Title
Assessing the Potential to Reduce U.S. Building CO2 Emissions 80% by 2050

Journal
Joule, 3(10)

ISSN
2542-4785

Authors
Langevin, Jared
Harris, Chioke B
Reyna, Janet L

Publication Date
2019-10-01

DOI
10.1016/j.joule.2019.07.013

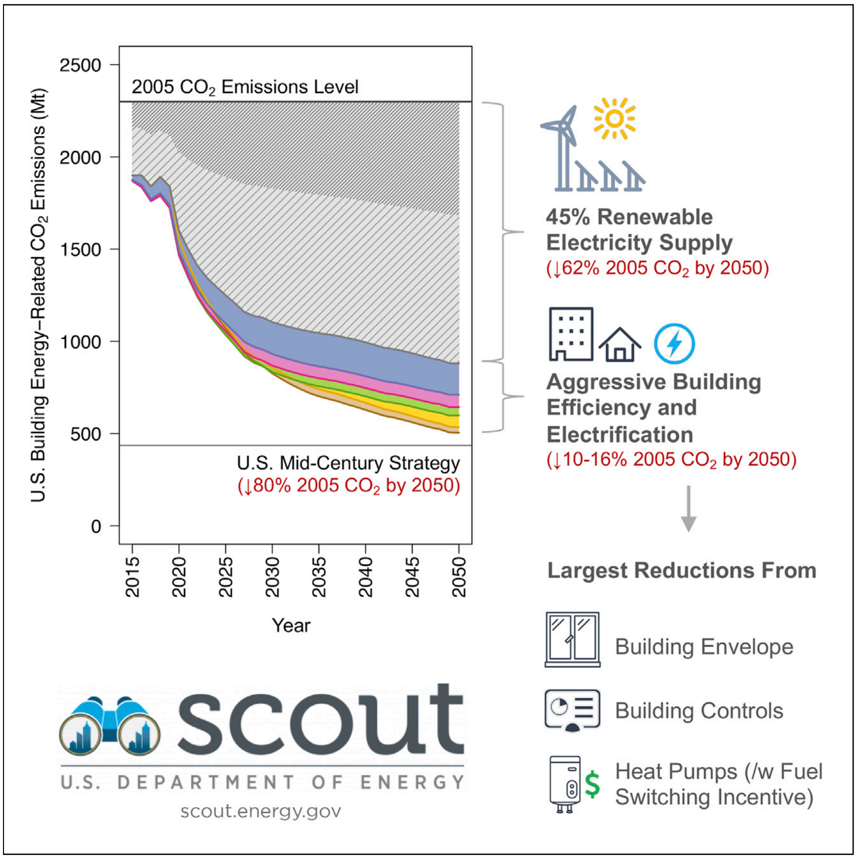
Peer reviewed

Joule

CellPress

Article

Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050



Buildings are responsible for 36% of CO_2 emissions in the U.S. and will thus be integral to climate change mitigation. We use Scout, a reproducible model of U.S. building energy use, to assess whether buildings can reduce CO_2 emissions 80% by 2050, finding that aggressive efficiency measures and low-carbon electrification can reduce emissions 72%–78%. The analysis establishes a basis for periodic reassessment of building technology development pathways that can drive long-term reductions in U.S. CO_2 emissions.

Jared Langevin, Chioke B. Harris, Janet L. Reyna

jared.langevin@lbl.gov

HIGHLIGHTS

U.S. building CO_2 emissions could be reduced up to 78% by 2050

Efficiency and low-carbon electrification are required to achieve this impact

Reductions are driven by heating energy use in existing residential buildings

Envelope, controls, and fuel switching measures drive cost-effective reductions

Langevin et al., Joule 3, 1–22

https://doi.org/10.1016/j.joule.2019.07.013

Please cite this article in press as: Langevin et al., Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050, Joule (2019), https://doi.org/10.1016/j.joule.2019.07.013

Joule

CellPress

Article

Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050

Jared Langevin,[1,3,*] Chioke B. Harris,[2] and Janet L. Reyna[2]

SUMMARY

Buildings are responsible for 36% of CO_2 emissions in the United States and will thus be integral to climate change mitigation; yet, no studies have comprehensively assessed the potential long-term CO_2 emissions reductions from the U.S. buildings sector against national goals in a way that can be regularly updated in the future. We use Scout, a reproducible and granular model of U.S. building energy use, to investigate the potential for the U.S. buildings sector to reduce CO_2 emissions 80% by 2050, consistent with the U.S. Mid-Century Strategy. We find that a combination of aggressive efficiency measures, electrification, and high renewable energy penetration can reduce CO_2 emissions by 72%–78% relative to 2005 levels, just short of the target. Results are sufficiently disaggregated by technology and end use to inform targeted building energy policy approaches and establish a foundation for continual reassessment of technology development pathways that drive significant long-term emissions reductions.

Context & Scale

The U.S. remains the second-largest contributor to global greenhouse gas emissions, and substantial reductions are necessary to reduce the risk of catastrophic climate change. The U.S. Mid Century Strategy (MCS) sets a goal of reducing total emissions 80% by 2050 relative to 2005 levels; as the buildings sector comprises 36% of energy-related CO_2 emissions in the U.S., it is a critical piece of the MCS reduction strategy. We assess the feasibility of reducing U.S. building CO_2 emissions 80% by 2050 using a reproducible and granular model of U.S. building energy use. Our results can inform energy and climate policy-making at the regional, national, and global levels and provide a benchmark for assessing emissions reductions in other sectors of the economy.

INTRODUCTION

The United States (U.S.) remains the second-largest contributor to global greenhouse gas (GHG) emissions,[1] and substantial reductions are necessary to reduce the risk of catastrophic climate change.[2] The U.S. Mid-Century Strategy (MCS) outlines a pathway to reduce GHGs by 80% below 2005 levels by 2050, examining GHG reductions by sector.[3] In 2018, the U.S. buildings sector was responsible for 36% of national energy-related CO_2 emissions,[4] making it a critical component of the MCS reduction strategy. Most GHG emissions from the buildings sector are from energy use in buildings, with the bulk of emissions being CO_2. Energy use in the buildings sector serves many important economic, comfort, and quality of life functions. There are over 325 million people in the U.S.,[5] the vast majority of whom use energy in multiple buildings every day; moreover, U.S. population and total building energy use continues to grow.[6] The heterogeneity of occupant needs and behaviors combined with the diversity of building energy end uses increases the complexity of modeling buildings, but this diversity also provides a plethora of opportunities for reducing emissions.

In the U.S., diverse stakeholders are interested in identifying cost-effective strategies for reducing CO_2 emissions over both short- and long-term time horizons. A tool that offers a transparent framework for identifying these reduction strategies in the buildings sector can help governments deploy their limited resources for optimal impact. Emission reductions in the buildings sector can generally come from either electrification or energy efficiency improvements in building equipment, materials, or operations. Electrification of building technologies could be an attractive option because fossil fuel-based equipment can typically be swapped for electric equivalents without significant modifications to the building, though key barriers to electrification exist.[7] Many device-based efficiency upgrades similarly involve minimal disruption, however, effectively reaching the MCS targets will likely require advancement in more complex systems such as the building envelope or control systems.[3] In addition to providing CO_2 reductions, increasing building energy efficiency also has multiple co-benefits such as improving occupant comfort and worker productivity,[8,9] while accelerating economic growth[10] and job creation.[11] Additionally, previous work shows that demand-side changes in energy efficiency can more cost-effectively reduce CO_2 than supply-side improvements in the carbon intensity of electricity generation—even after accounting for the dramatic cost reductions in renewable generation in recent years.[12–14] Furthermore, lacking large-scale, cost-effective reserve capacity or electricity storage alternatives, demand-side energy flexibility is needed to accommodate the variability inherent in renewable generation at high penetration levels.[15–17] For all of these reasons, robust analyses are necessary to identify specific efficiency and electrification measures for achieving CO_2 emissions reductions in the buildings sector and to understand the costs associated with these measures.

Several existing studies have examined the potential contribution of building energy efficiency to national climate goals, including notable models developed for China,[18] the United Kingdom,[19] Norway,[20] Belgium,[21] Japan,[22] and Sweden.[23] For the U.S., such studies employ models with one or more key shortcomings that limit their applicability to developing climate change mitigation strategies for the buildings sector. Primarily, none of the models identified are developed to support continuous updating, with the majority of studies being a single-time snapshot of scenarios.[24–30] Climate change mitigation will be a decades-long effort, and developing effective mitigation strategies will require models that are regularly updated with the best available data on a range of exogenous factors—technology R&D investment and technology commercialization, changes in the electricity generation mix, and evolving consumer behavior and preferences. Secondly, many of the studies identified use a top-down approach, which aggregates the total savings available from the buildings sector and focuses on macroeconomic trends rather than specific policy- or technology-driven savings.[6,24,28,29,31,32] Without a breakdown of energy end uses under transparent supply-side assumptions, this type of modeling is highly impractical for targeted climate change mitigation strategy development in the buildings sector. Few of the identified models are openly available,[30] and much of the data underlying building stock models are proprietary or outdated,[25,30,33–35] which makes reproduction and validation by the scientific community extremely difficult. Additionally, even openly available models are technically complex and require significant technical expertise to generate results.[36] Finally, many of the models are limited in geographical and temporal scope; few existing model time horizons extend beyond 2035,[25–27,33] masking the difficulties of achieving necessary longer-term reductions in CO_2, and many models focus only on a portion of the country or building stock.[28–30,35,37–39] Given these limitations of previous work, there is a strong need for a transparent and reproducible model of technology change and CO_2 reduction pathways to meet the MCS goals in the buildings sector that leverages the best available data and is subject to annual review and updates.

Modeling the U.S. Buildings Sector with Scout

To address the limitations of previous work, we develop Scout, an openly-available model for estimating the short- and long-term impact of building energy efficiency on U.S. national primary energy use, CO_2 emissions, and operating costs.

Scout analyses are organized around detailed energy conservation measure (ECM) definitions that can be reviewed by users via a web app (scout.energy.gov); users

[1]Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

[2]Buildings and Thermal Sciences Center, National Renewable Energy Laboratory, Golden, CO 15013, USA

[3]Lead Contact

*Correspondence: jared.langevin@lbl.gov

https://doi.org/10.1016/j.joule.2019.07.013

may also create custom ECMs to incorporate into analyses using a standard web form. Scout ECM definitions reflect current knowledge of technology cost and energy performance and support bottom-up modeling of end use and technology-level impacts. Scout estimates future changes in primary energy use, CO_2 emissions, and associated costs in a three-stage approach: (1) ECMs are defined by their unit-level energy performance, installed cost, and lifetime; by the segments of baseline building energy use that they affect; and by their market entry year. Operation-phase site energy use baselines are drawn from the U.S. Energy Information Administration's (EIA) 2018 Annual Energy Outlook (AEO) projections[4] and converted to primary energy use using fuel-specific factors that are described further in the Supplemental Information, (2) ECM penetration rates in the affected segments of baseline building energy use are estimated, and the effects of competition between technologies on ECM penetration are calculated, and (3) the impact of each ECM and the total ECM portfolio on total national primary energy use, CO_2 emissions, and operating costs is estimated, along with the cost effectiveness of individual ECMs.

Additional details on the data and calculation procedures used in Scout analyses are provided in the Experimental Procedures and Supplemental Information.

For this study, we use Scout (v0.4.3) to project reductions in building operation-phase CO_2 emissions and primary energy use through 2050 and compare these reductions against targets in the MCS, assessing the following research questions:

- Can building energy-related CO_2 emissions be reduced 80% by 2050 relative to 2005 levels under plausible scenarios of efficient technology deployment, electrification, and renewable electricity penetration?
- Which energy end uses and building types most influence reductions in overall building CO_2 emissions?
- Which specific building technologies achieve the largest cost-effective CO_2 emissions reductions?

We assess these questions using multiple scenarios that explore uncertainty in the progression of both demand- and supply-side conditions that affect building energy use and CO_2 emissions. For electric power supply, we consider two levels: one corresponding to the AEO reference case ("RB"), and another corresponding to the AEO $25 carbon allowance fee side case ("HR"), which achieves a high level of renewable electricity penetration—approximately 45% of total power generation by 2050.[4] Three different sets of ECMs are considered across the scenarios. The performance guidelines ECM set ("1T") includes currently available technologies that meet existing codes and/or voluntary recognition programs (e.g., ENERGY STAR). The best available ECM package ("2T") includes the most efficient commercially-available technologies. The prospective ECM package ("3T") includes research-grade technologies that could be released over the next decade as outlined by the U.S. Department of Energy's Building Technologies Office Multi-Year Program Plan.[40] Finally, we explore two levels of technology switching from on-site fossil fuels to electricity: the basic level ("FS0") introduces fuel switching without any capital cost incentives; and the incentivized level ("FS20") applies a capital cost "incentive" to reduce the installed cost of fuel switching measures by 20%.

Table 1 summarizes the combination of these electricity supplies, ECM sets, and fuel switching assumptions into 10 scenarios. We calculate each scenario's impact on CO_2 emissions and primary energy use, track the drivers of these impacts, and assess the degree to which emissions reductions are achieved cost-effectively. In scenarios 9 and 10, it is assumed that only the highest-performing prospective ECMs ("3T") are

Joule

CellPress

Table 1. Summary of U.S. Building Energy Use Scenarios Examined

Scenario		Power Supply	ECM Set(s)	Fuel Switching
No.	Label			
1	RB 1T	reference (RB)	performance guidelines (1T)	no
2	RB 1T-2T	reference	guidelines, best available (2T)	no
3	RB 1T-2T-3T	reference	guidelines, best available, prospective (3T)	no
4	RB 1T-2T-3T FS0	reference	guidelines, best available, prospective	yes (FS0)
5	RB 1T-2T-3T FS20	reference	guidelines, best available, prospective	yes + 20% cost credit (FS20)
6	HR 1T-2T-3T	high renewables (HR)	guidelines, best available, prospective	no
7	HR 1T-2T-3T FS0	high renewables	guidelines, best available, prospective	yes
8	HR 1T-2T-3T FS20	high renewables	guidelines, best available, prospective	yes, +20%
9	HR 3T FS0	high renewables	prospective	yes
10	HR 3T FS20	high renewables	prospective	yes, +20%

available on the market. While in practice it is unlikely that consumers would accept this restricted set of technology choices, we include these scenarios to demonstrate the importance of technology mix assumptions to estimated CO_2 emissions and energy use reductions, and to highlight the effects of technology lock-in, which is addressed further in the Discussion section. Additional detail on scenario assumptions, results assessment criteria, and emissions reduction targets is available in the Experimental Procedures section.

RESULTS

By 2050, Aggressive Building Efficiency, Incentivized Electrification, and High Renewable Penetration Can Reduce CO_2 Emissions Up to 78% Relative to 2005

Figure 1 plots the magnitude of each scenario's total impact on U.S. building CO_2 emissions and primary energy use from 2015–2050 relative to 2005 levels. Emissions impacts are compared against the U.S. CO_2 reduction targets for 2020 (announced at COP15), 2025 (announced at COP21), and the MCS target of an 80% reduction compared to 2005 emissions levels by 2050.

The top row of Figure 1 shows that while nearer-term CO_2 emissions reduction targets (through 2025) are achievable under the modeled scenarios, the 2050 target is only approached by scenarios with high renewable energy penetration on the energy supply-side and aggressive penetration of high-performance building technologies coupled with switching of fuel-fired equipment to electricity. Even so, the best-case scenarios do not quite achieve the 2050 CO_2 reduction goal: scenario 10 (HR 3T FS20), which assumes high renewable supply, penetration of only the highest performing building technologies, and incentivized fuel switching, reduces CO_2 emissions by 78% compared to 2005 levels (98% of the 2050 target). Scenario 8 (HR 1T-2T-3T FS20), which assumes a more realistic mix of available building technologies and incentivized fuel switching, reduces CO_2 emissions by 74% compared to 2005 levels (93% of the 2050 target), while scenario 7 (HR 1T-2T-3T FS0), which removes fuel switching incentives, reduces CO_2 emissions by 72% compared to 2005 levels (90% of the 2050 target).

