 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 Supplementary Fig. S1-S5.

Fig. 1B shows the CO_2 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 CO_2 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 CO_2. The *Carbon Pricing* scenario achieves a similar level of emissions as the *Optimistic EE* scenario in 2050. Under the *Optimistic EE & Carbon Pricing* scenario, CO_2 emissions decline by 1,222 MMT in 2050, a 33% reduction. The CO_2 emission reductions under the *Optimistic EE & Carbon Pricing* scenario are greater than the sum of the reductions combined from *Optimistic EE* and *Carbon Pricing* separately, which is 1,183 million metric tons 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 Supplementary Materials Section 4). Supplementary Fig. S6 presents the CO_2 emissions disaggregated by end-use sector.

Fig. 2 illustrates emissions from several non-CO_2 air pollutants associated with fossil fuel combustion across the entire energy system (see Methods). We observe emission reductions in the energy efficiency scenarios for nearly all non-CO_2 air pollutants we examine, driven by decreased consumption of fossil fuels (e.g., a 15% decline in coal and 19% decline in natural gas in the *Optimistic EE* scenario). For example, sulfur dioxide (SO_2) 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-CO_2 air pollutants except for ammonia (NH_3) and volatile organic compounds (VOCs). We present the detailed air pollutant emissions by sector and Census division in Supplementary Fig. S7-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 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 4,300 avoided premature deaths annually by 2050 while the *Optimistic EE* scenario results in 6,600 avoided premature deaths per year. The *Carbon Pricing* scenario results in 3,700 avoided deaths per year. The combined *Optimistic EE & 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 loses, 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 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 (MERV) 6-equivalent and MERV 11-equivalent filters are modelled in existing and new homes, respectively (see Section S5 for more detail).

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 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 timescale. A promising area for future study would be to combine multi-compartment 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.

As changes to infiltration, natural ventilation, and HVAC recirculation adoption are all central to changes to 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 US housing stock (which are based upon literature values) is estimated as $0.69 \pm 0.22\ hr^{-1}$. 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 hr^{-1}, 0.23±0.10 hr^{-1}, and 0.18±0.08 hr^{-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.

Fig. 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 non-linear effect resulting from variations in indoor emissions (e.g., cooking activity and frequency, electric versus natural gas stovetops/ovens, appliance usage, 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). Panel B shows the relative changes in response time, specifically the ability of homes to dissipate a pollution event, modeled as one hour of elevated emissions during stovetop cooking. This response time increases with greater building energy efficiency measures, largely due to 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. Panel C 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 like 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, Panel D displays 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 varies 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 Methods and 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. Based on the 2050 estimates of homes employing recirculation systems with filtration (i.e., 62%), worsened indoor air quality in the *Intermediate EE* scenario results in 2,500 premature deaths in 2050. The *Optimistic EE* scenario leads to 3,000 premature deaths. In a lower bound scenario where no homes have recirculation with filtration, the *Intermediate EE* and *Optimistic EE* scenarios lead to 4,400 and 5,500 premature deaths, respectively. In contrast, when the investments in recirculation with filtration are made in all homes, the *Intermediate EE* scenario results in only 1,400 premature deaths and the *Optimistic EE* scenario results in 1,500 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 1,800 and the *Optimistic EE* scenario by 3,600 (if investments in recirculation/filtration follow the patterns currently in the data). Supplementary Fig. S13 shows the net human health results for other years.

