The role of buildings in U.S. energy system decarbonization by mid-century

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Summary

Full decarbonization of the U.S. energy system to meet climate goals requires aggressive emissions reductions across energy end uses; however, prevailing policies focus on end-use electrification and clean energy supply rather than a broader set of demand-side solutions. We assess multiple CO_2 emissions reduction pathways to mid-century for U.S. buildings, which are among the largest sources of CO_2 emissions across end-use sectors. We find potential for up to a 91% reduction in building CO_2 emissions from 2005 levels by 2050 using a portfolio of efficiency, load flexibility, and electrification alongside rapid grid decarbonization. Demand-side measures could account for nearly half of overall emissions reductions, with building efficiency delivering more than double the emissions reductions of electrification measures in the near term. Further, building efficiency and flexibility would generate up to $122 billion in annual power system cost savings by 2050, offsetting nearly half the incremental cost of full grid decarbonization.

Introduction

The U.S. established an ambitious goal to reduce net greenhouse gas (GHG) emissions 50–52% from 2005 levels by 2030 and to reach net-zero emissions economy-wide by no later than 2050; this includes a goal to reach 100% carbon-free electricity by 2035 [1]. Ambition at the state level is similarly high: states representing over 50% of the U.S. population have set 100% carbon-free electricity goals for mid-century or earlier [2]. Achieving these goals will require unprecedented acceleration in the adoption of climate change mitigation solutions across every sector of the economy.

Within the U.S. energy sector, prevailing policy and analysis on decarbonization pathways have focused on supply-side solutions for low-carbon energy generation and carbon dioxide (CO_2) removal technologies rather than demand-side approaches, including those in buildings and other end-use contexts [3, 4]. This is despite emerging research suggesting these approaches are essential for climate change mitigation [5, 6, 7]. A recent review indicates demand-side solutions can provide 10–30% of the resources required for deep decarbonization across metrics including energy generation and peak capacity [8]. The Intergovernmental Panel on Climate Change (IPCC) recently published its Sixth Assessment Report (AR6) which includes, for the first time, dedicated chapters to demand for services and social aspects of mitigation; these chapters find with high confidence that demand-side options can reduce 40–70% of global GHG emissions in end-use sectors by 2050 compared to baseline scenarios [9].

Residential and commercial building energy consumption is a substantial driver of U.S. energy-related CO_2 emissions, accounting for 1.7 Gt CO_2 in 2021, or more than one-third of the U.S. total [10]. The buildings sector also accounts for 74% and 42% of the annual U.S. electricity and natural gas consumption by end-use sectors, respectively [10]. As a sector that contributes substantially to emissions from both power generation and from direct fossil fuel use, the built environment has an important role to play in the push towards a carbon-free U.S. economy.

Building decarbonization solutions improve the efficiency of energy end uses, increase the flexibility of building loads in response to electric grid needs, and/or convert building services to low-carbon sources of electricity. Of the three approaches, building energy efficiency is the most extensively studied and widely considered as a beneficial, low-cost option for mitigating climate change [11], though its role is shifting alongside aggressive decarbonization of the energy supply [12]. Building demand flexibility is a complementary solution that will play an increasingly important role as variable renewable energy accounts for a larger share of power generation capacity [13, 14, 15, 16]. Finally, building end-use electrification has emerged as a key pillar of economy-wide decarbonization, particularly as the carbon intensity of the grid has fallen over the past decade and as ambitious targets for power sector decarbonization have been announced [17]. The potential for building electrification is bolstered by improvements in the performance and cost characteristics of relevant technologies [18].

Recent studies on pathways to economy-wide decarbonization in the U.S. represent building sector solutions as part of an accelerated transition [19, 20, 21, 22, 23, 1, 24], and those with projections through mid-century reveal a number of common themes. First, final building energy demand is reduced significantly, with reductions ranging from 24–41% in 2050. Studies note higher rates of building energy reduction for thermal end uses, especially building heating and cooling, and reductions are typically higher in residential buildings [22]. Second, rates of building space and water heating electrification accelerate dramatically across studies: electric shares of new equipment sales in 2050 range from 85–90% for residential space heating, 55–75% for residential water heating, 71–80% for commercial space heating, and 40–60% for commercial water heating. Across most studies, however, universal electrification of building end uses does not occur by 2050. Third, regarding the power sector, studies assume a 70–100% reduction in fossil fuel use for electricity generation by 2050 [21, 22], with some assuming an aggressive target of achieving carbon-free electricity by 2035 [23, 1]. Finally, most studies project remaining building emissions in 2050: 48–214 Mt CO_2 in [21], 55–131 Mt CO_2 in [22], and roughly 100-300 Mt CO_2 in [1], depending on the scenario. In cases with aggressive grid decarbonization, remaining building emissions are owed primarily to the assumption that full electrification is not achieved across building end uses; these remaining emissions are addressed in net-zero pathways by negative emissions sources.

Due to their national and economy-wide scope, existing cross-sectoral decarbonization studies tend to represent building decarbonization solutions and adoption drivers with a coarse degree of detail and are limited in their reporting of the potential impacts of these demand-side solutions on specific energy end use segments. Further, despite calculating the total and net costs of deep decarbonization across sectors, these studies do not undertake detailed cost modeling for the building sector or assess the implications of ambitious building technology deployment scenarios on the power sector. Recent studies focused on residential building GHG emissions demonstrate the potential for deep emissions reductions, but have similar limitations to the cross-sectoral studies in their representation of technologies and costs [25, 26]. To the authors' knowledge, no existing deep decarbonization study quantifies energy and emissions reduction pathways and their cost implications for the whole U.S. buildings sector with a high degree of spatio-temporal resolution and technology-level detail.

In this paper, we estimate potential reductions in U.S. building energy consumption and CO_2 emissions through 2050 under multiple scenarios of demand-side efficiency, flexibility, electrification, and power sector decarbonization. Our study uses a comprehensive, bottom-up representation of commercialized and emerging measures for building decarbonization and identifies key policy-related drivers of building emissions reductions, including the range of building technology performance levels made available to consumers, rates of building load electrification, rates of building and technology stock turnover and accelerated replacement of existing building technologies, and decarbonization of the building electricity supply. Our analysis assesses the cross-sectoral linkages between decarbonization in the power sector and building technology deployment by quantifying the effects of demand-side building measures on electricity system costs, and we attribute our findings to specific measures and measure types, end uses, building types, and regions to inform concrete policy designs and priorities.

Building decarbonization measures, scenarios and metrics

We define a comprehensive set of building energy efficiency (EE), demand flexibility (DF), and end-use electrification (EL) technologies and operational approaches (collectively referred to as demand-side measures) that are deployed under 12 scenarios of U.S. building and power sector decarbonization from 2022-2050 as outlined in Table 1. Scenarios are organized into three groups, with one scenario in each group serving as a benchmark against which other group scenarios are compared to explore sensitivities to key input assumptions. The three benchmarks represent low, moderate, and aggressive potentials for building decarbonization, respectively. We quantify remaining CO_2 emissions from the building sector in 2050 for the benchmark scenarios in order to highlight the potential need for negative emissions solutions to offset these remaining emissions and fully decarbonize the buildings sector.

Demand-side measure deployment is assessed with the Scout model [27] relative to the EIA Annual Energy Outlook 2021 Reference Case forecast, which largely carries forward historical trends in building technology adoption and energy consumption. Scenario data for measure costs, hourly system load impacts, and estimates of annual building electricity demand through 2050 from Scout are coupled with power sector projections from the GridSIM model [28] to assess electricity CO_2 emissions and power system cost reductions across the full measure portfolio, as well as the total incremental costs of deploying individual measures. Full-portfolio reductions in CO_2 emissions from on-site combustion of fossil fuels are assessed by coupling Scout estimates of annual building fossil fuel demand through 2050 with EIA fossil fuel emissions intensities. Additional details on the modeling framework, measures, and scenarios are reported in the Methods.

Table 1: Scenario groups, benchmarks, and sensitivity cases. 12 scenarios are simulated: 3 benchmark scenarios represent low, moderate, and aggressive potentials for building decarbonization; the remaining 9 scenarios are used to explore key sensitivities relative to the benchmarks.

Scenario Group	Benchmark (BM) Scenario	Sensitivity Scenarios
1: Low	Demand-side measure deployment: - High rate of building electrification to heat pumps (HPs) only Grid decarbonization: GridSIM Reference Case	(1.1) Low BM without efficient electrification (electrification to a mix of resistance and HPs)
2: Moderate	Demand-side measure deployment: - Moderate rate of building electrification to HPs - Building technologies with breakthrough performance/cost enter the market by 2035 - Elevated building codes and standards take effect in 2030 - Additional near-term deployment of building envelope/control efficiency measures Grid decarbonization: 80% reduction vs. 2005 levels by 2050	(2.1/3.1) Moderate/Aggressive BM with early retrofits that accelerate the rate of baseline stock turnover (2.2/3.2) Moderate/Aggressive BMs without breakthrough technologies reaching the market (2.3/3.3) Moderate/Aggressive BMs without breakthrough technologies reaching the market or elevated building codes and appliance efficiency standards being enacted (2.4/3.4) Moderate/Aggressive BMs without any additional efficiency/flexibilty deployment beyond the reference case (electrification to HPs only)
3: Aggressive	Demand-side measure deployment: - High rate of building electrification to HPs - Building technologies with breakthrough performance/cost enter the market by 2030 - Elevated building codes and standards take effect in 2025 - Additional near-term deployment of building envelope/control efficiency measures Grid decarbonization: 100% reduction vs. 2005 levels by 2035	

Results

By 2050, U.S. building CO_2 emissions can be reduced up to 91% vs. 2005 levels without adding to electricity use given deployment of a broad suite of demand-side measures

First, we estimate the potential magnitude of changes in U.S. building electricity use, energy use and CO_2 emissions to 2050 under various scenarios of demand-side measure deployment and grid decarbonization, and demonstrate the sensitivity of these results to changes in model inputs that map to key policy levers. Figure 1 shows that U.S. building CO_2 emissions could be reduced up to 67% and 91% below 2005 levels by 2030 and 2050, respectively, under a scenario with aggressive deployment of efficiency and electrification, early retrofitting behavior, and a grid that fully decarbonizes by 2035 (scenario 3.1). Under this scenario, 210 Mt CO_2 emissions remain in 2050, which is consistent with remaining building emissions in previous deep decarbonization studies and could be addressed by negative emissions sources (see Discussion). The most aggressive scenario also avoids more than one-third of total building energy use and decreases total building electricity use 11% by 2050 despite the high level of building end-use electrification. Several other scenarios produce less favorable results, however. Moderate scenarios (2–2.4) fail to reduce building emissions more than 76% below 2005 levels, leaving a minimum of 549 Mt CO_2 unabated in 2050, which is inconsistent with plausible negative emissions offsets for the sector. Low potential scenarios (1–1.1), which push high electrification alone under slow grid decarbonization, are even further from a net-zero-compatible pathway, leaving a minimum of 1095 Mt CO_2 unabated in 2050 even under electrification to high efficiency heat pumps. Moreover, building electricity use increases by up to 23% in 2050 under the low potential scenarios, as well as in multiple other scenarios that remove key energy efficiency dynamics (2.3–2.4, 3.3–3.4).

The bottom left panel of Figure 1 isolates the contributions of demand-side measures to total building CO_2 emissions reductions. Full deployment of demand-side measures accounts for nearly half of total CO_2 reductions from the reference case in 2050 in scenarios where additional grid decarbonization beyond the reference case is assumed (43–46% in scenarios 2, 2.1, 3, and 3.1). The other half of CO_2 reductions is attributed to grid decarbonization, which reduces remaining reference case building electricity emissions after accounting for deployment of efficiency and flexibility measures. The influence of demand-side measures on CO_2 emissions reductions is strongly dependent on the deployment of efficiency: when only building electrification is assumed, the share of total CO_2 emissions reductions attributable to the demand side drops to 21% and 29% under power grids that are 80% decarbonized by 2050 and 100% zero-carbon by 2035, respectively (scenarios 2.4 and 3.4).

Building energy and CO_2 reductions through 2050 depend strongly on level of demand-side efficiency deployment

Decision-makers may use various regulations and market-based instruments to influence the adoption rates and performance of demand-side measures. Figure 2 compares reductions in annual site energy and CO_2 emissions from demand-side measures between the three benchmark scenarios and nine sensitivity cases in 2050. The comparisons isolate the influence of key dynamics that could be affected by policy levers: a decrease in the efficiency of electrification (scenario 1.1 vs. 1); the addition of early retrofits (2.1/3.1 vs. 2/3); failure to introduce breakthrough efficiency and more aggressive codes and standards (2.2/3.2 and 2.3/3.3 vs. 2/3, respectively); and removal of all additional market-viable efficiency deployment beyond the reference case — primarily existing building envelope retrofits and controls (2.4/3.4 vs. 2/3). Results for 2030 and cumulative changes in CO_2 from 2022–2050 are also reported in the Supplemental Information (Figures S1 and S2).

Assuming early retrofit behavior (scenarios 2.1/3.1) produces modest increases in 2050 annual site energy savings and avoided annual CO_2 in the range of +8–13%, relative to the moderate and aggressive benchmark scenarios (scenarios 2 and 3). The aggressive group benchmark (scenario 3), which does not assume early retrofitting behavior, nevertheless reduces annual building emissions to 89% below 2005 levels by 2050, or 252 Mt CO_2, which is still consistent with other economy-wide net-zero pathway studies [21, 1]. Indeed, the impacts of early retrofits on annual energy and CO_2 are more prominent in the near term (+26-38% in 2030, Figure S1). These findings suggest that most of the long-term decarbonization potential for U.S. buildings can be captured by ensuring that building technology choices from 2022 onward — driven by new building additions and end-of-life technology replacements — are pushed towards more efficient and flexible options served by low-carbon or carbon-free fuel sources.

In contrast to the incrementally positive impacts of early retrofits, decreasing the efficiency of electrification by assuming a large share of electric resistance equipment alongside heat pumps (scenario 1.1) has substantial negative impacts relative to the low potential benchmark (scenario 1), precluding 30% of annual site energy savings and 27% of annual CO_2 reductions. Similarly, in the moderate and aggressive benchmark scenarios, collective removal of three efficiency dynamics — breakthrough efficiency, aggressive codes and standards, and additional market-viable efficiency (scenarios 2.2–2.4 and 3.2–3.4) — significantly counteracts energy and CO_2 reductions, precluding 52–66% of annual site energy savings and 37–57% of annual CO_2 savings. Effects on cumulative CO_2 emissions, which encompass both near- and long-term measure impacts, are even greater

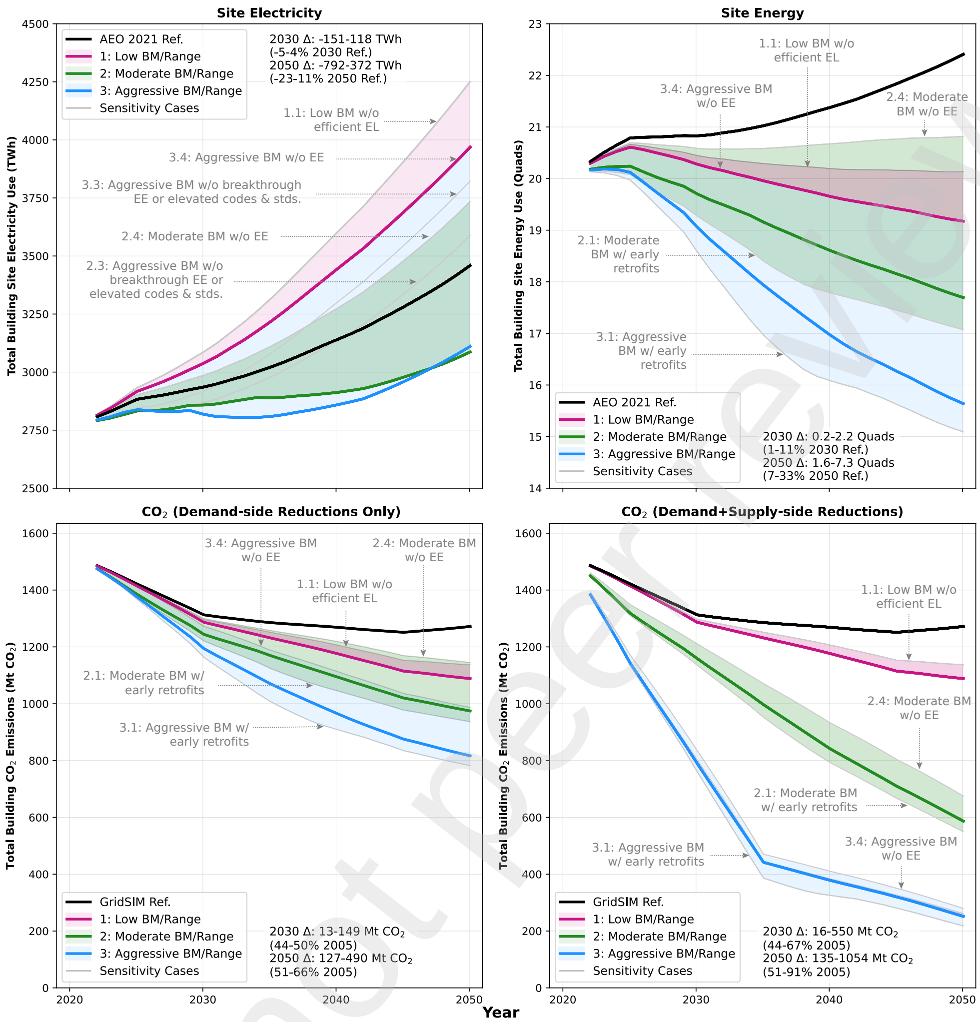

Figure 1: By 2050, U.S. building CO_2 emissions can be reduced up to 91% vs. 2005 levels without increasing electricity use given deployment of a broad suite of demand-side measures. Three benchmark (BM) scenarios representing low, moderate, and high building decarbonization futures are highlighted relative to the EIA Annual Energy Outlook (AEO) 2021 Reference Case forecast (electricity, energy) or relative to the AEO forecast with GridSIM Reference Case CO_2 intensities substituted for electricity (emissions) for the years 2022–2050. Nine additional scenarios are simulated to explore key sensitivities in the results; the sensitivity range around each benchmark scenario is denoted by colored shading. Bounding sensitivity scenarios for each benchmark are annotated, as are any other scenarios in which site electricity use increases by 2050 relative to the reference case (top left). The range of possible changes from the reference case across the full scenario set is summarized for 2030 and 2050. CO_2 emissions are separated into those resulting solely from the application of building efficiency, flexibility, and electrification ("Demand-side Reductions," bottom left) vs. those resulting from the joint consideration of demand-side measure deployment and decarbonization of remaining reference case building electricity demand ("Demand+Supply-side Reductions," bottom right).

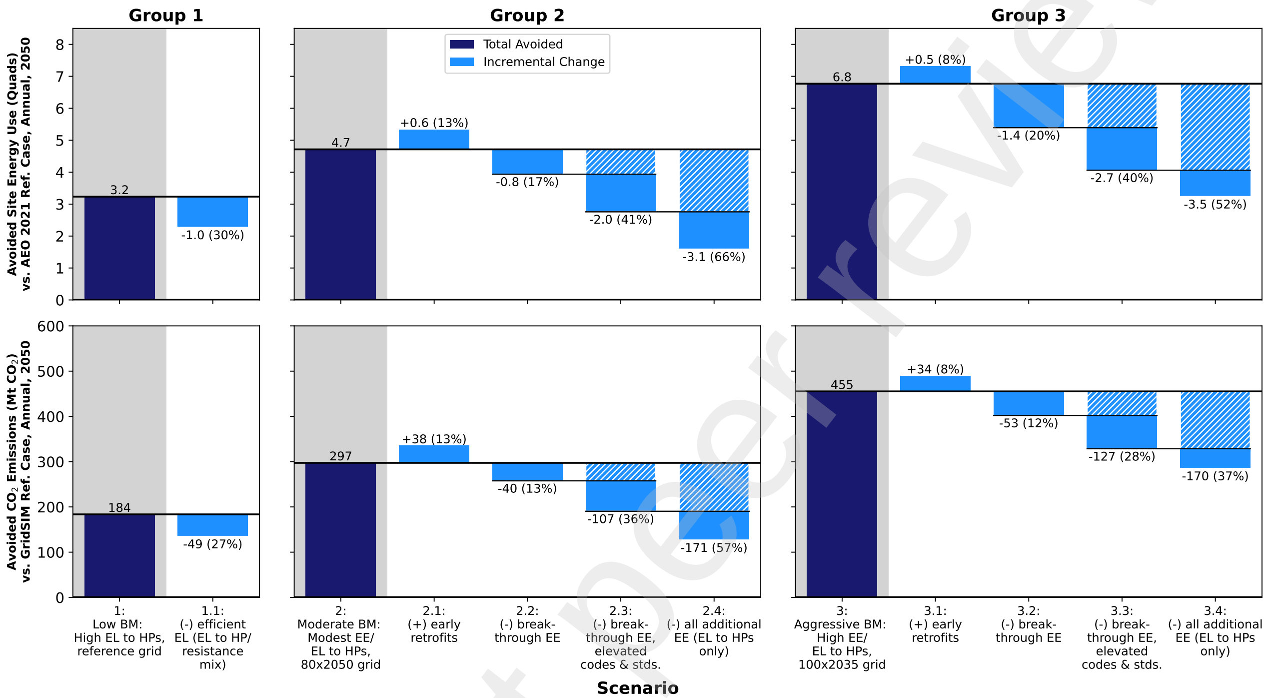

Figure 2: Building energy and CO_2 reductions through 2050 depend strongly on the level of demand-side efficiency deployment. Results for nine sensitivity side cases are organized into three groups and assessed relative to the 2050 avoided annual energy use and CO_2 emissions of the three benchmark (BM) scenarios (1, 2, and 3). The sensitivity cases assess the influence of five unique dynamics on annual energy and emissions: reductions in efficiency of electrification via substantial conversion from fossil-based heating and water heating to electric resistance technologies (1.1); failure to increase the market-available technology performance ceiling via eventual introduction of breakthrough efficiency technologies with very low cost and performance (2.2, 3.2); failure to increase the market-available technology performance floor via implementation of more aggressive building performance codes and appliance efficiency standards (2.3., 3.3); and failure to deploy additional market-viable efficiency options not represented in the reference case in the near-term — in particular, upgrades for certain envelope components in existing buildings and deployment of advanced operational controls (2.4, 3.4).

(Figure S2), with 49–69% of cumulative emissions reductions precluded by removing these efficiency dynamics in the moderate and aggressive potential groups. This is an initial reflection of the greater near-term influence of efficiency measures that will be further demonstrated in the next section. The incremental impacts of successively removing each efficiency dynamic appear comparable in magnitude, particularly for the energy use metric. These large negative effects are generally robust to the overall level of building and grid decarbonization (comparing groups 2 and 3), though the removal of breakthrough technologies is less impactful when such technologies are assumed to enter the market later (group 2). The removal of all three efficiency dynamics also has somewhat less influence on CO_2 reductions under full grid decarbonization by 2035 (group 3), where building electrification is most important to demand-side emissions reductions.

Demand-side measures contribute nearly half of total building CO_2 reductions by 2050; reductions are most strongly attributed to thermal energy service efficiency improvements and electrification in single family homes

Next, we attribute total building CO_2 emissions reductions to end-use sources, demonstrate the sequencing of CO_2 emissions reductions by measure type, and highlight the segments of building energy use with the greatest potential to drive CO_2 reductions. Figure 3 presents the end-use wedges of emissions reductions across the three benchmark scenarios. Reductions are largely attributable to thermal end uses: lower energy demand from heat transfer through the building envelope, and lower and/or less carbon-intensive HVAC and water heating equipment. In the moderate and high potential benchmarks (scenarios 2 and 3), where fossil-based equipment electrification is deployed in parallel with envelope improvements and more efficient and flexible electric equipment, envelope improvements account for the single-largest share of CO_2 emissions reductions (30–36%) among end uses. Reductions in HVAC and water heating energy use account for an additional 26–31% and 21–23% of total emissions reductions, respectively. While other end uses register reductions on the wedges in these scenarios — notably, computers and electronics, lighting, and cooking — collectively these end uses account for just 10–23% of total reductions in 2050.

The strong influence of envelope improvements on total CO_2 emissions reductions in Figure 3 is consistent across the moderate and aggressive benchmarks. Moreover, in both cases the relative influence of envelope impacts grows over time, comprising 1.4–1.5 times greater shares of total reductions in 2050 than in 2030, a reflection of slow rates of turnover in the baseline envelope stock. Further attribution of envelope measure impacts to those reducing electric vs. non-electric loads, however, reveals differences between the two benchmarks. A greater share of non-electric envelope impacts is observed in the moderate benchmark (48% vs. 16% in the aggressive benchmark), as lower equipment electrification rates leave more non-electric demand for envelope measures to affect through 2050. This result underscores the potential importance of envelope efficiency deployment as a hedge against slow rates of load electrification that would otherwise impede deeper levels of building sector emissions reductions.

The end-use reduction wedges in Figure 3 grow through 2050 with increasing deployments of building efficiency, electrification, and flexibility measures. In the moderate and aggressive benchmarks, these deployments occur alongside an electric grid that progressively decarbonizes beyond the reference case, and Figure 3 reiterates the finding from Figure 1 that demand-side measures contribute nearly half of total building sector emissions reductions by 2050. Figure 4 also shows that the relative influence of building decarbonization drivers changes depending on whether one takes a near-term (2022–2030) or long-term (2030–2050) perspective. Building efficiency measures

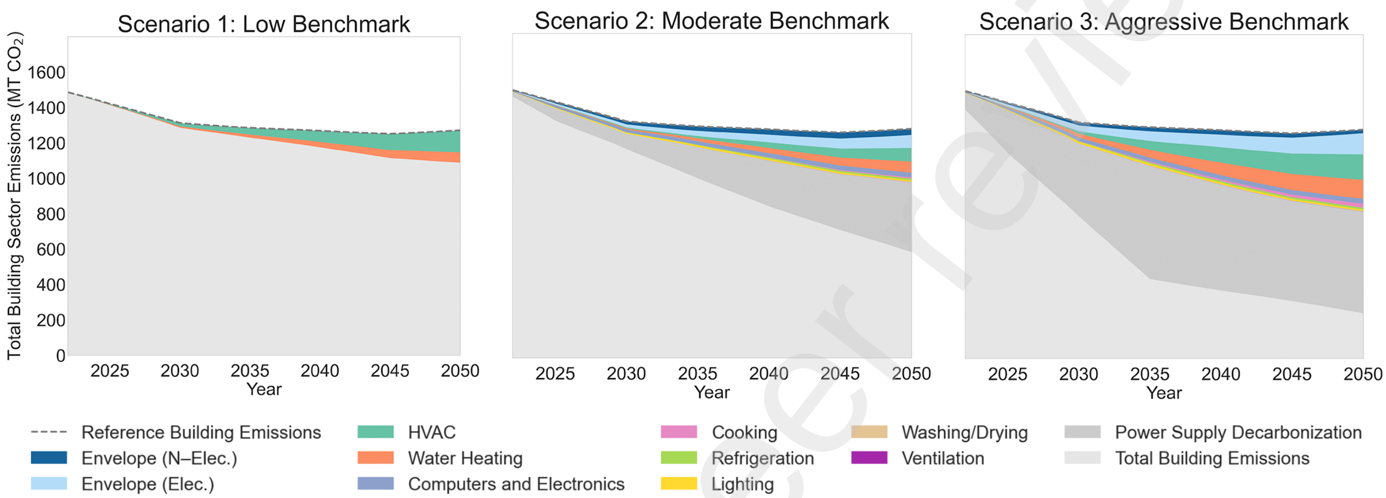

Figure 3: Demand-side measures contribute nearly half of total building CO_2 reductions by 2050 under moderate to aggressive decarbonization benchmarks; reductions are largely attributable to thermal end uses. Emissions reduction wedges are shown relative to a reference line that reflects AEO 2021 Reference Case building demand and fossil fuel emissions intensities with GridSIM emissions intensities for electricity, for each of the low, moderate, and aggressive benchmark scenarios (1, 2, and 3, respectively). Reductions from electrifying and improving the efficiency and flexibility of building end uses (demand-side measures) are indicated with colored wedges for each affected end use. Within the demand-side wedges, CO_2 reductions from improved envelope efficiency (which reduce demand for both electric and non-electric heating and cooling energy) are assessed before and reported separately from the overlapping reductions of measures that improve HVAC equipment efficiency. More broadly, reductions from electric efficiency and flexibility improvements are assessed before considering additional decarbonization of the power supply beyond the reference case, while reductions from electrification are staged in parallel with power supply decarbonization. Power supply decarbonization further reduces the emissions from any reference case building electricity that remains after accounting for deployment of efficiency and flexibility measures; these reductions are indicated with a dark gray wedge in each scenario.