Please cite this article in press as: Langevin et al., Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050, Joule (2019), https://doi.org/10.1016/j.joule.2019.07.013

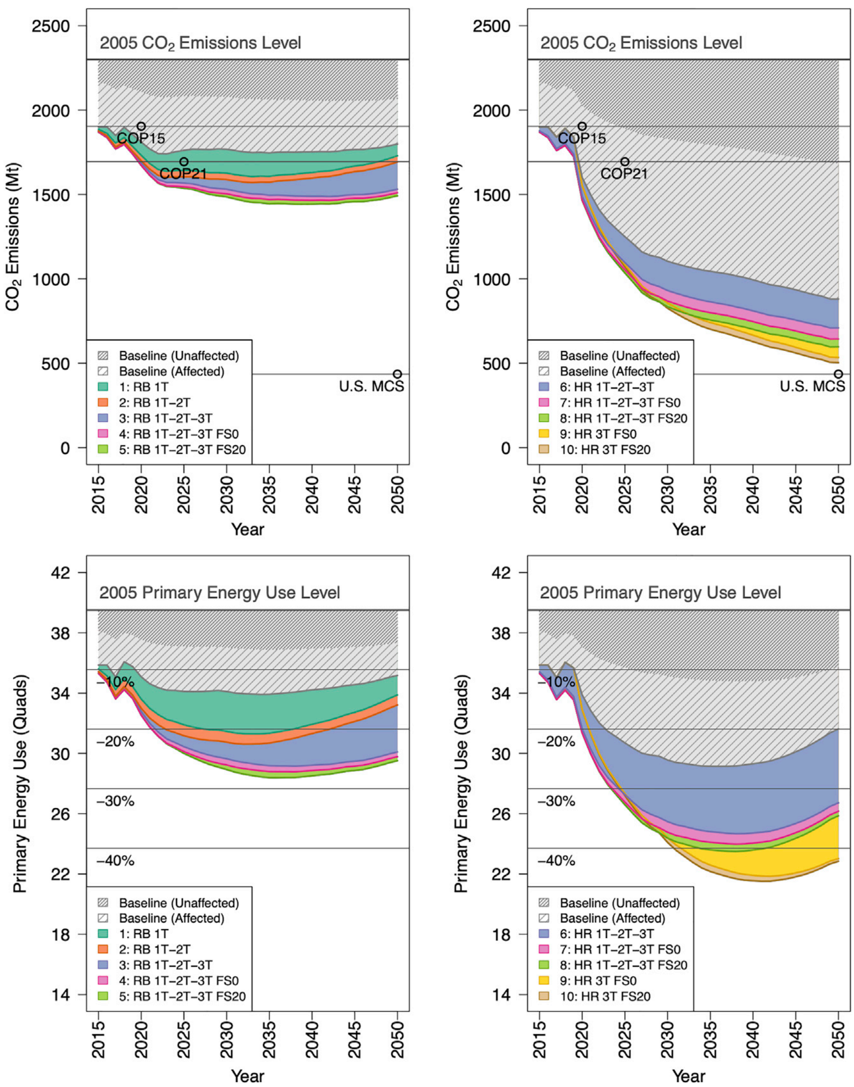


Figure 1. By 2050, Aggressive Building Efficiency, Incentivized Electrification, and High Renewable Penetration Can Reduce CO_2 Emissions Up to 78% Relative to 2005

Total annual avoided CO_2 emissions are plotted relative to 2005 baseline emissions (top row) and annual primary energy savings are plotted relative to 2005 baseline energy use (bottom row), for scenarios 1–5 (left column), which assume a "Reference Baseline" ("RB") energy supply consistent with the 2018 AEO reference case (31% renewable electricity by 2050), and scenarios 6–10 (right column), which assume a "High Renewables" ("HR") energy supply consistent with the highest 2018 AEO side case estimates of renewable electricity penetration (45% by 2050). Annual emissions and energy use savings already embedded in the baseline case through supply-side renewable penetration and efficiency are shown as hatched regions, with the more densely hatched region denoting savings in the portion of baseline emissions and energy use not affected by the chosen ECM sets and the less densely hatched region denoting additional savings in the portion of baseline emissions and energy use affected by the chosen ECM sets. By 2050, CO_2 emissions reductions range between 26–36% of 2005 levels for scenarios that assume a reference energy supply (scenarios 1–5), and between 70%–78% for scenarios that assume a high renewable energy supply (scenarios 6–10).

To realize these emissions reductions, the bottom right panel of Figure 1 shows that at least 35% of buildings' 2005 primary energy use must be eliminated. Roughly 20% of these energy savings are attributable to an increase in renewable energy supply, given baseline-case efficiency that holds 2050 energy demand to just above 2005 levels.[41,42] The remaining 15% of energy savings are attributable to additional building efficiency and electrification beyond the baseline case. In all scenarios that assume a comprehensive mix of competing measures (scenarios 3–8), total primary energy savings impacts peak between 2035–2040 and decline thereafter due to a trend in the baseline in which less-efficient nuclear generation increases to 22% of electricity supply by 2050 while more efficient combined-cycle natural gas supply decreases.[41,43] Examining the results for these scenarios against those of scenarios where *only* the best performing prospective technologies are represented on the market (scenarios 9 and 10), it is evident that competition with lower-performing technology options substantially reduces the impact potential for these prospective measures, shaving 8% off of the total energy savings potential by 2050. The adoption of lower-performing technologies in the early years of the analysis constrains the size of the baseline market that can be captured by later-arriving prospective technologies, a lock-in effect that is addressed further in the Discussion section.

Most of the emissions impacts in Figure 1 are attributable to supply-side integration of renewable power sources. Indeed, without considering any additional building efficiency improvements or fuel switching, scenarios that assume a high renewable energy supply (6–10) already achieve a 62% reduction compared to 2005 emissions levels (78% of the of the 2050 target) and comfortably surpass the 2020 and 2025 CO_2 reduction goals.

CO_2 Emissions Reductions Are Driven by the Heating, Water Heating, and Envelope End Uses in Existing Residential Buildings

The avoided CO_2 emissions and primary energy savings from the scenarios shown in Figure 1 can be split up, as in Figure 2, to show the contribution of individual building end uses toward these emissions reductions and energy savings. Figure 2 shows total annual avoided CO_2 emissions and primary energy savings derived solely from the measures. The heating, water heating, and envelope end uses yield the largest CO_2 emissions reductions in both the short- and long-term across all of the scenarios analyzed. Lighting is also a major contributor to avoided CO_2 emissions in most scenarios in 2030, but by 2050, as a result of emissions already averted through prior efficiency improvements in the lighting stock, further improvements yield limited additional savings for scenarios 2–8 and negative savings for scenarios 1 and 2.

Comparing scenarios 3 (RB 1T-2T-3T) and 4 (RB 1T-2T-3T FS0) reveals that switching from fossil fuels to electricity further reduces total CO_2 emissions—11% by 2030 and 8% by 2050. Fuel switching that occurs in conjunction with reductions in the CO_2 intensity of electricity generation can deliver substantially greater CO_2 reductions—35% by 2030 and, with a continuing transition toward zero-carbon generation, 39% by 2050—as indicated by a comparison between scenarios 6 (HR 1T-2T-3T) and 7 (HR 1T-2T-3T FS0). Moreover, adding incentives for fuel switching, as in scenario 8 (HR 1T-2T-3T FS20), is particularly valuable under these conditions, yielding an additional 19% and 26% reduction in CO_2 emissions in 2030 and 2050, respectively, compared to scenario 7 (HR 1T-2T-3T FS0). In 2050, scenarios 9 (HR 3T FS0) and 10 (HR 3T FS20) show greater CO_2 reductions than the other scenarios, with a substantially increased contribution from the building envelope, principally as a result of the removal of lower-performance, lower-cost technologies from the available ECMs, thus maximizing the impact of novel, next-generation technologies.

Comparing the avoided CO_2 emissions results for scenario 10 (HR 3T FS20) in both 2030 and 2050 further shows that the emissions reductions from end uses that are all-electric (e.g., cooling, lighting, and refrigeration) are diminished substantially

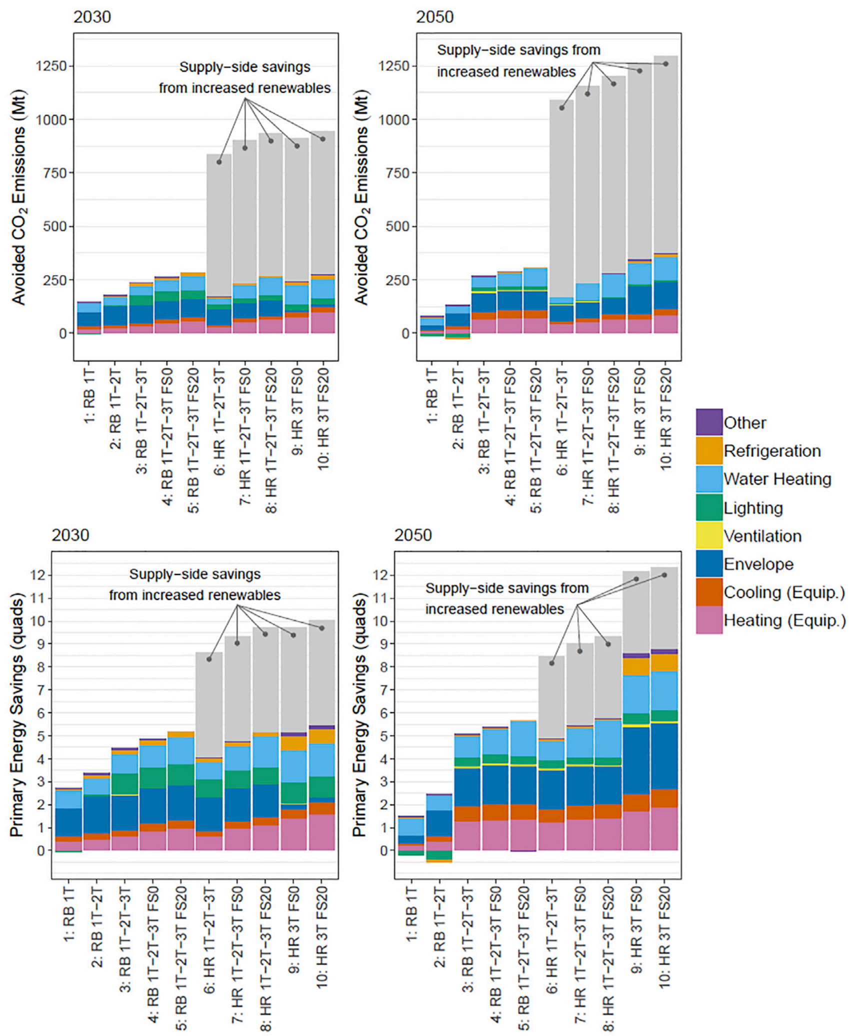


Figure 2. CO_2 Emissions Reductions Are Driven by the Heating, Water Heating, and Envelope End Uses

Total annual avoided CO_2 emissions (top row) and primary energy savings (bottom row) are shown split up by major building end uses for each of the scenarios in the years 2030 (left column) and 2050 (right column). Scenarios 1–5 assume a "Reference Baseline" ("RB") energy supply consistent with the 2018 AEO reference case (31% renewable electricity by 2050), while scenarios 6–10 assume a "High Renewables" ("HR") energy supply consistent with the highest 2018 AEO side case estimates of renewable electricity penetration (45% by 2050). These results are relative to the baselines in 2030 or 2050 and include only changes arising from the measures themselves. In these results, the scenarios that use the HR case as the baseline show the additional CO_2 emissions reductions and energy savings that come from a more rapid transition to renewable generation sources in that baseline as gray bars atop the savings from demand-side improvements shown by end use. Taken together, these bars show the total avoided CO_2 emissions and energy savings from both supply-side and demand-side changes in the HR-based scenarios. Emissions reductions and energy savings are largely attributable to end uses associated with on-site fossil fuel use—heating, water heating, and the building envelope; this result is particularly evident in 2050 under the "High Renewables" baseline.

by supply-side decarbonization; further efficiency improvements for these end uses are less important from a CO_2 emissions perspective since the energy they use is far less carbon-intensive in scenario 10 (HR 3T FS20). Conversely, for end uses that have a substantial share of fossil fuel-fired equipment (heating, water heating, and

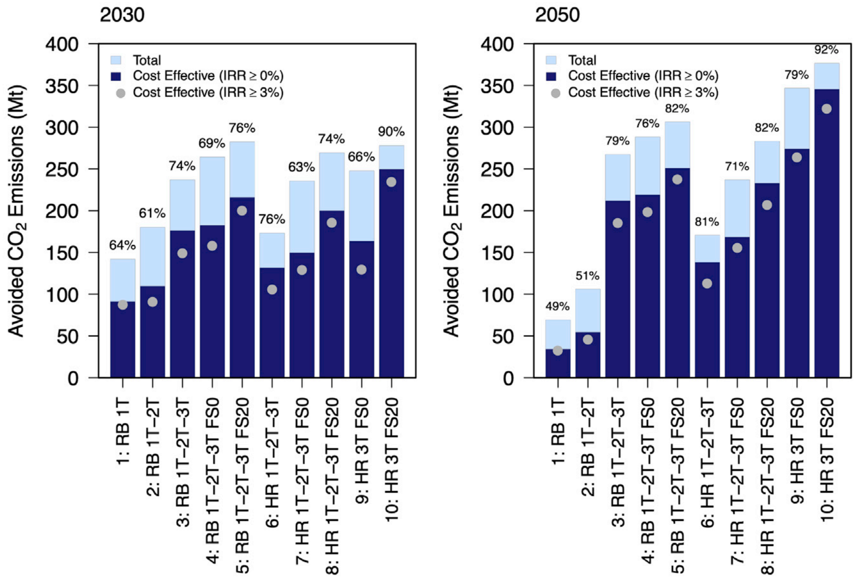


Figure 3. Scenarios That Deploy Prospective Technologies with Aggressive Cost and Performance Targets and Incentivize Fuel Switching Achieve Highly Cost-Effective Emissions Reductions

The cost-effective percentage of each scenario's avoided CO_2 emissions from building efficiency and end-use electrification is plotted for the years 2030 (left) and 2050 (right), using internal rate of return (IRR) $\geq$ 0 as a cost-effectiveness threshold. For reference, an alternate IRR threshold of 3% is shown that approximates the 10-year U.S. Treasury note yield across 2018,[44] considered a "risk-free" interest rate for investment decisions.[45] By 2050, scenarios that assume market penetration of prospective, high-performance building technologies consistently achieve 70% or more of their emissions reductions cost-effectively. Introducing fuel switching with incentives achieves up to a 66% increase in avoided CO_2 emissions at an equal or superior cost-effectiveness level.

heating associated with the building envelope), both efficiency improvements and fuel switching yield clear reductions in CO_2 emissions in that scenario.

Examining the contributions of different building types and vintages to avoided CO_2 emissions reveals that the majority of savings will come from the existing building stock. In particular, retrofitting existing residential buildings and upgrading their equipment presents the single largest opportunity for avoiding CO_2 emissions, comprising the majority of reductions in all scenarios in 2030 and many scenarios in 2050. These results are elaborated in Section S1.

Prospective Envelope, Controls, and Fuel Switching Heating and Water Heating Technologies Achieve the Largest Cost-Effective CO_2 Emissions Reductions

Given Scout's detailed representation of ECM installation and operating costs, energy performance, and lifetime characteristics, financial metrics can be calculated for individual ECMs in order to assess the overall cost effectiveness of each scenario's CO_2 emissions reductions, as in Figures 3 and 4. In Figure 3, the percentage of each scenario's emissions reductions that is contributed by ECMs with an internal rate of return (IRR) $\geq$0 is shown, where IRR is used as a consumer-focused cost-effectiveness threshold. Overall, the percentage of cost-effective emissions reductions shown in Figure 3:

- is lower for the scenarios that include only currently available technologies (scenarios 1 [RB 1T] and 2 [RB 1T-2T]) than for those that allow greater

Please cite this article in press as: Langevin et al., Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050, Joule (2019), https://doi.org/10.1016/j.joule.2019.07.013

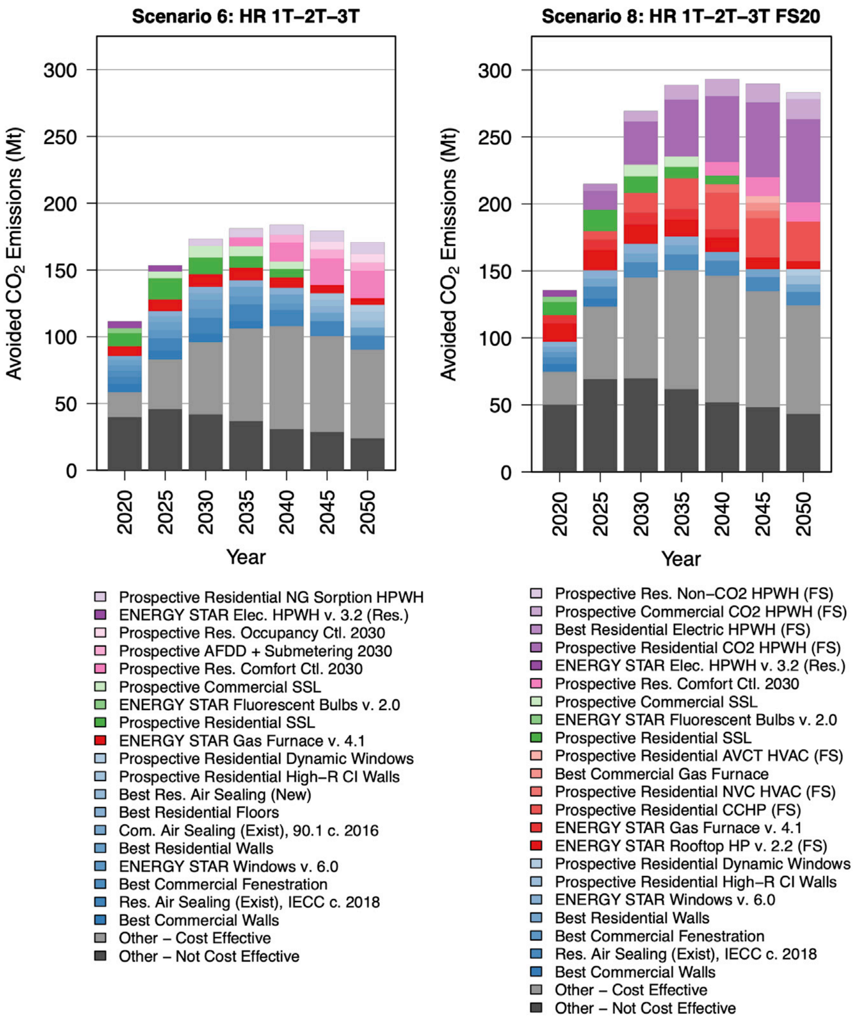


Figure 4. Prospective Envelope, Controls, and Fuel Switching Heating and Water Heating Technologies Achieve the Largest Cost-Effective CO_2 Emissions Reductions

Avoided CO_2 emissions are plotted from scenario 6 (HR 1T-2T-3T, at left) and scenario 8 (HR 1T-2T-3T FS20, at right), separately showing the building efficiency measures (ECMs) that yield the 10 largest emissions reductions with IRR $\geq$0 every 5 years across the model time horizon. ECM types (envelope, controls, water heating, HVAC, etc.) are grouped by bar color. Prospective envelope and controls ECMs yield the largest cost-effective emissions reductions in the absence of fuel switching (scenario 6), while heat pump technologies that replace fuel-fired water heating and heating technologies yield the largest cost-effective emissions reductions when they are introduced with a 20% capital cost credit (scenario 8).

penetration of target ECMs with more favorable capital cost characteristics (scenarios 3–10),

- decreases when fuel switching is introduced without incentives, relative to cases with no fuel switching (scenario 4 [RB 1T-2T-3T FS0] compared to scenario 3 [RB 1T-2T-3T], scenario 7 [HR 1T-2T-3T FS0] compared to scenario 6 [HR 1T-2T-3T]), and
- is at its highest when fuel switching is added with a 20% capital cost credit, relative to cases with no fuel switching or with fuel switching but no incentives (scenario 5 [RB 1T-2T-3T FS20] compared to scenarios 3 [RB 1T-2T-3T] and 4 [RB 1T-2T-3T FS0], scenario 8 [HR 1T-2T-3T FS20] compared to scenarios 6 [HR

1T-2T-3T] and 7 [HR 1T-2T-3T FS0], and scenario 10 [HR 3T FS20] compared to scenario 9 [HR 3T FS0]).