Fig. 4 presents the results from Panel C of 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 are 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 & 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 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 effect 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 under-projects renewables growth relative to the trends we have seen in the past two years (see Supplementary Fig. S27). In addition, the emissions results do not vary significantly using the EPA NEI 2017 data and 2017 as the base year for outdoor emission projections (see Supplementary Fig. S28). However, the results appear to be dominantly driven by the projections of the emission factors of fossil fuel consumption (see Supplementary Fig. 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 function. The results are consistent with the primary results (see Supplementary Table S3). The full set of sensitivity analyses is presented in the Supporting 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 6-11% decrease in energy-related CO_2 emissions, 4-11% decrease in SO_2 emissions, and 18-25% in decrease in primary $PM_{2.5}$ emissions in 2050. These outdoor emissions reductions can bring about considerable health benefits, which can reduce premature mortality by 3,700-7,800 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 6,800 avoided deaths annually in 2050) even after accounting for changes in indoor air quality (assuming 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 polices 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, like 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 effect 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 concentration-response 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 Supplementary Materials). In addition, our indoor air and health results are focused on $PM_{2.5}$ given its outsize 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 impact indoor-outdoor pollutant gradients. Gas-phase pollutants have compound-dependent deposition rates, potential repartitioning to the gas phase for VOCs, 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, 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, biological aerosols) due to decreased ventilation with outdoor air (*43*), while the indoor concentrations of those of outdoor origin (e.g., ozone, 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 significantly. 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 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 (Fig. S25-26). 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. Also, widespread bans on natural gas, as are occurring in some U.S. municipalities, would impact 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 post-processing estimations. We first run the scenarios in Yale-NEMS to project energy consumptions, CO_2 emissions, and local air pollutant emissions from the present to 2050. Based on 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. Finally, 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 Energy Information Administration 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 (RECS) (i.e., the base year of the module) out to 2050. Specifically, the RDM models residential energy demand with six sequential steps: (1) projecting the stocks of newly built and existing (carried forward or removed) houses based on the results from the Macroeconomic Activity Module (e.g., GDP and population projections); (2) projecting market shares for each available equipment type; (3) projecting end-use appliance stock within houses; (4) projecting building shell technology for space heating and cooling; (5) projecting distributed electricity generation in residential houses from solar, fuel cells, and small wind turbine systems; and (6) 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 (CBECS) to 2050. The module consists of five steps: (1) projecting commercial building floorspace; (2) projecting energy-consuming services demand; (3) forecasting electricity generation by distributed generation technologies; (4) determining equipment choices to meet the service demands; (5) 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 (IDM) (*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 heating, ventilation, and air conditioning, which primarily provide services for workers working indoors. Note 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 CO_2 emissions, and SO_2 and nitrogen oxides (NO_x) emissions from the electricity generating sector from present to 2050. To obtain broader insights on emissions, we use a post-processing approach to estimate the emissions of additional local air pollutants from burning fossil fuels in all energy-related sectors, such as NH_3, carbon monoxide (CO), $PM_{2.5}$, PM_{10}, 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 National Emissions Inventory (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 emissions 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 Supplementary 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., building shell efficiency index (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, $PM_{2.5}$ emission rates). See Supplementary Materials Section 5 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 modelled 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 which will affect pollutant exposure, a single compartment box model was chosen to reduce computational complexity and model overall US housing stock effects. Note that the modeling framework can be applied to other pollutants, but we focus on $PM_{2.5}$ due to 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.

Due to the non-linear distribution of indoor emission rates (see Supplementary Materials Section 5.3) 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 one-tenth 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 effect 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 model (AP3), 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.

Based on 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 concentration-response (C-R) functions from the epidemiology literature. Lastly, 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 NH_3, NO_x, primary $PM_{2.5}$, SO_2, 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 (CACES) website (https://www.caces.us).

The three IAMs have been utilized in various studies concurrently as an approach to shed light on uncertainty (*49*, *50*). Specifically in our paper, we first calculate 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 US 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 NH_3, NO_x, primary $PM_{2.5}$, SO_2, 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 standard errors, so it is not possible to estimate within-model uncertainty currently, but this is a prime area for future research.

Indoor health effect estimation

The effect of changes in indoor $PM_{2.5}$ concentrations on changes in premature mortality is estimated based on an epidemiology-based C-R function adjusted for time spent indoors in Logue et al. (2012) (*51*). Following Azimi and Stephens (2020), we further modify the C-R function to account for microenvironmental $PM_{2.5}$ concentrations and exposures (*52*). While the evidence on the variable effects of indoor vs. 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:

$$\Delta Y_{t,s,d} = y_0\left(exp\left(\beta_{t,s,d}^{OG} \times \theta^{home} \times \Delta C_{t,s,d}^{OG} + \beta_{t,s,d}^{IG} \times \theta^{home} \times \Delta C_{t,s,d}^{IG}\right) - 1\right) \times Pop_{t,s,d}, \quad (1)$$

where $\Delta Y_{t,s,d}$ indicates the changes in premature deaths in year t associated with the type of building stock s, $s \in$ {homes with recirculation, homes without recirculation}, and emissions decile d that defines the magnitude of indoor emissions in homes. y_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 as 0.69 (*6*). $\Delta C_{t,s,d}^{OG}$ represents the changes in indoor $PM_{2.5}$ concentrations ($\mu g/m^3$) that result from sources of outdoor origin, and similarly, $\Delta C_{t,s,d}^{IG}$ represents the changes in indoor $PM_{2.5}$ concentrations that result from indoor-generated sources.