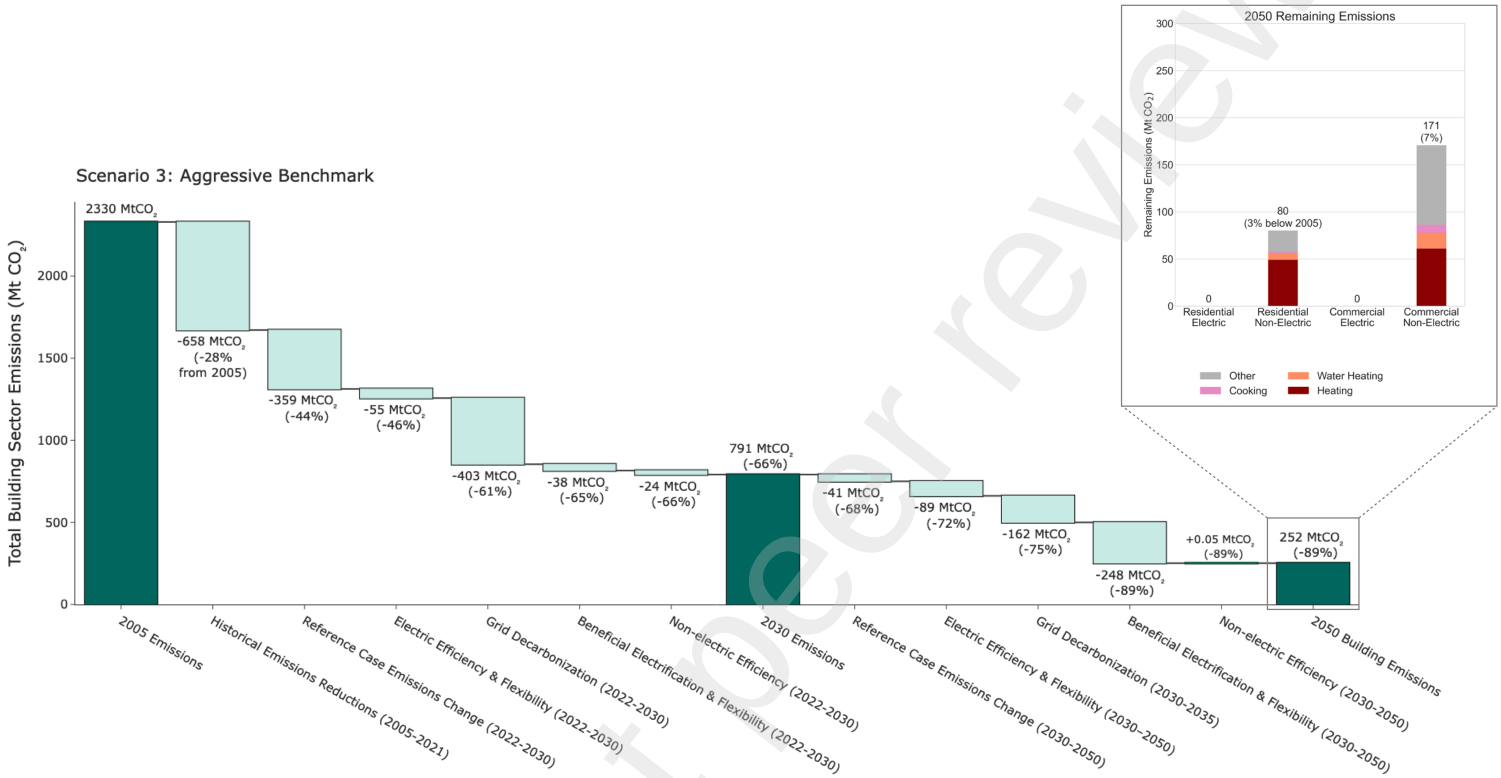

Figure 4: Under an aggressive decarbonization benchmark, demand-side efficiency measures drive near-term reductions in building CO_2 (through 2030), while electrification measures deliver the majority of their impacts in out years (2030-2050). Reductions from the 2005 buildings sector emissions level are broken out between 2005–2030 and between 2030–2050 by source: historical reductions (from 2005–2021); reductions projected in the reference case forecast; further demand-side reductions via building efficiency, flexibility and electrification beyond the reference case; and further decarbonization of the building electricity supply beyond the reference case. Reductions from electric efficiency and flexibility improvements are assessed before considering additional decarbonization of the power supply beyond the reference case, while reductions from electrification are staged in parallel with power supply decarbonization. Non-electric efficiency impacts are applied to any non-electric demand that remains after considering the deployment of building load electrification measures. Emissions that remain in 2050 are segmented in the call-out box by building type and end use; the 'Other' end use consists of miscellaneous loads such as water pumps, generators, grills, and manufacturing in commercial spaces [29].

demonstrate a greater degree of near-term influence, contributing more than double the reductions of building electrification measures between 2022–2030 in the aggressive benchmark, while electrification and grid decarbonization deliver almost three times the reductions of efficiency measures from 2030–2050 — a finding that is largely owed to the gradual ramp-up of load electrification rates (see Figures S14–S17). The influence of efficiency measures is more pronounced under moderate assumptions with slower rates of electrification and grid decarbonization (see Figure S4).

Under the aggressive decarbonization benchmark, Figure 4 shows that 252 Mt of annual building CO_2 emissions remain in 2050, or 11% of the sector's 2005 CO_2 emissions level. Given the full decarbonization of electricity supply in this benchmark, remaining emissions come from residual non-electric building energy demand. A large portion of these remaining non-electric emissions are attributable to heating, water heating, and cooking end uses (6% of 2005 levels) — particularly in commercial buildings, which face strong barriers to electrification [18] leading to lower electrification rates over the long term (see Figures S14–S17). While significant policy attention is focused on addressing such barriers, less is given to the larger segment of remaining non-electric "Other" building CO_2 emissions in Figure 4, which mostly come from loads like manufacturing in commercial spaces and residual fuel oil that EIA classifies as "non-building" [29]. These loads, which may be harder to electrify, would comprise nearly 5% of 2050 building sector emissions if left unaddressed.

Figure 5 presents further segmentation of demand-side CO_2 emissions reductions under the aggressive decarbonization benchmark, and it reveals a more diverse set of reduction opportunities than that suggested by the higher-level end-use attribution of Figure 3. Considered across the building sector as a whole in both 2030 and 2050, emissions reduction opportunities are strongly weighted towards single family homes in highly populated regions with large fossil-based heating service demands and higher reference case electricity emissions — in particular, the Great Lakes/Mid-Atlantic and Southeast. Within these region/building type segments, 2030 reductions are largely attributable to efficiency improvements that reduce non-electric heating energy — primarily improvements to the building envelope — and this is especially true for the Great Lakes/Mid-Atlantic segments, given the near-term dominance of fossil-based heating service in this region. By 2050, however, end-use and measure type contributions are distributed across multiple categories, with substantial reductions coming from electric heating, cooling, and water heating efficiency and greater influence coming from electrification measures that reduce fossil demand and the associated potential for non-electric efficiency impacts over the long term.

The dominant influence of single family homes on total CO_2 emissions reductions in Figure 5 is further demonstrated by the similarities between residential-only results (Figure S5) and the results shown in Figure 5. Emissions reductions in commercial buildings are far more heterogeneous and less concentrated around a handful of influential reduction segments, given the wide variety of commercial building types and uses (Figure S5). Nevertheless, when aggregated across building types, commercial building emissions reductions constitute an important driver of building sector decarbonization (also see Figure S8). In 2030, for example, commercial measures contribute 35% of total reductions across regions and 41% of reductions in the highly influential Southeast region. These shares lessen by 2050, given acceleration in residential electrification and reference case efficiency improvements in key segments of near-term commercial emissions reductions such as retail lighting. Still, the 2050 commercial reductions remain substantial at 28% of total reductions across regions. Five commercial building types — retail, education, hospitality, offices, and assembly buildings — are consistently among the top contributors to emissions reductions in the most influential regions. Commercial heating reductions are notable, but primarily in colder regions such as the Great Lakes/Mid-Atlantic, Northeast, and Upper Midwest. Other commercial end uses — notably

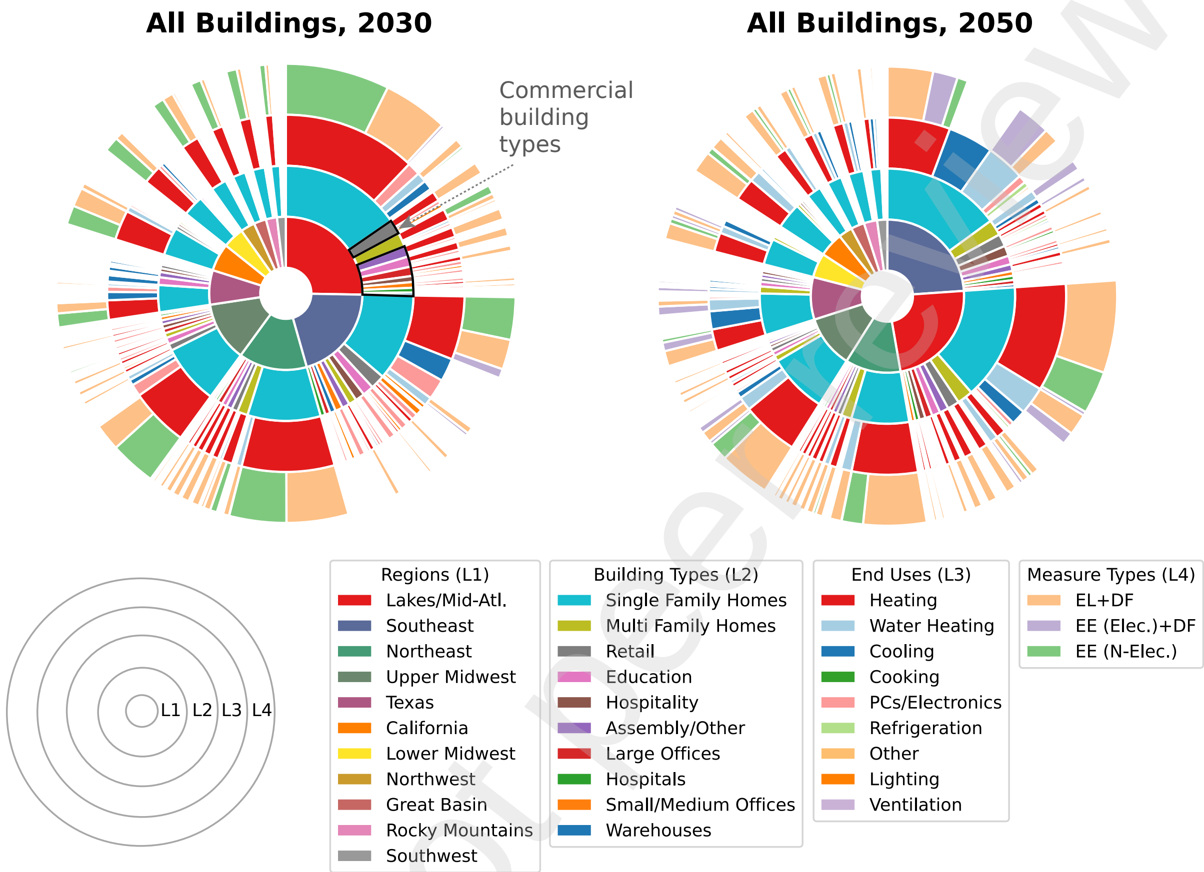

Figure 5: Under an aggressive decarbonization benchmark, building CO_2 emissions reduction opportunities are strongly weighted towards single family homes in highly populated regions with large fossil-based heating service demands and higher reference case electricity emissions. The plot further segments the aggressive decarbonization benchmark scenario's total building emissions reductions in 2030 (left) and 2050 (right), across all building types. Emissions reductions are segmented across the following dimensions, beginning with the inner ring of each plot and moving outwards: region (aggregations of 25 EIA Electricity Market Module regions [30] to 11 higher-level regions); building type (aggregations of the three residential and 11 commercial EIA Annual Energy Outlook building types to two and eight residential and commercial building types, respectively); energy end use; and measure type (electrification paired in some cases with flexibility (EL+DF), electric efficiency paired in some cases with flexibility (EE (Elec.)+DF), and non-electric efficiency (EE (N-Elec.)). White regions of the plot denote aggregations of very small segments.

lighting in the near term, computers (PCs)/electronics, and cooking in hospitality environments — are attributed reduction shares that are comparable to or greater than those of heating in warmer regions like the Southeast.

Aggressive deployment of building efficiency and flexibility measures generates up to $122 billion in annual power system cost savings by 2050, offsetting nearly half the incremental cost of full grid decarbonization

Finally, we examine the implications of widespread demand-side measure deployment in buildings for power sector decarbonization. Specifically, we analyze the same measures and grid scenarios discussed previously under the moderate and aggressive decarbonization benchmark scenarios (2 and 3) to determine the extent to which the demand-side measures impact bulk power system generation and transmission costs and to gain insight into the cost-effectiveness of the measure portfolio.

Given that the focus of this analysis is on power sector cost savings, we specifically analyze measures that reduce building electricity use. When considering electrification measures, we assess the potential benefits of efficient building end-use electrification relative to a baseline that deploys a substantial portion of less efficient resistance heating and water heating equipment in lieu of heat pumps (consistent with scenario 1.1, see Methods). This allows us to isolate the impacts of efficiency, including deployment of more efficient building end-use electrification measures.

Decarbonizing the U.S. power supply will require a large build-out of renewable generation, energy storage, and flexible clean generation technologies with significant implications for costs. Under moderate to aggressive grid decarbonization in the absence of additional building efficiency, flexibility, and efficient end-use electrification measures, the total amount of generation capacity needed in 2050 is 2.6–3.2 times the current amount of power system capacity (Figure S9). The increase is due to the incremental load growth from inefficient building end-use electrification and electrification of transportation, as well as satisfying the goal of a deeply decarbonized power sector. This compares to approximately 50% higher generation capacity in 2050 under Reference Case assumptions that are limited to the impacts of existing state-level climate legislation. By 2050, in the absence of new demand-side measures, we estimate $390–527 billion per year in capital expenditures and production costs (Figure S10). This range is 1.8–2.4 times the $217 billion of forecasted 2050 annual expenditures in the Reference Case.

Building end-use efficiency and flexibility can reduce the cost of decarbonizing the power sector by reducing overall electricity consumption and peak demand, and shifting usage to hours when it is less costly to serve. The result is a reduction both in fixed generation and transmission costs (i.e., capital investment and fixed operations and maintenance) and in variable generation costs (i.e., fuel and variable operations and maintenance). Figure 6 shows that by 2050, we estimate that these benefits could amount to gross cost savings of $78–122 billion per year, or 39–45% of the incremental cost of additional power supply decarbonization before accounting for the cost of the portfolio of demand-side measures. Consistent with the estimates of emissions savings, HVAC and envelope measures account for a large share of total cost savings due to the overall magnitude of heating and cooling loads and the high efficiency of technologies that are available to reduce them. Additionally, a majority of the cost reduction potential (69–72%) is attributable to residential measures, which generally have larger energy savings potential than commercial measures.

The gross benefits discussed above do not account for the costs of the demand-side measures. Under the aggressive benchmark, where technologies with breakthrough cost and performance char-

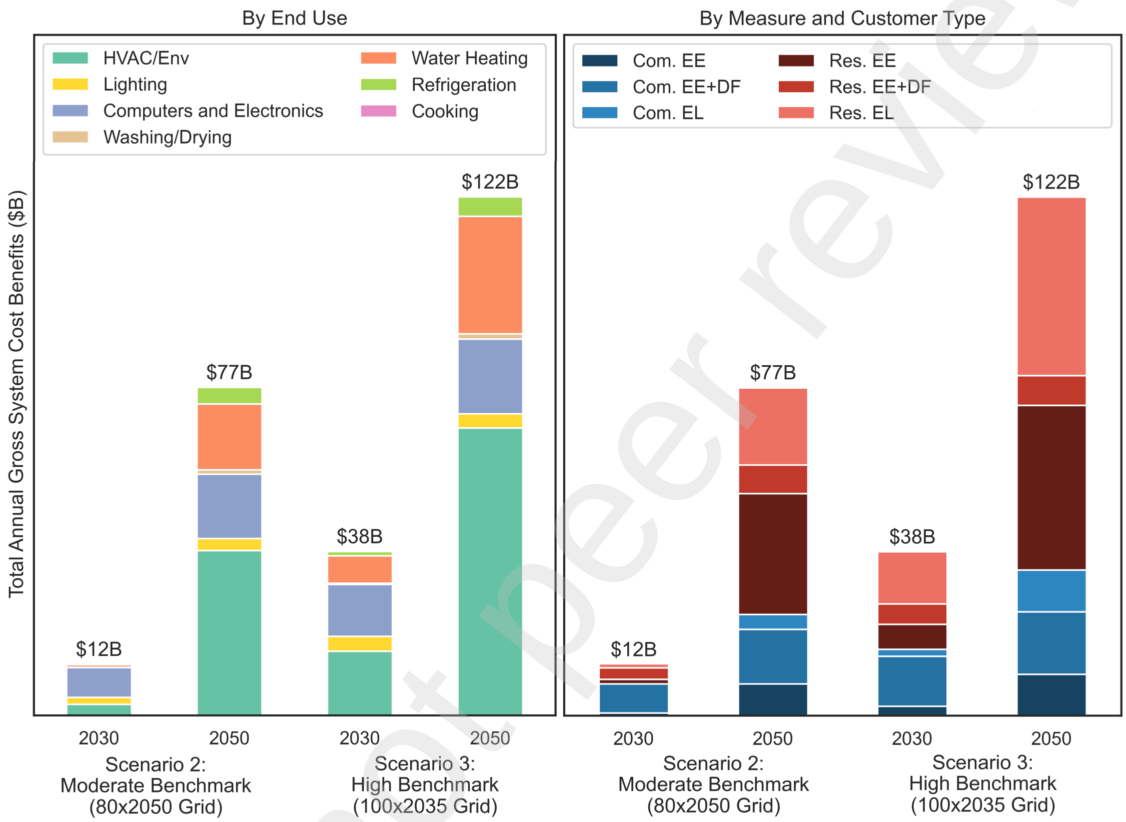

Figure 6: Moderate to aggressive deployment of building efficiency and flexibility measures generates \$77–\$122 billion in annual power system cost savings by 2050, or 39–45% of the incremental cost of additional power supply decarbonization before accounting for the cost of the portfolio of demand-side measures. Gross benefits represent avoided power system generation costs given full deployment of the measure portfolio. Electrification (EL) measure benefits involve switching from an inefficient to an efficient EL measure, yielding positive power system benefits in our analysis. Electrification measures with demand flexibility are included in the EL category. Non-electric measures are excluded from these results, thus excluding natural gas system cost savings.

acteristics are assumed to enter the market earlier, and the total cost of demand-side measure deployment is generally lowest, the total incremental cost of the measure portfolio in 2050 is $136 billion, of which 90% is covered by the $122 billion in system cost savings benefits that the measure portfolio generates. This estimate is strongly influenced, however, by a small portion of measures with high incremental deployment costs that are more than double their benefits (Figure S12). Generally, these high-cost measures are packages of best currently market-available HVAC equipment and envelope efficiency improvements. Excluding this high-cost portion of the measure portfolio retains most of its system cost benefits ($111 billion) but at roughly half the total incremental deployment cost ($73 billion). These findings suggest that initiatives aimed at reducing the incremental costs of installing the highest-performing HVAC and envelope technologies on the market today would be one of the most effective strategies for driving down the overall costs of reducing building electricity demand to support accelerated grid decarbonization.

Discussion

We show that strategic reduction and management of U.S. building energy demand alongside grid decarbonization could sharply decrease building sector CO_2 emissions by mid-century, up to a 91% reduction from 2005 levels. A reduction of this magnitude would avoid nearly one quarter of the annual CO_2 emissions projected for the energy system in 2050 under reference case conditions, more than 1 Gt CO_2 in absolute terms. Moreover, our results demonstrate that demand-side solutions greatly reduce the costs of power sector decarbonization, avoiding up to well over $100 billion per year in power system costs by 2050. There are no "silver bullet" solutions for building decarbonization; rather, large emissions and system cost reductions require a broad focus on measures that improve the efficiency and flexibility of building energy services alongside widespread electrification of fossil-based building loads. Because building end-use electrification can only happen gradually, building efficiency and flexibility are important near-term strategies with substantial contributions to overall reductions in building sector CO_2 emissions and power system costs through 2050. Efficiency and flexibility can also support increased electrification at all scales: at the building scale (e.g., by decreasing the required capacity of electrified heating and water heating equipment); at the distribution scale (e.g., by mitigating new loads that could necessitate infrastructure upgrades); and at the bulk power scale (e.g., by reducing the system peak generation capacity needed to serve electrified end uses).

Our analysis directly represents a heterogeneous portfolio of building solutions and quantifies their individual and collective contributions to energy system CO_2 emissions reductions through mid-century. This approach contrasts markedly with that of previous cross-sectoral decarbonization studies, which tend to reduce building sector decarbonization to aggressive load electrification and lack the detailed, bottom-up treatment of building technology development and deployment dynamics that is needed to guide real-world policy approaches.

While our results encourage more substantive consideration of buildings as a critical demand-side resource for energy system decarbonization, our data also underscore the unprecedented scale and speed with which building technology development and deployment must occur to enable the deepest levels of building sector emissions reductions and power system benefits by 2050. Table 2 shows that in our aggressive benchmark, 97 million fossil-based and resistance furnaces and 139 million fossil-based and resistance water heaters are converted to heat pumps in residences between 2022–2050 — a nearly four- and twelve-fold increase in the deployment of residential air source heat pumps and heat pump water heaters over the reference case, respectively. Commercial heat pumps

Table 2: Achieving the deepest building CO_2 reductions by mid-century requires deployment of high performance building technologies and operational approaches at an unprecedented scale and speed. The actions shown reflect an aggressive benchmark in which building efficiency, flexibility, and electrification are aggressively deployed alongside a power grid that decarbonizes 100% by 2035.

Advancement	Residential			Commercial		
	2030	2050	Annualized △ (2022-2050)	2030	2050	Annualized △ (2022-2050)
Convert fossil-fired and resistance heating/WH equipment to HPs	43M units	236M units	8M units/yr (49% sales)	84 TBtus service demand	740 TBtus service demand	26 TBtus service demand/yr (20% sales)
HPWHs	27M units	139M units	5M units/yr	33 TBtus demand	314 TBtus demand	11 TBtus demand/yr
ASHPs	16M units	97M units	3M units/yr	50 TBtus demand	426 TBtus demand	15 TBtus demand/yr
Envelope retrofits at or above ESTAR/IECC/90.1 levels in the column year	32M homes	105M homes	4 M homes/yr (3% existing homes)	14 Bsf	45 Bsf	1.5 Bsf/yr (1.8% existing sf)
Roofs	32M homes	105M homes	4 M homes/yr	12 Bsf	45 Bsf	2 Bsf/yr
Windows	27M homes	104M homes	4 M homes/yr	14 Bsf	45 Bsf	2 Bsf/yr
Walls* and/or floors	8M homes	32M homes	1 M homes/yr	4 Bsf	17 Bsf	1 Bsf/yr
New building shells constructed at or above ESTAR/IECC/90.1 levels in the column year	10M homes	35M homes	1 M homes/yr (93% new homes)	14 Bsf	62 Bsf	2 Bsf/yr (86% new sf)
Pair new/replacement HVAC equipment w/ advanced controls** that enable demand management	15% of all installed units	75% of all installed units	3% of all installed units	7% of all service demand	53% of all service demand	2% of all service demand
Pair new/replacement lighting and plug load equipment w/ advanced controls** that enable demand management	16% of all installed units	34% of all installed units	1% of all installedunits	27% of all service demand	45% of all service demand	2% of all service demand

*Includes air sealing

**Controls measures at or above the 'Best' performance tier

serve 740 more TBtus of heating and water heating service demand annually by 2050 than in the reference case, an eleven-fold increase. These heat pump deployments occur alongside widespread building shell retrofits to more efficient components — by 2050, 105 million of the homes and 45 billion of the commercial square feet built by 2022 have undergone at least one component retrofit at or above the latest ENERGY STAR/IECC/ASHRAE 90.1 performance levels, implying efficiency retrofit rates of 3% and 1.8% per year, respectively. Another 35 million homes and 62 billion commercial square feet added in 2022 or later are at or above this shell performance tier, or 93% and 86% of new residential and commercial construction over this period, respectively. Finally, advanced controls unlock more efficient and flexible energy management capabilities in many buildings — such controls are deployed with 75% of total residential HVAC units and serve roughly half of total commercial HVAC, lighting, and plug load energy by 2050.

Even if these lofty deployment milestones are achieved, additional advancements will be needed to address building CO_2 emissions that could remain by 2050 — at least 210 Mt CO_2 annually, in our assessment (scenario 3.1). Two possible sources of negative emissions can offset remaining building CO_2 emissions: 1) land use, land-use change, and forestry; and 2) negative emissions technologies (NETs). These negative emissions sources could provide roughly 800 Mt CO_2-eq and potentially up to 500 Mt CO_2 in the U.S., respectively [31, 32]. Allocated proportionally to end-use sector contributions to U.S. greenhouse gas emissions [31], these offsets amount to just over 400 Mt CO_2 for buildings, enough to address the remaining building CO_2 emissions in our most aggressive decarbonization scenarios (3–3.1). However, available offsets will likely need to be weighted towards harder-to-abate energy services such as aviation, long-distance transport, and shipping [33], and large uncertainties concerning the scalability of NETs make them a high-risk bet for building emissions offsets [34]. Blending renewable hydrogen fuel with the U.S. natural gas supply or replacing natural gas with hydrogen entirely could further abate up to 61 Mt CO_2 from U.S. building heating by 2050 [35]. Existing evidence casts doubt on the widespread use of hydrogen heating, however, given disadvantages on economics, efficiency, and resource intensity [36], and hydrogen heating may present particular affordability issues for the customers that are least able to electrify equipment [37].

Our building CO_2 emissions estimates could be affected by further consideration for the fugitive emissions associated with building operations: emissions from leakage of building equipment refrigerants and from methane leaks in the natural gas supplied to buildings. An initial assessment of these two fugitive sources demonstrates that accounting for avoided methane leakage delivers around 1.8–3.5X the CO_2-eq impacts of accounting for refrigerant leakage, resulting in small but notable overall effects on total estimated CO_2-eq emissions reductions (see Supplemental Information Section 3 and Figure S28). This finding is supported by the limited existing literature on this topic [38, 39]; however, such studies concern the individual building scale rather than the stock scale reflected here. Moreover, fugitive emissions estimates may be sensitive to assumptions about reference case developments in equipment refrigerants and considerable uncertainties in estimated methane leakage rates. We consider the estimation of fugitive emissions in buildings, as well as the assessment of embodied emissions generated outside the building operation phase, to be important areas for further analysis.

The U.S transition to a low-carbon energy system is well underway, with energy-related CO_2 emissions having fallen steadily over the past decade. But achieving the deeper levels of emissions reductions targeted by economy-wide decarbonization plans will require a comprehensive mix of solutions addressing both the generation and end uses of energy. Buildings occupy a critical intersection between energy supply and demand and, as such, offer a wide range of opportunities to reduce or enable reductions in U.S. CO_2 emissions. As the power grid decarbonizes, building electrification is a clear strategy for reducing emissions, but building efficiency and flexibility are equally essential, both to limit the scale of the required supply-side transformation and to facilitate high rates of electrification — a true "all-of-the-above" menu of solutions to dramatically reduce CO_2 emissions and address the climate crisis.

Experimental Procedures

Building and grid modeling frameworks

Figure 7 summarizes key data produced by the building and grid models used in this analysis and highlights model linkages. Here we describe the each of these models and their interaction in greater detail.

Scout modeling of the building sector

Building decarbonization solutions are represented using Scout (scout.energy.gov), a hybrid (Q1/Q4 [40]) building stock modeling framework for estimating the short- and long-term annual impacts of energy efficiency, flexibility, and electrification measures on building energy use, CO_2 emissions, and operating costs at the scale of U.S regions or across the U.S. as a whole. Simulations are consistent with Scout v0.7.3 [41]. Here we focus on key elements of Scout's modeling approach for the current

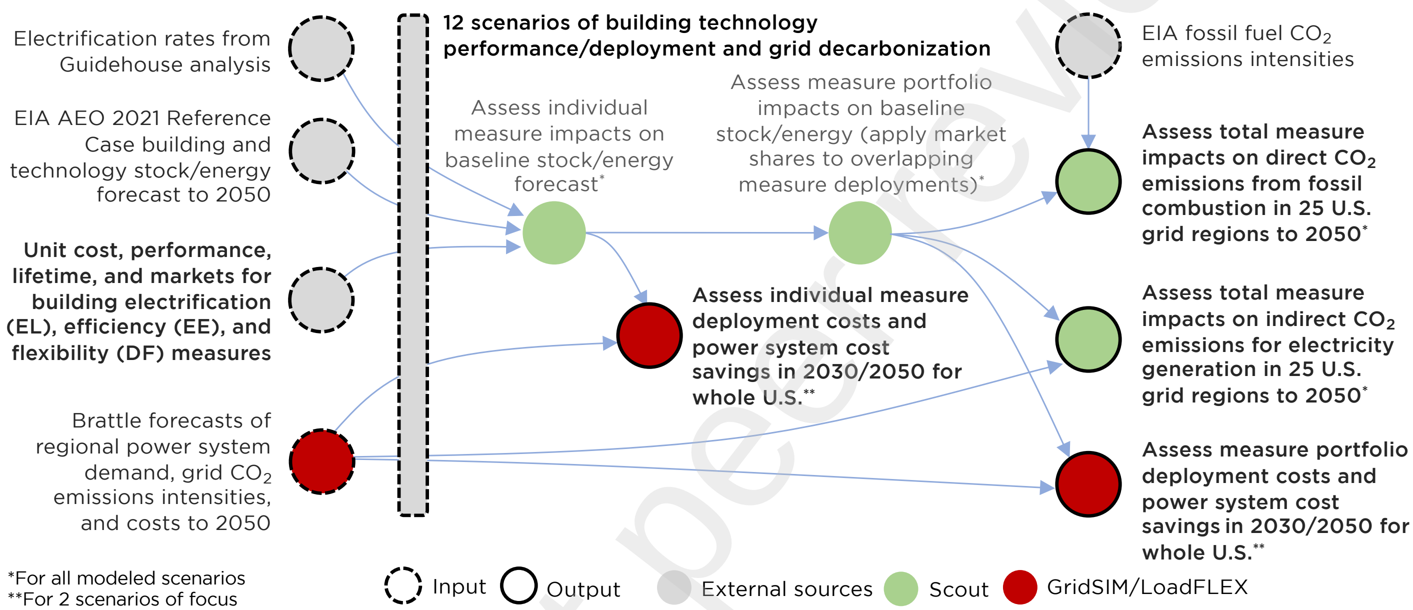

Figure 7: Results are generated through an integrated demand- and supply-side modeling workflow and outputs. Demand-side measures (building efficiency, flexibility, and electrification) are assessed with the Scout model relative to the EIA Annual Energy Outlook 2021 Reference Case forecast from 2022-2050, with rates of building electrification exogenously determined via target scenarios developed in consultation with Guidehouse. Resultant Scout scenario measure costs, hourly system load impacts, and estimates of annual building electricity demand through 2050 are coupled with power sector projections from the GridSIM model to assess measure-level deployment costs, electricity CO_2 emissions reductions, and power system cost reductions. Direct reductions in CO_2 emissions from on-site combustion of fossil fuels are assessed by coupling Scout estimates of annual building fossil fuel demand through 2050 with EIA fossil fuel emissions intensities.

assessment; further details are found in Supplemental Information Section 2.1.1 as well as in the Methods and Supplemental Information of [15] and [42].