Incentivized fuel switching is particularly cost-effective in Figure 3 under a high renewable energy supply: moving from scenario 6 (HR 1T-2T-3T) to scenario 8 (HR 1T-2T-3T FS20), for example, a 112 Mt (or 66%) decrease in emissions is observed with a slight increase in the percentage of cost-effective emissions reductions (from 81% in scenario 6 to 82% in scenario 8).

Figure 4 breaks down the cost-effective CO_2 emissions reductions of scenarios 6 (HR 1T-2T-3T) and 8 (HR 1T-2T-3T FS20) by contributing ECMs, highlighting the 10 ECMs that contribute the largest cost-effective emissions reductions for every five years in the modeling time horizon. Cost-effective emissions reductions are derived from a mix of ECM types that tends to grow more diverse over time. For example, in scenario 6 the top 10 cost-effective ECMs contribute two-thirds of total cost-effective CO_2 emissions reductions in 2020, but by 2050 this contribution drops to just over half as more ECMs enter the cost-effective mix. Total cost-effective emissions reductions also tend to increase over time, as a share of total emissions reductions, as more prospective ECMs with favorable capital cost and energy performance characteristics penetrate the ECM mix.

In the absence of any assumed fuel switching (scenario 6), prospective controls ECMs that optimally tune building operations to occupant needs and diagnose operational faults lead the cost-effective CO_2 reductions, owing to the large size of the applicable baseline energy use segments for these ECMs and their aggressive cost and performance characteristics. Envelope ECMs contribute somewhat smaller but consistent cost-effective emissions reductions across the full model time horizon—particularly air sealing and highly-insulating windows and walls.

Given the addition of incentivized fuel switching (scenario 8), heat pump ECMs that replace fuel-fired water heating and heating technologies show much larger contributions to cost-effective CO_2 emissions reductions. The impact of these technologies is particularly apparent in the residential sector, where by 2050, prospective heat pump water heaters are the single greatest cost-effective contributor to avoided CO_2 emissions, and cold-climate heat pumps also yield substantial cost-effective emissions reductions. Indeed, cold-climate heat pumps drive marked increases in the total cost-effective avoided CO_2 emissions of northern climates under fuel switching incentives; this result is elaborated in Section S1.

DISCUSSION

Leveraging the capabilities of Scout, a widely-accessible modeling program designed to facilitate explorations of building energy use and emissions savings at the national scale, we yield new insights about the potential contribution of building energy efficiency and electrification to achieving U.S. MCS goals. We simulate a range of possible building efficiency, electrification, and energy supply scenarios that draw from hundreds of detailed, publicly-available representations of efficiency measures, each of which is either currently on the market or targeted for near-term market entry by current policy programs. Scenario impacts are assessed relative to highly granular, annually updated projections of baseline energy use and emissions that are made publicly available by the U.S. EIA. Realistic dynamics in baseline and efficient stock turnover and efficient measure competition are accounted for, and are based on endogenous building and technology stock characteristics—in contrast with the exogenous technology penetration assumptions of many previous studies.[33,34,46,47]

Our analysis finds that under a reference-case energy supply scenario, continued market penetration of building efficiency measures that correspond to current energy performance guidelines would be sufficient to meet the near-term (2020 and 2025) MCS CO_2 emissions reductions targets. By 2050, however, none of the considered efficiency measure sets—including those that assume the market introduction of aggressive efficiency measures currently in the research stage and incentivized fuel switching to electricity—is able to achieve more than a 36% reduction compared to 2005 emissions levels, less than half of the 80% emissions reduction target in the MCS.

This finding highlights the significance of assessing national building efficiency potential over a longer time horizon ($\geq$ 30 years), as this horizon reveals important limits to sustained growth in the CO_2 emissions reductions and energy savings potential of buildings sector interventions. By the year 2050, the energy performance of baseline-case building technologies has improved substantially, reducing, eliminating, or reversing the relative performance advantages of many of the lower-performing ECMs in our analysis. The effects of this baseline improvement are evident in Figure 1, where the CO_2 emissions reductions and primary energy savings of scenarios 1 and 2, which include only currently available ECMs, converge toward the baseline level after the year 2030; in Figure 2, where the lighting end use contribution to emissions reductions and primary energy savings is reduced by more than half between 2030 and 2050 across scenarios 2–8, and is negative for scenarios 1 and 2; and in Figure 3, where the percentage of cost-effective emissions reductions is about 10% lower for scenarios 1 and 2 than many of the more aggressive efficiency scenarios in 2030, with the disparity increasing to about 20% by 2050. These trends could be counteracted by policies that significantly improve best available technology cost and performance beyond what is currently available on the market.

Furthermore, the adoption of existing cost-effective technologies locks in higher CO_2 emissions and energy use[48,49] while dampening the long-term energy and CO_2 savings from emerging technologies that will enter the market over the next decade. This effect is best seen by comparing the primary energy savings trends of scenarios 9 and 10 in Figure 1, which idealistically assume only high performing, emerging technologies enter the market, with the primary energy savings trends of scenarios 6–8, which include lower performing technologies in the available measures. By 2050, primary energy savings relative to 2005 are diminished by about 8% between the former and latter set of scenarios, as the lower performing technologies of scenarios 6–8 capture substantial portions of the available baseline markets in early years and "lock-out" the later-arriving emerging technology sets from these captured market segments, dragging down long-term CO_2 emissions reduction potential. These lock-in effects are also relevant to fuel switching measure deployment strategies. For example, deferring the market entry of fuel switching measures to later years with more renewable electricity generation would be unlikely to yield emissions reductions benefits because this approach allows the lock-in of earlier arriving, fuel-fired technologies with comparatively higher emissions profiles. Lock-in of low-performing building technologies is counteracted by policies that ensure the progressive removal of these technologies from the market while pushing for earlier introduction of high-performing alternatives that take full advantage of renewable electricity supply.

While aggressive U.S. building efficiency alone fails to satisfy the 80% emissions reduction target by 2050, coupling efficiency with a low-carbon electricity supply and end use electrification (scenarios 7–10) gets close, ultimately achieving a 72%–78% reduction compared to 2005 CO_2 emissions levels. In the scenarios with these three conditions and a realistic technology mix (scenarios 7 and 8), the majority of CO_2 emissions reductions are attributable to a dramatic reduction in the CO_2 intensity of the electricity supply from greater renewable energy penetration. Supply-side advancements should not, however, be taken as a silver bullet for emissions reductions. This study's most aggressive supply-side CO_2 reductions assume EIA's highest projections of renewable energy growth, which are driven by a sustained \$25/t CO_2 price that seems unlikely to materialize soon in the U.S. Moreover, high levels of variable renewable energy integration will require increased demand-side energy flexibility to ensure grid reliability,[15–17] suggesting that the buildings sector, which is responsible for 75% of U.S. electricity use,[50] has a significant role to play in enabling renewable energy growth.

Most important, high renewable energy growth alone achieves only a 62% reduction compared to 2005 emissions levels by 2050, falling well short of the 80% MCS target. To reach within 10% of this target, additional building efficiency and electrification beyond the baseline case that eliminates at least 15% of 2005 primary energy use is also needed, and efficiency and electrification are shown to be cost-effective pathways for emissions reductions. In Figure 3, for example, roughly 80% of 2050 CO_2 emissions reductions are achieved cost-effectively for scenarios that include aggressive efficiency measures without fuel switching (scenarios 3 and 6), and greater than 80% of 2050 CO_2 emissions reductions are achieved cost-effectively for scenarios that add incentivized fuel switching to electricity (scenarios 5, 8, and 10). Incentivized fuel switching has much larger effects on emissions under a high renewable energy supply, driving a 66% increase in demand-side emissions reductions from scenario 6 to 8 (high renewable supply) compared to a 14% increase from scenario 3 to 5 (reference-case supply), for example. Achieving these synergistic impacts across supply- and demand-side energy will require coordinated policies that encourage robust renewable energy penetration while pushing for aggressive building efficiency improvements, increased building electric load flexibility, and strong incentives for end use electrification. The design of electrification incentives must incorporate strategies for addressing non-economic barriers to fuel switching, such as lack of required infrastructure, lack of local installers with appropriate technical expertise to install electric equipment, and concerns about the reliability of electric equipment versus fuel-fired alternatives.

Given the disaggregated manner in which Scout represents U.S. building energy use, CO_2 emissions, and the measures that influence energy and CO_2 trajectories, our results highlight specific opportunities for advancing building efficiency and end use electrification. End uses associated with on-site fossil fuel use offer the largest CO_2 emissions reduction opportunities—heating, water heating, and the building envelope. The emissions reduction potential of end uses that rely exclusively on electricity, such as cooling, refrigeration, and lighting, are limited by improvements in supply-side CO_2 intensity; further improvements in the efficiency of these end uses are somewhat less important in a high renewable penetration future, rather, technology R&D to enable or enhance flexibility in the timing of demand from these end uses will be critical to enabling high renewable penetration levels.[15–17] Emissions reductions come largely from existing residential buildings; thus, cost-effective solutions for accelerated replacement of the existing residential technology stock with more efficient alternatives are critical to achieving the avoided CO_2 emissions potential suggested by these results. Large-scale retrofits of existing buildings have historically been challenging to implement, even when cost-effective,[51] underscoring the need to better understand the drivers of building retrofit decisions such that new mechanisms for accelerating these decisions can be developed.

At the level of individual efficiency measures, building envelope and controls ECMs tend to make the largest cost-effective contributions to CO_2 emissions reductions when fuel switching is excluded, while substantial contributions from heat pump water heaters and cold-climate heat pumps also emerge in scenarios that introduce incentivized fuel switching. The large, cost-effective emissions reductions from controls measures in our results is notable because such measures have not previously been included in national-scale analyses of building efficiency impact potential.[45] This omission has persisted despite the potential for such measures to affect large segments of national energy use across multiple end uses, often through easily updated software that can be implemented at low cost in both new and existing buildings.[52,53] Accordingly, building controls measures warrant stronger consideration in future analyses of national building efficiency potential and the program planning efforts that such analyses inform.

Our analysis does not cover all avenues for building efficiency, as 44% of baseline CO_2 emissions remain unaffected by the chosen ECM sets. Unlocking these portions of energy use and CO_2 emissions, which largely relate to miscellaneous energy loads (in particular, plug loads such as computers, TVs, and other small appliances), represents an opportunity to deliver additional emissions reductions from the buildings sector.

This study establishes a snapshot of buildings' CO_2 emissions reduction potential in the U.S. that will be frequently updated to reflect the latest developments in energy efficiency, renewable energy, and associated policy approaches. Going forward, the default set of ECMs and scenarios published online and reported in this paper will continue to be refined, and Scout's baseline data will be revised annually to reflect the latest version of the EIA AEO. These planned updates reflect the intention to maintain Scout as an accessible, flexible, and current resource for estimating the impacts of building technology developments on U.S. energy use and emissions. Regularly assessing these impacts will be essential to developing mitigation strategies for the environmental, economic, and social risks caused by a rapidly warming climate.

EXPERIMENTAL PROCEDURES

Overview of Scout Analysis Approach

This analysis of U.S. building energy use and CO_2 emissions uses Scout, an open-source software program developed by Lawrence Berkeley National Laboratory and the National Renewable Energy Laboratory for the U.S. Department of Energy. Scout estimates the national energy use, CO_2 emissions, and operating cost savings potential of emerging building technologies or operational approaches across a long time horizon; savings can be explored under multiple technology adoption cases nationally or for a subset of climate zones. Figure 5 provides an overview of the Scout analysis approach; key elements of this approach are described in greater detail below.

Scout analyses begin with individual ECMs, where an ECM improves upon the unit-level energy performance and/or operation of a comparable baseline technology or operational approach. ECM definitions are implemented in JSON-formatted files with a standardized key-value structure and are defined primarily by five attributes: applicable baseline market, year of market entry/exit, energy performance, installed cost, and lifetime.

An ECM's applicable baseline market represents a specific subset of total operation-phase energy use, CO_2 emissions, and costs associated with residential and commercial buildings in the U.S. Markets are non-overlapping; the sum of energy

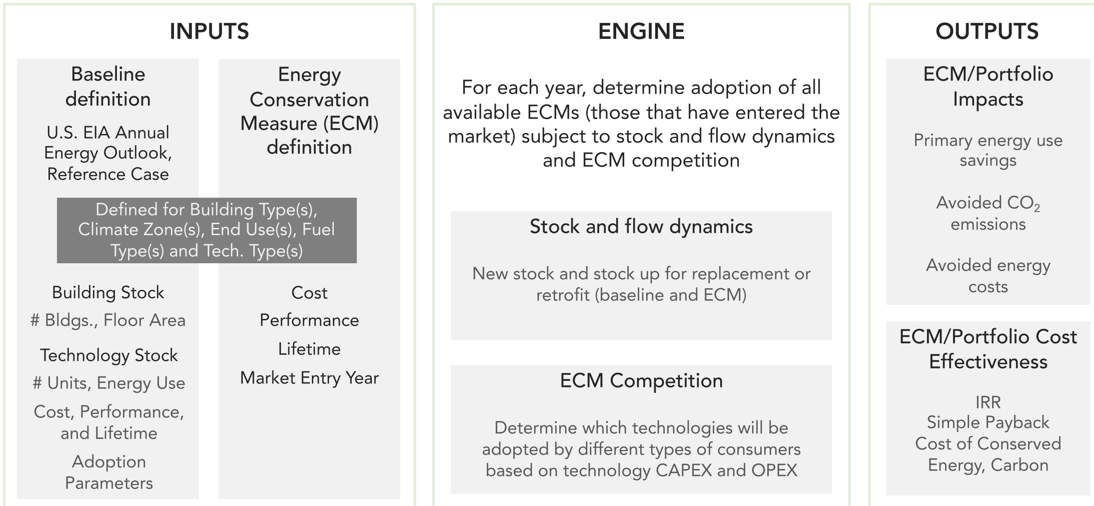


Figure 5. Overview of Scout Analysis Approach

The Scout analysis approach moves from the definition of efficient measures and the segments of baseline energy use that they affect to the estimation of measure market penetration and competition dynamics and finally to the calculation of measure impacts on energy use, CO_2 emissions, and operating costs, as well as measure cost effectiveness.

use in all markets is equal to the total energy use in residential and commercial buildings. Each market is defined by a climate zone, building type, fuel type, end use, and, if applicable, technology type. For example, a market might correspond to cooling with electric air-source heat pumps in single family homes in a southern climate zone. By default, baseline data are drawn from the EIA AEO reference case for the buildings sector.[4] Primary energy use baselines from EIA are adjusted to reflect a captured energy approach to renewable energy generation accounting, consistent with the recommendation in Donohoo-Vallett[54] and described further in the Supplemental Information section. An ECM's year of market entry represents the first year that the ECM is commercially available, while an optional year of market exit can reflect a future efficiency standard that renders the measure obsolete. Where no legislation precludes the future adoption of a measure, the measure may still be displaced through competition with other measures as described below and in Section S2.3. An ECM's energy performance is defined at the unit level and may be specified in absolute terms (e.g., U-value and solar heat gain coefficient for a window, or COP for a heat pump) or as a percentage relative savings. In the case of a relative energy performance input, percentage savings can remain constant over the modeling horizon or can be recalculated annually to account for performance improvements in the comparable baseline technology. An ECM's installed cost is also defined at the unit level and is specified in terms that vary by sector and applicable end use. Finally, the expected lifetime of an ECM is specified in years.