Both $\Delta C_{t,s,d}^{OG}$ and $\Delta C_{t,s,d}^{IG}$ are projected from our indoor air quality model and are relative to a baseline value of 0 $\mu g/m^3$, which is consistent with other recent studies (*52*, *53*). $Pop_{t,s,d}$ represents the total population. We take the total U.S. population forecasted in Yale-NEMS and disaggregate them 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 $\beta_{t,s,d}^{OG}$ is the modified $PM_{2.5}$ concentration-response coefficient for outdoor-generated sources, which is calculated as:

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

where β_0 is the $PM_{2.5}$ concentration-response coefficient from the epidemiological literature, assumed to be 0.0058 (95% CI: 0.0020–0.0104) (*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:

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

$F_{t,s,d}^{home}$ 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 (2020) (*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 (2020), we assume an equal C-R effect for indoor-generated $PM_{2.5}$ concentrations ($\beta_{t,s,d}^{IG}$) as outdoor-generated concentrations ($\beta_{t,s,d}^{OG}$).

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.

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Supplementary Materials

Supplementary material for this article is available at [LINK GOES HERE]

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Data and Code Availability Statement

This study uses the National Energy Modeling System (NEMS), which was modified for the purposes of our study. The code for the basic model is available upon request from the U.S. Energy Information Administration. Information on accessing the model is available here: https://www.eia.gov/outlooks/aeo/info_nems_archive.php (Accessed September 4, 2020). We have included all NEMS code that we modified for this study, along with all of the relevant input data, and the code for the mass balance box model on GitHub here: https://github.com/pei-huang/.

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

			Intermediate EE	Optimistic EE
Appliances and equipment[a]	Residential		20% (*28*),[c]	50% (*28*),[c]
	Commercial		20% (*28*),[c]	50% (*28*),[c]
Building shell[b]	Residential	Existing	2% per year (*27*, *30*),[d]	2.5% per year (*27*),[e]
		New	60% (*9*, *27*, *29*, *30*)	90% (*27*, *30*)
	Commercial	Existing	40% (*27*, *30*)	60% (*27*)
		New	60% (*9*, *27*, *29*, *30*)	90% (*27*, *30*)
	Industrial		60% (*27*, *30*)	90% (*27*, *30*)

Notes: [a]The appliances and equipment include those providing spacing heating, cooling, water heating, lighting, refrigeration, cooking, and numerous other services.
[b]Building shell includes the envelope materials for isolating indoors and outdoors of buildings, which primarily preserves heating and cooling inside buildings.
[c]The efficiency improvements for appliances and equipment are based on the advanced case of U.S. EIA's building-sector reports (*31*).
[d]The annual efficiency improvement can achieve around 50% cumulative improvements by 2050.
[e]The annual efficiency improvement can achieve around 60% cumulative improvements by 2050.

Table 2: Avoided premature mortality per year (shown for 2050) across the scenarios relative to the reference case in the United States.

	Intermediate EE	Optimistic EE	Carbon Pricing	Optimistic EE & Carbon Pricing
Avoided premature deaths resulting from reductions in outdoor pollutant emissions				
Estimated value	4300	6600	3700	11000
	(3700, 5000)	(5700, 7800)	(2900, 5100)	(9000, 13000)
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, 12000)
No investment	-79	1100	3700	5500
	(-4200, 3500)	(-4200, 5900)	(2900, 5100)	(-920, 11000)
Investment in all homes	2900	5100	3700	9500
	(1200, 4500)	(3000, 7300)	(2900, 5100)	(6300, 13000)

Notes: '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 other two provide bounds on the health effects of indoor air quality changes. The numbers in brackets 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 IAMs (i.e., AP3, EASIUR, and InMAP). For indoor air quality, we estimate the ranges of health outcomes based on the 95% CI of the C-R function coefficient from the epidemiology literature. The ranges of net health effects are combinations of the above two.