Scout analyses are founded on bottom-up representation and aggregation of specific segments of the U.S. building technology stock and its annual energy use, $S_y^{\text{euse-ref}}$, and CO_2 emissions, $S_y^{\text{carb-ref}}$, under reference case building and power sector evolution in each year y between 2022-2050:

$$S_y^{\text{euse-ref}} = \sum_r^R \sum_b^B \sum_f^{F_b} \sum_u^{U_{b,f}} \sum_t^{T_{b,f,u}} \sum_v^V S_{r,b,f,u,t,v,y}^{\text{stk-ref}} I_{r,b,f,u,t,v,y}^{\text{euse-ref}} \tag{1}$$

$$S_y^{\text{carb-ref}} = \sum_r^R \sum_b^B \sum_f^{F_b} \sum_u^{U_{b,f}} \sum_t^{T_{b,f,u}} \sum_v^V S_{r,b,f,u,t,v,y}^{\text{stk-ref}} I_{r,b,f,u,t,v,y}^{\text{carb-ref}} \tag{2}$$

where $S_{r,b,f,u,t,v,y}^{\text{stk-ref}}$ is the stock total for the typical reference case building technology in class t in year y that serves end use u with fuel type f in building type b, vintage v, and region r (e.g., the stock in a "microsegment" of the buildings sector, subsequently denoted by X); $I_{r,b,f,u,t,v,y}^{\text{euse,ref}}$ is the reference case site energy use per unit stock of the given technology microsegment in year y; and $I_{r,b,f,u,t,v,y}^{\text{carb-ref}}$ is the reference case average CO_2 emissions per unit stock deployed in year y (unit energy consumption multiplied by average CO_2 emissions per unit consumption). We draw reference case estimates of building technology stock evolution, unit energy consumption, and CO_2 emissions per unit fossil-based fuel consumption from the 2021 EIA Annual Energy Outlook (AEO) Reference Case [29]; reference case estimates of CO_2 emissions per unit electricity consumption are drawn from the Brattle GridSIM Reference Case (see below for additional details). The region set R is consistent with the 25 EIA Electricity Market Module (EMM) regions [43, 44], with aggregation to 11 higher-level regions for reporting purposes (see Supplemental Information section 2.2) and sets of building types (B), fuel types (F_b), end uses ($U_{b,f}$) and technology types ($T_{b,f,u}$) correspond to those used in the National Energy Modeling System (NEMS) building modules to develop the AEO forecast [43, 44]. The set of building vintages (V) reflects two bins — buildings constructed by 2022 and in 2022 or subsequent years, with associated implications for technology stock turnover calculations (see Supplemental Information section 2.1.1).

Changes in reference case building energy and emissions projections under various scenarios of building decarbonization are assessed at the level of individual building decarbonization measures, each of which is applied to particular segments of the reference case building stock during the year range that the measure is made available to energy consumers. Alternate scenario estimates of energy, $S_{y,m}^{\text{euse-alt}}$, and CO_2 emissions, $S_{y,m}^{\text{carb-alt}}$, are constructed that reflect the effects of measure m deployment through year y on reference case outcomes:

$$S_{y,m}^{\text{euse-alt}} = \sum_r^{R_m} \sum_b^{B_m} \sum_f^{F_{b,m}} \sum_u^{U_{b,f,m}} \sum_t^{T_{b,f,u,m}} \sum_v^{V_m} (S_{X,y}^{\text{stk-ref}} I_{X,y,m,mt}^{\text{euse-alt}} \sigma_{X,y,m} + S_{X,y}^{\text{stk-ref}} I_{X,y}^{\text{euse-ref}} (1 - \sigma_{X,y,m}))\, a_{X,y,m} \tag{3}$$

$$S_{y,m}^{\text{carb-alt}} = \sum_r^{R_m} \sum_b^{B_m} \sum_f^{F_{b,m}} \sum_u^{U_{b,f,m}} \sum_t^{T_{b,f,u,m}} \sum_v^{V_m} (S_{X,y}^{\text{stk-ref}} I_{X,y,mt}^{\text{carb-alt}} \sigma_{X,y,m} + S_{X,y}^{\text{stk-ref}} I_{X,y}^{\text{carb-ref}} (1 - \sigma_{X,y,m}))\, a_{X,y} \tag{4}$$

where region set R_m, building type and vintage sets (B_m and V_m), fuel types ($F_{b,m}$), end uses ($U_{b,f,m}$) and technology types ($T_{b,f,u,m}$) are the subsets of the sets in equations 1 and 2 that measure m applies to (an applicable "market"); $S^{\text{stk}-\text{ref}}_{X,y}$ is a single reference case building stock microsegment from the measure's applicable market in year y; $I^{\text{euse}-\text{ref}}_{X,y}$ and $I^{\text{carb}-\text{ref}}_{X,y}$ are the reference case energy and fuel CO_2 per unit stock deployed as described for equations 1 and 2; $I^{\text{euse}-\text{alt}}_{X,y,m,mt}$ and $I^{\text{carb}-\text{alt}}_{X,y,m,mt}$ are the same for the alternate case deployment of measure m of type mt; $\sigma_{X,y,m}$ is the portion of the reference case stock that has been captured by measure m through year y; and $a_{X,y,m}$ is a market share adjustment that accounts for economic competition between measure m, the reference case counterfactual technology, and any other alternate scenario measures that provide the same energy service through year y (see Supplemental Information section 2.1.1 for additional details on handling of stock turnover and overlaps across measures). Note that setting the $\sigma_{X,y,m}$ term in equations 3 and 4 to zero produces reference case counterfactual results at the measure level, $S^{\text{euse}-\text{ref}}_{y,m}$ and $S^{\text{carb}-\text{ref}}_{y,m}$, which are compared against the results of equations 3 and 4 to assess measure-specific energy and CO_2 impacts.

To facilitate representation of a wide range of building decarbonization solutions, the per-unit energy consumption and CO_2 emissions terms in equations 3 and 4, $I^{\text{euse}-\text{alt}}_{X,y,m,mt}$ and $I^{\text{carb}-\text{alt}}_{X,y,m,mt}$, are dependent on the measure type mt, and are calculated as follows:

$$I^{\text{euse}-\text{alt}}_{X,y,m,mt} = \begin{cases} I^{\text{euse}-\text{ref}}_{X,y}\, RP^{\text{euse}-\text{ann}}_{X,y,m}, & mt \in [EE, EL] \\ I^{\text{euse}-\text{ref}}_{X,y}\, RP^{\text{euse}-\text{tvar}}_{X,y,m} & mt \in [EE+DF, EL+DF] \end{cases} \tag{5}$$

$$I^{\text{carb}-\text{alt}}_{X,y,m,mt} = \begin{cases} I^{\text{carb}-\text{ref}}_{X,y}\, RP^{\text{euse}-\text{ann}}_{X,y,m}, & mt = EE \text{ or } mt = EL \text{ and } f \in X = \textit{electric} \\ I^{\text{carb}-\text{ref}}_{X,y}\, RP^{\text{euse}-\text{ann}}_{X,y,m}\,(\tau^{\text{alt}}_{r,f=elec,y}/\tau^{\text{ref}}_{r,f\in X,y}), & mt = EL \text{ and } f \in X \neq \textit{electric} \\ I^{\text{carb}-\text{ref}}_{X,y}\, RP^{\text{carb}-\text{tvar}}_{X,y,m} & mt \in [EE+DF, EL+DF] \end{cases} \tag{6}$$

where $RP^{\text{euse}-\text{ann}}_{X,y,m}$ and $RP^{\text{euse}-\text{tvar}}_{X,y,m}$ both denote the unit-level site energy consumption of measure m in year y relative to the counterfactual reference case technology that provides the same energy service[1], but the former is calculated using annual energy performance metrics (e.g., COP, EF, annual consumption ratios, etc.) while the latter accounts for time-varying relative energy performance across all hours in a year; $RP^{\text{carb}-\text{tvar}}_{X,y}$ is interpreted in the same manner as $RP^{\text{euse}-\text{tvar}}_{X,y}$ but for relative CO_2 emissions per unit instead of energy use; $\tau^{\text{ref}}_{r,f\in X,y}$ and $\tau^{\text{alt}}_{r,f=elec,y}$ are average annual CO_2 intensities for the reference case technology fuel type ($f \in X$) and electricity ($f = elec$), respectively, for a measure m that electrifies building loads ($mt = EL$) in region r and year y. The time-varying energy and CO_2 performance terms in equations 5–6 ($RP^{\text{euse}-\text{tvar}}_{X,y}$ and $RP^{\text{carb}-\text{tvar}}_{X,y}$) address measures with demand flexibility (DF) features that non-uniformly shed and/or shift building loads across time. Further details on the hourly load calculations for such measures are available [15] and hourly emissions and consumer cost calculations are further detailed in Supplemental Information section 2.1.3.

Equation 6 assesses each measure's CO_2 per unit stock $I^{\text{carb}-\text{alt}}_{X,y,m,mt}$ relative to a counterfactual term $I^{\text{carb}-\text{ref}}_{X,y}$ that reflects reference case fuel CO_2 intensities. In the case of a microsegment X

[1] Reference case technology performance characteristics are drawn from NEMS files "rsmeqp.txt" and "rsmlgt.txt" for residential non-lighting and lighting equipment, respectively, and from "ktek.csv" for commercial technologies; more details about these files are available in the EIA National Energy Modeling System documentation for buildings [44, 43]. Technology characteristic data for envelope and miscellaneous technologies are separately developed for Scout and are available: `https://github.com/trynthink/scout/blob/master/cpl_envelope_mels.json`

with an electric fuel type f, this effectively stages the CO_2 impacts of reductions in electricity consumption from demand-side measures *before* the impacts of additional grid decarbonization beyond the reference case. This approach differs from most previous cross-sectoral decarbonization studies[2], which tend to attribute reductions in existing electric CO_2 emissions to the power sector, thus precluding any CO_2 impacts from building electric efficiency. For electrification (EL) measures, the CO_2 impacts of changing from a fossil-based fuel and equipment type to electric equipment are assessed in parallel with grid decarbonization and attributed to the measure via the CO_2 intensity ratio ($\tau^{\text{alt}}_{r,f=elec,y}/\tau^{\text{ref}}_{r,f\in X,y}$). For non-electrification measures, the same ratio is applied to any reference case electricity that remains after measure deployment to account for the impacts of additional grid decarbonization on building CO_2 emissions.

Finally, alternate scenario energy and CO_2 results at the measure-level are aggregated across the full measure portfolio M to develop national-scale energy and CO_2 emissions time series from 2022-2050, $S_y^{\text{euse}-\text{alt}}$ and $S_y^{\text{carb}-\text{alt}}$, that can be directly compared against the reference case estimates of equations 1 and 2:

$$S_y^{\text{euse}-\text{alt}} = \sum_m^M S_{y,m}^{\text{euse}-\text{alt}} \quad (7) \qquad\qquad S_y^{\text{carb}-\text{alt}} = \sum_m^M S_{y,m}^{\text{carb}-\text{alt}} \quad (8)$$

While equations 1–2 and 7–8 focus on the whole U.S. buildings sector, other aggregations of the results to the regional level or across subsets of building types, fuel types, and measures are enabled by the bottom-up approach that is used to construct these high-level energy and emissions estimates.

GridSIM and LoadFlex modeling of the power sector

Power system outcomes are modeled with GridSIM [28], a proprietary long-term power system simulation and capacity expansion model developed by The Brattle Group. GridSIM analyzes how clean energy policies and technological change will affect future power system outcomes, particularly in high-renewable futures, over a multi-decade planning horizon. Like other expansion models, GridSIM identifies the cost-minimizing generation capacity expansion plan and accompanying power system operations, given information about existing power generation and transmission, and expectations about electricity demand, technology costs, fuel prices, and environmental policies, among other considerations.

GridSIM models electricity demand on a chronological hourly basis, so that storage can be scheduled and traditional generation can be committed to balance variable wind and solar output. This is necessary for representing the value of each technology and developing a credible investment trajectory in a high-renewable future.

Additionally, GridSIM incorporates how the effective load carrying capability (ELCC) of each type of variable wind and solar resource is likely to decline in the future with increasing penetration. It incorporates declining ELCC curves, accounting for correlated generation profiles and their coincidence with peak net loads. This, along with the chronological operations representation described above, enables GridSIM to project a realistic generation build mix and associated marginal costs. Table 3 summarizes key methodological elements of the GridSIM modeling framework as it was applied in this study, and further details are provided in Supplemental Information Section 2.2.1.

Brattle's LoadFlex model [50] is used in conjunction with GridSIM to calculate the economic benefits of measures with demand flexibility features at the grid level. LoadFlex simulates the

[2] A notable exception is [45], which also effectively assesses the emissions impacts of demand-side efficiency before the impacts of additional decarbonization of the electricity supply.

Table 3: Summary of key GridSIM modeling elements as applied in the current analysis.

Input	**Summary**
Geographic scope and resolution	Contiguous U.S., 25 EIA Electricity Market Module (EMM) regions [30].
Temporal scope and resolution	Annual results are forecasted between 2020 and 2050 in 5 year increments. Within a given projection year, GridSIM utilizes a "typical days" representation of hourly load conditions, which is a common approach for capacity expansion models. The 365 days of the year are clustered based on similarities in daily load level and hourly shape. Reducing the number of days modeled to a subset based on these representative clusters allows the model to capture the full range of load and renewable generation conditions that are necessary to consider from a planning standpoint, while keeping the model runtime manageable. Using typical days also allows the model to retain intra-day hourly chronology, which is important to accurately account for the impact of the hourly profiles of demand-side efficiency, flexibility, and electrification programs.
Load forecast	Reference case: Annual electricity projections are based on regional peak demand and energy forecasts from the 2021 AEO Reference Case [29]. Current load shapes are based on aggregated 2020 hourly utility load data from the FERC 714 dataset [46], with modifications to account for changes in the annual load factor implied in the AEO growth rates. Decarbonization scenarios (2 and 3): Additional incremental load is assumed to represent electrification of the transportation and buildings sectors. Elevated growth in transportation demand assumes that 95%, 50%, and 35% of light-duty, medium-duty and heavy-duty vehicles are electric by 2050, respectively. Elevated growth in building demand is consistent with deployment of the measure set assumed in this study's inefficient electrification scenario (1.1) at the electrification rate assumed for the given decarbonization scenario, which results in up to a 23% increase over reference building annual electricity demand by 2050 in the high decarbonization benchmark scenario (3).
Existing unit characteristics	The assumed capacity, heat rate, location, fixed O&M, and variable O&M of existing generation is based on assumptions in the 2021 AEO. Planned retirements of existing units are based on documentation of NREL's ReEDS model (Version 2019) [47].
New generator costs	Capital, variable O&M, and fixed O&M costs are based on the Moderate Case in NREL's 2021 Annual Technology Baseline [48].
Fuel prices	Near-term fuel prices are based on forward market data (where available), and blended to the long-run fuel price trajectory from the 2021 AEO.
Transmission	Transmission capability in GridSIM is represented as a "pipe and bubble" framework which aggregates transmission capacity into larger "pipes" between load and generation "bubbles" as defined by 25 EIA EMM regions. Transmission capacity is based on the 2021 AEO Reference Case [29]. Like most bulk system capacity expansion models, GridSIM does not model the distribution system.

hours of dispatch for each flexibility measure that maximize economic benefits across energy and generation capacity. If, on any day, shifting a measure's load from its baseline would result in a net increase in system costs rather than a reduction, the measure is not dispatched (i.e., no load is shifted from baseline). The dispatch of each measure is constrained by the physical behavior of each measure at the building level as represented in Scout; these constraints are further described in Supplemental Information Section 2.2.1.

Building–grid model coupling

Building and grid models are loosely coupled via a one-way exchange of data between GridSIM and Scout that occurs in both directions without any real-time feedback. Regarding the former, GridSIM projections establish reference and alternative scenario values for the CO_2 intensity of the building electricity supply, which are used to calculate the CO_2 per unit stock terms in equations 2 and 4. Regarding the latter, GridSIM estimates of power system costs are adjusted to reflect Scout estimates of hourly electricity demand impacts from building efficiency, flexibility, and efficient electrification deployment at the grid region level in a given year, taking into account seasonal changes in load shapes, $\Delta D_{r,y,h,m,mt}$:

$$\Delta D_{r,y,h,m,mt} = (D^{ref}_{r,y,h,m,mt} - D^{alt}_{r,y,h,m})\, a_{r,y,m} \tag{9}$$

where $D^{ref}_{r,y,h,m,mt}$ is the reference case electricity demand profile of all stock segments affected by measure m of type mt in grid region r, projection year y and hour h, $D^{alt}_{r,y,h,m}$ is the same profile after measure m is deployed in isolation (e.g., considering only the measure's unit-level impacts on load and baseline stock turnover across the grid region), and $a_{r,y,m}$ is a market share adjustment that accounts for competition between measure m and other technologies that provide the same end use service in region r through year y. The latter term in equation 9 enables aggregation of measure-level impacts across a full portfolio; excluding this term yields results for individual measures, before considering aggregation and competition across a portfolio.

The calculation of the reference case term $D^{ref}_{r,y,h,m,mt}$ in equation 9 differs by measure type mt. For efficiency and flexibility measures, the calculation bases reference case electricity demand on that of the appropriate counterfactual technology or technologies from the AEO forecast. For electrification measures, an "inefficient" electrification counterfactual is developed that assumes the deployment of a substantial mix of electric resistance heating and water heating alongside heat pumps to fulfill the added electric service. Settings for the inefficient counterfactual measures are consistent with those from scenario 1.1 in Table 4 and are described further in the next section.

Measure-level results from equation 9 are multiplied by GridSIM's marginal cost forecasts for each grid region and summed across all hours of the year, regions, and measures to develop portfolio-level estimates of avoided system cost benefits in year y, ΔB_y:

$$\Delta B_y = \sum_{m}^{M} \sum_{r}^{R_m} \sum_{h=1}^{8760} \Delta D_{r,y,h,m,mt}\, M_{r,y,h} \tag{10}$$

where $M_{r,y,h}$ is the GridSIM marginal system cost forecast (2020$/MWh) for region r, projection year y, and hour of the year h, and system costs are inclusive of energy, capacity (generation/transmission), and, if applicable, renewable energy credits (RECs) but do not include distribution costs. To ensure internal consistency between the avoided system cost estimates and the treatment of electrification load impacts in equation 9 as incremental to an inefficient electrification reference, the added regional electricity demand from inefficient electrification is reflected in the GridSIM capacity expansion forecast that determines the marginal system costs $M_{r,y,h}$ of equation 10. Additional details on GridSIM's marginal cost outputs are available in Supplemental Information Section 2.2.2.

Finally, incremental measure deployment costs are calculated to enable direct comparisons between measure costs and benefits. As with system cost savings, incremental costs are calculated first at the measure-level, and then aggregated to a portfolio-level estimate in year y, ΔC_y:

$$\Delta C_y = \sum_{m}^{M} \Delta I_{y,m}\, CRF_m\, S_{y,m}^{\text{stk-ref}} \sigma_{y,m}\, a_{y,m}, \tag{11}$$

$$CRF_m = \frac{i\,(1+i)^l}{(1+i)^l - 1} \tag{12}$$

where $\Delta I_{y,m}$ is the incremental, unit-level installed cost of measure m in 2020\$ compared with a counterfactual reference case technology in year y, CRF_m is a capital recovery factor that annualizes incremental measure costs using the assumed real interest rate $i = 8\%$ and measure lifetime l, $S_{y,m}^{\text{stk-ref}}\,\sigma_{y,m}$ is the total portion of applicable reference case stock that the measure captures through year y before competition, and $a_{r,y,m}$ adjusts for competition of measure m with other measures in the portfolio.

Building decarbonization scenarios

Table 4 details the 12 scenarios considered in this study along with key modeling assumptions. Individual scenarios are distinguished by the three demand-side measure features introduced previously — energy efficiency (EE), load electrification (EL), and demand flexibility (DF) — and by four input dimensions that span both the demand- and supply-side of building energy use:

- Market-available technology performance range: the energy performance levels of building technologies available for purchase by end-use consumers, bounded by a minimum performance "floor" and a maximum performance "ceiling". DF measure features are integrated with a subset of EE measures, and thus the level of DF deployment depends on scenario settings for the EE dimension.
- Electrification of building loads: the rate at which fossil-based equipment is converted to electric service via EL measures, and the efficiency level of the converted equipment. As with the market-available technology performance range dimension, DF features are integrated with a subset of EL measures.
- Early retrofits: a small but increasing fraction of consumers that choose to replace existing building equipment and/or shell components before the end of their useful lifetimes.
- Power sector: the annual average CO_2 emissions intensity of the electricity supplied to the buildings sector across the modeled time horizon (2022-2050).

Here we elaborate on the measure features and input dimensions that distinguish our modeling scenarios.

Table 4: Summmary of modeling scenarios and key assumptions. Scenarios are differentiated by the degree of demand-side building efficiency, flexibility, and electrification deployment as well as by the degree of decarbonization of the electricity supplied to buildings. Three benchmark scenarios are highlighted in gray; remaining scenarios in each group are used to explore key sensitivities relative to the benchmarks.

Scenario	Scenario Narrative	Market-Available Technology Performance Range			Electrification of Load		Early Retrofits	Power Grid
		Raise Floor	Raise Ceiling	Additional Efficiency not in Ref. Case*	Switching Rate	Efficiency Level		
1: Low Benchmark (BM), High EL to HPs under reference grid	**Decision-makers use regulations and market-based instruments to dramatically accelerate electrification (EL) to heat pumps (HPs), but progress on electric grid decarbonization stalls, leaving the power sector short of full decarbonization by 2050.**	N/A			Guidehouse Most Aggressive (see Table 6 for details)	Switch to HPs (mix of HP performance levels depends on EE column settings)	N/A	GridSIM Reference Case
1.1: Low BM w/o efficient EL	Consumers are not pushed to switch to heat pumps and a substantial amounut of additional electric resistance heating and water heating is deployed.					Switch to BAU sales mix of HPs/resistance (53% HPs/47% resistance res.heating, 9%/91% res. water heating, 56%/44% com. heating, 4%/96% com. water heating)		
2: Moderate BM, Modest EE and EL to HPs under 80x2050 grid	**Decision-makers rely mostly on market-based instruments to moderately increase deployment of energy efficient technology (EE) and EL to HPs; the power sector continues to decarbonize rapidly, but some electricity emissions remain in 2050.**	Moderate (elevated codes and standards take effect in 2030)	Moderate (breakthrough tech. enters market in 2035)	Represented (Additional HVAC, lighting, and plug load controls; efficient window and roof replacements)	Guidehouse Optimistic (see Table 6 for details)	Switch to HPs		Moderate (80% reduction in grid emissions from 2005 levels by 2050)
2.1: Moderate BM w/ early retrofits	A small but increasing percentage of consumers chooses to replace equipment and/or certain building shell components before the end of their useful lifetimes.						Represented (see Table 7 for details)	
2.2: Moderate BM w/o breakthrough EE	Efficient technologies with very high performance and low cost characteristics never materialize on the market.		N/A				N/A	
2.3: Moderate BM w/o breakthrough EE or elevated codes & stds.	Failure to implement codes and standards that raise the market-available technology performance floor to the latest ESTAR/IECC/90.1 levels.	N/A						
2.4 Moderate BM w/o EE	No additional near-term deployment of efficiency beyond the reference case (e.g., no envelope upgrades in existing homes, no deployment of advanced controls).			N/A				
3: Aggressive BM, High EE and EL to HPs under 100x2035 grid	**Decision-makers use both regulations and market-based instruments to dramatically accelerate deployment of EE and EL to HPs, while the grid fully decarbonizes well before mid-century.**	Aggressive (elevated codes and standards take effect in 2025)	Aggressive (breakthrough tech. enters the market in 2030)	Represented	Guidehouse Most Aggressive			Aggressive (100% zero-carbon grid by 2035)
3.1: Aggressive BM w/ early retrofits	See 2.1.						Elevated	
3.2: Aggressive BM w/o breakthrough EE	See 2.2.		N/A				N/A	
3.3: Aggressive BM w/o breakthrough EE or elevated codes & stds.	See 2.3.	N/A						
3.4: Aggressive BM w/o EE	See 2.4.			N/A				

*Ref. Case = AEO 2021 Reference Case projections

Scenario measure features

The EE, EL, and DF measure features considered in this study represent, respectively: persistent reductions in equipment energy use (e.g., via installation of a higher-performance device) or in the demand for energy services (e.g., via improved building envelopes or operational controls); conversions of fossil-based heating, water heating, and cooking to electric service; and load shedding and shifting in response to grid needs. Measure features are sometimes mixed; for example, heat pump electrification (EL) measures or more efficient electric equipment (EE) measures can be scheduled to operate in off-peak hours on the grid in a given region to increase demand-side flexibility (DF). In each modeled year, measures compete for market share across four tiers of energy performance:

- Tier 0: AEO 2021 Reference Case counterfactual technologies, which reflect the sales-weighted average technology in the AEO forecast;
- Tier 1: Market-available technologies that meet the latest ENERGY STAR, IECC, or ASHRAE 90.1 performance guidelines in the projection year [51, 52, 53];
- Tier 2: The best performing technologies currently available on the market; and
- Tier 3: Breakthrough technologies with aggressive cost and performance targets that are assumed to be achieved at scale by the time of market entry in a future year.

While EE and EL measure features are represented across all four performance tiers, DF features are restricted to the best available performance tier (Tier 2). This restriction simplifies the handling of DF features in the analysis and reflects the assumption that such features are most likely to be packaged with higher-end technology offerings. Moreover, cost and performance characteristics for Tier 1 and 2 technologies are modified over time as needed to maintain a consistent incremental cost and performance difference from their Tier 0 counterfactuals across the model time horizon. Where possible, measure unit-level installed cost, performance, lifetime, and market/market entry settings are drawn from previous buildings sector analyses [42, 15] and updated to reflect the latest expectations and ambitions for building technology development. Table 5 outlines key data sources for these inputs at each measure tier and Table 6 includes detailed input values for key envelope, HVAC, and water heating measures across each of the tiers. Detailed inputs are also separately available for the core set of 170 individual building measure definitions used in scenario runs [54].

Table 5: Summary of building decarbonization measure energy performance tiers and key input data sources.

<table>
<tr><th rowspan="2">Measure performance tier</th><th rowspan="2">Features assessed</th><th rowspan="2">Market entry year</th><th colspan="2">Key data sources</th></tr>
<tr><th>Performance</th><th>Cost</th></tr>
<tr><td>0: AEO Reference Case counterfactual technologies</td><td>EL*</td><td rowspan="3">2022</td><td colspan="2">AEO 2021 Reference Case forecast [29]</td></tr>
<tr><td>1: Currently available ESTAR/IECC/90.1</td><td>EE, EL</td><td>Latest ENERGY STAR specifications [51]; IECC 2021 [52]; 90.1-2019 [53]</td><td>EIA equipment cost forecasts (major end use equipment) [55]; NREL Residential Measures Database (residential envelope) [56]; RS Means (residential/commercial envelope) [57]; Guidehouse Grid-Interactive Efficient Building (GEB) Technologies Data Report (plug loads) [58]</td></tr>
<tr><td>2: Currently best available on the market</td><td>EE, DF, EL</td><td>GEB Roadmap and underlying measure potential analysis (all EE+DF measures) [16, 15]; EIA equipment performance forecasts (major end use equipment EE) [55]</td><td>EIA equipment cost forecasts (major end use equipment EE cost component) [55]; Guidehouse GEB Technologies Data Report (DF cost component of all EE+DF measures, EE cost component for plug loads measures) [58]; NREL Residential Measures Database (envelope) [56]</td></tr>
<tr><td>3: Prospective cost and performance targets</td><td>EE, EL</td><td>2030 (high); 2035 (moderate)</td><td colspan="2">DOE BTO Roadmaps [59] or targets based on highest potential performance level when recent Roadmap is unavailable**</td></tr>
</table>

*When on the market, reference case heat pumps and/or a mix of reference case heat pumps and reference case electric resistance (for inefficient EL scenario 1.1) are subject to the same Guidehouse electrifcation rates as electrification measures in higher performance tiers; such reference case electrification technologies represent an efficiency gain over comparable fossil-based equipment.

**Relevant in particular to HVAC, water heating, and refrigeration technologies. For these technologies, an aggressive performance target is established for the market entry year using the high-end of currently market-available technologies as a benchmark; an installed cost is then calculated using Scout given this performance level to meet a 5 year consumer payback period. This process is consistent with that used to develop cost and performance targets in existing BTO Roadmaps, such as those for Windows & Envelope and Sensors & Controls. For ASHPs, separate cost targets are calculated in cold climates vs. non-cold climates; all HP targets are all based on a fuel switching context in which the HP is replacing fossil-based heating/water heating equipment.

Table 6: Detailed measure settings for residential and commercial envelope, HVAC, and water heating solutions across performance tiers.