Given one or more ECM definitions, Scout calculates the total impact of each ECM's adoption by consumers or organizations on metric M in year y under adoption case s, $M_{y,s}$:

$$M_{y,s} = \sum_{z}^{Z} \sum_{b}^{B} \sum_{f}^{F_b} \sum_{u}^{U_{b,f}} \sum_{t}^{T_{b,f,u}} \sum_{v}^{V} M_{z,b,f,u,t,v,y,s}\ a_{z,b,f,u,t,v,y,s} \quad \text{(Equation 1)}$$

$$M_{z,b,f,u,t,v,y,s} = M^{\text{base}}_{z,b,f,u,t,v,y,s} - M^{\text{ecm}}_{z,b,f,u,t,v,y,s} \quad \text{(Equation 2)}$$

where $M^{\text{base}}_{z,b,f,u,t,v,y,s}$ is the baseline quantity of impact metric M attributable to climate zone z, building type b, fuel type f, end use u, technology t, building vintage v, projection year y, and adoption case s, $M^{\text{ecm}}_{z,b,f,u,t,v,y,s}$ is the same quantity after ECM adoption, Z is the set of all climate zones affected by the ECM, B is the set of building types affected by the ECM, F_b is the set of fuel types for building type b that are affected by the ECM, $U_{b,f}$ is the set of end uses for building type b and end use u that are affected by the ECM, $T_{b,f,u}$ is the set of technologies for building type b, fuel type f, and end use u that are affected by the ECM and $a_{z,b,f,u,t,v,y}$ is a competition adjustment factor that removes overlaps between the applicable baseline market of the ECM and competing ECMs in a portfolio.

Scout baseline data are broken out by the 5 AIA climate zones,[55] requiring a translation from the census division breakout of AEO data; square-footage-based mapping factors derived from RECS 2009[56] and CBECS 2003[57] are used to make the translation. Baseline building types reflect the 3 residential and 11 commercial building types modeled in AEO,[45,58] and new and existing building vintages are defined. Baseline fuel types include electricity, natural gas, distillate, and other fuels. Baseline end uses reflect the 14 residential and 10 commercial end uses modeled in the AEO[45,58] with small modifications to the organization of residential end uses and addition of an envelope end use, where the latter comprises reductions in required heating and cooling energy use as a result of improvements to the building envelope—windows, air sealing, and insulation. Technology types reflect those associated with each end use in AEO with the exception of heating and cooling, where an additional distinction between equipment and "thermal load component" (envelope) technologies is made. More details on the definition of thermal load component technologies are available in Section S2.5.

ECM impact metrics include primary energy use ($E_{y,s}$, $E^{\text{base}}_{y,s}$, $E^{\text{ecm}}_{y,s}$), CO_2 emissions ($C_{y,s}$, $C^{\text{base}}_{y,s}$, $C^{\text{ecm}}_{y,s}$), and operating costs ($\psi_{y,s}$, $\psi^{\text{base}}_{y,s}$, $\psi^{\text{ecm}}_{y,s}$). Each impact is calculated under two distinct technology adoption cases. Under a technical potential (TP) adoption case, it is assumed that as soon as an ECM is introduced, all baseline markets that the ECM applies to instantaneously and completely switch to the new ECM, and the ECM retains a complete sales monopoly in subsequent years. Results from the TP case represent the maximum impact an ECM could have, limited only by baseline market size. In a maximum adoption potential (MAP) adoption case, it is assumed that an ECM is only able to capture the portions of applicable baseline markets that are associated with new construction and retrofit or replacement of existing technologies in a given year. Results from the MAP represent an ECM's maximum impact considering realistic building and equipment turnover and generally show a gradual accumulation of ECM savings over time.

Technology adoption assumptions are further distinguished by whether they account for competition across ECMs that apply to the same baseline stock segments (a "competed" case) or consider each ECM in isolation (an "uncompeted" case). In the competed case, ECM market shares are apportioned based on each measure's incremental capital and operating costs, where a measure with lower incremental capital costs and higher operating cost savings will capture a greater share of the baseline market (see Section S2.3 for details).

To assess building contributions to climate goals under realistic stock turnover and technology competition dynamics, in this paper we focus exclusively on competed MAP adoption case results.

In addition to CO_2 emissions, primary energy use, and operating cost impacts, Scout assesses each ECM's cost effectiveness, *CE*:

$$CE = f\left(\frac{M_{y,s}}{\sigma_y^{base}},\ l^{ecm},\ l^{base},\ CE^*,\ d\right) \quad \text{(Equation 3)}$$

where $M_{y,s}/\sigma_y^{base}$ is an ECM's stock-normalized impact on metric M in year y under adoption case s, l^{ecm} and l^{base} are the ECM and baseline technology lifetimes, respectively, CE^* is a cost effectiveness threshold (e.g., internal rate of return ≥ 0, simple payback ≤ 5, etc.), and d is a nominal discount rate.

The calculation methods for ECM impact estimates and cost-effectiveness assessments are further detailed in the Supplemental Information.

Simulated Building Efficiency and Electrification Scenarios

Scout's analysis capabilities are demonstrated in this paper through simulations of ten different scenarios of building efficiency, electrification, and electricity supply (Table 1). ECMs in each of the simulated scenarios apply to the following major end uses across all climate zones, building types, and fuel types: heating and cooling (as affected by both envelope and HVAC equipment ECMs), water heating, lighting, and refrigeration. Additionally, residential-sector ECMs apply to clothes washing and drying, and commercial-sector ECMs apply to ventilation. Controls ECMs apply across multiple end uses (heating, cooling, ventilation, and lighting).

The cost, performance, and lifetime inputs for each ECM included in this analysis are considered fixed across time. This reflects a deliberate choice to base our impact assessment solely on published ECM information (e.g., from performance guidelines, market data, or future targets in energy policy program documents) while avoiding the assumption that ECM characteristics incrementally improve after market introduction, which we do not have broad evidence for across our diverse set of ECMs. This assumption may be particularly inappropriate for prospective ECMs, which in many cases feature aggressive ECM performance and cost characteristics that leave little room for additional improvement.

The MAP of each scenario is simulated across the full model time horizon (2015–2050), accounting for realistic dynamics in stock turnover and ECM competition. Results are assessed in terms of each scenario's annual impact on national CO_2 emissions and primary energy use and in terms of ECM cost effectiveness. Specifically, results are viewed in the context of the following questions:

- What is the magnitude of each scenario's total impact on CO_2 emissions and primary energy use?
- Which end uses and ECMs contribute the most to each scenario's total CO_2 and energy impacts?
- To what degree are ECM impacts in each scenario achieved cost- effectively?

Total CO_2 emissions reductions are benchmarked against the GHG reduction goals laid out in the United States MCS for Deep Decarbonization.[3] In the MCS, CO_2 emissions reductions drive total GHG emissions reductions, therefore we apply targeted GHG reduction percentages to buildings sector CO_2 emissions for the appropriate reference year, 2005:

- 17% reduction from 2005 CO_2 emissions by 2020 (396 Mt CO_2 of 2330 Mt CO_2 emissions from the buildings sector in 2005[59]), a goal announced as part of the

Copenhagen Accord reached at the 2009 United Nations Climate Change Conference (COP15),

- 26%–28% reduction from 2005 CO_2 emissions by 2025 (here we choose the low end, 26%, corresponding to 606 Mt CO_2), a goal announced as part of the Paris Agreement reached at the 2015 United Nations Climate Change Conference (COP21), and
- 80% reduction from 2005 CO_2 emissions by 2050 (or 1864 Mt CO_2), a goal that was introduced in the MCS document.

The particulars of each scenario are summarized here, with scenario acronyms used throughout shown in parentheses. The full set of ECM definitions and raw results for each scenario is also publicly available.[60]

- Scenario 1: reference energy supply, energy performance guidelines ECMs (RB 1T). This scenario includes technologies that meet the minimum performance requirement for ENERGY STAR (most recent version), IECC 2018, or ASHRAE Standard 90.1-2016. For each building type, fuel type, and end use of interest, a relevant ENERGY STAR specification was sought first; if one did not exist, relevant performance criteria in the IECC standard were used; if no relevant IECC criteria existed, criteria from the ASHRAE standard were used. In the simulation of this portfolio, ECM performance is locked in future years at the currently available level, and no fuel switching is assumed (electric ECMs can only replace electric baseline technologies).
- Scenario 2: scenario 1 + best available ECMs (RB 1T-2T). This scenario adds ECMs that represent the most efficient technologies currently available on the market. Most ECM definitions for this portfolio are based on data from the EIA document titled "Updated Buildings Sector Appliance and Equipment Costs and Efficiency,"[61] specifically using the "High" technology cost and performance values reported for the year 2017. These data do not cover envelope ECMs (highly-insulating windows, air sealing, etc.); accordingly, best available envelope ECMs were based on the National Renewable Energy Laboratory's Residential Efficiency Measures database[62] in the residential sector and on the ASHRAE Advanced Energy Design Guidelines[63] in the commercial sector. As in scenario 1, the simulation of this portfolio locks ECM performance in future years at the currently available level, and no fuel switching is assumed.
- Scenario 3: scenario 2 + target ECMs (RB 1T-2T-3T). This scenario adds ECMs that represent prospective technologies with cost and performance targets that are more aggressive than those assumed for the most efficient technologies under the "business-as-usual" conditions. Most ECM definitions added in this scenario are based on cost and performance targets data from the U.S. Department of Energy's Building Technologies Office (BTO) Multi-Year Program Plan (MYPP).[40] The scenario also reflects updates to and expansions of the BTO MYPP technology set following its publication, particularly the development of new windows and envelope and sensors and controls targets,[52] both of which are to be published in forthcoming BTO technology development roadmaps. As in scenarios 1 and 2, no fuel switching was assumed when simulating this portfolio.
- Scenario 4: scenario 3 + fuel switching (RB 1T-2T-3T FS0). This scenario adds fossil fuels to the applicable baseline markets of electric ECMs, opening the potential for fuel switching from fossil fuels to electricity. Fuel switching is only represented in the ECM definitions through an expansion of the ECM's applicable baseline market and the replacement of the baseline fuel type's

energy costs and emissions intensities with that of the ECM's fuel type; no additional fuel switching costs (e.g., increased capital costs for new supporting infrastructure) are represented.

- Scenario 5: scenario 4 + 20% fuel switching incentive (RB 1T-2T-3T FS20). This scenario is identical to scenario 4, but with a 20% reduction in the installed cost of fuel switching measures.
- Scenarios 6–8: scenarios 3–5 + high renewable energy supply (HR 1T-2T-3T, HR 1T-2T-3T FS0, HR 1T-2T-3T FS20). These scenarios assume a higher degree of renewable penetration than all previous scenarios, reducing the CO_2 emissions intensity of electricity. Specifically, default Scout site-source energy conversion factors and CO_2 emissions intensities are updated to reflect data from the EIA's ''25 dollar carbon allowance fee'' side case, which yields approximately 32% renewable electricity generation by 2025 and 45% renewable electricity by 2050[41] (compared to approximately 22% renewable electricity by 2025 and 31% renewable electricity by 2050 in the reference case that underpins the default Scout site-source conversion and CO_2 emissions intensities data).
- Scenario 9: target ECMs only + fuel switching + high renewable energy penetration (HR 3T FS0). This scenario maintains the high renewable energy penetration assumption of scenarios 6–8 but restricts the ECM set to prospective technologies only, such that these technologies do not face any competition from ECMs in the performance guidelines and best available categories.
- Scenario 10: scenario 9 + 20% fuel switching incentive (HR 3T FS20). This scenario is identical to scenario 9, but with a 20% reduction in the installed cost of fuel switching measures.

These ten scenarios are not exhaustive; they aim to explore reductions in building CO_2 emissions and energy use across a full spectrum of demand-side technology deployment and renewable electricity supply conditions. These range from business-as-usual renewable electricity penetration with only lower-performing building technologies on the market (scenario 1) to high renewable electricity penetration with only high-performing building technologies on the market (scenario 10). Intermediate scenarios reveal how incremental changes in scenario assumptions between these two extremes yield associated changes in emissions and energy use.

Analysis Limitations

The current analysis omits a few potentially important avenues for increasing buildings' contributions to energy and CO_2 emissions reductions, which could be added in future updates using the Scout platform. First, the ECM set examined in this study leaves nearly half (44%) of baseline building energy use unaffected. Much of this energy use comes from a diverse array of electronic devices and other miscellaneous plug loads.[64] Technologies that enable supervisory control across several of these miscellaneous loads and more efficient versions of components or architectures that are common to several of these devices could offer further opportunities for efficiency and therefore warrant consideration in future analyses. Second, our analysis did not explore the potential effect of higher retrofit rates on energy and CO_2, conservatively assuming based on previous studies[65,66] that 1% of the baseline technology stock is subject to retrofit in each year of the analysis. Programs designed to accelerate retrofit rates can counteract the technology lock-in effects that limit penetration of higher-performing prospective efficiency measures, increasing the long-term energy and CO_2 impacts of these prospective measures.[67,68] Finally, while we do include ECMs with synergistic effects across multiple end uses in our analysis (e.g., controls and envelope ECMs), the energy and CO_2 impacts of whole building integrative design approaches have been suggested to exceed that of technology- or end use-focused improvements by virtue of targeting system-level efficiencies that yield greater energy savings while reducing equipment capacity requirements.[69] To date, the impacts of whole building design approaches are not well-quantified in a broadly representative way for buildings.[25]

Counteracting these additional avenues for impact is the possibility that Scout's ECM competition method inflates estimated energy use and CO_2 emissions reductions; indeed, the magnitude of this paper's estimated reductions are somewhat larger than those of a recent DOE study that explores a similar range of technology deployment scenarios in the buildings sector.[70] Specifically, while Scout accounts for competition across all ECMs included in a given analysis, the approach does not account for any direct competition between ECMs and comparable baseline technologies on the market in each year, essentially excluding the latter from the impact estimations. To the extent that these typical baseline technologies are lower performing than the lowest performing ECMs in our analysis,[61] their exclusion removes another source of drag on the market penetration and impacts of the ECMs that are included in our analysis, potentially leading to the overstatement of ECM impacts.

This study also excludes potential impacts from energy efficiency rebound beyond that embedded in the AEO baseline, which assumes a 15% "take-back" of an efficiency measure's savings due to rebound.[45,58,71] Here, "rebound" refers to the phenomenon where a lower marginal cost of building services drives increased use of those services.[72] Estimates of the the rebound effect's magnitude vary substantially and the true value of this effect is especially difficult to know across long-term time horizons; however, a review of the literature for buildings gives a likely range of 5%–10%.[73,74] Previous studies suggest that the very low to moderate magnitude of rebound effects is not substantial enough to mitigate the impacts of efficiency on CO_2 emissions.[71] In the current study, any additional rebound effects would apply to all scenarios, thus we expect that introducing such effects would not meaningfully change the principal conclusions of our comparisons across scenarios and associated technologies. Nevertheless, we acknowledge that in the absence of parallel market-based instruments that improve the robustness of efficiency impacts to such behavioral responses,[71] rebound effects could reduce the magnitude of energy and emissions impacts reported in this analysis–at least over the short-run time horizons for which this effect has been previously studied.

Finally, the use of the EIA AEO baseline in Scout introduces an additional limitation: AEO estimates of future building energy use reflect a temperature forecast that extrapolates historically observed trends in heating and cooling degree days. These historical trends might not hold under future climate change scenarios,[75] thus previous studies have explored the effects of adjustments to the NEMS temperature forecast.[76] In the current analysis, an underestimation of changing temperature trends will, on average, overstate the impact potential of heating ECMs while understating the impact potential of cooling ECMs. Consequently, the results will underestimate total CO_2 emissions reductions under high renewable electricity penetration, since substantial portions of building heating are fossil-fueled while virtually all building cooling is electric.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.joule.2019.07.013.

ACKNOWLEDGMENTS

This work was authored by Alliance for Sustainable Energy, LLC, the manager and operator of the National Renewable Energy Laboratory for the U.S. Department of Energy (DOE) under contract no. DE-AC36-08GO28308 and by the Regents of the University of California under contract no. DE-AC02-05CH11231. Funding was provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Building Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

AUTHOR CONTRIBUTIONS

Conceptualization, J.L., C.B.H., and J.L.R.; Methodology, J.L. and C.B.H.; Software, J.L. and C.B.H.; Validation, J.L. and C.B.H.; Investigation, J.L. and C.B.H.; Data Curation, J.L. and C.B.H.; Writing – Original Draft, J.L., C.B.H., and J.L.R.; Writing – Review and Editing, J.L., C.B.H., and J.L.R; Visualization, J.L. and C.B.H.; Project Administration, J.L. and C.B.H.; Funding Acquisition, J.L. and C.B.H.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: March 15, 2019
Revised: June 10, 2019
Accepted: July 15, 2019
Published: August 15, 2019

REFERENCES

1. International Energy Agency. IEA Energy Atlas. http://energyatlas.iea.org/#!/tellmap/1378539487.
2. Masson-Delmotte, V., Zhai P., Pörtner H.-O., Roberts D., Skea J., Shukla P.R., Pirani A., Moufouma-Okia W., Péan C., Pidcock R., Connors S., Matthews J.B.R., Chen Y., Zhou X., Gomis M.I., Lonnoy E., Maycock T., Tignor M., and Waterfield T. (2018). Global warming of 1.5°C: An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.
3. United States Mid-Century Strategy For Deep Decarbonization. (2016) (The White House).
4. U.S. Energy Information Administration (2018). Annual Energy Outlook. https://www.eia.gov/outlooks/archive/aeo18/.
5. U.S. Census Bureau (2018). U.S. Census Bureau QuickFacts: United States. https://www.census.gov/quickfacts/fact/table/US/PST045218#PST045218.
6. Berardi, U. (2017). A cross-country comparison of the building energy consumptions and their trends. Resour. Conserv. Recy *123*, 230–241.
7. Deason, J., Wei, M., Leventis, G., Smith, S., and Schwartz, L. (2018). Electrification of buildings and industry in the United States: Drivers, barriers, prospects, and policy approaches. Technical Report.
8. Ryan, L., and Campbell, N. (2012). Spreading the Net: The Multiple Benefits of Energy Efficiency Improvements (International Energy Agency).
9. Adhvaryu, A., Kala, N., and Nyshadham, A. (2018). The Light and the Heat: Productivity Co-Benefits of Energy-Saving Technology (National Bureau of Economic Research).
10. Rajbhandari, A., and Zhang, F. (2018). Does Energy Efficiency Promote Economic Growth? Evidence from a Multi-Country and Multi-Sector Panel Data Set. Energy Econ *69*, 128–139.
11. Ellis, D., and Fazeli, S. (2018) U.S. Energy and Employment Report. National Association of State Energy Officials and Energy Futures Initiative.
12. Gillingham, K., and Stock, J.H. (2018). The Cost of Reducing Greenhouse Gas Emissions. J. Econ. Perspect. *32*, 53–72.
13. Nauclér, T., Enkvist, P., Pestiaux, J., and Dinkel, J. (2009). Pathways to a low-carbon economy: Version 2 of the global greenhouse gas abatement cost curve (McKinsey & Company).
14. Prindle, W. (2009). Energy Efficiency as a Low-Cost Resource for Achieving Carbon Emissions Reductions (United States Environmental Protection Agency).
15. Denholm, P., and Hand, M. (2011). Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. Energy Policy *39*, 1817–1830.
16. Mai, T., Hand, M.M., Baldwin, S.F., Wiser, R.H., Brinkman, G.L., Denholm, P., Arent, D.J., Porro, G., Sandor, D., Hostick, D.J., et al. (2014). Renewable Electricity Futures for the United States. IEEE Trans. Sustain. Energy *5*, 372–378.
17. Mitchell, C. (2016). Momentum is increasing towards a flexible electricity system based on renewables. Nat. Energy *1*.
18. Zhou, N., Khanna, N., Feng, W., Ke, J., and Levine, M. (2018). Scenarios of energy efficiency and CO_2 emissions reduction potential in the buildings sector in China to year 2050. Nat. Energy *3*, 978–984.
19. Natarajan, S., Padget, J., and Elliott, L. (2011). Modelling UK domestic energy and carbon emissions: an agent-based approach. Energy Build *43*, 2602–2612.