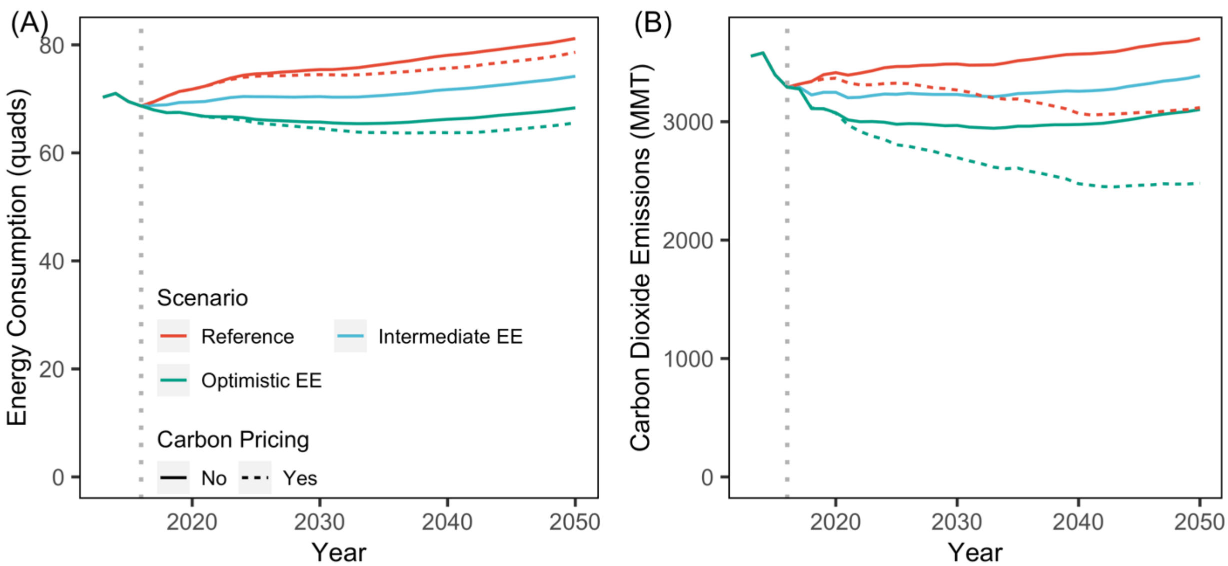

Fig. 1: Projected energy consumption and CO_2 emissions from the residential, commercial, and industrial sectors in the United States. Energy consumption in Panel (A) include all fossil fuel and electricity consumption in the residential, commercial, and industrial sectors. Panel (B) shows carbon emissions associated with electricity consumption, which is generated by the electric power sector. The vertical dotted lines separate historical and projected data.