Measure	Performance Tier	Affected Markets	Market Entry Year	Building Type	Energy Performance	Installed Cost
Reference case ASHP (EL)	0	All unitary fossil-based HVAC equipment*, associated envelope (EL, EL+DF); All electric resistance or air source heat pump HVAC equipment, associated envelope (EE, EE+DF)	2022	Residential	4.63 COP (cooling), 2.58 COP (heating)	$5150/unit (new homes); $9150-10150/unit (existing homes)
				Commercial	3.4 BTU out/BTU in	$141/kBtu/h cooling
ESTAR ASHP, 90.1/IECC Envelope (EL, EE)	1			Residential	Equipment: 4.69 (cooling), 2.70 (heating) Envelope components: R-2.5-3.7, 0.25-0.4 SHGC (windows); R-15-25 (walls); R-47-60 (roofs); R-15-31 (floors); 5 ACH (air sealing)	Equipment: $6100/unit (new homes); $11100/unit (existing homes) Envelope components: $48/ft^2 glazing (windows); $8.9/ft^2 wall (walls); $2.1/ft^2 roof (roofs); $5/ft^2 footprint (floors); $0-$1.2/ft^2 wall (new-existing air sealing)
				Commercial	Equipment: 3.4 BTU out/BTU in Envelope components: R-2.25-2.98 (windows); R-16.8-25.3 (walls);R-0-19.6 (floors); R-25-31 (roofs); 0.4 CFM/ft^2 @ 0.3 in. w.c. (air sealing)	Equipment: $141/kBtu/h cooling Envelope components: $56.2/ft^2 glazing (windows); $27.4/ft^2 wall (walls); $5/ft^2 footprint (floors); $6.3/ft^2 roof (roofs); $0-$0.9/ft^2 wall (new-existing air sealing)
Best Available ASHP, Envelope (EL+DF, EE+DF)	2			Residential	EL, EL+DF: consistent with residential ASHP + envelope/pre-cooling load savings shape from [15] with additional efficiency bump to 4.55 COP (cooling) and 1.88 COP (heating) to account for change from fossil to typical** electric equipment (relative to which the savings in [15] are assessed) EE, EE+DF: consistent with residential ASHP + envelope/pre-cooling load savings shape from [15]	Equipment: $6357/unit (new homes); $11357/unit (existing homes) Envelope components: $57/ft^2 glazing (windows); $10.8/ft^2 wall (walls); $4.5/ft^2 roof; $5-6.8/ft^2 footprint (new-existing floors); $0.31-$2/ft^2 wall (new-existing air sealing)
				Commercial	EL, EL+DF: consistent with commercial HVAC + envelope/pre-cooling load savings shape from [15] with additional efficiency bump to 4.13 COP (cooling) and 2.32 COP (heating) to account for change from fossil to typical** electric equipment (relative to which the savings in [15] are assessed) EE, EE+DF: consistent with commercial HVAC + envelope/pre-cooling load savings shape from [15]	Equipment: $178/kBtu/h cooling Envelope components: $56.2/ft^2 glazing (windows); $37-41.8/ft^2 wall (walls); $7/ft^2 roof (roofs); $10-11.9/ft^2 footprint (floors); $0.46-$2.2/ft^2 wall (new-existing air sealing)
Prospective ASHP, Envelope, Controls (EL, EE)	3	All fossil-based HVAC equipment***, associated envelope (EL, EL+DF); All electric resistance or air source heat pump HVAC equipment***, associated envelope (EE, EE+DF)	2030/2040 (equipment and windows/all other envelope, high); 2035/2040 (equipment and windows/all other envelope, moderate)	Residential	Equipment: 12 COP (cooling), 6 COP (heating) Envelope components: R-13, 0.09 SHGC cooling (windows); +R-40 (walls add-on); R-15-31 (floors); 1 ACH (air sealing) Controls: 30% heating and cooling savings*****	Equipment: $5520/unit (non-cold climates); $6223/unit (cold climates) Envelope components: $55/ft^2 glazing (windows), $0.75/ft^2 wall (walls add-on); $0.79/ft^2 footprint (floors); $0.9-$1.2/ft^2 wall (new-existing air sealing) Controls: $0.5/ft^2 floor*****
				Commercial	Equipment: 12 COP (cooling), 6 COP (heating) Envelope components: R-10, 0.09 SHGC cooling (windows); +R-40 (walls add-on); +R-50-64 (roofs add-on); 0.2 CFM/ft^2 @ 0.3 in. w.c. (air sealing) Controls: 30% HVAC savings	Equipment: $51/kBtu/h cooling (non-cold climates); $41 kBtu/h cooling (cold climates) Envelope components: $66/ft^2 glazing (windows); $1.9/ft^2 wall (walls); $0.55/ft^2 roof (roofs); $0.16-$0.53/ft^2 wall (new-existing air sealing) Controls: $1/ft^2 floor
ESTAR HPWH (EL, EE)	1	All fossil-based storage water heating equipment (EL, EL+DF); All electric storage water heating equipment	2022	Residential****	EL, EL+DF: 3.30 UEF (new homes); 2.2 UEF (existing homes, which assumes integrated 120V to avoid panel upgrade) EE, EE+DF: 3.30 UEF	$2075/unit
Best Available HPWH (EL+DF, EE+DF)	2			Residential	EL, EL+DF: consistent with HPWH load savings shape from [15] with additional efficiency bump to 1.13 UEF to account for change from fossil to typical** electric equipment (relative to which the savings in [15] are assessed) EE, EE+DF: consistent with HPWH load savings shape from [15]	$2756/unit
				Commercial****	3.9 BTU out/BTU in	$299/kBtu/h water heating
Prospective HPWH (EL, EE)	3		2030 (high); 2035 (moderate)	Residential	3.55 UEF	$2266/unit
				Commercial	3.9 BTU out/BTU in	$33/kBtu/h water heating

*Excludes large commercial boiler/chiller configurations.

**Per market share-weighted electric equipment performance from AEO 2021 Reference Case forecast.

***Assumes prospective breakthrough ASHP technology is able to serve large commercial heating and cooling needs; prospective residential controls measures are limited to single and multi-family homes, and prospective commercial controls measures are limited to offices, schools, food service, and retail buildings.

****ESTAR residential HPWH and Best commercial HPWH settings are consistent with Reference Case HPWH performance.

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Scenario input dimensions

The settings for four key input dimensions distinguish the 12 scenarios outlined in Table 4: market-available technology performance range, rate and efficiency of load electrification, early retrofit assumptions, and degree of power grid decarbonization.

A scenario's market-available technology performance range denotes the lowest and highest–performing technologies made available to consumers in a given year (the bounding technology performance "floor" and "ceiling"). In our scenarios, the technology performance floor is represented by either Tier 0 or 1 technologies, depending on assumptions about building performance codes and appliance efficiency standards. When more aggressive codes and standards are not assumed (scenarios 1-1.1, 2.3-2.4, 3.3-3.4), the technology floor is set to the Tier 0 level, consistent with the reference case counterfactual technology. Scenarios that assume enactment of more aggressive codes and standards by a certain year (2-2.2, 3-3.2) remove the Tier 0 technologies from market competition in that year and set the performance floor to be consistent with Tier 1 technologies for the remainder of the modeling time horizon. Similarly, the technology performance ceiling is represented by Tier 2 or 3 technologies, depending on assumptions about the introduction of technologies with breakthrough cost and performance characteristics. When breakthrough technology introduction is not assumed (scenarios 1-1.1, 2.2-2.4, 3.2-3.4), the technology performance ceiling is set to Tier 2; otherwise, the ceiling is set to Tier 3 beginning in the year that breakthrough technology introduction is assumed (as in scenarios 2-2.1 and 3-3.1). Step changes in both the technology performance floor and ceiling are implemented on a technology class-by-class basis but are reflected globally across all building energy segments that associate with the technology class.

Rates of building heating, water heating, and cooking load electrification are exogenously specified based on a separate analysis conducted in consultation with Guidehouse. The analysis pairs Guidehouse's expert judgement of HVAC and water heating market characteristics and key adoption drivers and barriers with an assessment of equipment stock turnover and shipments to develop four plausible scenarios of conversions from fossil-based to electric equipment in the residential and commercial heating and water heating sub-sectors. The Guidehouse conversion scenarios demonstrate differing degrees of movement in annual sales towards heat pumps by a given year under varying assumptions about federal and utility incentives, state and local restrictions, and product innovations (see Table S1). Conversion rates are distinguished by region, building type, fuel, equipment type and scenario, as shown in Figures S14-S17 for the two electrification scenarios adapted for our analysis, "Optimistic" (used in scenarios 2-2.4) and "Most Aggressive" (used in scenarios 1-1.1 and 3-3.4). The weighted average national heat pump sales shares as a portion of total unitary AC plus heat pump and total storage water heater sales are shown in Table 7, which provides values assumed in other recent studies for context. We also assume natural gas cooking conversions, which were not assessed in the Guidehouse analysis; here, we set conversion rates to the values developed for the heating end use on the recommendation of the Guidehouse analysts. Further details about the conversion rates and adaptation of the Guidehouse analysis are available in Supplemental Information section 2.1.2.

Electrification conversions generally occur with high efficiency in our scenarios, as fossil-based heating and water heating equipment moves to air source heat pumps and heat pump water heaters, respectively. Ground-source heat pump (GSHP) adoption is represented at AEO 2021 Reference Case levels across all scenarios. In scenario 1.1., we explore the implications of "inefficient" electrification of heating and water heating, where fossil-based equipment is converted to a mix of heat pumps and electric resistance heating and water heating. The share of heat pumps vs. resistance in the technology mix is consistent with AEO 2021-forecasted electric equipment sales shares in

Table 7: Comparison of the Guidehouse 2030 and 2050 heat pump sales shares consistent with the electrification rates assumed in this study against 2019 heat pump sales shares and heat pump sales shares assumed in other recent decarbonization studies that addressed the buildings sector. Guidehouse heating sales shares are relative to total sales of unitary AC equipment plus heat pumps; rates for comparable studies are typically relative to total heating equipment sales. Sales shares are exclusive to heat pumps and do not include electric resistance technologies.

Sub-sector	2019 US HP Sales Market Share*	Guidehouse				USF, Evolved Energy, LBNL [22]		Energy Innovation [23]		Princeton [21]		ACEEE [19]	
		Optimistic		Most Aggressive		BASE 350		NDC Pathway		E+		NREL EFS High	
		2030	2050	2030	2050	2030	2050	2030	2050	2030	2050	2030	2050
Residential heating	37%	50%	76%	75%	90%	60%	85%			60%	90%	61%	86%
Residential water heating	1%	20%	60%	50%	85%	45%	55%	100%		45%	60%	44%	59%
Commercial heating	9%**	20%	42%	30%	85%	50%	75%			50%	80%	39%	71%
Commercial water heating	0.10%	5%	30%	10%	50%	45%	60%			40%	60%	18%	40%

*Based on AHRI and DOE Rulemakings market share and shipments data

**Based on RTU market data

2021 — 53% heat pumps (including GSHPs)/47% resistance (residential heating), 9%/91% (residential water heating), 56%/44% (commercial heating), 4%/96% (commercial water heating) [60, 61]. Cooking electrification is conservatively assumed to occur without any efficiency gain across scenarios.

Two scenarios in our analysis (2.1 and 3.1) assume that a small fraction of consumers decides to replace existing equipment and/or envelope components before the end of their useful lifetimes, thus accelerating the pace with which building decarbonization measures can penetrate baseline markets. Annual early retrofit fractions are specified separately by building and equipment or envelope component type as summarized in Table 8. Residential and commercial fractions are initialized for the start year 2022 on the basis of building renovation data from the American Housing Survey (AHS) and EIA Commercial Building Energy Consumption Survey (CBECS), respectively [62, 63]. To produce these initial rate estimates, we focus on the proportion of buildings in the data that report retrofitting a given technology before the end of its expected useful lifetime. For example, for commercial HVAC equipment, we find the total number of buildings constructed between 1990 and 2008 that report an HVAC renovation during that period, under the assumption that HVAC equipment typically functions for 20 years and thus would not be regularly replaced until 2010 at the earliest. We divide this number by the total number of buildings constructed in that time period, and annualize by dividing the result by 18 years (2008-1990). To represent the effects of building policies that encourage early retrofitting behavior [64, 65], we represent a fourfold escalation in each initial annual rate by 2035, with rates remaining at the 2035 value in all subsequent years. For electrification measures, we represent 100% conversion of any baseline stock that turns over and converts to electric service via early retrofits, assuming that consumers who are persuaded to undergo early retrofits will also be encouraged to electrify their equipment.

Finally, power grid decarbonization is represented at three levels in our analysis, all of which are based on GridSIM forecasts. The lowest level, reference case grid reflects only the impacts of already-enacted state-level renewable portfolio standard (RPS) mandates; this trajectory is paired in scenarios 1 and 1.1 with the most aggressive rates of building electrification to explore the emissions implications of accelerating electrification under a slowly decarbonizing grid. Moderate scenarios

Table 8: Rates of early retrofit assumed in scenarios 2.1 and 3.1 and supporting data sources. Early retrofit rates represent equipment or envelope component replacements before end-of-life; initial rates increase through 2035 and remain flat thereafter.

Building Type	Data source	Component retrofitted (year range)	Starting annual early retrofit rate (%)	by 2035 (4X)
Commercial	CBECS 2012 [63]	Lighting (2000-2008)	1.5	6
		HVAC (1990-2008)	0.9	3.6
		Roof (1990-2008)	0.6	2.4
		Windows (1990-2008)	0.3	1.2
		Insulation (1990-2008)	0.3	1.2
	Use com. HVAC	Water heating	0.9	3.6
	N/A	All other	0	0
Residential	AHS 2019 [62]	HVAC (1990-2008)	0.5	2
		Roof (1990-2008)	0.27	1.08
		Windows (1990-2008)	0.23	0.92
		Insulation (1990-2008)	0.06	0.24
	Use res. HVAC	Water heating	0.5	2
	Use com. lighting	Lighting	1.5	6
	N/A	All other	0	0

(2-2.4) reflect a grid that is decarbonized 53% vs. 2005 levels by 2030 and 80% by 2050, which is consistent with the 2050 reduction goal of the 2016 U.S. Mid-Century strategy [66] and results in similar grid development to existing modeling scenarios that assume low renewable energy costs [67]. Finally, our most aggressive scenarios (3-3.4) reflect a grid that is 79% decarbonized by 2030 and 100% decarbonized by 2035, consistent with the Biden-Harris Administration clean electricity goal [1]. As described in Table 3 and Supplemental Information section 2.2.1, overall growth in electricity demand is consistent with the AEO 2020 Reference Case in the GridSIM reference forecast, but reflects higher levels of transportation and building electricity demand growth in the 80x2050 and 100x2035 scenarios.

Analysis limitations

Key methodological limitations are grouped into those concerning the buildings and power system modeling for this study.

Regarding the buildings modeling, rates of end-use electrification are determined based on exogenously developed scenarios; the scenarios reflect expert judgments of plausible levels of fossil-based equipment conversions to heat pumps under different market and regulatory conditions paired with analysis of HVAC and water heating stock totals and rates of stock turnover. This approach reflects the lack of reliable bottom-up models of consumer electrification decisions in the buildings context. The electrification rates in our analysis can serve as useful benchmarks for policy programs that seek to drive the levels of building emissions reductions estimated in our study; however, additional research is needed to compare the conversion rates used in our analysis against real-world data on consumer fuel switching costs and decision-making across U.S. regions, both historically and given additional policy support for electrification in the coming years.

Second, our building decarbonization scenarios reflect the effects of an increased technology performance floor — e.g., through more aggressive building performance codes and appliance efficiency standards — as an increase in minimum market-available technology performance levels across all regions that begins in a certain year. While appliance efficiency standards can be increased across regions via federal regulations, building performance codes are adopted at the local and state levels and, in practice, adoption timelines for more aggressive codes will vary from jurisdiction to jurisdiction. Moreover, our analysis represents the effects of more aggressive codes on market-available technology performance levels in both new construction and retrofit contexts, though currently most building codes only apply to the former.

Third, we generate grid profiles of hourly building demand and demand reductions based on data from a previous study [15] and inherit the data limitations noted in that study: possible under-representation of the diversity in end-use load profiles, a coarse resolution of representative weather conditions that drive loads, and the use of typical meteorological year weather conditions that do not reflect the most extreme within-year variations in hourly weather patterns or the effects of climate change. An additional limitation is the use of typical electric heating load profiles to assess the hourly load impacts of heat pump measures not specifically assessed in [15]: in practice, temperature responses can vary across different heat pumps [68]. Taken together, these limitations could collectively result in either under- or over-estimation of the peak load impacts of building efficiency and flexibility measures, with associated implications for grid modeling estimates.

Finally, we note key limitations in the scope of our demand-side analysis. First, the building decarbonization measures we explore do not include emerging community/district-level decarbonization strategies, such as renewable geothermal heating and cooling on campuses or in urban centers, which may become increasingly important in the U.S. for decarbonizing dense clusters of large commercial buildings. Second, we assess only operation-phase building emissions and do not account for other life-cycle GHG emissions associated with building material manufacturing, transport, construction, and disposal. These emissions are an important source of building sector GHG contributions, and will only grow in significance as operational emissions from buildings are reduced to support economy-wide decarbonization goals.

Regarding power system modeling, our estimates of avoided power system costs only include avoided generation costs (capital expenditures and production costs) and avoided transmission costs. The analysis does not currently account for distribution costs, which would need to increase to accommodate new electrification-related load. Taking these additional costs into account would increase the overall power system costs across all grid scenarios, and would likewise increase the gross benefits of the demand-side measures by avoiding generation, transmission, and distribution costs. We identify the assessment of avoided distribution costs as an important opportunity for expanding our research.

Second, geographic variation in the power system modeling is limited to 25 regions. We do not account for nodal variation in prices, which would require significant computational power in a national modeling study. We also do not account for transmission congestion within regions. Representation of these additional within-region constraints likely would result in larger estimates of power system investment, and higher demand-side measure benefits in our study.

Third, we estimate the cost-effectiveness of demand-side measures based on marginal costs. For this study, GridSIMs generation capacity expansion decisions do not endogenously account for interactions between demand-side and supply-side resource options. GridSIM does have the capability to allow demand-side and supply-side measures to compete, and this could provide valuable insight regarding the quantity and type of power generation resources that would be avoided through demand-side investment, as well as a more robust view of how power system operations would change due to the addition of cost-effective demand-side measures.

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Declaration of Interests

The authors have no competing interests to declare.

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Supplemental Information

1 Additional results

1.1 Building sector modeling

Figures S1 to S8 present alternate versions of the main results from Scout modeling of the building sector.

Figure S1 demonstrates the sensitivity of 2030 building energy and CO_2 emissions avoided by demand-side measures to changes in key dynamics that could be affected by policy levers, providing a nearer-term lens on the 2050 results shown in Figure 2. The influence of early retrofitting behavior and additional deployment of efficient envelopes and controls beyond the reference case is notably more prominent in the near-term than under a longer-term perspective. While early retrofitting increases the 2030 energy and CO_2 reduction potential of demand-side measure deployments by 26-38% across the moderate and aggressive decarbonization scenarios, failure to increase deployment of efficient envelopes and controls beyond the reference case precludes 66-81% of 2030 energy and CO_2 reduction potential across these scenario groups. Of the other dynamics examined, only the removal of more aggressive codes and standards in scenario group 3 registers influence in Figure 2, albeit to a smaller degree than the early retrofit or additional efficiency dynamics. Note that in this aggressive scenario group, such codes and standards begin having effect in 2025, while in the moderate scenario group 2 these effects aren't represented until 2030.

Figure S2 shows the influence of the same sensitivity dynamics on cumulative avoided building CO_2 emissions between 2022-2050. Because the cumulative CO_2 metric captures the impacts of sensitivity dynamics across the full time horizon, and early retrofits and additional efficiency deployments both have more notable impacts in the near-term per Figure S1, greater sensitivity to these two dynamics is observed under the cumulative metric than under the annual one shown in Figure 2 for 2050.

Figures S3 and S4 show the staging of building CO_2 emissions reductions and remaining building CO_2 emissions in 2050 under less aggressive scenario assumptions than is reflected in Figure 4. Under the low decarbonization benchmark (Figure S3), in which only accelerated electrification is assumed alongside reference case grid decarbonization, building sector CO_2 emissions are reduced just 45% by 2030 and 53% by 2050 vs. 2005 levels — far out of step with a net-zero compatible pathway for the sector. In this case, a wide variety of building end uses contribute to remaining CO_2 emissions from buildings in 2050, with notable contributions from cooling and commercial refrigeration, ventilation, and computers and electronics alongside the thermal and "Other" end uses that drive remaining emissions under the aggressive benchmark (Figure 4). Under the moderate decarbonization benchmark (Figure S4), which represents moderate increases in deployment of both electrification and parallel efficiency and flexibility measures, the influence of efficiency deployment vs. electrification is more pronounced than in the aggressive benchmark (Figure 4), as efficiency measures deliver more than four times the reductions of building electrification measures between 2022–2030 and roughly equal reductions between 2030–2050; this compares with just over two times more reductions from efficiency vs. electrification between 2022–2030 and three times *less* between 2030–2050 under the aggressive benchmark.

Figure S5 shows the residential and commercial-specific versions of the segmentation of avoided CO_2 from Figure 5. The Figure demonstrates that reductions in commercial buildings are far more heterogeneous than those in residential buildings, and are less concentrated around a handful of influential reduction segments given the wide variety of commercial building types and uses. Figures S6 and S7 show detailed segmentation of avoided building CO_2 emissions in 2030 and 2050 under less aggressive scenario assumptions than are reflected in Figures 5 and S5. Results for the low decarbonization benchmark (Figure S6) demonstrate the distribution of CO_2 reductions in a future with high building electrification to heat pumps and no other demand-side changes. Here, reductions are more heavily concentrated towards single family heating in colder regions with a large installed base of gas heating equipment (Great Lakes/Mid-Atlantic, Northeast, Upper Midwest, and California). Given parallel deployment of efficiency measures in the moderate decarbonization benchmark (Figure S7), near-term (2030) reductions are more strongly driven by envelope efficiency improvements in single family homes with non-electric heating, while by 2050 the strongest influences are from electrification and electric efficiency measures.

Finally, Figure S8 presents an alternate segmentation of total avoided building CO_2 emissions in 2030 and 2050 across all three benchmark scenarios that facilitates direct comparison of emissions reductions across building and measure type categories. Of particular note in Figure S8: the strong comparative influence of residential vs. commercial electrification, given the greater magnitude of existing fossil-based loads for residential and the higher rates of electrification assumed for residential buildings; the high relative near-term significance of both residential and commercial electric efficiency and of envelope efficiency in residential buildings with non-electric heating, particularly under more moderate rates of electrification (scenario 2); and the sharp increase in CO_2 emissions reductions from electrification measures, particularly in residential buildings, under a long-term (2050) vs. short-term (2030) perspective.

1.2 Power sector modeling

1.2.1 GridSIM energy and capacity results

Figure S9 presents power system capacity and generation mixes for each of the three grid scenarios modeled in GridSIM — a reference case, a moderate case with 80% grid CO_2 reduction vs. 2005 levels by 2050 (80x2050), and an aggressive case with 100% grid CO_2 reduction by 2035 (100x2035). Results for the latter two cases reflect additional load growth from electrification of transportation and buildings. In these two cases, rates of building end-use electrification are consistent with this paper's moderate and aggressive decarbonization benchmarks (scenarios 2 and 3 in Table 4), but the electrified equipment is deployed with a lower efficiency level (consistent with settings from scenario 1.1 in Table 4). Growth in building demand otherwise follows that of the 2021 AEO Reference case. Transportation electrification assumes that 95%, 50%, and 35% of light-duty, medium-duty and heavy-duty vehicles are electric by 2050, respectively.

The reference case supply forecast satisfies baseline load growth and clean energy constraints consistent with state mandated RPS targets. This leads to a 50% increase in national installed capacity (ICAP) from 2020–2050. The majority of capacity additions are firm dispatchable natural gas combined-cycle (CC) and combustion-turbine (CT) plants, with additional growth in clean resources (solar, land-based wind, and offshore wind) to satisfy state RPS targets. The generation mix is around 30% renewable and 45% carbon-free by 2050, in compliance with state RPS targets and demand growth. Natural gas is the primary fuel type for more than half of national generation in each year of the study horizon.

The 80x2050 decarbonization scenario supply forecast satisfies additional transportation and building electrification load that is incremental to the reference case, in addition to achieving 80%

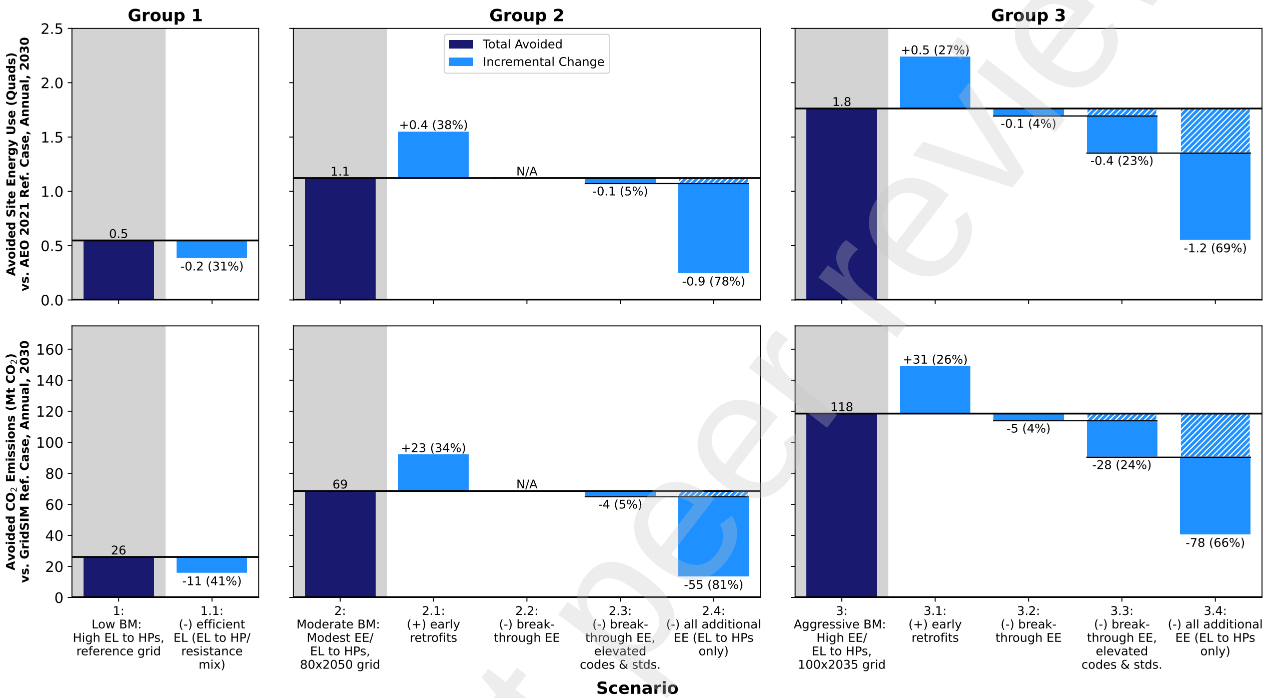

Figure S1: Sensitivity of annual building energy use and CO_2 in 2030 to changes in policy-related dynamics. Results for nine sensitivity side cases are organized into three groups and assessed relative to the annual avoided energy use and CO_2 emissions of the three benchmark scenarios (1, 2, and 3). The sensitivity cases assess the influence of five unique dynamics on annual energy and emissions: reductions in efficiency of electrification via substantial fuel switching from fossil-based heating and water heating to electric resistance technologies (1.1); failure to increase the market-available technology performance ceiling via eventual introduction of breakthrough efficiency technologies with very low cost and performance (2.2, 3.2); failure to increase the market-available technology performance floor via implementation of more aggressive building performance codes and appliance efficiency standards (2.3., 3.3), and; failure to deploy additional market-viable efficiency options not represented in the reference case in the near-term — in particular, upgrades for certain envelope components in existing buildings and deployment of advanced operational controls (2.4, 3.4).

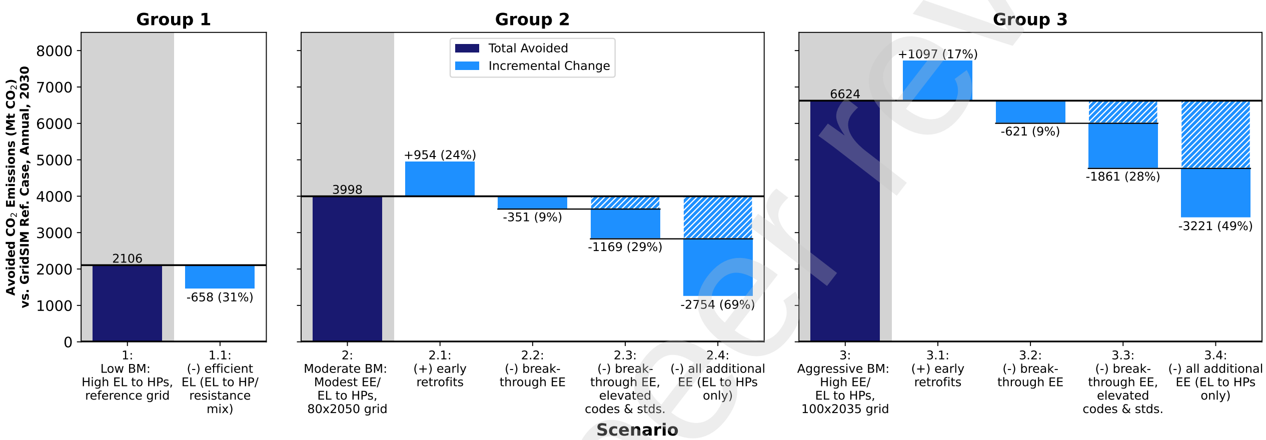

Figure S2: Sensitivity of building CO_2 in to changes in policy-related dynamics, 2022-2050. Results for nine sensitivity side cases are organized into three groups and assessed relative to the cumulative avoided CO_2 emissions of the three benchmark scenarios (1, 2, and 3) between 2022-2050. The sensitivity cases assess the influence of five unique dynamics on cumulative emissions: reductions in efficiency of electrification via substantial fuel switching from fossil-based heating and water heating to electric resistance technologies (1.1); failure to increase the market-available technology performance ceiling via eventual introduction of breakthrough efficiency technologies with very low cost and performance (2.2, 3.2); failure to increase the market-available technology performance floor via implementation of more aggressive building performance codes and appliance efficiency standards (2.3., 3.3), and; failure to deploy additional market-viable efficiency options not represented in the reference case in the near-term — in particular, upgrades for certain envelope components in existing buildings and deployment of advanced operational controls (2.4, 3.4).