20. Sandberg, N.H., and Brattebø, H. (2012). Analysis of energy and carbon flows in the future Norwegian dwelling stock. Build. Res. Inf. *40*, 123–139.

21. Hens, H., Verbeeck, G., and Verdonck, B. (2001). Impact of energy efficiency measures on the CO_2 emissions in the residential sector, a large scale analysis. Energy Build *33*, 275–281.

22. Yamaguchi, Y., Shimoda, Y., and Mizuno, M. (2007). Proposal of a modeling approach considering urban form for evaluation of city level energy management. Energy Build *39*, 580–592.

23. Mata, É., Kalagasidis, A.S., and Johnsson, F. (2013). A modelling strategy for energy, carbon, and cost assessments of building stocks. Energy Build *56*, 100–108.

24. Pacala, S., and Socolow, R. (2004). Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies. Science *305*, 968–972.

25. National Research Council. (2010). Energy Efficiency in Residential and Commercial Buildings. In Real Prospects for Energy Efficiency in the United States (The National Academies Press), pp. 41–119.

26. Huang, Y.J., and Brodrick, J. (2000). A Bottom-Up Engineering Estimate of the Aggregate Heating and Cooling Loads of the Entire US Building Stock Prototypical Residential Buildings. In ACEEE Summer Study on Energy Efficiency in Buildings, pp. 135–148.

27. Bouton, S., Creyts, J., Livingston, J., and Nauclér, T. (2010). Energy Efficiency: a compelling global resource (McKinsey & Company).

28. Yang, C., Yeh, S., Ramea, K., Zakerinia, S., McCollum, D., and Bunch, D. (2014). Modeling Optimal Transition Pathways to a Low Carbon Economy in California (University of California, Davis Institute of Transportation Studies).

29. McCollum, D., Yang, C., Yeh, S., and Ogden, J. (2012). Deep greenhouse gas reduction scenarios for California – Strategic implications from the CA-TIMES energy-economic systems model. Energy Strategy Rev. *1*, 19–32.

30. Reyna, J.L., and Chester, M.V. (2017). Energy efficiency to reduce residential electricity and natural gas use under climate change. Nat. Commun. *8*, 14916.

31. Allouhi, A., El Fouih, Y., Kousksou, T., Jamil, A., Zeraouli, Y., and Mourad, Y. (2015). Energy consumption and efficiency in buildings: Current status and future trends. J. Cleaner Prod. *109*, 118–130.

32. Hojjati, B., and Wade, S.H. (2012). U.S. household energy consumption and intensity trends: a decomposition approach. Energy Policy *48*, 304–314.

33. Electric Power Research Institute (EPRI). (2014). U.S. Energy Efficiency Potential Through 2035 (Electric Power Research Institute).

34. Gowrishankar, V., and Levin, A. (2017). America's Clean Energy Frontier: The Pathway to a Safer Climate Future (National Resources Defense Council).

35. Williams, J.H., Debenedictis, A., Ghanadan, R., Mahone, A., Moore, J., Morrow, W.R., III, Price, S., and Torn, M.S. (2012). The Technology Path to Deep Greenhouse Gas Emissions Cuts by 2050: The Pivotal Role of Electricity. Science *335*, 53–59.

36. Wilson, E., Christensen, C., Horowitz, S., Robertson, J., and Maguire, J. (2017). Electric End-Use Energy Efficiency Potential in the U.S. Single-Family Housing Stock (National Renewable Energy Laboratory).

37. Morrison, G.M., Yeh, S., Eggert, A.R., Yang, C., Nelson, J.H., Greenblatt, J.B., Isaac, R., Jacobson, M.Z., Johnston, J., Kammen, D.M., et al. (2015). Comparison of low-carbon pathways for California. Clim. Change *131*, 545–557.

38. Griffith, B., Long, N., Torcellini, P., Judkoff, R., Crawley, D., and Ryan, J. (2007). Assessment of the Technical Potential for Achieving Zero-Energy Commercial Buildings (National Renewable Energy Laboratory).

39. Griffith, B., Long, N., Torcellini, P., and Judkoff, R. (2008). Methodology for Modeling Building Energy Performance across the Commercial Sector (National Renewable Energy Laboratory).

40. U.S. Department of Energy (2016). Building Technologies Office Multi-Year Program Plan (United States Department of Energy).

41. U.S. Energy Information Administration (2018). https://www.eia.gov/outlooks/archive/aeo18/tables_side.php.

42. U.S. Energy Information Administration (2008). Annual Energy Outlook 2008. https://www.eia.gov/outlooks/archive/aeo08/aeoref_tab.html.

43. U.S. Energy Information Administration. Table 8.1. Average Operating Heat Rate for Selected Energy Sources. https://www.eia.gov/electricity/annual/html/epa_08_01.html.

44. U.S. Department of the Treasury (2018). Daily treasury yield curve rates. https://www.treasury.gov/resource-center/data-chart-center/interest-rates/pages/TextView.aspx?data=yieldYear&year=2018.

45. U.S. Energy Information Administration (2018). Commercial demand module of the national energy modeling system: model documentation 2012.

46. Brown, R., Borgeson, S., Koomey, J., and Biermayer, P. (2008). U.S. Building Sector Energy Efficiency Potential (Lawrence Berkeley National Laboratory).

47. Electric Power Research Institute (2009). Assessment of achievable potential from energy efficiency and demand response programs in the U.S. (2010–2030).

48. Lucon, O., Ürge-Vorsatz, D., Zain Ahmed, A., Akbari, H., Bertoldi, P., Cabeza, L.F., Eyre, N., Gadgil, A., Harvey, L.D.D., Jiang, Y., Liphoto, E., Mirasgedis, S., Murakami, S., Parikh, J., Pyke, C., Vilariño, M.V., et al. (2014). Buildings. In Climate Change 2014: mitigation of climate change. contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change (Cambridge University Press), pp. 671–739.

49. Seto, K.C., Davis, S.J., Mitchell, R.B., Stokes, E.C., Unruh, G., and Ürge-Vorsatz, D. (2016). Carbon Lock-In: Types, Causes, and Policy Implications. Annu. Rev. Environ. Resour. *41*, 425–452.

50. U.S. Energy Information Administration (2019). Annual Energy Outlook 2019, Table: Energy Consumption by Sector and Source. https://www.eia.gov/outlooks/aeo/data/browser//?id=2-AEO2019cases=ref2019sourcekey=0. Accessed 06-10-2019.

51. Bardhan, A., Jaffee, D., Kroll, C., and Wallace, N. (2014). Energy efficiency retrofits for U.S. housing: Removing the Bottlenecks. Reg. Sci. Urban Econ *47*, 45–60.

52. Sofos, M., and Langevin, J. (2018). Advancements in Smart Building Technologies R&D Focus Areas. In ACEEE Summer Study on Energy Efficiency in Buildings, pp. 1–12.

53. Brambley, M.R., Haves, P., Torcellini, P., and Hansen, D. (2005). Advanced Sensors and Controls for Building Applications: Market Assessment and Potential R&D Pathways (Pacific Northwest National Laboratory).

54. Donohoo-Vallett, P. (2016) Accounting Methodology for Source Energy of Non-Combustible Renewable Electricity Generation.

55. U.S. Energy Information Administration (2019). AIA climate zones - RECS 1978–2005. https://www.eia.gov/consumption/residential/maps.php.

56. U.S. Energy Information Administration (2009). Residential Energy Consumption Survey Public Use Microdata. https://www.eia.gov/consumption/residential/data/2009/csv/recs2009_public.csv.

57. U.S. Energy Information Administration (2003). Commercial Buildings Energy Consumption Survey Public Use Microdata, File 1: General Building Information and Energy End Uses. https://www.eia.gov/consumption/commercial/data/2003/csv/FILE01.csv.

58. U.S. Energy Information Administration (2018). Residential Demand Module of the National Energy Modeling System: Model Documentation (Energy Information Administration).

59. U.S. Energy Information Administration (2011). Emissions of Greenhouse Gases in the U.S., Tables 8–9. https://www.eia.gov/environment/emissions/ghg_report/.

60. Harris, C.B. and Reyna, J.L. https://doi.org/10.5281/zenodo.3158930.

61. U.S. Energy Information Administration (2018). Updated Buildings Sector Appliance and Equipment Costs and Efficiencies.

62. National Renewable Energy Laboratory (2018). National residential efficiency measures database home page. https://remdb.nrel.gov/. Accessed 12-18-2018.

Please cite this article in press as: Langevin et al., Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050, Joule (2019), https://doi.org/10.1016/j.joule.2019.07.013

63. ASHRAE (2014). Advanced Energy Design Guide for Small to Medium Office Buildings: Achieving 50% Energy Savings Toward a Net Zero Energy Building (ASHRAE).

64. Fares, R., Sofos, M., Langevin, J., Hosbach, R., Meier, A., and Butzbaugh, J. (2018). Improving Characterization of Miscellaneous Energy Loads in Energy Demand Models. In ACEEE Summer Study on Energy Efficiency in Buildings, pp. 1–12.

65. Zhai, J., Leclaire, N., and Bendewald, M. (2011). Deep energy retrofit of commercial buildings: A key pathway toward low-carbon cities. Carbon Manag *2*, 425–430.

66. Neme, C., Gottstein, M., and Hamilton, B. (2011). Residential Efficiency Retrofits: A Roadmap for the Future (Regulatory Assistance Project Eds).

67. Sebi, C., Nadel, S., Schlomann, B., and Steinbach, J. (2019). Policy strategies for achieving large long-term savings from retrofitting existing buildings. Energy Effic. *12*, 89–105.

68. Nadel, S. (2016). Pathway to Cutting Energy Use and Carbon Emissions in Half (American Council for An Energy Efficient Economy).

69. Lovins, A.B. (2018). How big is the energy efficiency resource? Environ. Res. Lett. *13*, 09041.

70. U.S. Department of Energy. (2017) Energy CO_2 Emissions Impacts of Clean Energy Technology Innovation and Policy.

71. Greening, L.A., Greene, D.L., and Difiglio, C. (2000). Energy efficiency and consumption – the rebound effect – a survey. Energy Policy *28*, 389–401.

72. Wiesmann, D., Lima Azevedo, I., Ferrão, P., and Fernández, J.E. (2011). Residential electricity consumption in Portugal: Findings from top-down and bottom-up models. Energy Policy *39*, 2772–2779.

73. Gillingham, K., Kotchen, M.J., Rapson, D.S., and Wagner, G. (2013). Energy policy: the rebound effect is overplayed. Nature *493*, 475–476.

74. Gillingham, K., Rapson, D., and Wagner, G. (2016). The Rebound Effect and Energy Efficiency Policy. Rev. Environ. Econ. Policy *10*, 68–88.

75. Vose, R.S., Easterling, D.R., Kunkel, K.E., LeGrande, A.N., and Wehner, M.F. (2017). Temperature Changes in the United States. In Climate Science Special Report: Fourth National Climate Assessment. In U.S. Global Change Research Program, I. Volume, D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock, eds., pp. 185–206.

76. Hadley, S.W., Erickson, D.J., Hernandez, J.L., Broniak, C.T., and Blasing, T.J. (2006). Responses of energy use to climate change: A climate modeling study. Geophys. Res. Lett. *33*, 2–5.

JOUL, Volume *3*

Supplemental Information

Assessing the Potential to Reduce U.S. Building CO_2 Emissions 80% by 2050

Jared Langevin, Chioke B. Harris, and Janet L. Reyna

Supplemental Information

1 Supplemental Data

Figure S1 shows the contributions to avoided CO_2 emissions and primary energy savings from new and existing residential and commercial buildings. In Scout, "new" buildings comprise all buildings built starting in the first year of the modeled time horizon (2015), while "existing" buildings are all of the buildings that existed prior to that year. In 2030, CO_2 emissions reductions are dominated by existing buildings in both the residential and commercial sectors. By 2050, more of the total avoided CO_2 emissions from commercial buildings come from new construction than from existing buildings, but existing residential buildings continue to yield a plurality of total emissions reductions. The change in the relative contribution from new and existing commercial buildings is a result of the faster turnover in commercial buildings compared to residential buildings; the majority of commercial buildings in 2050 are "new." This turnover reduces the CO_2 emissions reductions available from the existing commercial building stock, even in Scenarios 9 (HR 3T FS0) and 10 (HR 3T FS20), where only aggressive measures are included. When only currently available technologies are considered, as in Scenarios 1 (RB 1T) and 2 (RB 1T-2T), net emissions reductions from commercial buildings are negative by 2050; this result underscores the importance of continual investments in building energy efficiency R&D. Regardless of the year investigated, residential buildings contribute a substantially greater share of emissions reductions compared to commercial buildings. This result reflects the greater baseline CO_2 emissions from residential buildings combined with the measures included in this analysis impacting a greater share of total residential building energy use. The primary energy savings results in Figure S1 parallel the findings from the CO_2 emissions results.

Figure S2 breaks down avoided CO_2 emissions and primary energy savings by AIA climate zone [1]. Although energy and emissions reductions are similar across the three southern climate zones (3–5), reductions in northern-most climate zone 1 are comparatively lower and reductions in northern climate zone 2 are comparatively higher than those in the southern climates. In the case of climate zone 1, a smaller amount of floorspace in this region explains the muted energy and emissions reductions [2, 3]. In climate zone 2, higher efficiency heating equipment drives large overall energy and emissions reductions—particularly in the scenarios where fuel switching is assumed, which produces a notable increase in the emissions reductions of this climate zone. This result is further illustrated in Figure S3.