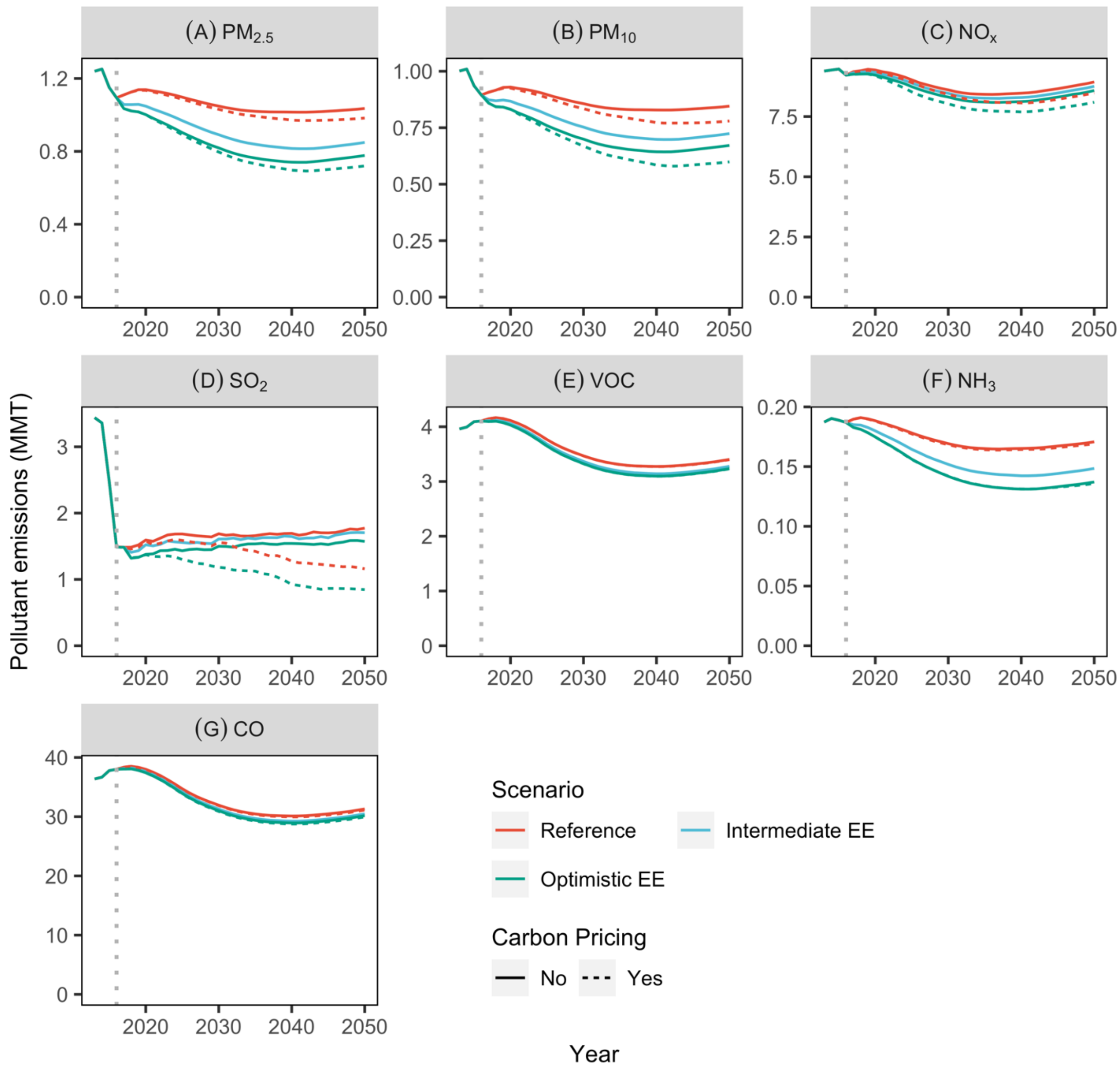

Fig. 2: Projected energy-related local air pollutant emissions in the United States. Each panel presents the projected results for a pollutant. The vertical dotted lines separate historical and projected data.