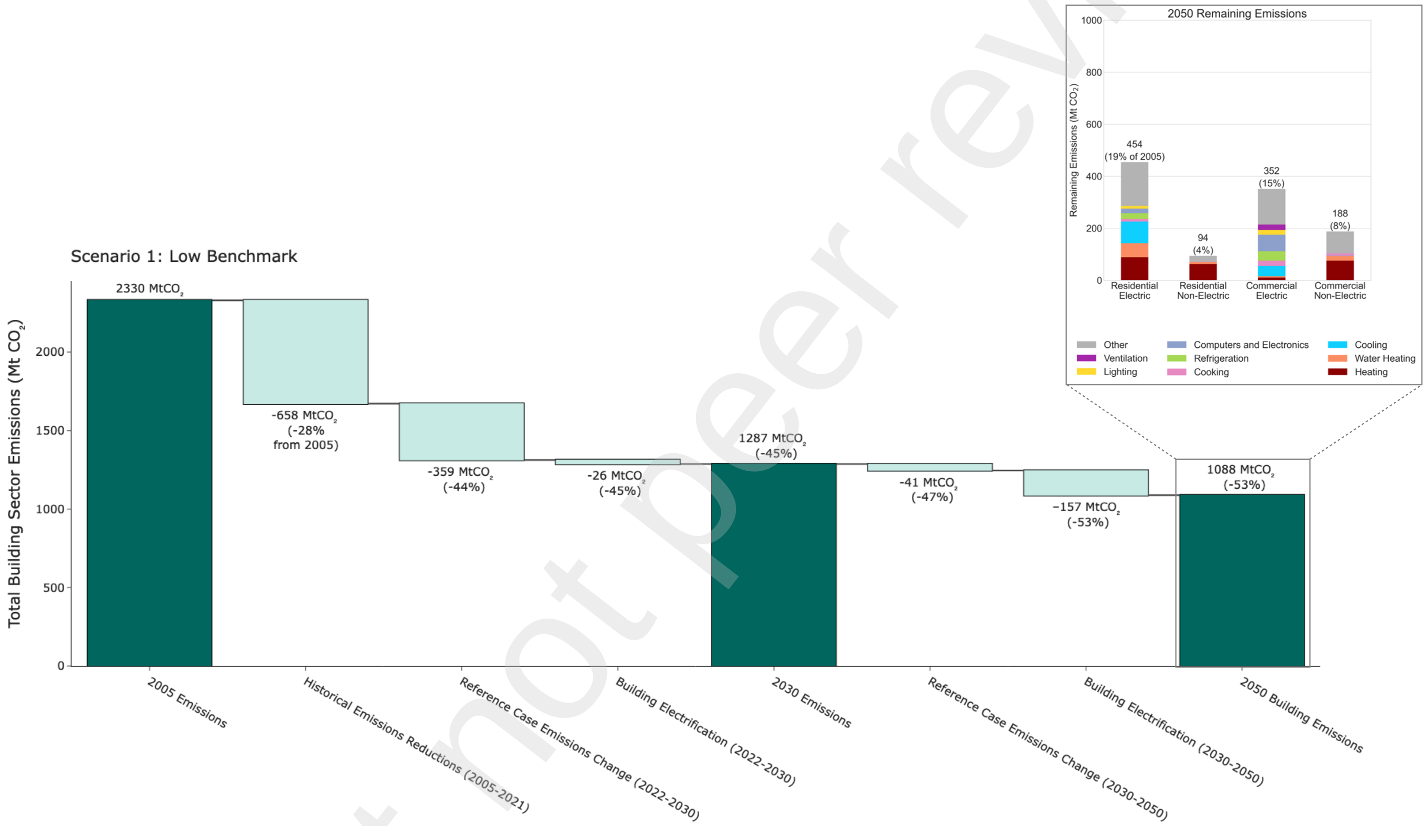

Figure S3: Staging of building CO_2 emissions reductions and remaining emissions in 2050 under low decarbonization benchmark. Reductions from the 2005 building sector emissions level are broken out between 2005-2030 and between 2030-2050 by source: historical reductions (from 2005-2021); reductions projected in the reference case forecast; and further demand-side reductions via building electrification beyond the reference case.

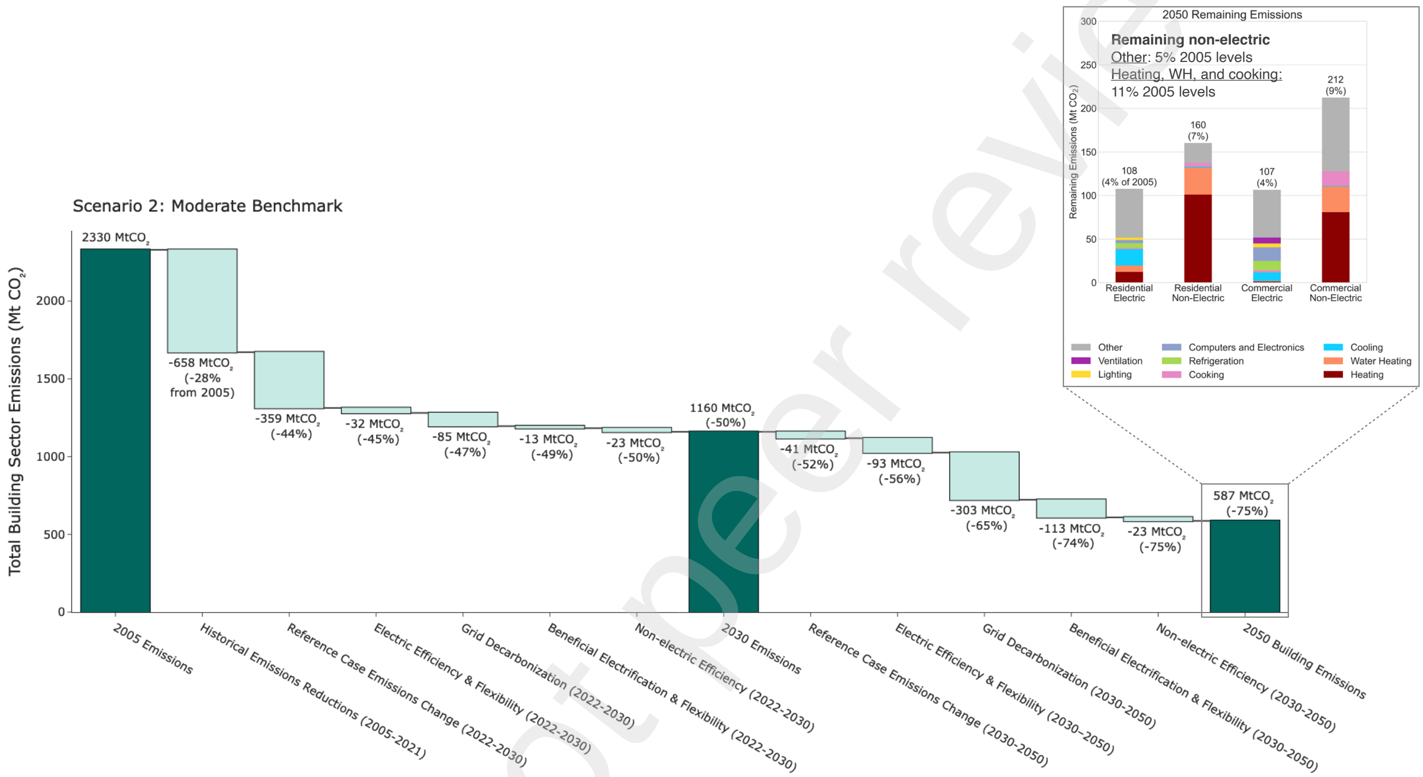

Figure S4: Staging of building CO_2 emissions reductions and remaining emissions in 2050 under moderate decarbonization benchmark. Reductions from the 2005 building sector emissions level are broken out between 2005-2030 and between 2030-2050 by source: historical reductions (from 2005-2021); reductions projected in the reference case forecast; further demand-side reductions via building efficiency, flexibility and electrification beyond the reference case; and further decarbonization of the building electricity supply beyond the reference case. Reductions from energy efficiency are grouped into measures that reduce demand for electric vs. non-electric energy; the former type of efficiency measure is staged first, while the latter type of efficiency measure is applied to any non-electric demand that remains after considering the deployment of building load electrification measures with parallel decarbonization of the electricity supply.

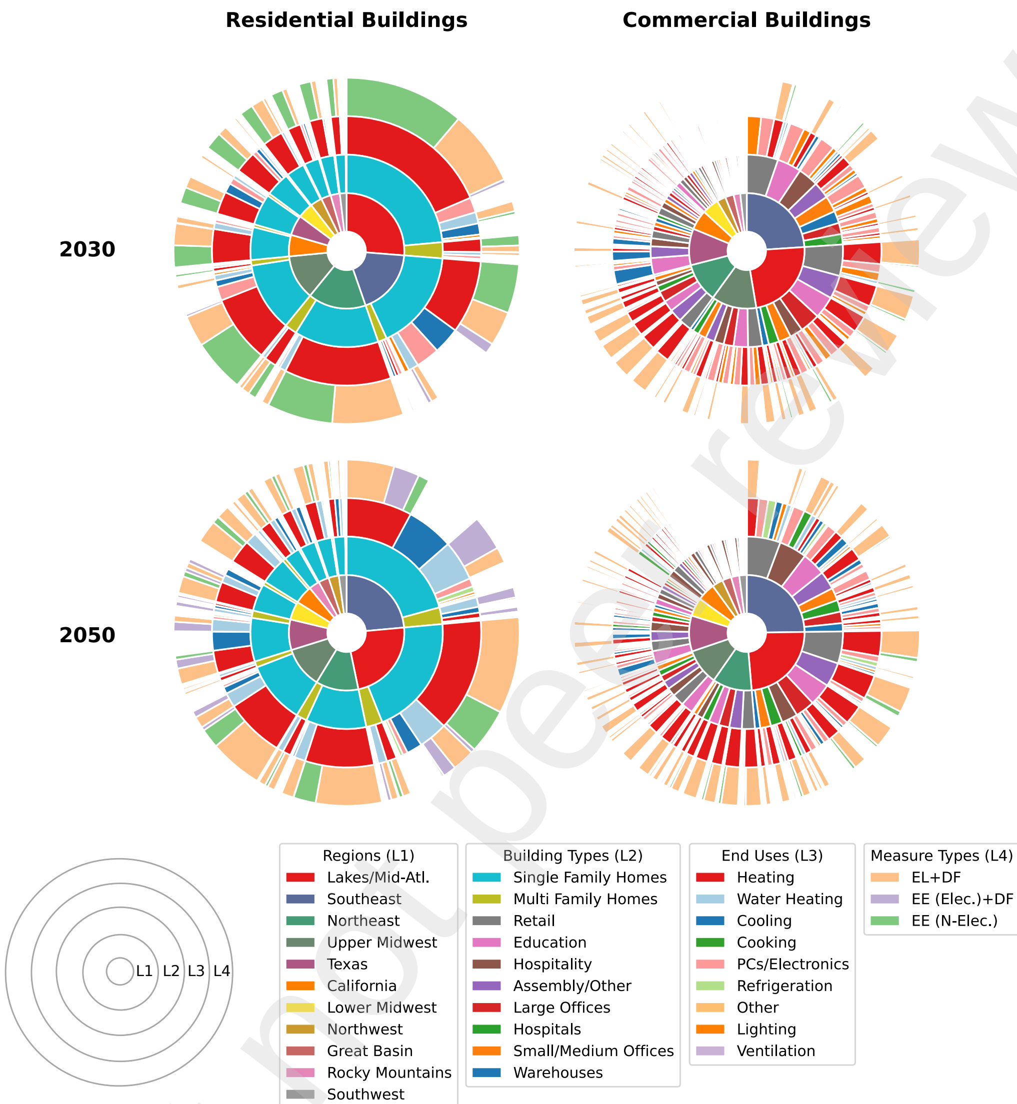

Figure S5: Segmentation of avoided building CO_2 emissions under aggressive decarbonization benchmark, residential- and commercial-only focus. The plot further segments the scenario's total building emissions reductions in 2030 (top row) and 2050 (bottom row), constrained to residential (left column) or commercial (right column) building types only. Emissions reductions are segmented across the following dimensions, beginning with the inner ring of each plot and moving outwards: region (aggregations of 25 EIA Electricity Market Module regions [1] to 11 higher-level regions); building type (aggreagations of the 3 residential and 11 commercial EIA Annual Energy Outlook building types to 2 and 8 residential and commercial building types, respectively); energy end use; and measure type (electrification paired in some cases with flexibility (EL+DF), electric efficiency paired in some cases with flexibility (EE (Elec.)+DF), and non-electric efficiency (EE (N-Elec.)). White regions of the plot denote aggregations of very small segments.

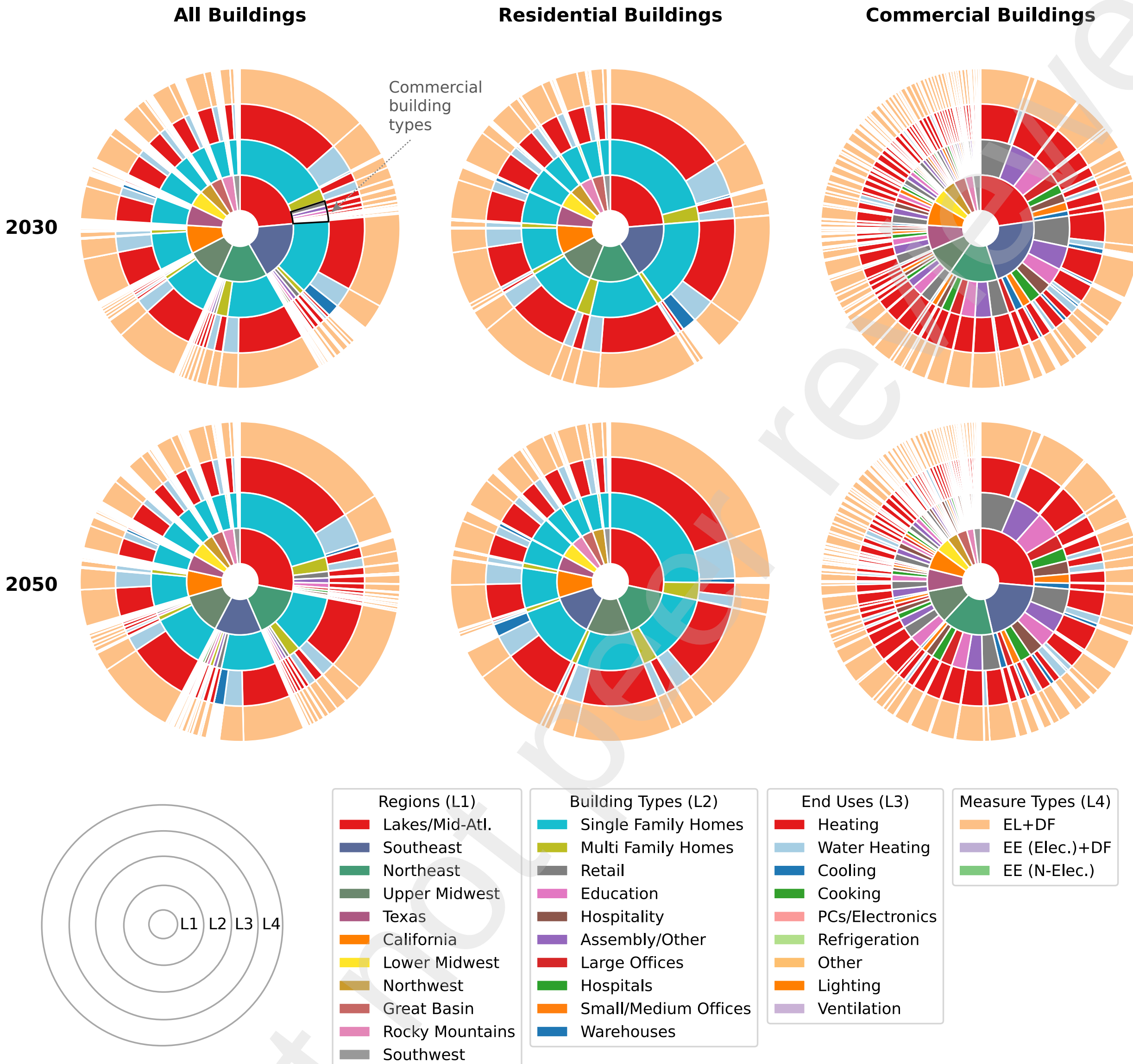

Figure S6: Segmentation of avoided building CO_2 emissions under low decarbonization benchmark. The plot further segments the scenario's total building emissions reductions in 2030 (top row) and 2050 (bottom row), across all building types (left column) or constrained to residential (middle column) or commercial (right column) building types only. Emissions reductions are segmented across the following dimensions, beginning with the inner ring of each plot and moving outwards: region (aggregations of 25 EIA Electricity Market Module regions [1] to 11 higher-level regions); building type (aggreagations of the 3 residential and 11 commercial EIA Annual Energy Outlook building types to 2 and 8 residential and commercial building types, respectively); energy end use; and measure type (electrification paired in some cases with flexibility (EL+DF), electric efficiency paired in some cases with flexibility (EE (Elec.)+DF), and non-electric efficiency (EE (N-Elec.)). The low decarbonization benchmark exclusively deploys electrification (EL) measures, thus no impacts are attributed to energy efficiency (EE) measure types. In each plot, the top three regional segments are highlighted with color (inner ring), as are the top segments for each level nested within those regions (e.g., building type, end use, measure type); all other segments are shaded gray. In the plots covering all building types, the aggregation of commercial building types is highlighted with a thick gray border. White regions of the plot denote aggregations of very small segments.

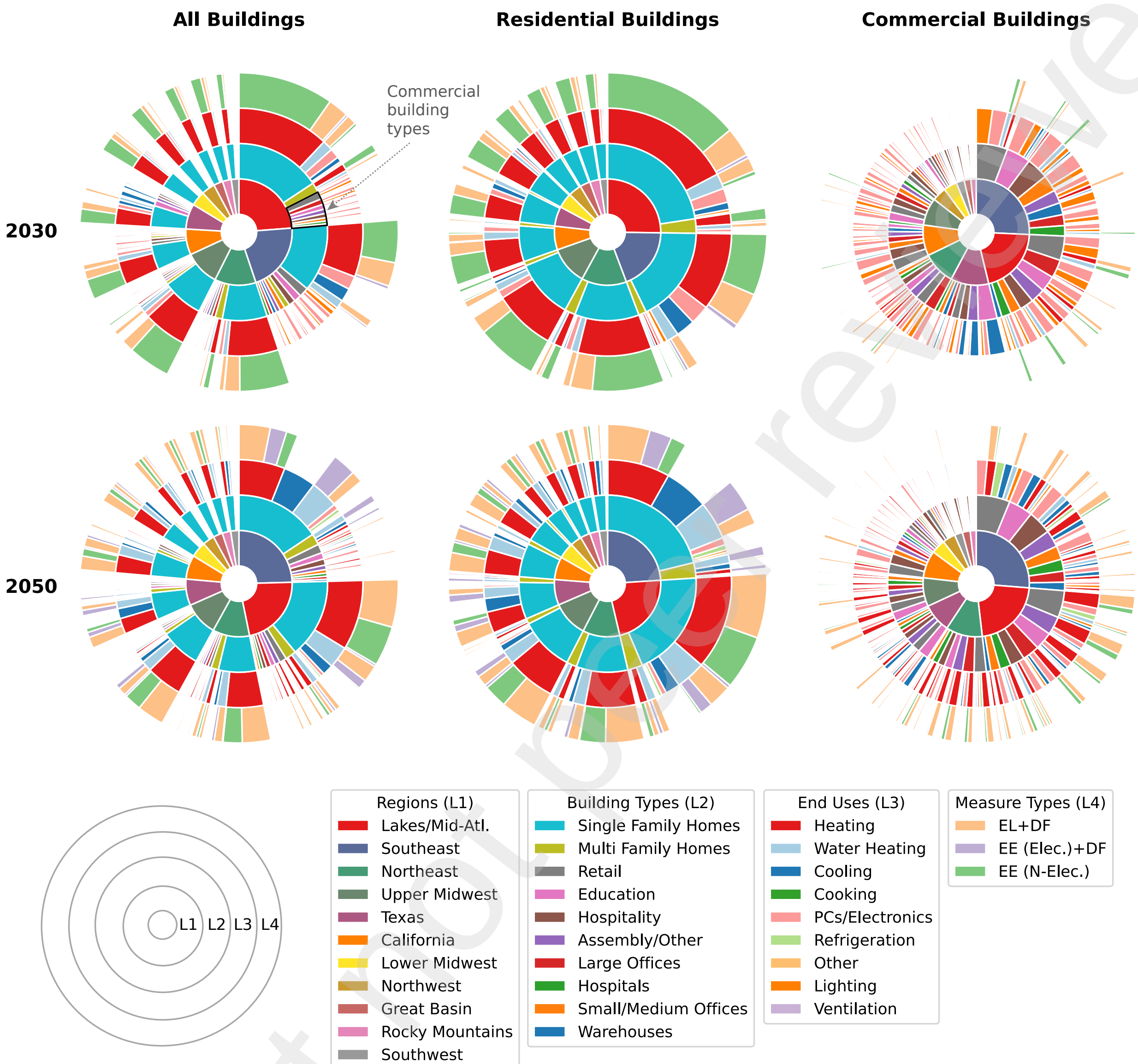

Figure S7: Segmentation of avoided building CO_2 emissions under moderate decarbonization benchmark. The plot further segments the scenario's total building emissions reductions in 2030 (top row) and 2050 (bottom row), across all building types (left column) or constrained to residential (middle column) or commercial (right column) building types only. Emissions reductions are segmented across the following dimensions, beginning with the inner ring of each plot and moving outwards: region (aggregations of 25 EIA Electricity Market Module regions [1] to 11 higher-level regions); building type (aggreagations of the 3 residential and 11 commercial EIA Annual Energy Outlook building types to 2 and 8 residential and commercial building types, respectively); energy end use; and measure type (electrification paired in some cases with flexibility (EL+DF), electric efficiency paired in some cases with flexibility (EE (Elec.)+DF), and non-electric efficiency (EE (N-Elec.)). In each plot, the top three regional segments are highlighted with color (inner ring), as are the top segments for each level nested within those regions (e.g., building type, end use, measure type); all other segments are shaded gray. In the plots covering all building types, the aggregation of commercial building types is highlighted with a thick gray border. White regions of the plot denote aggregations of very small segments.

Figure S8: Building type, end use, and measure type attribution of avoided building CO_2 emissions in 2030 and 2050 for three decarbonization benchmark scenarios. Figure rows from top to bottom show avoided emissions for each of the low, moderate, and aggressive benchmark scenarios (1, 2, and 3), respectively; columns from left to right show 2030 and 2050 results, respectively. Reductions from fuel switching in the residential sector are consistently large in magnitude across scenarios (except for in Scenario 2, in which residential non-electric efficiency shows larger impacts in 2030 due to share of non-electric fossil load that can be reduced via efficiency in residential buildings in the near term in that scenario). End use savings are driven by HVAC and water heating equipment along with electric envelope efficiency across scenarios.

decarbonization of the grid vs. 2005 levels by 2050. This leads to more installed capacity by 2050 than the reference case, an increase of 160% (compared to an increase of 50% in the reference case). More ICAP is required to meet load and resource adequacy constraints through carbon-free generation than with firm dispatchable resources due to intermittent generation profiles and declining effective load carrying capacity (ELCC) (see Section 2.2 for further description). The carbon constraint increases the development of all types of renewables and with some growth in natural gas CCs in order to meet increased demand. The generation mix is 80% carbon-free by 2050, with 70% of generation from renewables. New hydrogen-fueled CCs help meet 2050 clean generation needs in addition to renewable resources and existing clean generators, like nuclear.

The 100x35 decarbonization scenario supply forecast satisfies additional building electrification load beyond the reference and 80x2050 cases, in addition to achieving full grid decarbonization by 2035. This leads to more total capacity than the other two cases due to increased load from inefficient measures and more aggressive carbon constraints. In 2050, total ICAP is 220% greater than 2020 ICAP, with additional solar, wind, hydrogen burning CCs, and nuclear small modular reactor (SMR) capacity. Some fossil fuel generation remains online after the power sector has decarbonized. This generation exists exclusively for reliability purposes, would be utilized infrequently, and could run on renewable gas in the rare instances when needed.

1.2.2 GridSIM system cost results

Figure S10 presents total power system costs across all three GridSIM scenarios in 2030 and 2050. The three scenarios are consistent with those reflected in Figure S9 and the 80x2050 and 100x2035 cases reflect the same additional load growth from transportation electrification and inefficient building electrification. Power system costs include the fixed and variable costs needed to construct and operate generation and transmission assets. These include the fixed O&M, variable O&M, fuel costs, generating unit start costs, capital expenditures for new generation assets, and capital expenditures for new transmission assets. By 2050, in the absence of new demand-side measures to counter higher electric load growth in the 80x2050 and 100x2035 cases, we estimate $390–527 billion per year in capital expenditures and production costs. This range is 1.8–2.4 times the $217 billion of forecasted 2050 annual expenditures in the Reference Case.

Figure S11 presents five-year annual averages for both marginal energy ($2022/MWh) and capacity ($2022/MW-yr) costs through 2050 for each GridSIM scenario. In all cases, marginal power system costs increase in real terms over time, mostly due to costs associated with meeting resource adequacy and hourly energy needs in later years with higher demand. Reference costs increase by 60% from 2030 to 2050. Marginal energy costs decline slightly in real terms nationally through the study horizon. Many regions see slight declines, while others see slight increases. Marginal capacity costs increase in real terms for most regions throughout the study horizon.

The 80x2050 decarbonization case shows higher annual marginal system costs than in the reference case due to higher load from transportation electrification and inefficient building electrification and greater need for zero-carbon resources. In 2030, costs are only 10% higher than the reference case, while 2050 costs are 80% higher as the system moves to mostly zero-carbon. Marginal energy costs increase in real terms for most regions by the end of the study horizon. Through 2030, marginal energy costs remain low, with renewables entering the market to satisfy state driven clean energy requirements and take advantage of federal incentives prior to their step down. Energy costs increase in later years in order to meet increased load with a mix of firm generation, renewables, transmission capacity expansion, and higher cost zero-carbon firm generation.

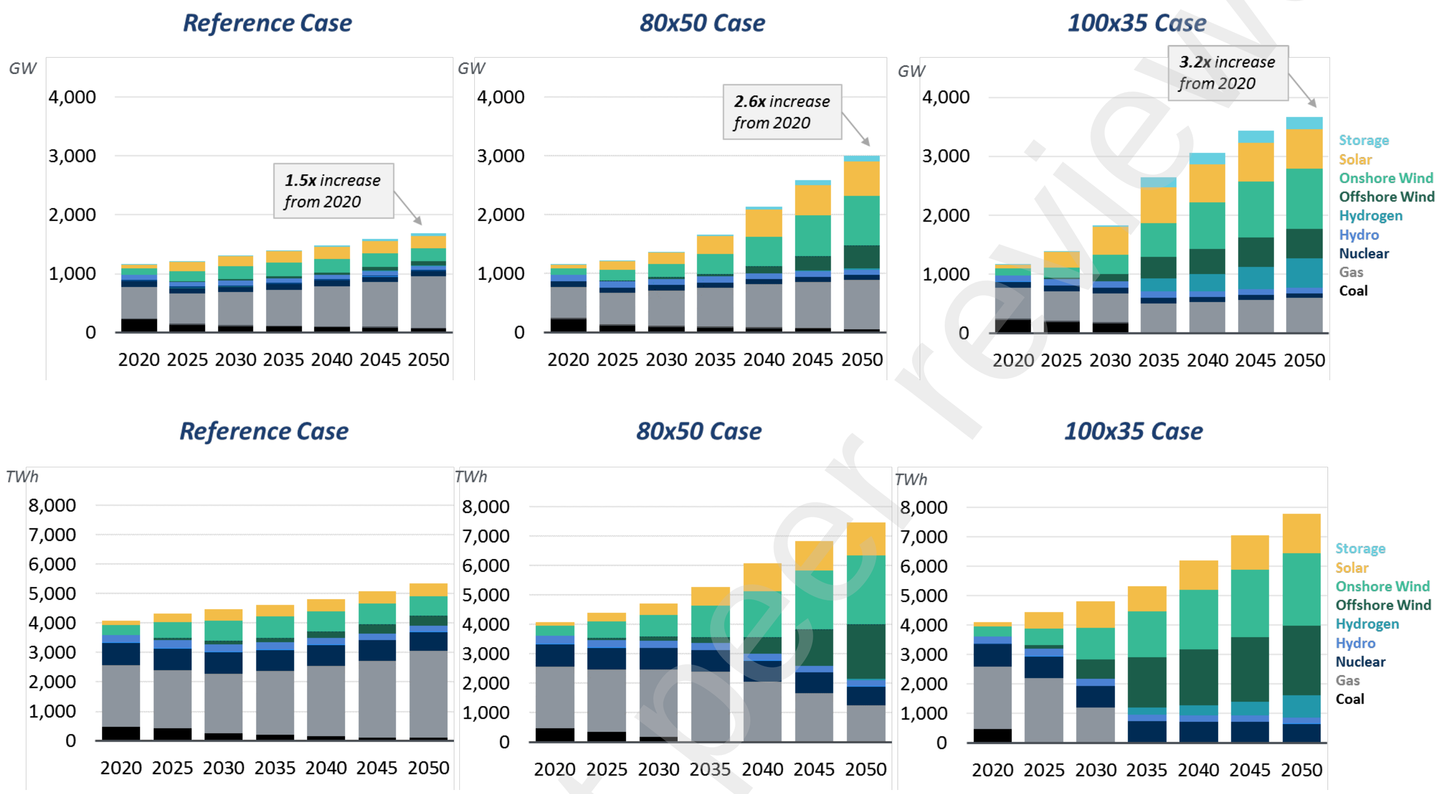

Figure S9: Total installed U.S. generation capacity and annual generation between 2020–2050 under the GridSIM reference case and moderate–aggressive grid decarbonization with inefficient building electrification. GridSIM projections of total installed generation capacity (top row) and annual generation (bottom row) are shown for the GridSIM reference case, (left), a moderate grid decarbonization case with 80% grid CO_2 reduction vs. 2005 levels by 2050 (middle), and an aggressive grid decarbonization case with 100% grid CO_2 reduction by 2035 (right). Capacity and generation projections in the 80x2050 and 100x2035 cases reflect rates of building end-use electrification from this paper's moderate and aggressive decarbonization benchmarks (scenarios 2 and 3 in Table 4), but the electrified equipment is deployed with a lower efficiency level (consistent with settings from scenario 1.1 in Table 4). Growth in building demand otherwise follows that of the 2021 AEO Reference case. Transportation electrification is also reflected and it is assumed that 95%, 50%, and 35% of light-duty, medium-duty and heavy-duty vehicles are electric by 2050, respectively. In the 100x35 case, some fossil fuel capacity remains online after the power sector has been decarbonized. This capacity exists exclusively for reliability purposes, would be utilized infrequently, and could run on renewable gas in the rare instances when it is needed. In addition to the resource types listed in the figure legend, the capacity and generation mixes include pumped hydrogen, biogen, and geothermal generation, though they are not readily visible to due to their small contribution relative to total installed capacity and generation.