Figure S3 breaks down the cost-effective CO_2 emissions reductions of Scenarios 6 (HR 1T-2T-3T) and 8 (HR 1T-2T-3T FS20) in the year 2050 by contributing energy conservation measures (ECMs) and AIA climate zone [1], highlighting the 10 ECMs that contribute the largest cost-effective emissions reductions in each climate zone. In the absence of fuel switching (Scenario 6), prospective

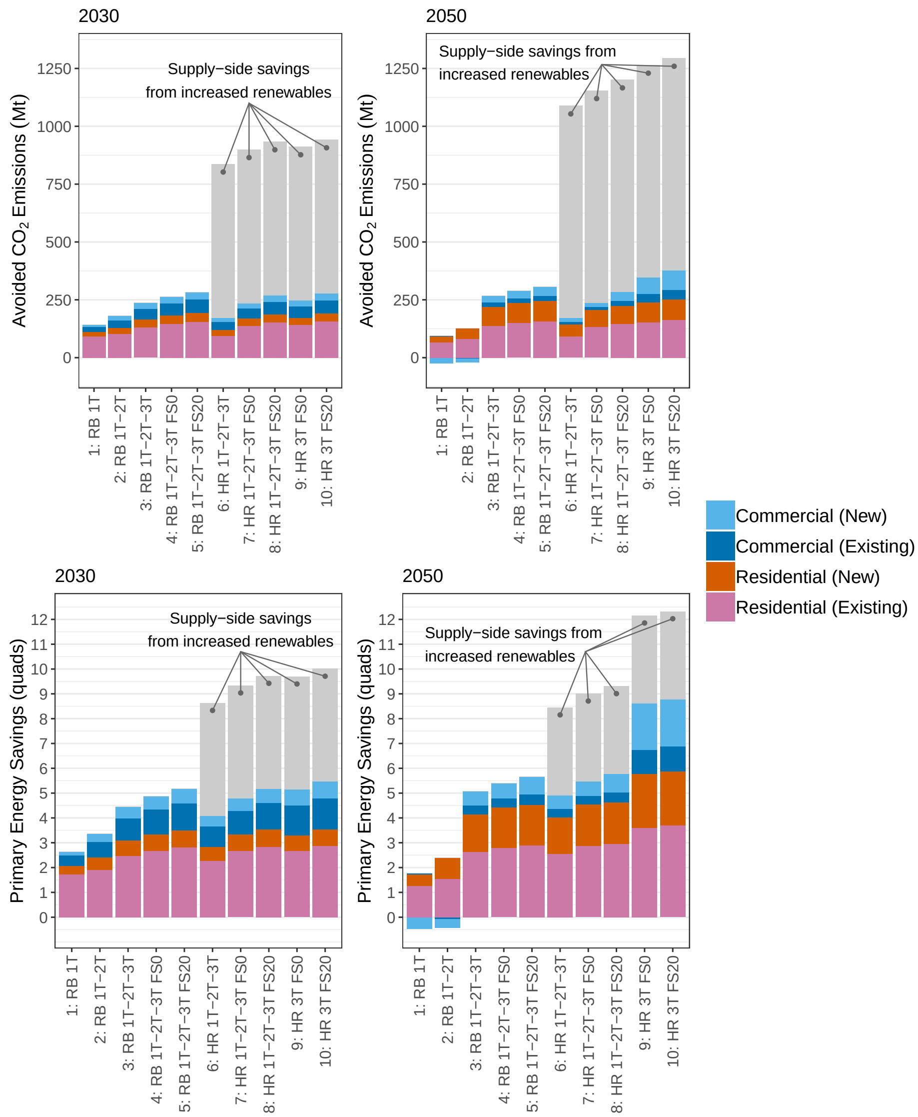


Figure S1: CO_2 emissions reductions are driven by existing residential buildings. Avoided CO_2 emissions (top row) and energy savings (bottom row) corresponding to the years 2030 (left column) and 2050 (right column) are shown for the scenarios considered in this study, with the totals divided by the contributions from new and existing residential and commercial buildings. The results in this figure are equivalent to the results in Figure 2, but with different divisions. As in Figure 2, additional supply-side energy savings and avoided CO_2 emissions are shown with gray bars for each of the "High Renewables" scenarios.

envelope and controls ECMs yield the largest cost-effective emissions reductions across all climate zones, and total cost-effective emissions reductions are relatively similar across climate zones 2–5. Given the introduction of a 20% capital cost credit for fuel switching (Scenario 8), heat pump technologies that replace fuel-fired water heating and heating technologies drive cost-effective emissions reductions. In the northern climate zones (1 and 2), cold climate heat pumps bring the cost-effective emissions reductions of AIA climate zone 1 into near parity with those of the southern climate zones (3–5) and raise the total cost-effective emissions reductions of AIA climate zone 2 to almost double the level of the southern climate zones. This result reflects the large magnitude of fuel-fired heating energy use in the northern climates, which the Annual Energy Outlook (AEO) estimates will be responsible for 1.6 quads of primary energy use and 89 Mt of CO_2 emissions by 2050 [4]. Reducing this large segment of energy use and emissions by switching fuel-fired heating equipment to more efficient alternatives that leverage renewable electricity supply presents a significant opportunity for emissions reductions in residential buildings.

2 Supplemental Experimental Procedures

Sections 2.1 to 2.5 detail the calculation steps that are required to conduct a full Scout analysis. For brevity, the equations in these sections use the symbol X to denote the climate zone (z), building type (b), fuel type (f), end use (u), and technology type (t) subscripts first introduced in equation 1.

2.1 Determining baseline energy use, CO_2 emissions, and operating cost segments

To calculate an ECM's impact potential and cost-effectiveness, the size of the baseline energy use, CO_2 emissions, and operating cost segments that the ECM applies to must first be determined.

Baseline segment sizes are initially determined by total number of technology stock units that are representative of the segment and the total primary energy use of those units. The total number of technology stock units, $\sigma^{\text{base}}_{X,v,y}$, is broken out by building vintage v and year y:

$$\sigma^{\text{base}}_{X,v,y} = \sigma^{\text{ref}}_{X,y}\, \xi^{\text{vint}}_{b,v,y}\, \xi^{\text{scale}}_{X,v} \tag{1}$$

$$\xi^{\text{vint}}_{b,v,y} = \begin{cases} \dfrac{\sum_{i=0}^{y} B^{\text{new}}_{z,b,i}}{B^{\text{total}}_{z,b,y}} & \text{if } v = \text{new} \\ 1 - \dfrac{\sum_{i=0}^{y} B^{\text{new}}_{z,b,i}}{B^{\text{total}}_{z,b,y}} & \text{otherwise} \end{cases} \tag{2}$$

where $\sigma^{\text{ref}}_{X,y}$ is the total number of comparable baseline technology stock units

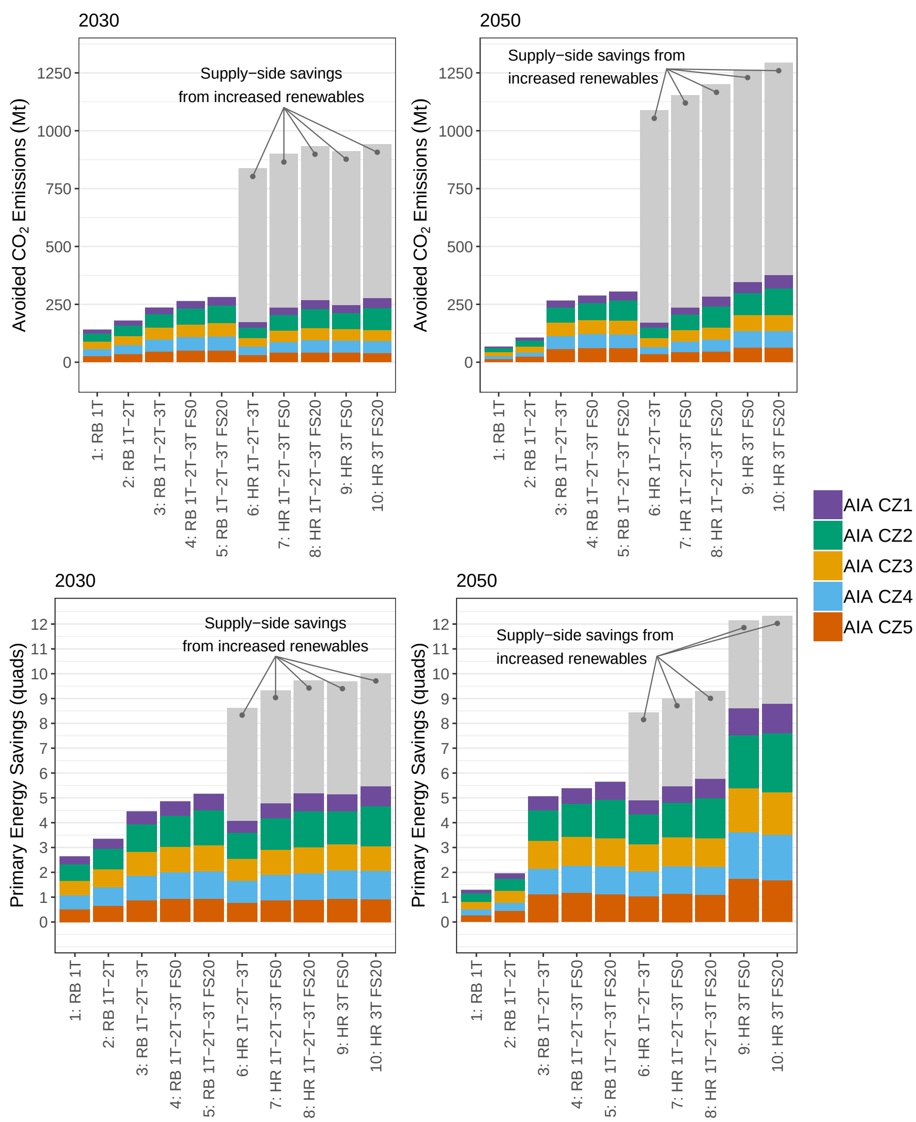


Figure S2: CO_2 emissions reductions are largest in the northern AIA climate zone 2, particularly when fuel switching is assumed. AIA climate zones are numbered sequentially from 1 (northern-most) to 5 (southern-most). Avoided CO_2 emissions (top row) and energy savings (bottom row) corresponding to the years 2030 (left column) and 2050 (right column) are shown for the scenarios considered in this study, with the totals divided by the contributions from each AIA climate zone. The results in this figure are equivalent to the results in Figure 2, but with different divisions. As in Figure 2, additional supply-side energy savings and avoided CO_2 emissions are shown with gray bars for each of the "High Renewables" scenarios.

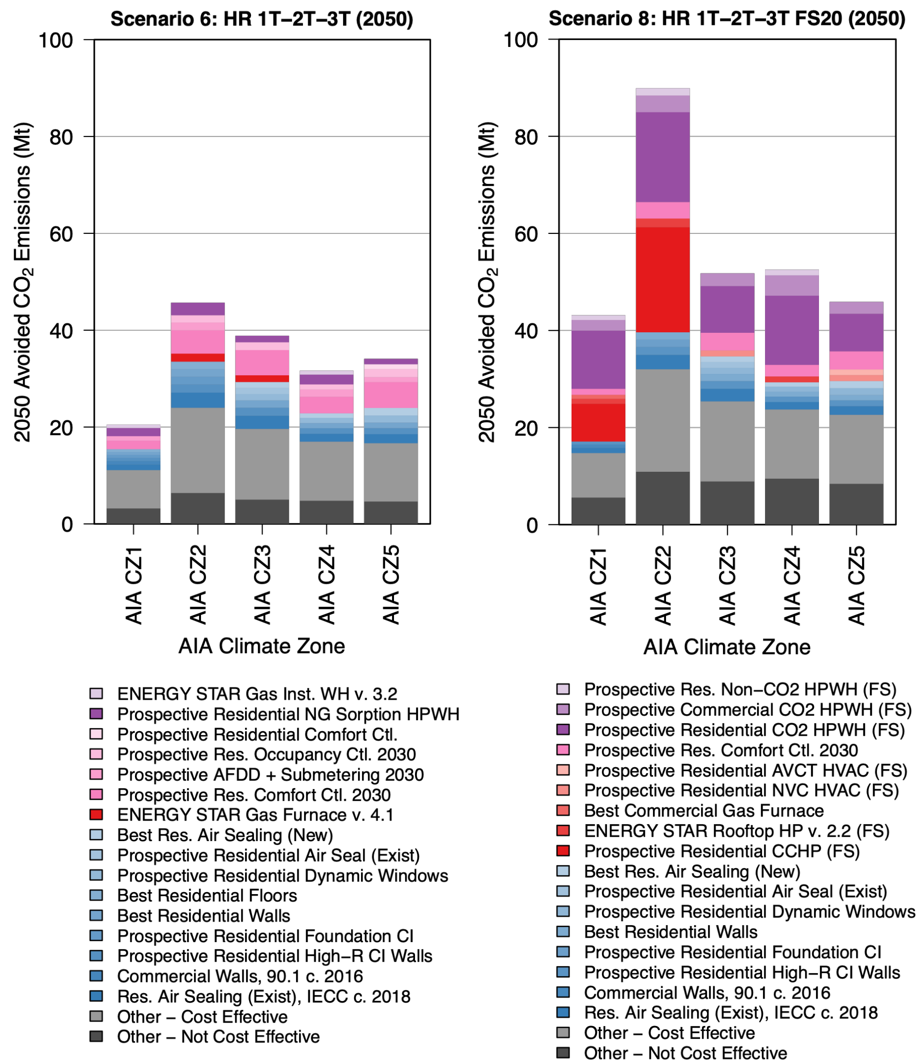


Figure S3: Heat pump technologies that replace fuel-fired water heating and heating technologies drive cost-effective emissions reductions given fuel switching incentives. Avoided CO_2 emissions in the year 2050 are plotted from Scenario 6 (HR 1T-2T-3T, at left) and Scenario 8 (HR 1T-2T-3T FS20, at right), separately showing the building efficiency measures (ECMs) that yield the 10 largest emissions reductions with IRR ≥ 0 in each AIA climate zone. AIA climate zones are numbered sequentially from 1 (northern-most) to 5 (southern-most). The results in this figure are similar to the results in Figure 4, but with a focus on the year 2050 and divisions by AIA climate zone. As in Figure 4, ECM types (envelope, controls, water heating, HVAC, etc.) are grouped by bar color.

in the AEO reference case,[1] $\xi^{\text{vint}}_{b,v,y}$ is the fraction of total technology stock associated with building vintage v, $\xi^{\text{scale}}_{X,v}$ is a user-specified fraction for scaling down the AEO reference case stock segment, $\sum_{i=0}^{y} B^{\text{new}}_{z,b,i}$ is the total number or floorspace of building type b newly constructed in climate zone z from the beginning of the model time horizon through year y of the AEO reference case, and $B^{\text{total}}_{z,b,y}$ is the total number or floorspace of building b in climate zone z and year y of the AEO reference case.

The total primary energy use attributable to $\sigma^{\text{base}}_{X,v,y}$, $E^{\text{base}}_{X,v,y}$, is defined as follows:

$$E^{\text{base}}_{X,v,y} = E^{\text{ref}}_{X,y}\, SS_{f,y}\, \xi^{\text{vint}}_{b,v,y}\, \xi^{\text{scale}}_{X,v} \tag{3}$$

where $E^{\text{ref}}_{X,y}$ is the total delivered (or "site") baseline energy use for a given stock segment in the AEO reference case[2] and $SS_{f,y}$ is the site-to-source energy conversion factor for baseline fuel type f and year y.

Site-to-source conversion factors $SS_{f,y}$ for all nonelectric fuels are assumed to be unity given the consumption of these fuels on-site. For electricity, the site-to-source factor $SS_{f=\text{elec},y}$ is calculated as:

$$SS_{f=\text{elec},y} = \frac{\left(\Omega^{\text{site}}_{y} + \Omega^{\text{loss}}_{y}\right)\left(1 - \tau_y + \frac{3412}{9510}\tau_y\right)}{\Omega^{\text{site}}_{y}} \tag{4}$$

where Ω^{site}_{y} is total delivered electricity for residential and commercial buildings in year y, Ω^{loss}_{y} is total electricity-related generation, transmission, and distribution losses in year y,[3] τ_y is the fraction of total power generated from noncombustible renewable sources (wind, solar, geothermal, hydroelectric),[4] and the constant $3412/9510$ is the inverse of the energy conversion efficiency assumed by EIA for noncombustible renewable generators. The latter two terms reflect Scout's use of a *captured energy* approach to renewable energy generation accounting, which is different from EIA's *fossil fuel equivalency* approach [5]. Specifically, where AEO assigns renewable generators the conversion efficiency of an average fossil generator (3,412 Btu output divided by 9,510 Btu input, or 35%), the captured energy approach assumes no conversion losses for noncombustible renewable generation sources (3,412 Btu input and output or 100% efficiency).

Given a baseline segment's total primary energy use $E^{\text{base}}_{X,v,y}$, the CO_2 emissions associated with that energy use, $C^{\text{base}}_{X,v,y}$, are calculated:

---

[1] Drawn from the "RESDBOUT.txt" file for the residential sector; AEO does not model number of technology units for the commercial sector, thus floorspace by building type from file "KDBOUT.txt" is used as a proxy for technology stock.

[2] Drawn from "RESDBOUT.txt" for the residential sector and "KSDOUT.txt" for the commercial sector.

[3] Total delivered electricity and electricity-related losses data for the residential and commercial sector are drawn from AEO Summary Table A2.

[4] Calculated by summing electric power from conventional hydroelectricity, geothermal, solar thermal, solar photovoltaic, and wind for year y from AEO Summary Table A17 and dividing by total electric power for year y from AEO Summary Table A2.

$$C^{\text{base}}_{X,v,y} = E^{\text{ref}}_{X,y}\, SS_{f,y}\, CI_{f,y}\, \xi^{\text{vint}}_{b,v,y}\, \xi^{\text{scale}}_{X,v} \tag{5}$$

where $CI_{f,y}$ is the CO_2 emissions intensity for primary energy of baseline fuel type f in year y, calculated as:

$$CI_{f,y} = \frac{C^{\text{ref}}_{f,y}}{E^{\text{base}}_{f,y}} \tag{6}$$

where $C^{\text{ref}}_{f,y}$ is the total CO_2 emissions reported for residential and commercial buildings, fuel type f, and year y in the AEO reference case,[5] and $E^{\text{base}}_{f,y}$ is the total primary energy use in residential and commercial buildings for the same fuel type f and year y.

Similarly, the energy costs associated with $E^{\text{base}}_{X,v,y}$, $\psi^{\text{base}}_{X,v,y}$, are calculated as:

$$\psi^{\text{base}}_{X,v,y} = E^{\text{ref}}_{X,y}\ SS_{f,y}\ FC_{b,f,y}\ \xi^{\text{vint}}_{b,v,y}\ \xi^{\text{scale}}_{X,v} \tag{7}$$

where $FC_{b,f,y}$ is the primary energy cost[6] for building type b and baseline fuel f in year y.

Section 2.2 describes how ECM impacts are calculated relative to these baseline segments of primary energy use, CO_2 emissions, and energy costs.

2.2 Calculating ECM impacts on baseline energy use, CO_2 emissions, and operating costs

ECM impacts on baseline segments of energy, CO_2, and cost can be calculated on an ECM-by-ECM basis, yielding results denoted as "uncompeted," or accounting for interactions between each ECM and other competing ECMs that are included in a portfolio, referred to as "competed" results. The equations in this section describe the calculation of "uncompeted" results; in Section 2.3, these equations are modified to account for competition between ECMs.