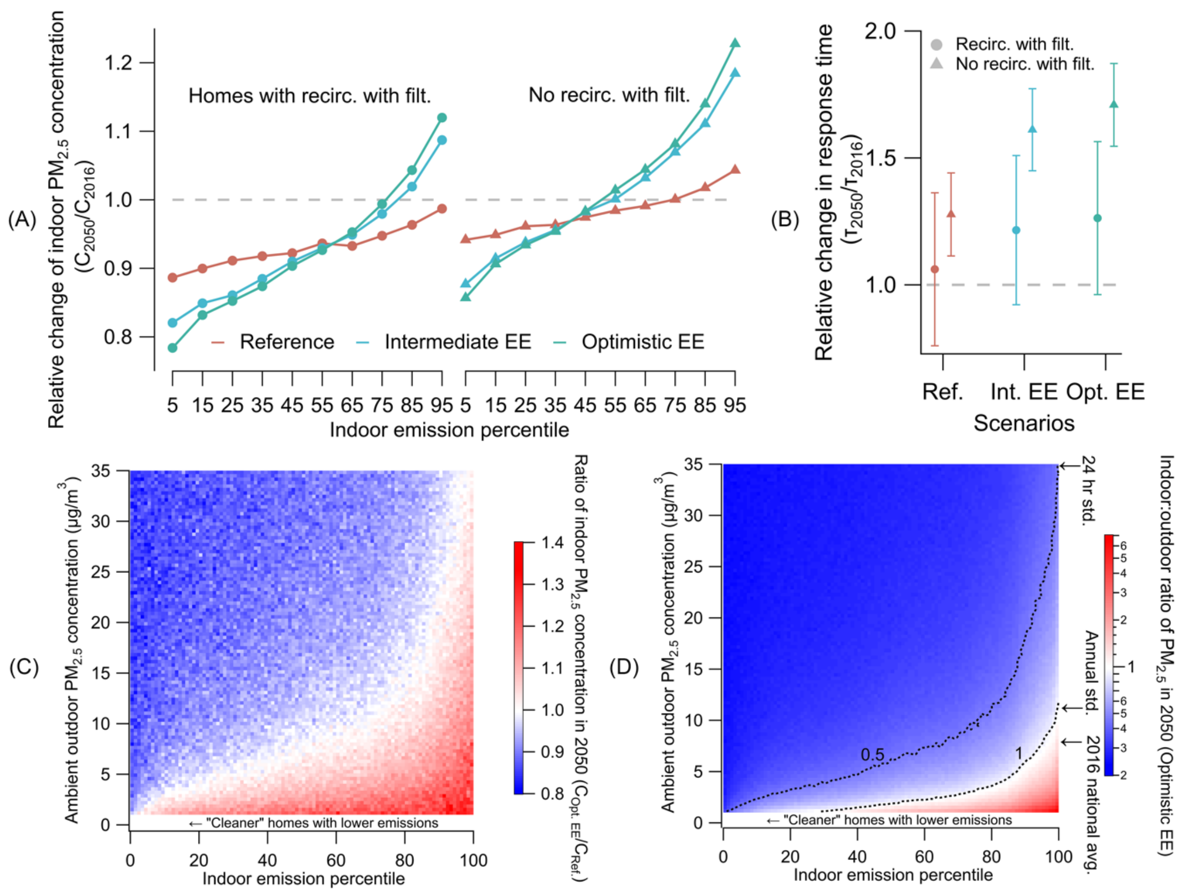

Fig. 3: Impact of projected energy efficiency scenarios on residential indoor air quality. (A) Relative change of residential indoor $PM_{2.5}$ concentration from 2016 to 2050 for homes with and without HVAC recirculation systems with particle filtration for each EE scenario as a function of indoor emission percentile (lower meaning 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 hr of stove top cooking). Error bars indicate standard deviation. (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 μg/m^3 to include the 24 hr standard (shown in (D) alongside annual primary standard and 2016 average).

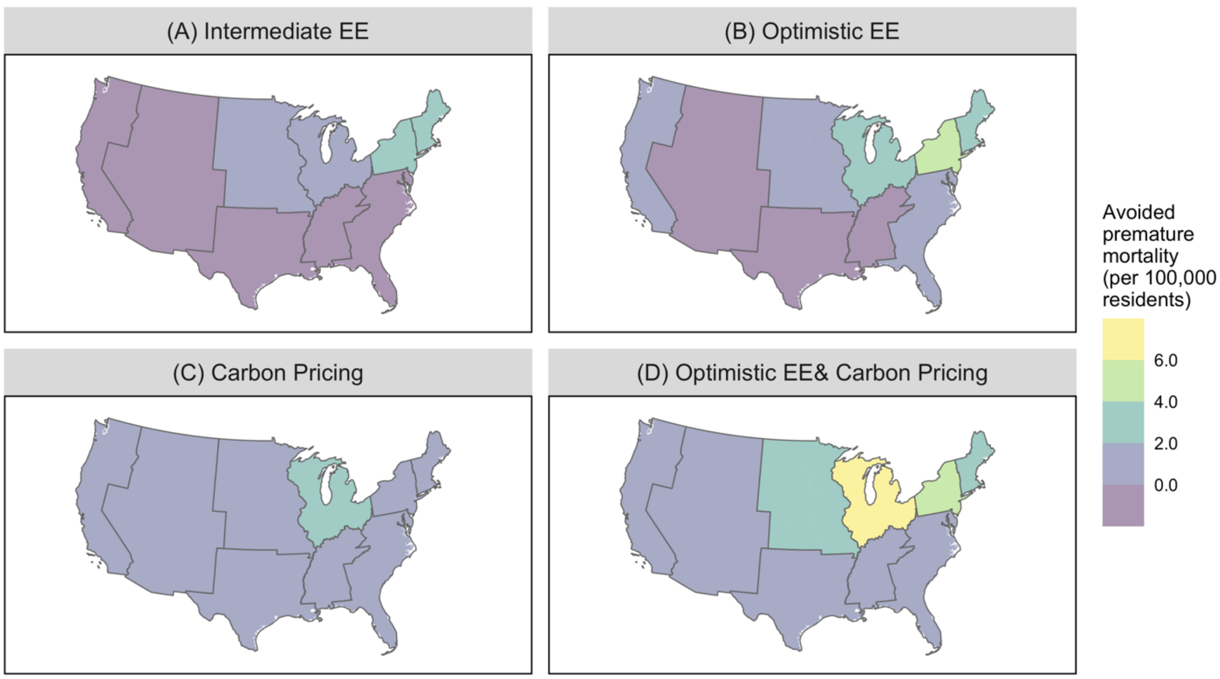

Fig. 4: Net benefits of avoided premature mortality per 100,000 residents per year in the U.S. Census divisions. The results are the net mean effects of changes in outdoor and indoor air quality (assuming current patterns of investment in indoor air recirculation systems with filtration) relative to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