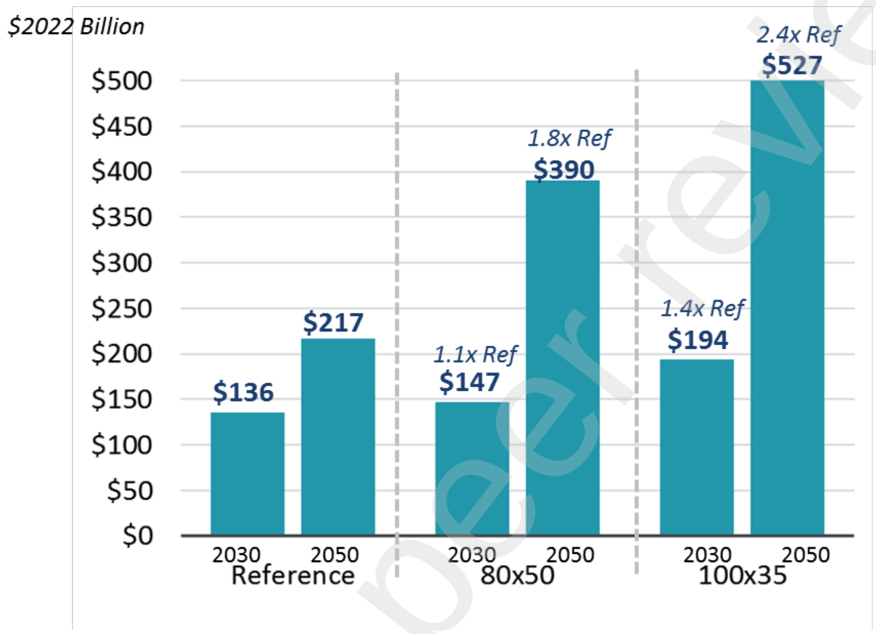

Figure S10: Annual U.S. bulk power system costs in 2030 and 2050 under the reference case and moderate–aggressive grid decarbonization with inefficient building electrification. GridSIM projections of total bulk power system costs in 2030 and 2050 are shown for the GridSIM reference case, (left), a moderate grid decarbonization case with 80% CO_2 reduction vs. 2005 levels by 2050 (middle), and a high grid decarbonization case with 100% grid CO_2 reduction by 2035 (right). System costs in the 80x2050 and 100x2035 cases reflect rates of building end-use electrification from this paper's moderate and aggressive decarbonization benchmarks (scenarios 2 and 3 in Table 4), but the electrified equipment is deployed with a lower efficiency level (consistent with settings from scenario 1.1 in Table 4). Growth in building demand otherwise follows that of the 2021 AEO Reference case. Transportation electrification is also reflected and it is assumed that 95%, 50%, and 35% of light-duty, medium-duty and heavy-duty vehicles are electric by 2050, respectively. Costs shown are power generation costs (capital expenditures and production costs), expanded transmission infrastructure costs, and exclude federal tax subsidy costs (ITC/PTC). Electricity distribution related costs and energy costs from other sectors are not modeled.

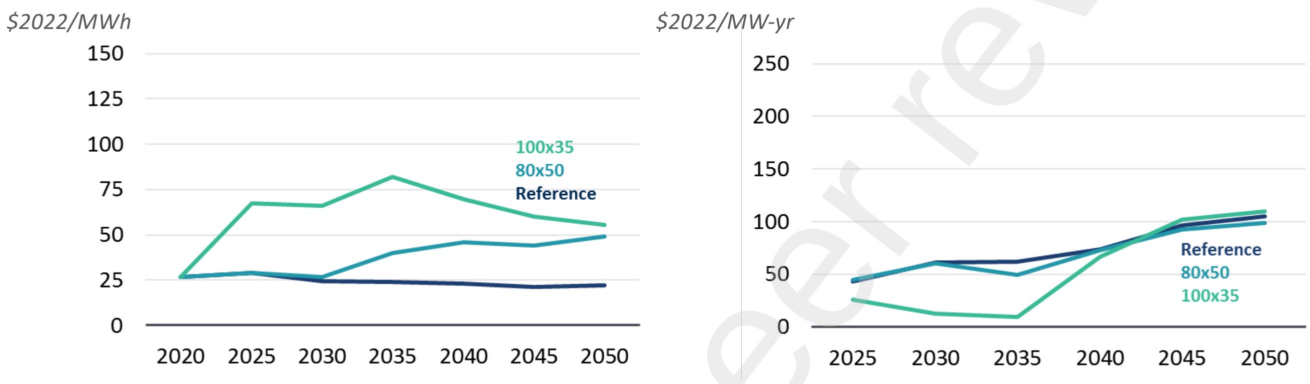

Figure S11: Five-year annual average marginal energy and capacity costs between 2020–2050 under the GridSIM reference case and moderate–aggressive grid decarbonization with inefficient building electrification. GridSIM projections of five-year annual average marginal energy (left) and capacity (right) costs are shown for the GridSIM reference case, a moderate grid decarbonization case with 80% grid CO_2 reduction vs. 2005 levels by 2050, and an aggressive grid decarbonization case with 100% grid CO_2 reduction by 2035. Marginal cost projections in the 80x2050 and 100x2035 cases reflect rates of building end-use electrification from this paper's moderate and aggressive decarbonization benchmarks (scenarios 2 and 3 in Table 4), but the electrified equipment is deployed with a lower efficiency level (consistent with settings from scenario 1.1 in Table 4). Growth in building demand otherwise follows that of the 2021 AEO Reference case. Transportation electrification is also reflected and it is assumed that 95%, 50%, and 35% of light-duty, medium-duty and heavy-duty vehicles are electric by 2050, respectively.

Marginal capacity costs remain flat in most regions through 2030 and increase in later years as the system decarbonizes and needs additional generation capacity to satisfy resource adequacy requirements.

In the 100x2035 decarbonization case, marginal system costs are notably higher compared to the other scenarios. In 2030, costs are 40% higher than in the reference case, and in 2050, costs are 140% higher. The higher costs are driven by additional capital expenditures needed to build clean generation and transmission capacity to satisfy resource adequacy. Marginal energy costs increase through 2035 as firm generation burns high cost zero-carbon fuels to serve demand. Energy costs are significantly higher than the other scenarios due to high hydrogen fuel costs and increased transmission capacity expenditures. Costs decline in real terms towards the end of the study horizon as fuel prices decline with clean firm-generation technology advancements. Marginal capacity costs are comparable to the other two cases and remain high through the study horizon. There is a drop in capacity costs for many regions around 2035 when the carbon constraint is the most binding constraint in the model, driving a high carbon price. There is a trade-off between energy, capacity, and carbon market prices in deep decarbonization power system modeling.

Finally, Figure S12 compares the potential reductions in annual power system costs from the full deployment of individual demand-side efficiency, flexibility, and efficient electrification measures against the total annualized incremental cost of deploying these measures in 2050; the Figure also indicates each measure's level of total annual CO_2 reductions (through the size of each scatter point on the plot). Here, demand-side measure deployment levels are consistent with the moderate and aggressive decarbonization scenarios from Table 4 (scenarios 2 and 3, respectively), and the forecasted hourly marginal system costs that are attached to measures' hourly load impacts (see Equation 10) are consistent with annual results shown for the 80x2050 and 100x2035 grid cases in Figure S11. Results in Figure S12 are calculated based on levels of individual measure deployment that do not account for competition across the demand-side measure portfolio; therefore, the costs and benefits reflect full deployment of each measure in isolation, constrained only by the rates of baseline stock turnover and electrification that are assumed for the given scenario.

Figure S12 shows that across scenarios, residential HVAC/envelope and water heating measures tend to offer the largest potential annual system cost savings and CO_2 reductions. Moreover, the low and high performance tiers of these measures (ESTAR/90.1/IECC and Breakthrough Technology, see Methods) tend to generate system cost savings benefits that are commensurate with the measures' incremental deployment costs. Measures represented with the unit-level characteristics of technologies at the best performance levels currently available on the market tend to have notably higher deployment costs, however. This is particularly true for measures that affect HVAC/envelope, and it reflects both the relatively higher cost of installing HVAC equipment and envelope components at these performance levels, based on current market data, and the assumption that these measures are deployed as packages, with the incremental costs of all HVAC and envelope improvements borne simultaneously (see Supplemental Information Section 2.1.1). Total portfolio costs and benefits, which are calculated by adjusting down the individual measure results of Figure S12 to reflect the market competition simulated in Scout, are strongly influenced by both the high deployment costs of best available HVAC/envelope and by the degree of deployment achieved by the low cost/high impact measures — particularly the Breakthrough Technology tier, which begins entering the market earlier in the aggressive benchmark than in the moderate benchmark (2030 vs. 2035). In the aggressive case, total portfolio benefits and annualized costs in 2050 are $122 and $135 billion, respectively, for a benefit-cost ratio of 0.9; excluding the influence of very high cost measures in Figures S12 with costs that are greater than 2X benefits,

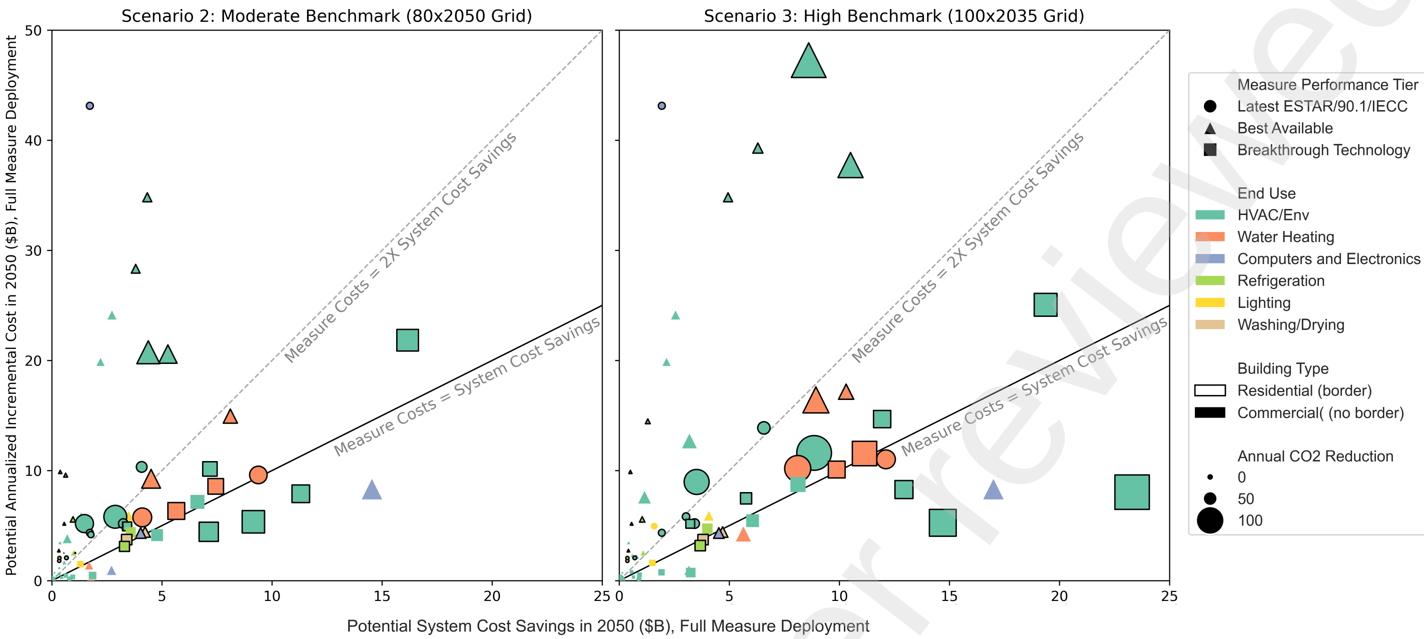

Figure S12: Potential annual deployment costs, system cost savings, and avoided CO_2 emissions of building efficiency, flexibility, and efficient electrification measures in 2050. The annualized incremental cost of deploying each measure in full across the U.S. building stock in 2050 (y axis) is compared against its annual system cost savings potential in 2050 (x axis); diagonal lines benchmark 1:1 and 2:1 ratios between measure deployment costs and system cost savings, respectively. Each measure's total annual CO_2 emissions reduction potential in 2050 is indicated by its point size on the scatter plot, with larger point sizes indicating larger emissions reduction potential. Measure potentials are assessed in isolation: constraints from stock turnover and electrification rates are reflected, but competition with overlapping measures in the portfolio is not reflected. The shape of each measure point indicates its energy performance tier above comparable reference case technologies, from the lowest tier (ENERGY STAR/IECC/90.1) to the highest tier (Breakthrough Technology); performance tiers are described further in the Methods. Furthermore, the color of each measure point indicates the end use service that the measure affects, and residential measure points are distinguished from commercial measure points via a black border.

however, these totals change to $112 billion in benefits and $73 billion in costs, for a benefit-cost ratio of 1.5. In the moderate case, total portfolio benefits and annualized costs in 2050 are $77 and $117 billion, respectively, for a benefit-cost ratio of 0.7; excluding the influence of the high cost measures, these totals change to $67 in benefits and $57 billion in costs, for a benefit-cost ratio of 1.2. These results do not account for additional benefits that would be expected from the deployment of demand-side measures that avoid fossil-based power generation and reduce CO_2 emissions, such as avoided social costs of carbon and reductions in public health costs.

1.2.3 GridSIM emissions results

Figure S13 presents power sector emissions by scenario through 2050. In the reference case, annual carbon emissions decrease through 2035, mostly due to state RPS targets maturing in the

2030s. Additional load growth and reliance on fossil generation causes total annual emissions to increase in the later years of the study horizon. The reference case assumes no additional adoption of clean energy policies at the state or national level beyond what exist at the time of this study.

In the 80x2050 decarbonization scenario, annual carbon emissions decline linearly throughout the study horizon due to a modeling assumption that the requirements of the federal carbon policy decline linearly to an 80% reduction by 2050 relative to 2005 levels. In early years, state RPS policies are more aggressive than the federal carbon reduction mandate.

The 100x2035 decarbonization scenario shows annual carbon emissions decline through 2035 then remain at zero through the study horizon. Through 2035, carbon emissions decline slightly faster than the mandated reductions due to the front loading of renewable development to take advantage of expiring tax credits, in addition to satisfying near term state RPS targets.

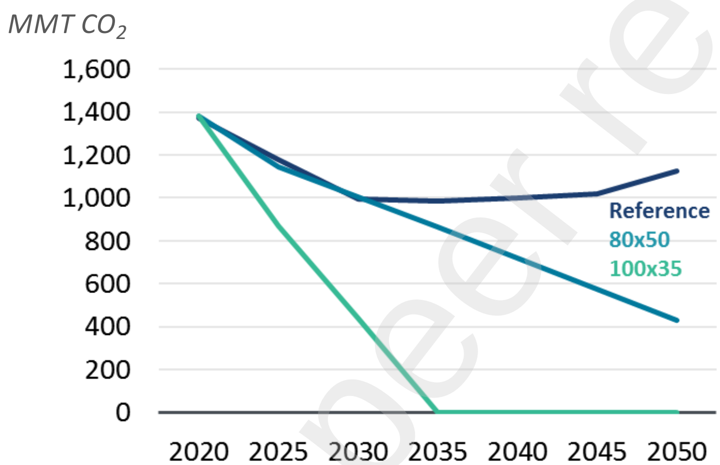

Figure S13: Annual power sector CO_2 emissions between 2020–2050 under the GridSIM reference case and moderate–aggressive grid decarbonization. GridSIM projections of total power sector CO2 emissions are shown for the GridSIM reference case, a moderate grid decarbonization case with 80% grid CO_2 reduction vs. 2005 levels by 2050, and an aggressive grid decarbonization case with 100% grid CO_2 reduction by 2035. GridSIM emissions rates are used to represent three levels of power sector decarbonization in this paper's overall scenario set (see Table 4).

2 Additional methodological details

2.1 Scout modeling of the building sector

2.1.1 Building technology stock turnover and measure interactions

Scout represents the effects of turnover in both the building stock (new additions, demolitions) and the stocks of technologies that are installed to provide energy services within buildings. Building and technology stocks are separated into new and existing bins, where the former is defined as all buildings/technology stocks that are constructed/added after the beginning of the modeling time horizon onward (2022-2050) and the latter is defined as all buildings/technology stocks that were already constructed/installed as of the beginning of the modeling time horizon. Rates of building construction and demolition are resolved by region and building type and consistent with the 2021 AEO Reference Case forecast and supporting National Energy Modeling System (NEMS) Macroeconomic Activity Module (MAM). The AEO Reference Case forecast also provides baseline projections of building technology stock evolution by technology class, including estimated growth in the technology stocks associated with new building construction, decay in technology stocks associated with building demolitions, and the effects of consumer switching from one technology class to another [2].

Changes to baseline technology stocks under alternate scenarios of building sector development depend on the annual rates with which reference case technologies in a certain baseline microsegment are displaced by more efficient, flexible, and/or electrified alternatives in new and existing buildings, $\lambda_{r,b,t,v,y}$:

$$\lambda_{r,b,t,v,y} = \begin{cases} \frac{B^{\text{new,ref}}_{r,b,y}}{\sum_{i=2022}^{y} B^{\text{new,ref}}_{r,b,i}} + \lambda^{rpl_{2022+}}_{r,b,t,v,y}, & v = new \\ \lambda^{rpl_{2022-}}_{r,b,t,y} + \lambda^{rpl_{2022+}}_{r,b,t,v,y} + \lambda^{rple_{2022-}}_{b,t,y}, & v = existing \end{cases} \tag{1}$$

where $B^{new,ref}_{r,b,y}$ is the total number of new homes (residential) or square feet (commercial) of building type b constructed in region r and year y in the AEO Reference Case forecast;[1] $\lambda^{rpl_{2022+}}_{r,b,t,v,y}$ are the portions of technologies of type t that were installed after the beginning of the modeling time horizon (2022) and have reached the end of their useful lifetimes, respectively; $\lambda^{rpl_{2022-}}_{r,b,t,y}$ is the portion of technologies of type t that were installed before the beginning of the modeling time horizon, have not already been replaced, and have reached the end of their useful lifetimes; and $\lambda^{rple_{2022-}}_{b,t,y}$ is the portion of technologies of type t that were installed before the beginning of the modeling time horizon, have not already been replaced, and are retired before the end of their useful lifetimes. Typical reference case technology lifetimes for major equipment categories are drawn from the AEO Reference Case forecast, while lifetimes for envelope and miscellaneous technologies are separately compiled based on a variety of sources.[2] By default, early retirement rates are assumed to be zero, but these rates are set to non-zero values in the scenarios from Table 4 that explore the effects of accelerated stock turnover, as further detailed in Table 8 in the Methods.

Annual stock turnover rates determine the portion of the baseline stock that a measure can capture in each year of the modeling time horizon, $\sigma_{X,y}$, introduced in the main text in equations 3 and 4:

$$\sigma_{X,y} = \frac{\sum_{i=2022}^{y} S^{\text{stk}-\text{ref}}_{X,i}\, \lambda_{r,b,t,v,i}\, \gamma_{X,i}}{S^{\text{stk}-\text{ref}}_{X,y}}, \tag{2}$$

where X is a shorthand for the baseline technology microsegment defined by region r, building type b and vintage v, fuel type f, end use u, and technology type t; $S^{\text{stk}-\text{ref}}_{X,i}$ is a single reference

[1]Drawn from "RESDBOUT.txt" and "KDBOUT.txt" for residential and commercial buildings, respectively; more details about these files are available in the EIA National Energy Modeling System documentation for buildings [3, 4]

[2]Drawn from "rsmeqp.txt" and "rsmlgt.txt" for residential non-lighting and lighting equipment, respectively, and from "ktek.csv" for commercial technologies; more details about these files are available in the EIA National Energy Modeling System documentation for buildings [3, 4]. Technology characteristic data for envelope and miscellaneous technologies are separately developed for Scout and are available: `https://github.com/trynthink/scout/blob/master/cpl_envelope_mels.json`.

case building stock microsegment from the measure's applicable market in year i; and $\gamma_{X,i}$ is a constraint placed on a measure's applicable market when it is not on the market ($\gamma_{X,i}$ = 0) or to represent exogenously-defined limitations — in the case of electrification measures, for example, this variable represents the exogenously-determined portion of a fossil-based equipment market that is converted to electric service in year y.[3]

Stock turnover also factors into the determination of each measure's unit-level energy performance level, introduced in the main text in equation 5:

$$RP^{\text{euse}}_{X,y,m} = RP^{\text{euse}-\text{cpt}}_{X,y,m}\,\Phi^{\text{cpt}}_{X,y,m} + RP^{\text{euse}}_{X,y-1,m}\,(1-\Phi^{\text{cpt}}_{X,y,m}), \tag{3}$$

$$\Phi^{\text{cpt}}_{X,y,m} = \frac{S^{\text{stk}-\text{ref}}_{X,y}\,\lambda_{r,b,t,v,y}\,\gamma_{X,y}}{\sum_{i=y_0^m}^{y} S^{\text{stk}-\text{ref}}_{X,i}\,\lambda_{r,b,t,v,i}\,\gamma_{X,i}} \tag{4}$$

where $RP^{\text{euse}}_{X,y,m,M}$ is the measure's unit-level energy performance level relative to the counterfactual reference case technology across all captured stock, calculated based on either annual or hourly data ($RP^{\text{euse}-\text{ann}}_{X,y,m}$ and $RP^{\text{euse}-\text{tvar}}_{X,y,m}$ in main text equation 5), $RP^{\text{euse}-\text{cpt}}_{X,y,m}$ is the measure's unit-level relative energy performance level for stock captured in year y only, $\Phi^{\text{cpt}}_{X,y}$ is the fraction of the total stock captured by the measure that is captured in year y only, and y_0^m denotes the first year that measure m is available on the market.

Baseline stock captured by a measure in isolation is further adjusted to account for competition with other measures in the portfolio that apply to the same segments of baseline technology stock.[4] A measure- and segment-specific competition adjustment factor, $a_{X,y,m}$, is calculated for each year y:

$$a_{X,y,m} = \begin{cases} \theta^{\text{mkt}}_{X,y,m,M} + \theta^{\text{scale}}_{X,m,M}, & y = y_E \\ (\theta^{\text{mkt}}_{X,y,m,M} + \theta^{\text{scale}}_{X,m,M})\,\Phi^{\text{cmp}}_{X,y,M} + & \\ a_{X,y-1,m}(1-\Phi^{\text{cmp}}_{X,y,M}), & \text{otherwise} \end{cases} \tag{5}$$

where $\theta^{\text{m,mkt}}_{X,y,M}$ is a measure's market share when competed in measure set M in year y, $\theta^{\text{scale}}_{X,m,M}$ is additional market share conferred on measure m when one or more competing measures apply to only part of the competed baseline stock segment,[5] $\Phi^{\text{cmp}}_{X,y,M}$ is the fraction of a common baseline stock segment that the measure set M competes for in year y, and y_E is the earliest market entry year across the measure set M.

The competed market share $\theta^{\text{mkt}}_{X,y,m,M}$ is calculated differently depending on which building type (residential or commercial) a measure applies to, adapting the approach used in EIA's simulations of technology adoption for the AEO. Specifically, the approach uses a logistic regression

[3] As stated in the Methods, exogenous electrification conversion rates do not apply to the portion of the existing stock turnover fraction ($\lambda_{r,b,t,v=exist,y}$) that represents early retrofit decisions, when such decisions are assumed.

[4] In the case of EL measures, the portion of the referece case fossil-based equipment stock that converts to electricity is dictated by the exogenous Guidehouse electrification scenarios described in section 2.1.2; therefore, reference case fossil equipment is not directly competed with the EL measures, and these measures only compete against other EL measures in the analysis.

[5] Applicable when a user specifies a market scaling fraction, ξ^{scale}_X, for one or more of the competing measures. In such cases, the portion of the baseline segment that the measure(s) does (do) not apply to is divided up across all other competing measures in accordance with their relative market shares.

model and a cost model to assign market shares in the residential and commercial sectors, respectively, estimating market shares as a trade off between a measure's capital and operating costs:

$$\theta^{\text{mkt}}_{X,y,m,M} = \begin{cases} \dfrac{\exp((\beta_1)_{X,y}\ U_{X,y,m} + (\beta_2)_{X,y}\ \psi_{X,y,m,mt})}{\sum_{k=1}^{M} \exp((\beta_1)_{X,y}\ U_{X,y,k} + (\beta_2)_{X,y}\ \psi_{X,y,k})}, & b \in \text{residential} \\ \displaystyle\sum_{u=1}^{U_{b,f,m}} \sum_{d=1}^{D} \theta_{u,d}, & b \in \text{commercial} \end{cases} \tag{6}$$

where $U_{X,y,m}$, $U_{X,y,k}$, $\psi_{X,y,m,mt}$, and $\psi_{X,y,k,mt}$ are the unit-level installed capital and annual operating costs in year y for individual measures m and k within set M, respectively,[6] $(\beta_1)_{X,y}$ and $(\beta_2)_{X,y}$ are choice coefficients from the AEO reference case[7] that weight the influence of capital and operating costs on market share in the residential sector,[8] D is a set of discount rates from the AEO reference case[9] 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 measure m when it has the lowest life cycle cost (capital plus operating costs) of all competing measures in set M for end use u within the measure's applicable end use set $U_{b,f,m}$ under discount rate d;[10] when measure m does not have the lowest life cycle cost of competing measures in set M for end use u and discount rate d, $\theta_{u,d}$ is zero.

The calculation of operating costs in equation 6 requires annual projections of average retail rates by fuel and customer type (residential/commercial); moreover, assessment of demand flexibility measures requires further resolution of annual average retail rates to an hourly timescale. Retail rate projections are drawn from the AEO cases that most closely align with our scenario's supply-side assumptions: the AEO 2021 Reference Case for scenario group 1 in Table 4, and the AEO 2021 Low Renewable Cost side case for both scenario groups 2 and 3 in Table 4 [2]. Operating cost calculations vary by measure type:

[6] Reference case technology installed cost characteristics are drawn from NEMS files "rsmeqp.txt" and "rsmlgt.txt" for residential non-lighting and lighting equipment, respectively, and from "ktek.csv" for commercial technologies; more details about these files are available in the EIA National Energy Modeling System documentation for buildings [3, 4]. Technology characteristic data for envelope and miscellaneous technologies are separately developed for Scout and are available: `https://github.com/trynthink/scout/blob/master/cpl_envelope_mels.json`

[7] Drawn from 'rsmeqp.txt' and 'rsmlgt.txt' for major equipment and lighting technologies; more details about these files are available in the EIA NEMS documentation for the residential sector [3].

[8] The NEMS documentation notes that the ratio of these coefficient approximates the discount rate used in valuing operating cost savings from more efficient equipment.

[9] 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 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 [4], p. 224.

[10] The market shares are summarized in table E-1 of the EIA National Energy Modeling System documentation for the commercial sector [4], p. 224.

$$\psi_{X,y,m,mt} = \begin{cases} I^{\text{euse-ref}}_{X,y}\,\rho^{\text{ref}}_{r,b,f\in X,y}\,RP^{\text{euse-ann}}_{X,y,m}, & mt = EE \text{ or } mt = EL \text{ and } f \in X = electric \\ I^{\text{euse-ref}}_{X,y}\,\rho^{\text{alt}}_{r,b,f=elec,y}\,RP^{\text{euse-ann}}_{X,y,m} & mt = EL \text{ and } f \in X \neq electric \\ I^{\text{euse-ref}}_{X,y}\,\rho^{\text{ref}}_{r,b,f\in X,y}\,RP^{\text{ecost-tvar}}_{X,y,m} & mt \in [EE+DF, EL+DF] \end{cases} \tag{7}$$

where $\rho^{\text{ref}}_{r,b,f\in X,y}$ and $\rho^{\text{alt}}_{r,b,f=elec,y}$ are the reference case retail price of fuel f in microsegment X and the alternate scenario price of electricity in region r, building type b, and year y, respectively, and $RP^{\text{ecost-tvar}}_{X,y,m}$ accounts for time-varying relative energy performance and assigns corresponding time-varying electricity rates across all hours in a year for measures with demand flexibility (DF) features. The method for determining hourly retail electricity rates and re-aggregating to the annual relative energy cost metric in equation 7 is detailed in section 2.1.3. Assignment of reference vs. alternate scenario prices in equation 7 is consistent with the assumed staging of impacts from reductions in consumption, fuel switching, and grid decarbonization described for main text equation 6 (e.g., reductions in consumption and associated energy cost savings are staged before additional grid decarbonization beyond the reference case, while changes in energy costs from fuel switching are staged in parallel with the additional grid decarbonization).