ECM impacts on baseline segments of energy, CO_2, and cost first depend upon the fractions of baseline stock that the ECM captures. These fractions are used to track the total number of baseline stock units in building vintage v and year y that have been captured by the ECM under adoption case s, $\sigma^{\text{ecm}}_{X,v,y,s}$:

$$\sigma^{\text{ecm}}_{X,v,y,s} = \sigma^{\text{base}}_{X,v,y}\ (\phi^{\text{cmp}-\text{cpt}}_{X,v,y,s} + \phi^{\text{cpt}}_{X,v,y,s}) \tag{8}$$

where $\phi^{\text{cmp}-\text{cpt}}_{X,v,y,s}$ is the fraction of a given baseline stock segment of vintage v that an ECM competes for and captures in year y under adoption case s and $\phi^{\text{cpt}}_{X,v,y,s}$ is the fraction (≤ 1) of a given baseline stock segment of vintage v that an ECM has captured in all years before year y under adoption case s.

The primary energy use associated with a given stock segment after ECM adoption, $E^{\text{ecm}}_{X,v,y,s}$, is calculated by applying ECM relative energy performance

[5] From AEO Summary Table A18.
[6] From AEO Summary Table A3.

values to the competed and captured portions of baseline energy use, also accounting for any differences in site-source conversion factors between the ECM and baseline technology's fuel type:

$$E^{\text{ecm}}_{X,v,y,s} = E^{\text{base}}_{X,v,y}\left(\phi^{\text{cmp-cpt}}_{X,v,y,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}} + (\phi^{\text{cmp}}_{X,v,y,s} - \phi^{\text{cmp-cpt}}_{X,v,y,s})\right) + E^{\text{base}}_{X,v,y}(1-\phi^{\text{cmp}}_{X,v,y,s})\left(\phi^{\text{cpt}}_{X,v,y-1,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}} + (1-\phi^{\text{cpt}}_{X,v,y-1,s})\right) \tag{9}$$

where $\phi^{\text{cmp}}_{X,v,y,s}$ is the fraction of a given baseline stock segment of vintage v that an ECM competes for in year y under adoption case s, $RP_{X,y}$ is the overall energy performance of the captured stock relative to the comparable baseline technology energy performance in year y, and $SS_{f^{\text{ecm}},y}$ is the site-to-source energy conversion factor for ECM fuel type f.

Similarly, the CO_2 emissions associated with the given stock segment after ECM adoption, $C^{\text{ecm}}_{X,v,y,s}$, are calculated as follows:

$$C^{\text{ecm}}_{X,v,y,s} = C^{\text{base}}_{X,v,y}\left(\phi^{\text{cmp-cpt}}_{X,v,y,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}}\frac{CI_{b,f^{\text{ecm}},y}}{CI_{f,y}} + (\phi^{\text{cmp}}_{X,v,y,s} - \phi^{\text{cmp-cpt}}_{X,v,y,s})\right) + C^{\text{base}}_{X,v,y}(1-\phi^{\text{cmp}}_{X,v,y,s})\left(\phi^{\text{cpt}}_{X,v,y-1,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}}\frac{CI_{b,f^{\text{ecm}},y}}{CI_{f,y}} + (1-\phi^{\text{cpt}}_{X,v,y-1,s})\right) \tag{10}$$

where $CI_{b,f^{\text{ecm}},y}$ is the CO_2 emissions intensity for primary energy of ECM fuel type f used in building type b in year y.

Finally, the energy costs associated with the given stock segment after ECM adoption, $\psi^{\text{ecm}}_{X,v,y,s}$, are calculated as:

$$\psi^{\text{ecm}}_{X,v,y,s} = \psi^{\text{base}}_{X,v,y}\left(\phi^{\text{cmp-cpt}}_{X,v,y,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}}\frac{FC_{b,f^{\text{ecm}},y}}{FC_{b,f,y}} + (\phi^{\text{cmp}}_{X,v,y,s} - \phi^{\text{cmp-cpt}}_{X,v,y,s})\right) + \psi^{\text{base}}_{X,v,y}(1-\phi^{\text{cmp}}_{X,v,y,s})\left(\phi^{\text{cpt}}_{X,v,y-1,s} RP_{X,y}\frac{SS_{f^{\text{ecm}},y}}{SS_{f,y}}\frac{FC_{b,f^{\text{ecm}},y}}{FC_{b,f,y}} + (1-\phi^{\text{cpt}}_{X,v,y-1,s})\right) \tag{11}$$

where $FC_{b,f^{\text{ecm}},y}$ is the primary energy cost for ECM fuel type f used in building type b in year y.

Each of the energy, CO_2, and cost outcomes described previously depends on competed and captured stock fractions ($\phi^{\text{cmp}}_{X,v,y,s}$, $\phi^{\text{cmp-cpt}}_{X,v,y,s}$, and $\phi^{\text{cpt}}_{X,v,y,s}$) as well as the relative energy performance of the captured stock $RP_{X,y}$. The following paragraphs provide further detail on the calculation of these four common variables.

First, the fraction of a given stock segment for building vintage v in year y that an ECM competes for under adoption case s, $\phi^{\text{cmp}}_{X,v,y,s}$, is defined as:

$$\phi^{\text{cmp}}_{X,v,y,s} = \phi^{\text{cmp-cpt}}_{X,v,y,s} = \begin{cases} 0, & y < y_e \\ 1, & s = \text{TP and } y = y_e \\ \lambda^{\text{new}}_{X,v,y} + (1-\lambda^{\text{new}}_{X,v,y})\lambda^{\text{repl}}_{X,v,y}, & v = \text{new} \\ \lambda^{\text{repl}}_{X,v,y}, & \text{otherwise} \end{cases} \tag{12}$$

where y_e is the ECM's market entry year, which must be greater than or equal to the first year in the modeling time horizon, TP denotes the technical potential adoption case, $\lambda^{\text{new}}_{X,v,y}$ and $\lambda^{\text{repl}}_{X,v,y}$ are segment-specific rates of new technology stock additions and replacements/retrofits in year y, respectively. Note that it is assumed that no competed stock returns to the baseline technology, thus $\phi^{\text{cmp}}_{X,v,y,s}$ = $\phi^{\text{cmp-cpt}}_{X,v,y,s}$.

$\lambda^{\text{new}}_{X,v,y}$ and $\lambda^{\text{repl}}_{X,v,y}$ are further defined as:

$$\lambda^{\text{new}}_{X,v,y} = \begin{cases} \dfrac{\sigma^{\text{base}}_{X,v,y} - \sigma^{\text{base}}_{X,v,y-1}}{\sigma^{\text{base}}_{X,v,y}}, & y > y_0 \text{ and } v = \text{new and } \sigma^{\text{base}}_{X,v,y} \neq 0 \\ 1, & y = y_0, \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$\lambda^{\text{repl}}_{X,v,y} = \begin{cases} w_X \, \phi^{\text{uncpt}}_{X,v,y,s}, & v = \text{new and } y_s \leq y \leq y_f \text{ or } v \neq \text{new} \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

where y_0 denotes the first year in the modeling time horizon, w_X is a baseline stock turnover rate that captures both end-of-life replacement and elective retrofit of the baseline technology, $\phi^{\text{uncpt}}_{X,v,y,s}$ is the fraction of baseline stock that could possibly be replaced or retrofitted in year y and adoption case s, and y_s and y_f are the years in which new stock previously captured by the comparable baseline technology starts and finishes turning over as a result of replacement and retrofit.[7]

The baseline stock turnover rate, w_X, is defined as:

[7]Where the start year occurs one baseline technology lifetime after the first year in the modeling horizon and the end year occurs two baseline technology lifetimes after the first year of ECM market entry (one lifetime before the previously captured baseline stock begins turning over, another lifetime beyond that before the previously captured baseline stock finishes turning over).

$$w_X = \frac{1}{l_X^{\text{base}}} + \rho \tag{15}$$

where ρ is a constant global or ECM-specific retrofit rate that may be specified by the user.[8]

The fraction of the baseline stock available for retrofit or replacement, $\phi_{X,v,y,s}^{\text{uncpt}}$, is further defined as:

$$\phi_{X,v,y,s}^{\text{uncpt}} = \begin{cases} \dfrac{\sigma_{X,v,y_{e-1}}^{\text{base}}}{\sigma_{X,v,y}^{\text{base}}}, & v = \text{new and } \sigma_{X,v,y}^{\text{base}} \neq 0 \text{ and } y_e \neq y_0 \\ 1, & v \neq \text{new and } 1 - \phi_{X,v,y-1,s}^{\text{cpt}} \geq w_X \\ \dfrac{1 - \phi_{X,v,y-1,s}^{\text{cpt}}}{w_X}, & v \neq \text{new} \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

The fraction of a given stock segment for building vintage v in year y that an ECM captures in all years through year y under adoption case s, $\phi_{X,v,y,s}^{\text{cpt}}$ (≤ 1), is defined as:

$$\phi_{X,v,y,s}^{\text{cpt}} = \begin{cases} 0, & y \leq y_e \\ 1, & s = \text{TP} \\ \phi_{X,v,y,s}^{\text{cmp-cpt}} + \phi_{X,v,y-1,s}^{\text{cpt}}, & \text{otherwise} \end{cases} \tag{17}$$

Finally, the overall energy performance of the captured stock relative to the comparable baseline technology energy performance in year y, $RP_{X,y}$, is defined as:

$$RP_{X,y} = \begin{cases} RP'_{X,y}, & y = y_e \\ RP'_{X,y}\, w_{X,v} + RP_{X,y-1}(1 - w_{X,v}), & y > y_e \end{cases} \tag{18}$$

where $RP'_{X,y}$ is the energy performance of the competed and captured stock relative to the comparable baseline technology energy performance in year y, and w is the baseline technology stock turnover rate, as defined in equation 15. The energy performance of the competed and captured stock relative to the comparable baseline technology energy performance in year y, $RP'_{X,y}$, is further defined as:

[8] The current default global retrofit rate is 0.01.

$$RP'_{X,y} = \begin{cases} P^{\text{base}}_{X,y}/P^{\text{ecm}}_{X,v}, & \text{absolute units (inv.)} \\ P^{\text{ecm}}_{X,v}/P^{\text{base}}_{X,y}, & \text{absolute units} \\ \left(1 - \dfrac{P^{\text{base}}_{X,y}}{P^{\text{base}}_{X,y_a}}\right) P^{\text{ecm}}_{X,v}, & \text{dynamic relative units (inv.)} \\ \left(1 - \dfrac{P^{\text{base}}_{X,y_a}}{P^{\text{base}}_{X,y}}\right) P^{\text{ecm}}_{X,v}, & \text{dynamic relative units} \\ 1 - P^{\text{ecm}}_{X,v}, & \text{constant relative units} \end{cases} \tag{19}$$

where $P^{\text{ecm}}_{X,v}$ is the user-specified ECM energy performance value, $P^{\text{base}}_{X,y}$ is the comparable baseline technology energy performance value in year y from the AEO reference case,[9] and P^{base}_{X,y_a} is the comparable baseline technology energy performance value in a user-specified anchor year y_a. The particular form of $RP'_{X,y}$ is determined based on the performance units used for a given ECM. "Absolute units" are performance units specific to various technologies, such as COP for cooling systems, lumens per watt for lighting, or energy factor for dishwashers. "Relative units" are defined as an improvement in performance relative to the baseline, where "constant relative units" assume that the performance improvement remains constant from the market entry year y_e through the final year Y and "dynamic relative units" assume that the performance improvement is reduced as the performance of the baseline technology improves into the future. For technologies where lower numeric performance values indicate higher energy performance (improved efficiency),[10] the inverted form of the equation should be used, denoted by "(inv.)".

2.3 Adjusting ECM impacts for competition across an ECM portfolio

The ECM impact calculations of the previous section do not account for interactions between an ECM and other competing ECMs in a portfolio; resulting ECM impacts are therefore deemed "uncompeted." To assess an ECM's "competed" energy, CO_2 emissions, and cost impacts as part of an ECM portfolio, the ECM's "uncompeted" impacts must be adjusted down to account for competition with other ECMs in the portfolio that apply to the same segments of baseline technology stock. A segment-specific competition adjustment factor for building vintage v in year y under adoption case s, $a_{X,v,y,s}$, is calculated:

[9] Drawn from "rsmeqp.txt," "rsmlgt.txt," and "rsclass.txt" in the residential sector and "ktekx.xlsx" and "KSDOUT.txt" in the commercial sector. Baseline technology performance represents a typical level for comparable commercially available products in year y under the AEO reference case.

[10] As would be the case for an envelope with a lower outdoor air infiltration, for example.

$$a_{X,v,y,s} = \begin{cases} \theta^{\text{mkt}}_{K,X,v,y} + \theta^{\text{scale}}_{K,X,v}, & s = \text{TP or } y = y_E \\ (\theta^{\text{mkt}}_{K,X,v,y} + \theta^{\text{scale}}_{K,X,v})\,\Phi^{\text{cmp}}_{K,X,v,y} + & \\ a_{X,v,y-1}(1 - \Phi^{\text{cmp}}_{K,X,v,y}), & \text{otherwise} \end{cases} \tag{20}$$

where $\theta^{\text{mkt}}_{K,X,v,y}$ is an ECM's market share when competed in ECM set K in year y, $\theta^{\text{scale}}_{K,X,v}$ is additional market share conferred on an ECM when one or more competing ECMs apply to only part of the competed baseline stock segment,[11] $\Phi^{\text{cmp}}_{K,X,v,y}$ is the fraction of a given baseline stock segment of vintage v that the ECM set K competes for in year y under adoption case s, and y_E is the earliest market entry year across the ECM set K. Note that the market share adjustment for the technical potential (TP) adoption case does not depend on the technology stock-and-flow dynamics represented by $\Phi^{\text{cmp}}_{K,X,v,y}$, yielding an estimate of the technology's "long run" competed market share in each year.

The competed market share $\theta^{\text{mkt}}_{K,X,v,y}$ is calculated differently depending on which building type (residential or commercial) an ECM applies to, following the approach used in EIA's simulations of technology adoption for the AEO. Specifically, the EIA approach uses a logistic regression model and a cost model to assign market shares in the residential and commercial sectors, respectively, estimating market shares as a trade off between an ECM's capital and operating costs:

$$\theta^{\text{mkt}}_{K,X,v,y} = \begin{cases} \dfrac{\exp((\beta_1)_{X,y}\; I^{\text{ecm}}_{X,v,y,d} + (\beta_2)_{X,y}\; \psi^{\text{ecm}}_{X,v,y,d})}{\sum_{k=1}^{K} \exp((\beta_1)_{X,y}\; I_{k,X,v,y,d} + (\beta_2)_{X,y}\; \psi_{k,X,v,y,d})}, & b \in \text{residential} \\ \displaystyle\sum_{d=1}^{D} \theta_{u,d}, & b \in \text{commercial} \end{cases} \tag{21}$$

where $I^{\text{ecm}}_{X,v,y,d}$, $\psi^{\text{ecm}}_{X,v,y,d}$, $I_{K,X,v,y,d}$, and $\psi_{K,X,v,y.d}$, are the annual, unit-level capital and operating costs for an individual ECM and across the ECM set K, respectively, $(\beta_1)_{X,y}$ and $(\beta_2)_{X,y}$ are choice coefficients from the AEO reference case[12] that weight the influence of capital and operating costs on market share in the residential sector, D is a set of discount rates from the AEO reference case[13] that weight the influence of capital and operating costs on market share in the commercial sector, and $\theta_{u,d}$ is the market share assigned to an ECM that

[11] Applicable when a user specifies a market scaling fraction, $\xi^{scale}_{X,v}$, for one or more of the competing ECMs. In such cases, the portion of the baseline segment that the ECM(s) does (do) not apply to is divided up evenly across all other competing ECMs.

[12] Drawn from "rsmeqp.txt" and "rsmlgt.txt" for major equipment and lighting technologies; more details about these files are available in the EIA National Energy Modeling System documentation for the residential sector [6].

[13] Each discount rate represents a combination of a constant risk-free interest rate and a time-preference premium rate that represents the degree to which a given decision maker accepts

applies to end use u when it has the lowest life cycle cost (capital plus operating costs) of all competing ECMs in set K under discount rate d[14]; when an ECM does not have the lowest life cycle cost of competing ECMs in set K under discount rate d, $\theta_{u,d}$ is zero.

In a maximum adoption potential scenario, an ECM's annual market shares are weighted by the fractions of baseline and efficient stock that the ECM set can realistically compete for in each year. The fraction of a given stock segment of vintage v that an ECM set K collectively competes for in year y under adoption case s, $\Phi^{\text{cmp}}_{K,X,v,y}$, is defined as:

$$\Phi^{\text{cmp}}_{K,X,v,y} = \Phi^{\text{cmp}-\text{cpt}}_{K,X,v,y} = \begin{cases} \Lambda^{\text{new}}_{X,v,y} + (1 - \Lambda^{\text{new}}_{X,v,y})\,\Lambda^{\text{repl}}_{X,v,y}, & v = \text{new} \\ \Lambda^{\text{repl}}_{X,v,y}, & \text{otherwise} \end{cases} \tag{22}$$

where $\Lambda^{\text{new}}_{X,v,y}$ and $\Lambda^{\text{repl}}_{X,v,y}$ are segment-specific rates of new technology stock additions and replacements/retrofits, respectively. Again, because no competed stock is assumed to return to the baseline technology, $\Phi^{\text{cmp}}_{K,X,v,y}$ equals $\Phi^{\text{cmp}-\text{cpt}}_{K,X,v,y}$. $\Lambda^{\text{new}}_{X,v,y}$ and $\Lambda^{\text{repl}}_{X,v,y}$ are further defined as:

$$\Lambda^{\text{new}}_{X,v,y} = \lambda^{\text{new}}_{X,v,y} \tag{23}$$

$$\Lambda^{\text{repl}}_{X,v,y} = \Lambda^{\text{repl, base}}_{X,v,y} + \Lambda^{\text{repl, K}}_{X,v,y} \tag{24}$$

where $\Lambda^{\text{new}}_{X,v,y}$ assumes the same stock turnover dynamics as in the uncompeted ECM calculations (equation 13) because new stock additions are not affected by the dynamics of ECM competition, $\Lambda^{\text{repl, base}}_{X,v,y}$ is the rate of previously captured baseline stock replacement and retrofit in year y, and $\Lambda^{\text{repl, K}}_{X,v,y}$ is a general rate of ECM replacement across ECM set K in year y.

$\Lambda^{\text{repl, base}}_{X,v,y}$ is determined by the comparable baseline technology's lifetime l^{base} and user-defined retrofit rate ρ, encapsulated in the baseline turnover rate w_X defined by equation 15:

$$\Lambda^{\text{repl, base}}_{X,v,y} = \begin{cases} w_X\,\Phi^{\text{uncpt}}_{X,v,y}, & v = \text{new and } y_s \leq y \leq y_f \text{ or } v \neq \text{new} \\ 0, & \text{otherwise} \end{cases} \tag{25}$$

As for the individual ECM calculations described in the previous section, y_s and y_f are the years in which new stock previously captured by the comparable baseline technology starts and finishes turning over through replacement and

investment risks. Rates are drawn from the AEO reference case file "kprem.txt" and are summarized in Table E-1 of the EIA National Energy Modeling System documentation for the commercial sector [7], p. 228.

[14] The market shares are summarized in Table E-1 of the EIA National Energy Modeling System documentation for the commercial sector [7], p. 228.

retrofit, and $\Phi^{\text{uncpt}}_{X,v,y}$ represents the upper bound on the baseline replacement and retrofit rate in year y:

$$\Phi^{\text{uncpt}}_{K,X,v,y} = \begin{cases} \dfrac{\sigma^{\text{base}}_{X,v,y_{E-1}}}{\sigma^{\text{base}}_{X,v,y}}, & v = \text{new and } \sigma^{\text{base}}_{X,v,y} \neq 0 \text{ and } y_E \neq y_0 \\ 1, & v \neq \text{new and } 1 - \Phi^{\text{cpt}}_{K,X,v,y-1} \geq w_X \\ \dfrac{1 - \Phi^{\text{cpt}}_{K,X,v,y-1}}{w_X}, & v \neq \text{new} \\ 0, & \text{otherwise} \end{cases} \tag{26}$$

Similarly, the general ECM replacement rate $\Lambda^{\text{repl, K}}_{X,v,y}$ is determined based on average ECM lifetime l^{K} and the user-defined retrofit rate ρ:

$$\Lambda^{\text{repl, K}}_{X,v,y} = \begin{cases} \left(\dfrac{1}{l^{\text{K}}_X} + \rho\right) \Phi^{\text{cpt}}_{K,X,v,y-1}, & l^{\text{K}} - y - y_E \leq 0 \\ 0, & \text{otherwise} \end{cases} \tag{27}$$

In equations 26 and 27, $\Phi^{\text{cpt}}_{K,X,v,y}$ is the fraction (≤ 1) of an existing baseline stock segment of vintage v that an ECM set K has collectively captured in all years through year y:

$$\Phi^{\text{cpt}}_{K,X,v,y} = \begin{cases} 0, & y \leq y_E \\ \Lambda^{\text{repl, base}}_{X,v,y} + \Phi^{\text{cpt}}_{K,X,v,y-1}, & \text{otherwise} \end{cases} \tag{28}$$

Because $\Phi^{\text{cpt}}_{K,X,v,y}$ tracks captured *baseline* stock, the ECM replacement/retrofit rate $\Lambda^{\text{repl, K}}_{X,v,y}$ is excluded from this calculation.

2.4 Calculating ECM cost-effectiveness

ECM cost-effectiveness is assessed alongside impact metrics through cost-effectiveness thresholds that reflect both an individual consumer's perspective and the perspective of an organization investing in an ECM portfolio. The variables in these equations are summed across all vintages v and the indices in X, thus the variables and cost-effectiveness metrics are generally only indexed by year and, if applicable, scenario.

Consumer-level cost-effectiveness metrics. These metrics represent the cost-effectiveness criteria that an individual consumer might use when deciding whether to invest in one or more ECMs. Consumer-level metrics do not vary with adoption case or ECM competition.

The first consumer-level cost-effectiveness metric used in Scout is the simple payback in year y, π_y:

$$\pi_y = \frac{I_y/\sigma_y^{\text{base}}}{\left(\sum_{i=1}^{l^{ecm}} \psi_i\right)/\sigma_y^{\text{base}}} \tag{29}$$

where $I_y/\sigma_y^{\text{base}}$ is the ECM's maximum[15] total incremental capital cost normalized by the total applicable stock in year y, and $(\sum_{i=1}^{l^{ecm}} \psi_i)/\sigma_y^{\text{base}}$ is the ECM's maximum total lifetime energy cost savings normalized by the total applicable stock in year y.

The second consumer-level cost-effectiveness metric used in Scout is the internal rate of return (IRR) in year y, IRR_y. IRR is the discount rate that makes the net present value (NPV) of all ECM cash flows equal to zero for the same year. NPV is generically defined as:

$$NPV = R_0 + \sum_{i=1}^{n} \frac{R_i}{(1+d)^i} \tag{30}$$

where R_0 is the initial cost of a project, R_i is the net cash flow of a project during a given time interval i, and d is the discount rate. To calculate an ECM's IRR from equation 30, NPV is set to zero, R_0 is replaced by the ECM's stock-normalized incremental capital cost, $I_{y,0}/\sigma_y^{\text{base}}$, R_i is replaced by the sum of stock-normalized annual energy cost savings, $\psi_y/\sigma_y^{\text{base}}$, and any avoided capital costs in period i, $I_{y,i}/\sigma_y^{\text{base}}$,[16] for an ECM deployed in year y, and IRR_y replaces the discount rate d:

$$NPV = 0 = I_{y,0}/\sigma_y^{\text{base}} + \sum_{i=1}^{l^{ecm}} \frac{\psi_y/\sigma_y^{\text{base}} + I_{y,i}/\sigma_y^{\text{base}}}{(1+IRR_y)^i} \tag{31}$$

Portfolio-level cost-effectiveness metrics. These metrics represent the cost-effectiveness criteria that an organization might use when deciding which ECMs within a portfolio yield the largest energy savings or avoided CO_2 emissions impacts for a given level of investment.

The first portfolio-level cost-effectiveness metric used in Scout is the cost of conserved energy in year y, CCE_y:

$$CCE_{y,s} = \frac{I_{y,0}/\sigma_y^{\text{base}} + \sum_{i=1}^{l^{ecm}} \frac{I_{y,i}/\sigma_y^{\text{base}}}{(1+d)^i}}{\sum_{i=1}^{l^{ecm}} \frac{E_{y,s}/\sigma_y^{\text{base}}}{(1+d)^i}} \tag{32}$$

where $E_{y,s}/\sigma_y^{\text{base}}$ is the ECM's stock-normalized energy savings in year y and adoption case s. A nominal discount rate d of 7% is used in equations 32 and 33.

[15] Corresponding to the technical potential adoption case without any competition.

[16] Avoided capital costs are assessed for lighting ECMs that offer longer lifetimes than a comparable baseline lighting technology, thereby avoiding future purchases of the baseline technology.

The second portfolio-level cost-effectiveness metric used in Scout is the cost of conserved carbon in year y, CCC_y, which is calculated in the same way as the CCE:

$$CCC_{y,s} = \frac{I_{y,0}/\sigma_y^{\text{base}} + \sum_{i=1}^{l^{ecm}} \frac{I_{y,i}/\sigma_y^{\text{base}}}{(1+d)^i}}{\sum_{i=1}^{l^{ecm}} \frac{C_{y,s}/\sigma_y^{\text{base}}}{(1+d)^i}} \tag{33}$$

where $C_{y,s}/\sigma_y^{\text{base}}$ is the ECM's stock-normalized avoided CO_2 emissions in year y and adoption case s.

The CCE and CCC can be compared to the cost of energy and a theoretical carbon price, respectively, as a measure of cost-effectiveness. Note that results for these metrics are dependent on both adoption case s and the inclusion or exclusion of ECM competition from the calculations, as competition influences the total amount of energy or carbon savings that an ECM can achieve relative to a fixed baseline stock segment.

2.5 Special cases in the ECM impact calculations

Add-on ECMs. In some cases, an ECM does not replace the service of a comparable baseline technology, but rather enhances the performance of that technology. Examples include a sensing and controls ECM that more efficiently manages the operational schedule of an HVAC unit through a building automation system or a window attachment that reduces solar heat gains and thus reduces the cooling energy used to remove these heat gains from the building.

In such "add-on" ECM cases, the ECM's total installed cost is calculated as the sum of the user-defined ECM cost and that of the baseline technology the ECM is coupled with. Similarly, when the energy performance of such an ECM is specified in absolute terms, its absolute performance value is added to that of the baseline technology to arrive at the relative energy performance value required in equation 18:

$$RP'_{X,y} = \begin{cases} \dfrac{P_{X,y}^{\text{base}}}{P_{X,v}^{\text{ecm}} + P_{X,y}^{\text{base}}}, & \text{absolute units (inv.)} \\ \dfrac{P_{X,v}^{\text{ecm}}}{P_{X,y}^{\text{base}} + P_{X,v}^{\text{ecm}}}, & \text{absolute units} \end{cases} \tag{34}$$

Thermal load components. Heating and cooling ECMs may affect either HVAC equipment (e.g., a more efficient heat pump) or a component of the building envelope or internal gains that dictates heating and cooling demand (e.g., a more efficient window). In the latter case, estimating ECM energy savings requires understanding how much of a building's total heating and cooling energy use can be attributed to each of these components of thermal load. Specifically, we determine the segment of baseline energy use (and CO_2 and cost) for climate zone z, building type b, fuel type f, end use

$u \in (heating, cooling)$ and year y that is attributable to thermal load component technology t, $E^{\text{base}}_{z,b,f,u,t,v,y}$:

$$E^{\text{base}}_{z,b,f,u,t,v,y} = E^{\text{base}}_{z,b,f,u,v,y} \varrho_{z,b,u,t} \tag{35}$$

where $E^{\text{base}}_{z,b,f,u,t,v,y}$ is equivalent to the output of equation 3, $E^{\text{base}}_{z,b,f,u,v,y}$ is the total primary energy use for a given heating or cooling stock segment across all thermal load components affecting that segment, and $\varrho_{z,b,u,t}$ is the fraction of $E^{\text{base}}_{z,b,f,u,v,y}$ that is attributable to heat transfer through thermal load component technology t. $\varrho_{z,b,u,t}$ is based on earlier building simulation studies that attribute residential [8] and commercial [9] heating and cooling loads to the following components:

- **Residential thermal load components**: roof, wall, infiltration, ground, windows solar gain, windows conduction, equipment gain, people gain.
- **Commercial thermal load components**: roof, wall, ground, floor, infiltration, ventilation, windows solar gain, windows conduction, lighting gain, equipment gain, people gain, other heat gain.

In commercial buildings, the inclusion of lighting gains as a thermal load component enables accounting for the secondary effects of lighting efficiency measures on heating and cooling energy use, where a reduction in waste heat from lights because of the ECM yields an associated increase in building heating energy use and decrease in cooling energy use. These secondary heating and cooling effects are factored into all baseline energy use and energy savings estimates for commercial lighting ECMs.

Interactions between envelope and HVAC equipment ECMs. Another special case occurs when both building envelope ECMs (e.g., highly insulating windows, air sealing measures) and HVAC equipment ECMs (e.g., an air source heat pump) are present in analysis, because they affect the same segment of baseline energy use (heating and cooling), but do so in different ways. Namely, while envelope ECMs reduce heating and cooling energy demand, HVAC equipment and controls ECMs reduce the energy that is required to supply heating and cooling to the building.

Accordingly, ECMs affecting the building envelope and HVAC equipment do not directly compete to replace the same baseline service, but they do have overlapping impacts on heating and cooling energy use, as well as associated CO_2 emissions and operating costs. To remove these overlaps, adjustment factors are developed that scale down the baseline and efficient energy use, CO_2 emissions, and operating costs calculated for envelope ECMs by the relative savings impacts of overlapping HVAC ECMs, and vice versa:

$$\zeta^{\text{base, env}}_{z,b,f,u,v,y} = (1 - \gamma_{z,b,f,u,v,y}) + \gamma_{z,b,f,u,v,y} \left(\frac{\Delta^{\text{env}}_{z,b,f,u,v,y}}{\Delta^{\text{hvac}}_{z,b,f,u,v,y} + \Delta^{\text{env}}_{z,b,f,u,v,y}} \right) \tag{36}$$

$$\zeta^{\text{base, hvac}}_{z,b,f,u,v,y} = (1-\gamma_{z,b,f,u,v,y}) + \gamma_{z,b,f,u,v,y}\left(\frac{\Delta^{\text{hvac}}_{z,b,f,u,v,y}}{\Delta^{\text{hvac}}_{z,b,f,u,v,y}+\Delta^{\text{env}}_{z,b,f,u,v,y}}\right) \quad (37)$$

$$\zeta^{\text{ecm, env}}_{z,b,f,u,v,y} = \zeta^{\text{base, env}}_{z,b,f,u,v,y}(1-\Delta^{\text{hvac}}_{z,b,f,u,v,y}) \quad (38)$$

$$\zeta^{\text{ecm, hvac}}_{z,b,f,u,v,y} = \zeta^{\text{base, hvac}}_{z,b,f,u,v,y}(1-\Delta^{\text{env}}_{z,b,f,u,v,y}) \quad (39)$$

where $\zeta^{\text{base, env}}_{z,b,f,u,v,y}$, $\zeta^{\text{ecm, env}}_{z,b,f,u,v,y}$, $\zeta^{\text{base, hvac}}_{z,b,f,u,v,y}$, and $\zeta^{\text{ecm, hvac}}_{z,b,f,u,v,y}$ are additional adjustments applied to baseline and post-ECM segments of energy use, CO_2 emissions, or operating costs ($M^{\text{base}}_{z,b,f,u,t,v,y,s}$ and $M^{\text{ecm}}_{z,b,f,u,t,v,y,s}$ in equation 2 to resolve overlaps between envelope and HVAC ECMs, or vice versa, $\gamma_{z,b,f,u,v,y}$ is the fraction of total energy use in climate zone z, building type b, fuel type f, end use u (heating or cooling), building vintage v, and year y that is overlapping across envelope and HVAC ECMs, $\Delta^{\text{env}}_{z,b,f,u,v,y}$ is the total energy savings of all envelope ECMs in the overlapping segment after competition divided by the total energy use of the overlapping segment, and $\Delta^{\text{hvac}}_{z,b,f,u,v,y}$ is the total energy savings of all HVAC ECMs in the overlapping segment after competition divided by the total energy use of the overlapping segment.

ECM package definitions. Finally, Scout allows the aggregation of individual ECM definitions into ECM packages, representing a case where a consumer or organization adopts multiple ECMs at the same time (though note that ECM packages were not defined or assessed for the current analysis.) ECM packages sum together all of the stock, energy, carbon, and cost data calculated as decribed above for each individual ECM in the package. In cases where two ECMs to be packaged affect the same baseline energy use segment(s), a simple average of the overlapping ECMs' energy, carbon, and cost impacts is taken and these averaged impacts are added to the package data.[17]

Users may assign additional cost and/or performance benefits from packaging in the ECM package definition, where each benefit is represented as a percentage improvement in the aggregate cost and performance level of the package. As an example, this feature may be used to represent the effects of a vendor discount that incentivizes installing several measures at once over piecemeal installation of each measure separately.

Supplemental References

[1] U.S. Energy Information Administration. AIA Climate Zones—RECS 1978–2005. https://www.eia.gov/consumption/residential/maps.php. Accessed 05-22-2019.

[17] More sophisticated handling of this case is planned in future Scout development, where the approach resembles that used to adjust for interactions between envelope and HVAC equipment ECMs.

[2] U.S. Energy Information Administration. 2009 RECS Survey Data—Microdata—Data files—recs2009_public.csv. https://www.eia.gov/consumption/residential/data/2009/csv/recs2009_public.csv. Accessed 05-22-2019.

[3] U.S. Energy Information Administration. 2003 CBECS Survey Data—Microdata—File 1: General Building Information and Energy End Uses. https://www.eia.gov/consumption/commercial/data/2003/csv/FILE01.csv. Accessed 05-22-2019.

[4] U.S. Energy Information Administration. Annual Energy Outlook 2018. https://www.eia.gov/outlooks/archive/aeo18/. Accessed 06-10-2019.

[5] P. Donohoo-Vallett. Accounting Methodology for Source Energy of Non-Combustible Renewable Electricity Generation. U.S. Department of Energy, Washington, D.C., 2016.

[6] U.S. Energy Information Administration. Residential Demand Module of the National Energy Modeling System: Model Documentation. U.S. Energy Information Administration, Washington, D.C., 2018.

[7] U.S. Energy Information Administration. Commercial Demand Module of the National Energy Modeling System: Model Documentation 2012. U.S. Energy Information Administration, Washington, D.C., 2018.

[8] J. Huang, J. Hanford, and F. Yang. Residential Heating and Cooling Loads Component Analysis. Lawrence Berkeley National Laboratory, Berkeley, CA, 1999.

[9] J. Huang and E. Franconi. Commercial Heating and Cooling Loads Component Analysis. Lawrence Berkeley National Laboratory, Berkeley, CA, 1999.