Heating and cooling energy use and CO_2 emissions may be affected by measures that improve the efficiency of HVAC equipment, add operational controls, or upgrade components of the building envelope. Since these overlapping measures do not provide the same type of energy service, their overlaps are not accounted for by the competition adjustment in equation 5 and require a different approach to account for overlapping impacts. This issue is addressed in the best available performance tier (Tier 2 in Methods) by representing the deployment of such measures simultaneously as a package with relative energy performance characteristics that account for the joint influence of contributing measures. In the other performance tiers, however, the deployment of HVAC equipment efficiency, controls, and envelope measures is decoupled, with timing dictated by the stock turnover characteristics of each individual measure. To address overlaps in these cases, adjustment factors are developed that scale down the baseline and efficient energy use and CO_2 emissions for the individual HVAC and control measures in a manner that considers their direct intersection together with the influence of parallel envelope improvements:

$$\zeta^{\text{ref, eqp}}_{X,y} = (1-\gamma_{X,y}) + \gamma_{X,y}\left(\frac{\Delta^{\text{eqp}}_{X,y}}{\Delta^{\text{eqp}}_{X,y}+\Delta^{\text{ctls}}_{X,y}}\right) \tag{8}$$

$$\zeta^{\text{ref, ctls}}_{X,y} = (1-\gamma_{X,y}) + \gamma_{X,y}\left(\frac{\Delta^{\text{ctls}}_{X,y}}{\Delta^{\text{eqp}}_{X,y}+\Delta^{\text{ctls}}_{X,y}}\right) \tag{9}$$

$$\zeta^{\text{alt, eqp}}_{X,y} = \zeta^{\text{ref, eqp}}_{X,y}(1-\Delta^{\text{ctls}}_{X,y})(1-\Delta^{\text{env}}_{z,b,f,u,v,y}) \tag{10}$$

$$\zeta^{\text{alt, ctls}}_{X,y} = \zeta^{\text{ref, ctls}}_{X,y}(1-\Delta^{\text{eqp}}_{X,y})(1-\Delta^{\text{env}}_{z,b,f,u,v,y}) \tag{11}$$

where $\zeta^{\text{ref, eqp}}_{X,y}$, $\zeta^{\text{ref, ctls}}_{X,y}$, $\zeta^{\text{alt, eqp}}_{X,y}$, and $\zeta^{\text{alt, ctls}}_{X,y}$ are additional adjustments applied to each measure's reference and alternate-scenario energy use and CO_2 emissions segments (see main text equations 3 and 4 and supporting explanation) to resolve overlaps between HVAC equipment, controls, and envelope measures, $\gamma_{X,y}$ is the fraction of total energy use in segment X and year y that is overlapping across the HVAC equipment efficiency and controls measures, $\Delta^{\text{eqp}}_{X,y}$ and $\Delta^{\text{ctls}}_{X,y}$ is the total energy savings of all HVAC and controls measures, respectively in the overlapping segment divided by the total energy use of the overlapping segment, and $\Delta^{\text{env}}_{z,b,f,u,v,y}$ is the total energy savings of all envelope measures that affect the same region r, building type b and vintage v, fuel type f, and end use u as segment X in year y, divided by the total energy use of that region, building type and vintage, fuel type, and end use.

Following the application of the adjustment factors in equations 8–11, affected measures are represented as a single measure bundle for subsequent competition and assessment against other measures in the analysis. We isolate the envelope-specific contributions to these measure bundles (as represented, for example, in Figure 3) by simulating the envelope portion of the bundle in isolation and calculating the ratio of envelope-isolated energy impacts to those of the full bundle, before competition with other measures; this ratio is subsequently applied to the bundle's impacts post-competition to assign the envelope portion of those impacts. The stock, installed cost, and lifetime characteristics of the measure bundle are anchored on those of the contributing HVAC equipment efficiency measure; thus, the bundle is effectively competed as an HVAC equipment measure with improved energy performance from parallel controls and/or envelope improvements. The incremental cost of the controls is considered in the competition; the incremental cost of envelope improvements is not considered in the competition, though it is reflected in the assessment of measure LCCEs per equation 11. We exclude envelope costs from the competition calculations because the NEMS-based market share functions in equation 6 are generally only appropriate for equipment purchase/replacement decisions and associated costs. This approach effectively assumes that consumers who opt for a given performance tier of HVAC/controls equipment will adopt from the same performance tier for envelope improvements. Improved understanding of consumer choices between candidate envelope technologies — particularly in the context of parallel HVAC equipment upgrades — is acknowledged as an important area of future work.

2.1.2 Exogenous electrification scenarios and rates

This analysis uses exogenous building electrification scenarios to project rates of fuel switching to electric technologies based on different policy and economic drivers related to incentives and regulations as well as new product innovations. Scenarios used in this analysis were developed in consultation with a team of HVAC market experts at Guidehouse. Four scenarios were developed to represent a range of plausible adoption trajectories for residential and commercial space heating and water heating technologies that are further resolved by existing heating fuel (electric resistance, natural gas, distillate/oil, and propane), heating system type (e.g., residential ducted furnace and storage water heater; commercial RTU and storage water heater), building vintage (new/existing), and U.S. Census Region (Northeast, South, Midwest, West).

The general methodology used to develop existing market shares and projected conversion rates through 2050 is as follows:[11]

1. EIA RECS [5] and CBECS [6] installed equipment bases for space heating and water heating technologies are converted to annual shipments for each fuel, building type, and region by assuming 15-year equipment lifetimes.

2. Census Bureau data on annual housing starts are specified for each equipment type and region, to further resolve shipments into new vs. existing building vintages.

[11] The data that underpin these calculations are also available upon reasonable request.

3. Conversion percentages that are resolved by fuel, building type and vintage, equipment type, and region are applied to estimate incremental heat pump (HP) sales in 2030.

4. Percentages of HP sales are calculated in reference to total storage water heater sales and unitary AC+HP sales in 2030.

5. Rates are projected forward to 2050 based on assessments of policy drivers that could accelerate (or slow) adoption (see Table S1).

6. Assumptions are checked against U.S. DOE rulemaking and Air-Conditioning, Heating, and Refrigeration Institute (AHRI) data [7] where available.

The four conversion scenarios and an example of the various policy and economic drivers that differentiate them for the residential unitary AC/HP market are presented in Table S1. As shown in the table, availability and level of federal or utility incentives, state or local restrictions, and new product innovations are the key differentiating factors considered. Similar qualitative scenario descriptions were created for each sector and end use (e.g., residential and commercial space and water heating) to develop sector-specific conversion shares. Table S2 presents heat pump sales market shares across sectors and equipment types for each of the four electrification scenarios. Sales shares of heat pumps are greater in residential than commercial and for space heating compared to water heating, and increase across scenarios through 2050, reaching a weighted average of 87% of new equipment sales in the most aggressive scenario.

Table S1: Exogenous electrification scenarios and descriptions of key policy and economic drivers for residential unitary AC/HP market.

Scenario	Federal / Utility Incentives	State / Local Restrictions	Product Innovations
Conservative	Modest federal, few utilities	Few for new construction (NC), none for existing	Low GWP refrigerants, grid interactive
Optimistic	Moderate, federal, more utilities	Some for NC, none for existing	Affordable CCHPs
Aggressive	Large federal, more utilities	More for NC, some for existing	Affordable CCHPs
Most Aggressive	Large federal, most utilities	Most for NC, most for existing	Affordable CCHPs

Table S2: Heat pump sales market shares by building sector and end use across exogenous electrification scenarios.

			Heat pump sales shares by scenario							
			Conservative		Optimistic		Aggressive		Most aggressive	
Segment	Representative equipment	2019 heat pump sales shares	2030	2050	2030	2050	2030	2050	2030	2050
Res. Space Heating	Central ducted furnace+AC/HP	37%	45%	61%	50%	76%	63%	85%	75%	90%
Res. Water Heating	Storage water heater	1%	10%	30%	20%	60%	40%	75%	50%	85%
Com. Space Heating	Rooftop unit	9%	15%	27%	20%	42%	25%	66%	30%	85%
Com. Water Heating	Storage water heater	0%	3%	20%	5%	30%	7%	45%	10%	50%
Weighted average of sales market shares:			27%	44%	34%	67%	50%	79%	61%	87%

We use the conversion rates from Guidehouse's scenarios to drive elevated heat pump adoption in comparison to reference case levels in our scenarios of demand-side measure deployment (see Table 4). Additional methodological notes and assumptions for our development of conversion rates based on the Guidehouse heat pump adoption scenarios are as follows:

- Conversion rates for commercial sector new construction were not calculated by Guidehouse due to limited data availability of commercial new construction characteristics; for commercial buildings, new construction conversion rates are assumed to match those in the existing building market.

- Conversion rates for commercial space heating were only calculated for rooftop units (RTUs); based on Guidehouse's review of available data and existing literature, these shares were replicated for non-RTU equipment with a conversion rate cap at 50% in 2050, which reflects specific challenges with HP conversions in commercial buildings (e.g., due to space, technology and other constraints).

- Due to limited availability of market data, conversion rates for commercial water heating were not initially modeled as part of the Guidehouse work. Because these still need to be represented in Scout for our analysis, the conversion rates for commercial water heating match those for commercial space heating but from the scenario that is one step less aggressive (e.g., commercial water heating conversion rates in the "Optimistic" scenario match those of commercial space heating conversion rates in the "Aggressive" scenario). Commercial water heating conversions are also capped at 40% in all scenarios for both existing/new construction based on a projection from the National Renewable Energy Laboratory's "High" scenario for 2050 from the Electrification Futures Study [8].

Figures S14–S17 present the conversion rates above the AEO reference case by building type and vintage, existing fuel type, and region for both space and water heating equipment for the "Optimistic" and "Most Aggressive" exogenous electrification scenarios, the two that were used in our analysis per the discussion in the Methods.

2.1.3 Hourly electric loads, emissions, and costs

Measures in the best available performance tier are represented with demand flexibility features that reduce and/or shift hourly building electric loads based on system load conditions, as described in detail in [9]. For this study, we expand the assessment of flexibility measures to represent their potential impacts on CO_2 emissions and consumer electricity costs. The former ensures that these measures' time-varying load impacts are appropriately reflected in annual emissions results, while the latter allows the representation of flexibility measures in the competition framework described in the previous section.

Hourly load impacts are calculated and re-aggregated to an annual basis as in [9], producing the time-varying energy term introduced in the main text in equation 5:

$$RP_{X,y,m}^{\text{euse-tvar}} = (1 - \frac{\sum_{h=1}^{8760} \Delta D_{X,y,h,m}}{S_{X,y}^{\text{euse-ref}}}) \tag{12}$$

where $D_{X,y,h,m}$ is the load impact of measure m in hour h of year y for energy use segment X.

To translate annual average grid CO_2 emissions factors and electricity retail rates to an hourly basis, we leverage Cambium [10], a publicly-available database that compiles NREL Standard Scenarios simulation data [11]. Regional hourly average emissions and marginal system cost data from Cambium are used to adjust average annual grid emissions factors and retail prices up or down to reflect sub-annual variations in these variables. Hourly adjustments are re-aggregated to

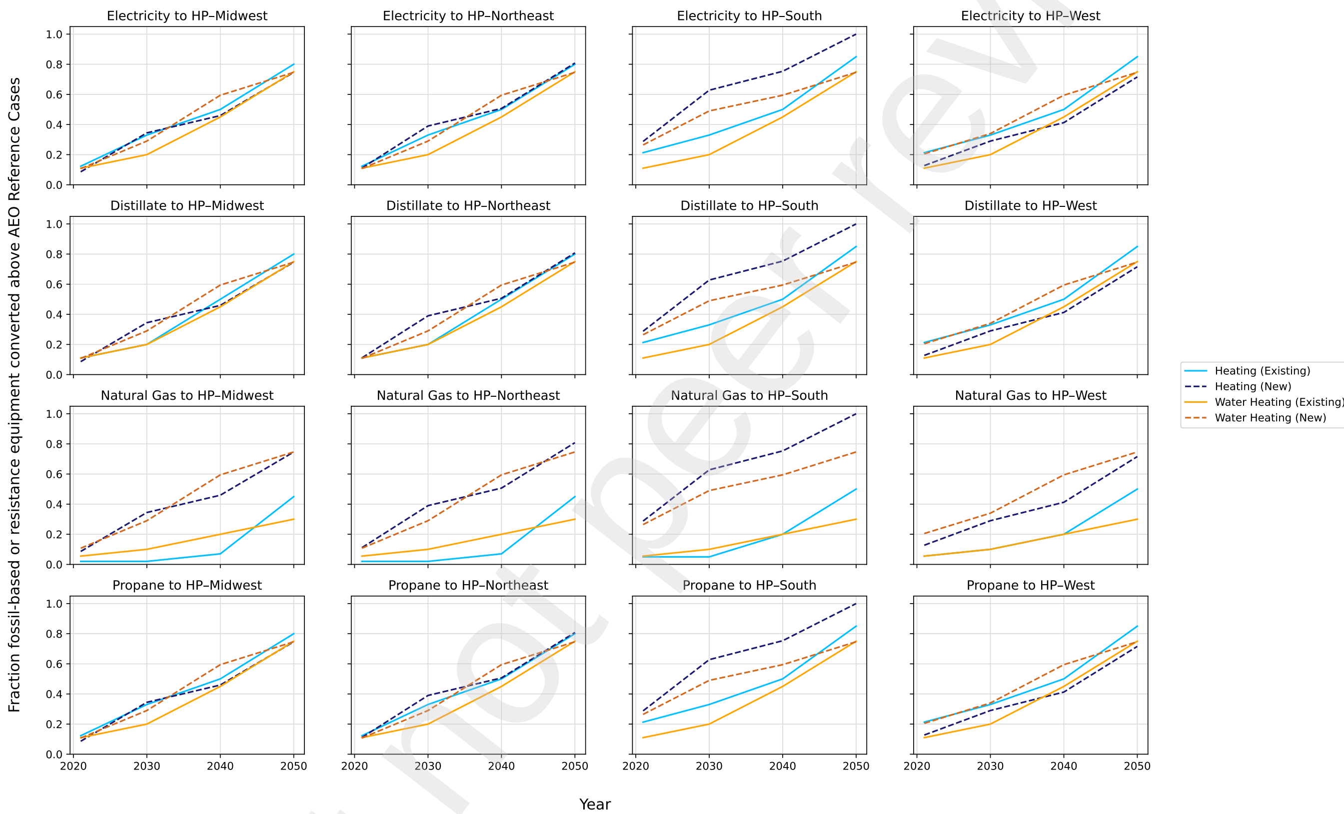

Figure S14: Fossil-based and electric resistance equipment conversion rates in residential buildings, Optimistic scenario.

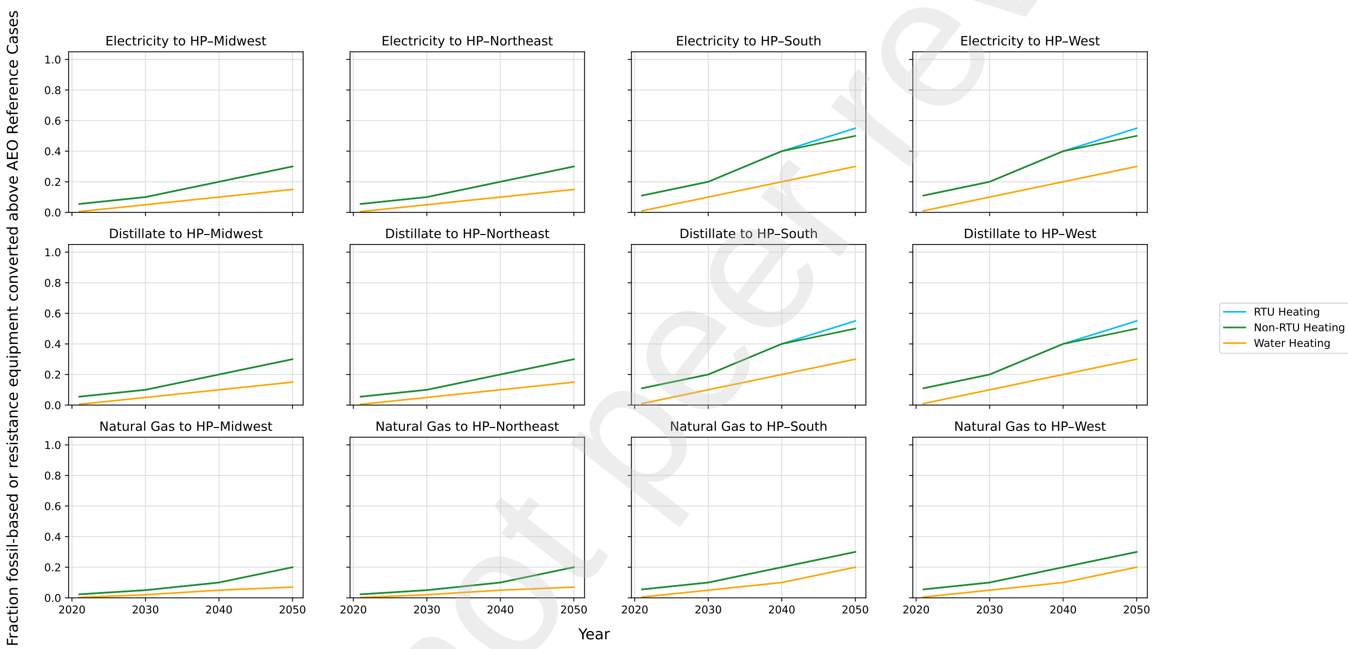

Figure S15: Fossil-based and electric resistance equipment conversion rates in commercial buildings, Optimistic scenario.

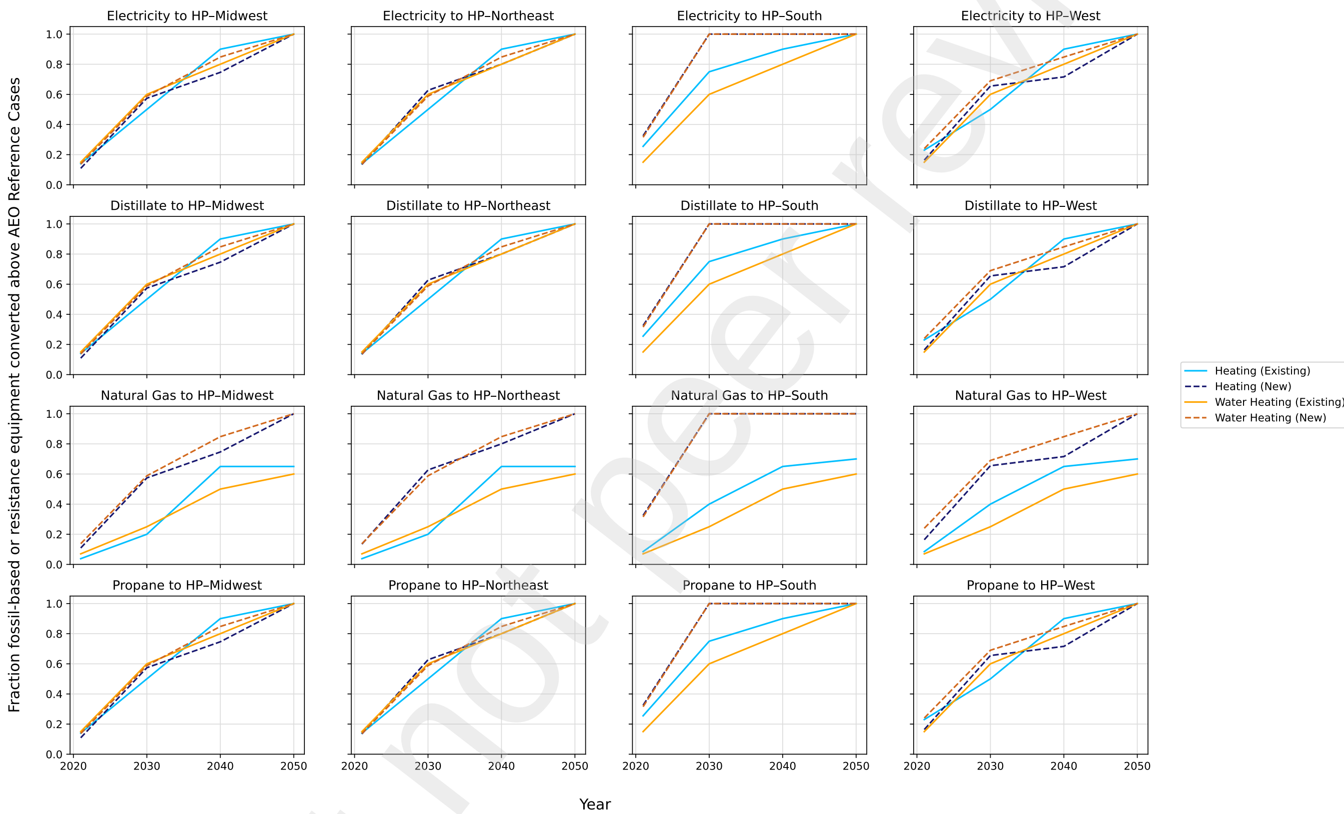

Figure S16: Fossil-based and electric resistance equipment conversion rates in residential buildings, Most Aggressive scenario.

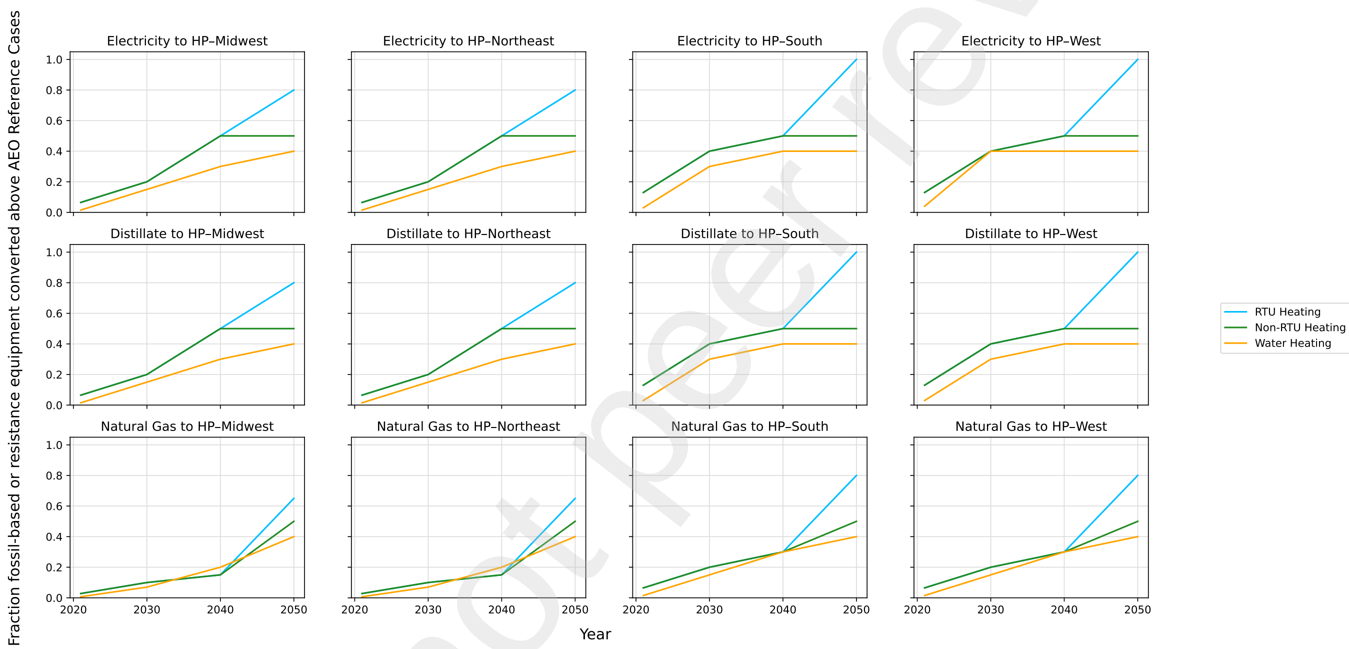

Figure S17: Fossil-based and electric resistance equipment conversion rates in commercial buildings, Most Aggressive scenario.

an annual basis to determine the time-varying emissions and operating cost terms introduced in the main text in equations 6 and 7, respectively:

$$RP^{\text{carb}-\text{tvar}}_{X,y,m} = \begin{cases} (1 - \dfrac{\sum_{h=1}^{8760} \Delta D_{X,y,h,m} \frac{\tau^{\text{ref}-\text{cmb}}_{r,y,h}}{(\sum_{h=1}^{8760} \tau^{\text{ref}-\text{cmb}}_{r,y,h})/8760}}{S^{\text{euse}-\text{ref}}_{X,y}}), & mt = EE + DF \text{ or } \\ & mt = EL + DF \text{ and } \\ & f \in X = electric \\ (1 - \dfrac{\sum_{h=1}^{8760} \Delta D_{X,y,h,m} \frac{\tau^{\text{alt}-\text{cmb}}_{r,y,h}}{(\sum_{h=1}^{8760} \tau^{\text{alt}-\text{cmb}}_{r,y,h})/8760}}{S^{\text{euse}-\text{ref}}_{X,y}})\,(\tau^{\text{alt}}_{r,f=elec,y}/\tau^{\text{ref}}_{r,f\in X,y}) & mt = EL + DF \text{ and } \\ & f \in X \neq electric \end{cases} \tag{13}$$

$$RP^{\text{ecost}-\text{tvar}}_{X,y,m} = \begin{cases} (1 - \dfrac{\sum_{h=1}^{8760} \Delta D_{X,y,h,m} \frac{\rho^{\text{ref}-\text{cmb}}_{r,y,h}}{(\sum_{h=1}^{8760} \rho^{\text{ref}-\text{cmb}}_{r,y,h})/8760}}{S^{\text{euse}-\text{ref}}_{X,y}}), & mt = EE + DF \text{ or } \\ & mt = EL + DF \text{ and } \\ & f \in X = electric \\ (1 - \dfrac{\sum_{h=1}^{8760} \Delta D_{X,y,h,m} \frac{\rho^{\text{alt}-\text{cmb}}_{r,y,h}}{(\sum_{h=1}^{8760} \rho^{\text{alt}-\text{cmb}}_{r,y,h})/8760}}{S^{\text{euse}-\text{ref}}_{X,y}})\,(\rho^{\text{alt}}_{r,f=elec,y}/\rho^{\text{ref}}_{r,f\in X,y}) & mt = EL + DF \text{ and } \\ & f \in X \neq electric \end{cases} \tag{14}$$

where $\tau^{\text{ref}-\text{cmb}}$, $\tau^{\text{alt}-\text{cmb}}$, $\rho^{\text{ref}-\text{cmb}}_{r,y,h}$, and $\rho^{\text{alt}}_{r,f=elec,y}$ are reference and alternate case average hourly emissions and marginal system costs[12] from Cambium, respectively, in hour h of year y and region r. Reference case hourly grid emissions and cost data correspond to the Cambium Mid-Case; alternate case emissions and costs correspond to the Cambium Mid-Case 95 by 2050 scenario for the grid conditions represented in scenario group 2 of Table 4, and to the Mid-Case 95 by 2035 scenario for the grid conditions represented in scenario group 3 of Table 4.

2.2 GridSIM and LoadFlex modeling of the power sector

2.2.1 Key modeling assumptions

Geographic and temporal scope

GridSIM models the contiguous U.S. based on the 25 EIA Electricity Market Module (EMM) regions [1], which are aggregated into 11 higher-level regions for reporting purposes [13]. All loads and generators are assigned one zone with transmission capability allowing hourly energy transfer between neighboring zones. The modeling timeframe in this study is 2020 to 2050 in five year increments.

[12] Inclusive of grid capacity, energy, ancillary service, and policy costs.

[13] The aggregation is as follows: Northwest (NWPP); Great Basin (BASN); California (CASO, CANO); Rocky Mountains (RMRG); Upper Midwest (SPPN, MISW, MISC); Lower Midwest (SPPC, SPPS); Great Lakes/Mid-Atlantic (MISE, PJMW, PJMC, PJME); Texas (TRE); Southwest (SRSG); Southeast (PJMD, SRCA, SRSE, FRCC, MISS, SRCE); Northeast (NYCW, NYUP, ISNE).

Transmission topology and limits

Transmission capability in GridSIM is represented as a 'pipe and bubble' framework that aggregates transmission capacity into larger 'pipes' between load and generation 'bubbles' as defined by the 25 EIA EMM regions. Existing transmission capacity is based on the 2021 AEO Reference Case. The transmission capacity dictates maximum power flows in and out of neighboring regions. Energy price separation occurs between zones when transmission lines are fully loaded. Like most bulk system capacity expansion models, GridSIM does not model the distribution system.

GridSIM models transmission capacity expansion as an option for a cost-optimal future energy system. Increased transmission capacity of modeled 'pipes' is a build option to meet demand as an alternative to or in addition to new generating capacity. Transmission capacity cost assumptions are from EIA AEO 2021 for each of the larger 'pipes' connecting neighboring region pairs. These assumptions rely on per kW-mile costs and average distances between the centroid of each region to arrive at overnight $/kW transmission costs that are then levelized with financing assumptions. Costs for new transmission expansion are reflected in the hourly marginal energy cost outputs in the model. Marginal energy costs are high in hours that drive transmission investment, often hours of high regional load and low local resource availability.

Building and transportation loads

Reference case annual electricity projections are based on regional peak demand and total energy forecasts from the 2021 AEO Reference Case. Modeled system load shapes are aggregated 2020 hourly utility load data from the FERC 714 database [12] for each region, with modifications to account for changes in the annual load factor implied in AEO forecasts. Figures S18–S19 present regional baseline energy and peak forecasts, respectively.

The load forecasts for the moderate and aggressive benchmark decarbonization scenarios that we represent in the power system cost modeling (scenarios 2 and 3 in Table 4), with 80% grid decarbonization vs. 2005 levels by 2050 and 100% grid decarbonization by 2035, respectively) include additional electrification load that is incremental to the baseline load forecast. In these decarbonization scenarios, we assume that the transportation and building sectors will electrify as the electric system decarbonizes. Additional incremental transportation and building load increases annual energy and peak demand, in addition to adjusting system load shapes.

Rates of electrification assumed for the building sector in the moderate and aggressive decarbonization scenarios are consistent with those used in the Scout modeling of these scenarios, as further detailed in the Methods and in Supplemental Information section 2.1.2. Given these electrification rates, we develop inefficient counterfactuals for added building electrification load in GridSIM by assuming that building electrification occurs with the lower performance level of scenario 1.1 in Table 4, which represents a substantial amount of electrification to resistance-based heating and water heating. This results in up to a 23% increase in baseline building annual electricity demand by 2050 under the aggressive decarbonization counterfactual scenario.

Both decarbonization scenarios assume the same additional incremental load due to electrification of the transportation sector, beyond reference case transportation electrification. Elevated growth in transportation demand assumes that 95%, 50%, and 35% of light-duty, medium-duty, and heavy-duty vehicles, respectively, are electric by 2050. Electric vehicle (EV) sales are assumed to follow an S-Curve, which, along with expected EV lifetimes, determine the number of EVs on the road each year. Figure S20 shows forecasts of EV stocks for each vehicle class out to 2050.

Additional electrification load influences annual resource planning optimization and hourly dispatch decisions due to changes in annual energy demand and hourly shapes. Building sector

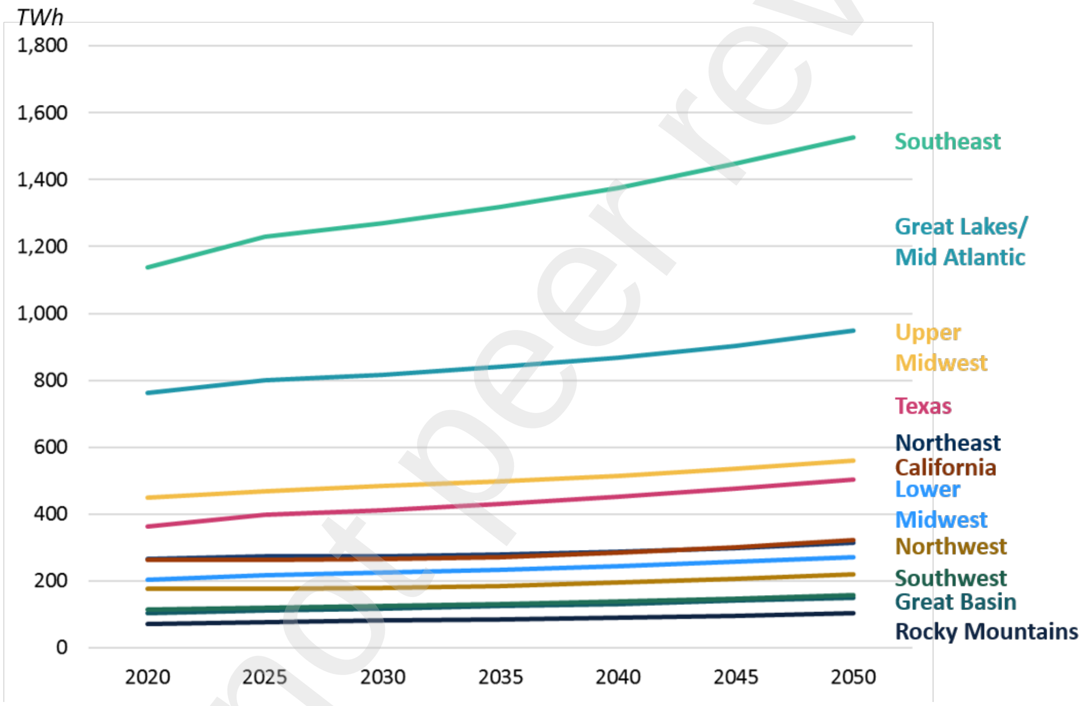

Figure S18: GridSIM baseline annual regional energy forecast for the 11 aggregations of the 25 EIA EMM regions used in this study.

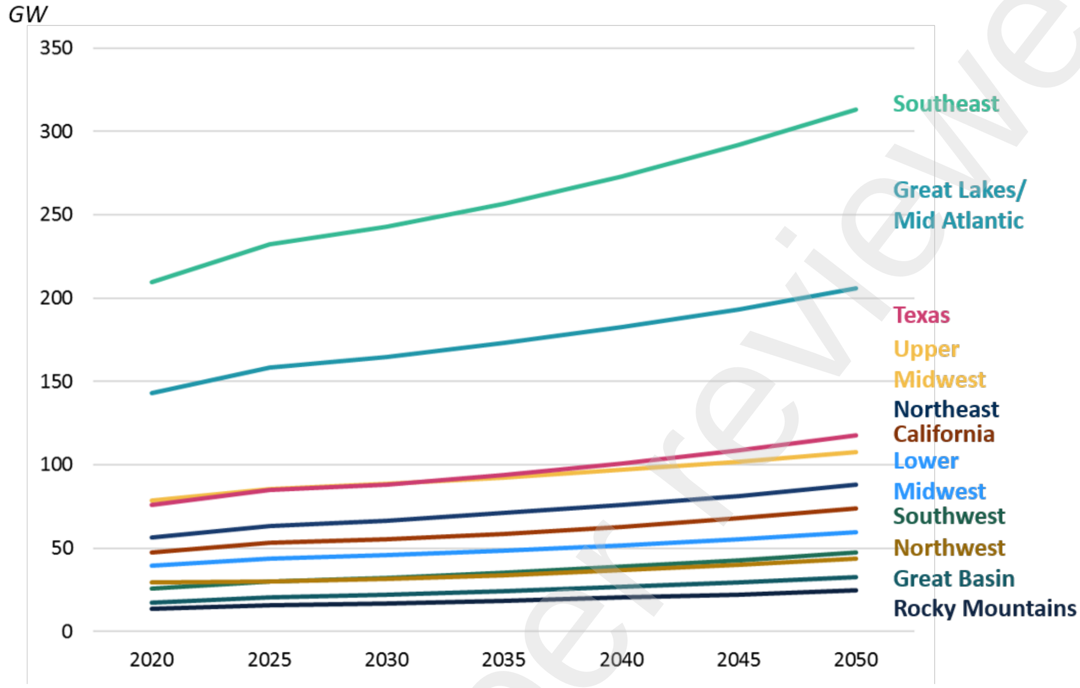

Figure S19: GridSIM baseline annual regional total peak demand forecast for the 11 aggregations of the 25 EIA EMM regions used in this study.

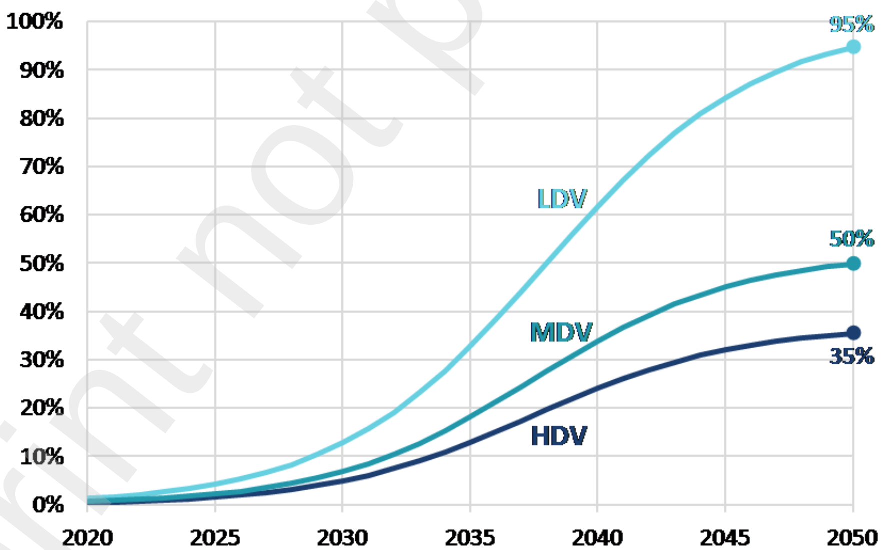

Figure S20: Electric vehicle stock penetration forecast between 2020–2050. Shown are projected penetration rates for light, medium, and heavy duty vehicles (LDV, MDV, and HDV, respectively). This forecast is used in both the moderate (80x2050) and aggressive (100x35) grid decarbonization scenarios.

electrification drives higher load in winter months primarily due to heating electrification. Electric vehicle load profiles are from the EVI-Pro Lite database [13] and reflect a composite of different charging options: Level 1 through Level 3 at different times of the day, and work, home, and public charger locations. Example weekday and weekend profiles are shown in Figure S21 for 10,000 unmanaged vehicles in California. Transportation electrification tends to increase load in evening hours when customers charge their vehicles after returning home from daily activities.

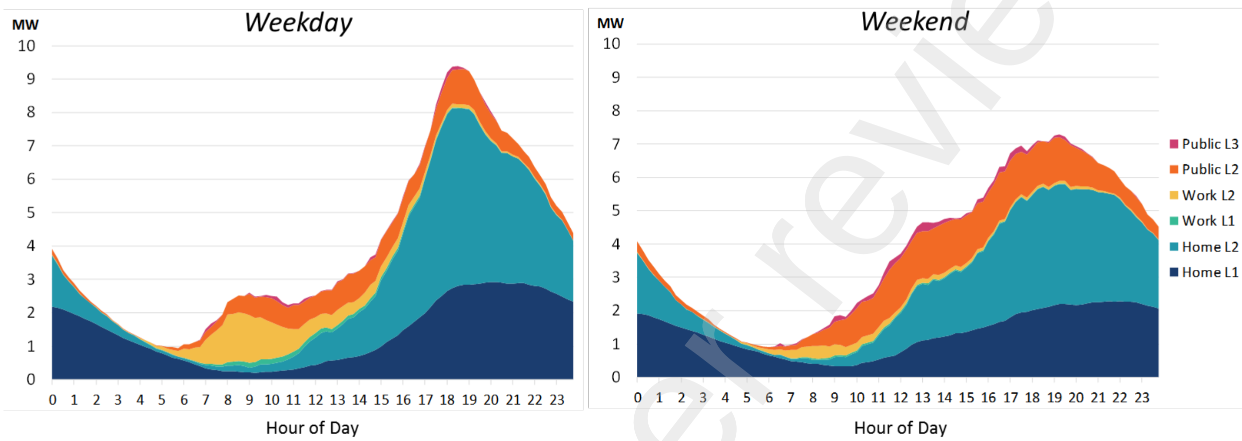

Figure S21: Illustrative electric light-duty vehicle charging load for 10,000 unmanaged EVs in CA.

Resource adequacy requirement

Each of the 25 modeled regions must satisfy local reserve margin requirements consistent with the AEO 2021 reference case. Planning reserve margin percentages represent the ratio of local available capacity above annual peak demand relative to peak demand in each region. Reserve margins ensure that additional capacity is available to provide system reliability during periods of unexpected high demand or unplanned resource outages.

The planning reserve margin (%) is held constant for each region through the study period, but because peak demand grows for each region, more capacity is needed in 2050 than in earlier years to satisfy the reserve requirement. Each region must have enough Unforced Capacity (UCAP) to satisfy the peak load plus the reserve margin in each year. In addition, certain restructured markets (i.e., ISO/RTOs) must jointly satisfy market-wide planning reserve margins in addition to zonal targets. For example, the California North (CANO) and California South (CASO) regions must each satisfy their regional reserve margins as set by the AEO in addition to jointly satisfy California ISO's 12% planning reserve margin.

Clean energy requirements

GridSIM enforces all legally binding state Renewable Portfolio Standards (RPS) that exist at the time of this study. Each state RPS is mapped to a respective region in order to satisfy the required proportion of generation from qualifying clean or renewable resources. Qualifying assets vary by region due to state-specific legislation. Additionally, certain states have megawatt procurement targets for clean resources that GridSIM enforces in the model. Both types of clean energy goals create shadow Renewable Energy Credit (REC) prices reflective of the value of clean energy in each region. The RPS and procurement mandates are the same for the reference case and the grid decarbonization cases.

The decarbonization scenarios include additional clean energy requirements mandated as national carbon constraints. Annual carbon emissions in all regions must achieve a reduction of 80% by 2050 and 100% by 2035, relative to 2005 emissions levels, in the 80x2050 and 100x2035 grid decarbonization scenarios, respectively.

Effective load carrying capability (ELCC)

GridSIM incorporates the declining effective load carrying capability (ELCC) of each type of variable wind and solar resource into resource planning decisions. At higher solar penetration levels, the resource adequacy value of new solar assets declines as simultaneous hourly generation shifts net peak into later hours of the day, reducing the ability of solar generation to meet peak load. Declining ELCC curves account for correlated renewable generation profiles and their coincidence with net peak loads. This, along with GridSIM's chronological operations representation of non-renewable generators and storage, enables GridSIM to project a realistic generation build mix and associated marginal costs in decarbonized power systems. Figure S22 presents an example of declining marginal capacity values for various renewable resources in summer as installed capacities increase.

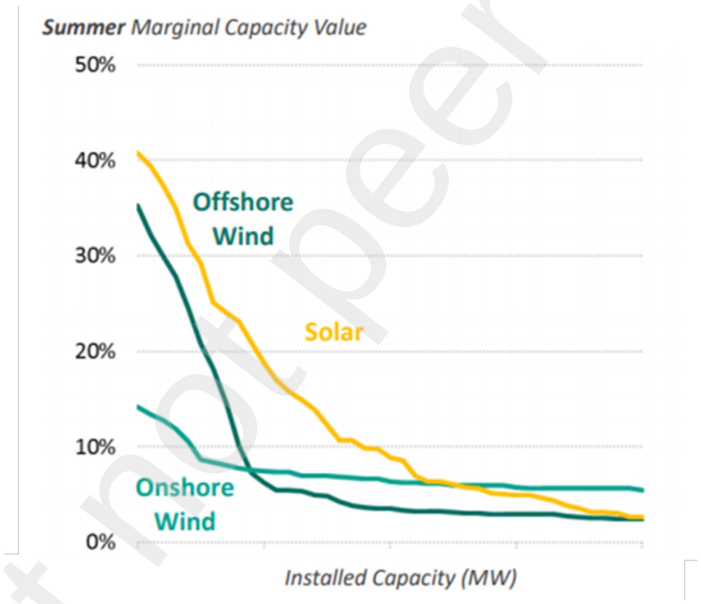

Figure S22: Example of declining marginal capacity value of renewable generation resources in the summer season.

Modeled representative periods

Within a given projection year, GridSIM utilizes a "typical days" representation of hourly load conditions, which is a common approach for capacity expansion models. The 365 days of the year are clustered based on similarities in daily load level, hourly load shape, and renewable generation profiles. Reducing the number of days modeled to a subset based on these representative clusters allows the model to capture the full range of load and renewable generation conditions that are necessary to consider from a planning standpoint while keeping the model run time manageable. Using typical days also allows the model to retain intra-day hourly chronology, which accurately accounts for the impact of the hourly profiles of demand-side efficiency, flexibility, and electrification measures.

The operating costs of existing and new resources are based on simulated chronological hourly dispatch of 49 representative days, including four representative days within each of the 12 months and the peak demand day. The four days within each month are selected by accounting for differences in demand and renewable generation within each month using a clustering algorithm. The operating cost of meeting hourly demand in each representative day is assigned a weighting based on the number of days within the month to which it is representative.

Existing and planned generators

GridSIM models existing generation and storage capacity with characteristics consistent with the AEO 2021 Reference Case. The location, capacity, heat rate, fixed operations and maintenance (FOM or fixed O&M) costs, and variable operations and maintenance (VOM or variable O&M) costs of GridSIM units are representative of existing units in each AEO region. GridSIM models "meta units" that aggregate capacity and operational characteristics over existing units from the AEO but are clustered into fewer, larger units by region, fuel type, and heat rate for fossil units. Figure S23 shows GridSIM's existing generation and storage capacity by region.

GridSIM models all planned assets as forced builds by region and fuel type to represent generation capacity with near-term commercial online dates, approved permits, and construction underway. This accounts for additional capacity that is highly likely to be built in each region before the model makes optimization decisions.

Existing and new generators must retire once they reach their respective retirement age, based on resource type from the NREL ReEDS model [14]. GridSIM can retire assets prior to the retirement age either partially or completely if cost-optimal.

Generator costs

GridSIM builds new generation capacity to satisfy load, resource adequacy, and clean energy requirements while minimizing the net present value of costs through the study period. New resource overnight capital cost assumptions are from NREL's 2021 Annual Technology Baseline (ATB) Moderate Case trajectories [15]. All resource costs vary by zone consistent with EIA AEO 2016 regional differentiation. Variable O&M costs and fixed O&M costs also come from the Moderate Case in NREL's 2021 ATB. Renewable and emerging resources see significant fixed cost declines in real terms throughout the study horizon.

Overnight capital costs for renewable and clean generation assets are expected to decline in real terms throughout the study horizon, as shown in Figure S24. Renewable assets (utility scale solar, land-based wind, and offshore wind) have additional capital cost of $300/kW incremental to costs in Figure S24, to account for transmission costs needed to interconnect renewables in resource rich areas to transmission lines and load pockets. The cost assumptions are based on a review of recent studies [16, 17].

Behind-the meter solar resources do not have the additional transmission cost adder referenced above because they are grid-connected at the distribution level. We apply a 150 GW national behind-the meter solar capacity limit, consistent with recent studies [18, 19, 20].

Renewable variable costs ranging from $2/MWh to $4/MWh for utility scale solar, land-based wind, and offshore wind are also modeled to represent basis differentials. Basis differentials account for the concentration of renewable development in resource rich areas that drive down

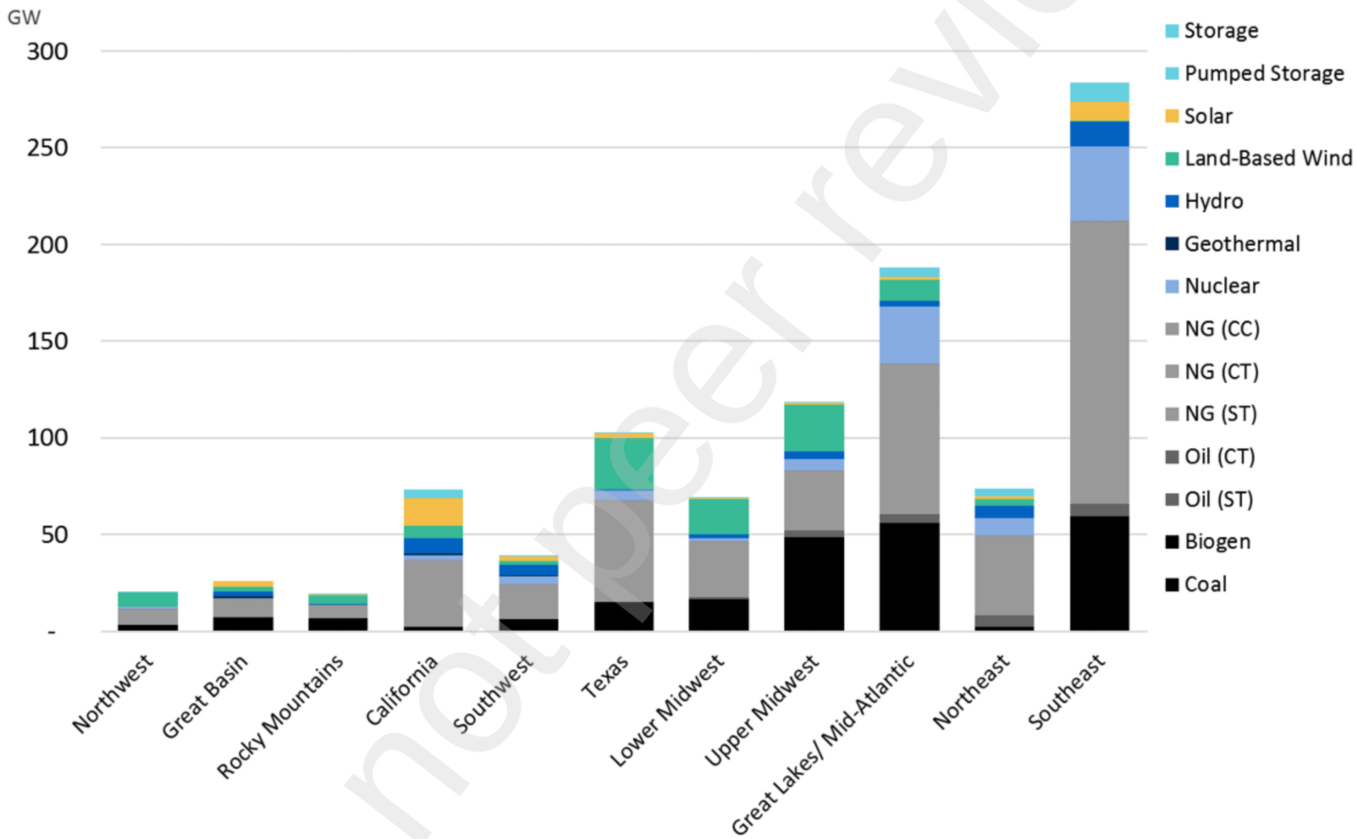

Figure S23: Existing generator capacity for the 11 aggregations of the 25 EIA EMM regions used in this study.

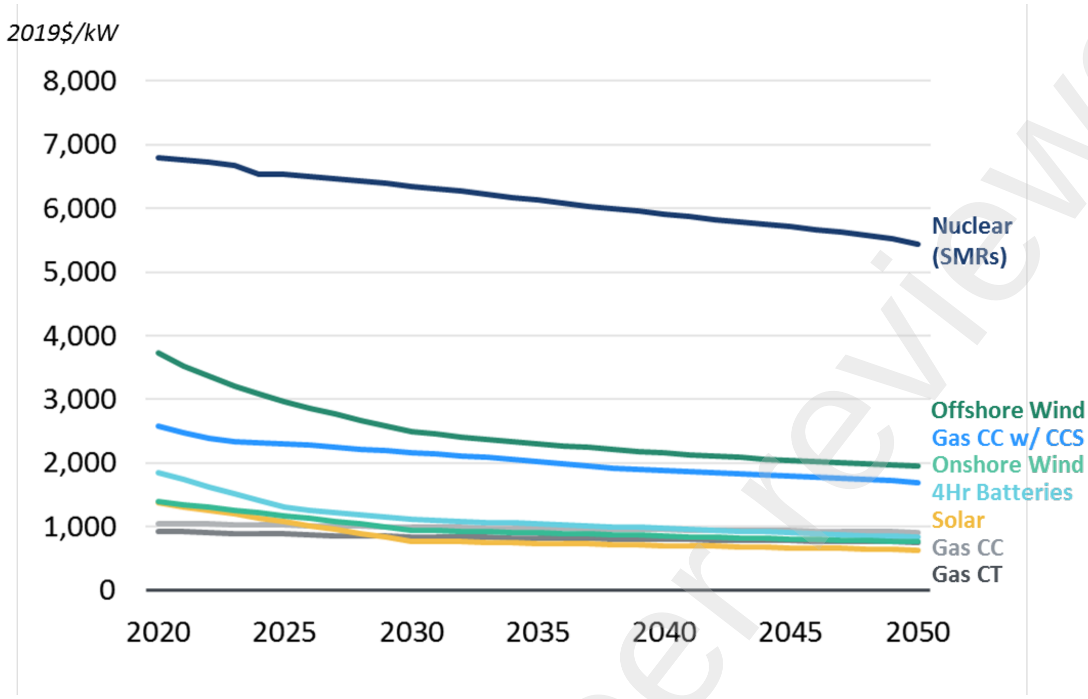

Figure S24: GridSIM overnight capital costs by technology.

energy prices at local price nodes, which is not captured by the "pipe and bubble" transmission representation in GridSIM.

Renewable profiles

Renewable generation profiles are from NREL's Renewable Energy Potential Model (ReV) [21] with adjustments based on regional historical capacity factors. Each solar and wind resource type has a different region specific profile based on five selected points in each region from the NREL ReV model. Existing solar asset profiles are a blend of fixed mount and single axis tracking technologies, while new solar plants are primarily based on single axis tracking profiles, the recently more prevalent technology.

Federal tax credits for renewables

GridSIM models a federal tax landscape that is representative of current and proposed legislation at the time of this study. These policies do not exactly replicate the Inflation Reduction Act or previous tax code, but are comparable in aggressiveness to their impacts on cost competitiveness of renewables. The policy landscape changes often, so for modeling purposes we extend tax credits beyond current expiration with the assumption that future policies will renew the Investment Tax Credit (ITC) and Production Tax Credit (PTC), as has occurred historically.

The PTC is a dollar tax credit amount awarded for each MWh of clean generation produced from qualifying technologies. The PTC applies only to onshore and offshore wind assets at $25/MWh in the beginning of the study horizon, stepping down to $15/MWh by 2023, and remaining at that level through 2050.

The ITC is a percentage tax credit applied to the total investment costs for new renewable assets. The ITC applies only to solar at 30% of total costs in the beginning of the study horizon, stepping down to 10% by 2027, and remaining at that level through 2050.

Fuel costs

Near term natural gas fuel prices are based on regional forward market data (where available) and blended to the long-run fuel price trajectory from the 2021 AEO. Gas price spot forwards are from 11/8/2021 and sourced from S&P Global Market Intelligence [22]. Coal and oil price trajectories are from the 2021 AEO for all years. Figures S25–S27 show these price projections by region. Figure S26 excludes NYUP, NYCW, and ISNE, which are regions without future coal demand and zero-priced forecasts from the AEO.

Flexibility measure dispatch

Dispatch of building demand flexibility measures is handled by the complementary LoadFlex model based on assumed constraints on a measure's load reduction or load building behavior, which are further defined here.

- Load reduction constraints:
  - A measure's load reduction can only happen once each day, across four consecutive hours per the peak period constraints established in [9].
  - The shape of the measure's load reduction during these four hours is taken from the savings profile from Scout, at the granularity of Measure x EMM Region x Day.
  - For example, if the measure's Scout savings profile shows savings of 25% of baseline in hour 1, 20% in hour 2, 15% in hour 3, and 10% in hour 4, then load reductions are allowed in any consecutive four hours of the day, with reductions calculated based on the same shape (i.e., 25% in hour 1, 20% in hour 2, etc.).
- Load building constraints:
  - A measure's load building is constrained by the ratio of load building to load reduction (MWh to MWh) observed in its Scout savings profile. This ratio is calculated at the granularity of Measure x EMM Region x Week.
  - Load building is assumed to be spread evenly over each hour, in equal MWh increments.
  - A measure's load building is also constrained in its timing relative to when load reduction occurs. Our modeling of this constraint varies by the type of measure, as informed by Scout documentation and model outputs.

  Flexibility measures are deployed in our analysis with packaged efficiency features; therefore, the dispatchable portion of these measures' hourly impacts must be isolated for use in LoadFLex. Here, we model versions of the measures without the flexibility features (e.g., with efficiency features only) and use the changes in hourly load shapes vs. the full measure versions with flexibility features to determine the dispatachable portion of the measure's hourly load impacts for LoadFlex.

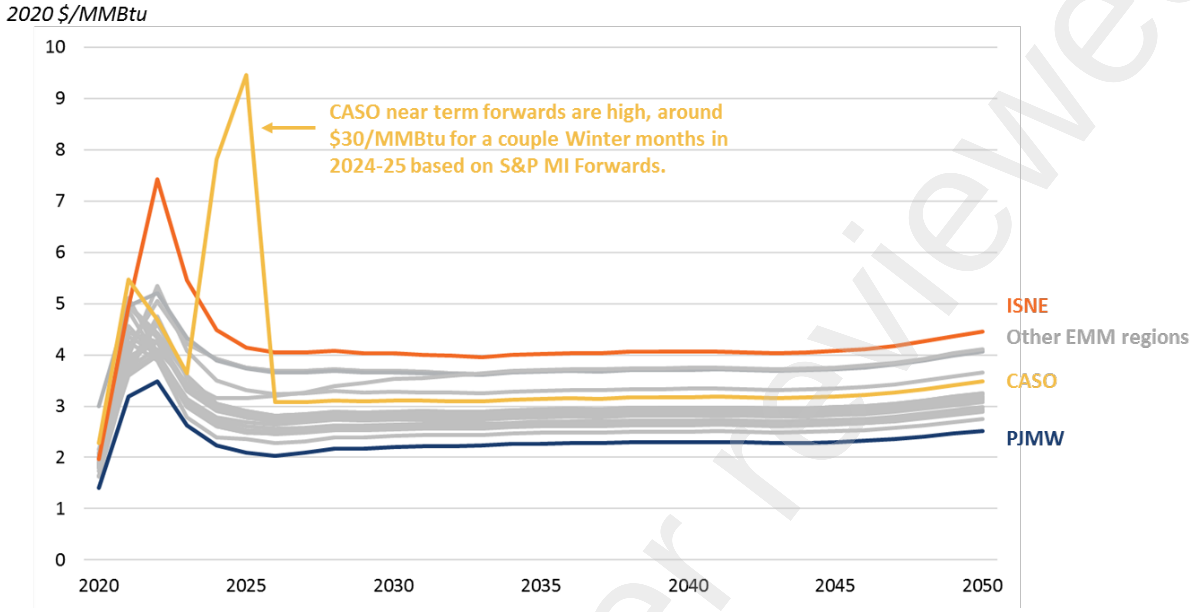

Figure S25: Natural gas fuel price forecasts by EMM region.

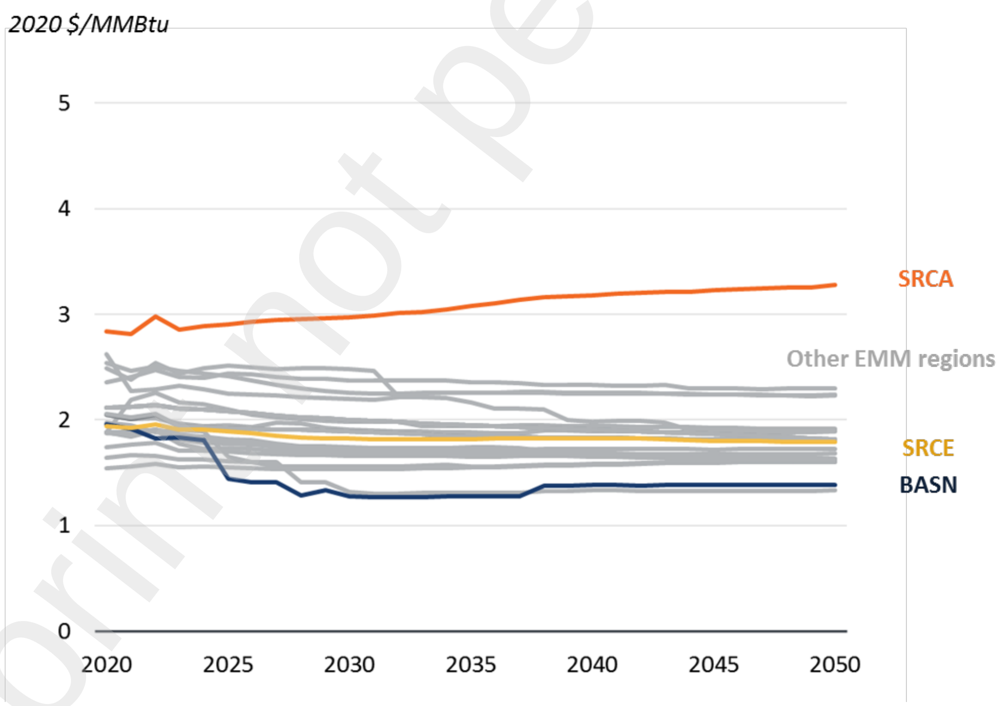

Figure S26: Natural gas fuel price forecasts by EMM region.

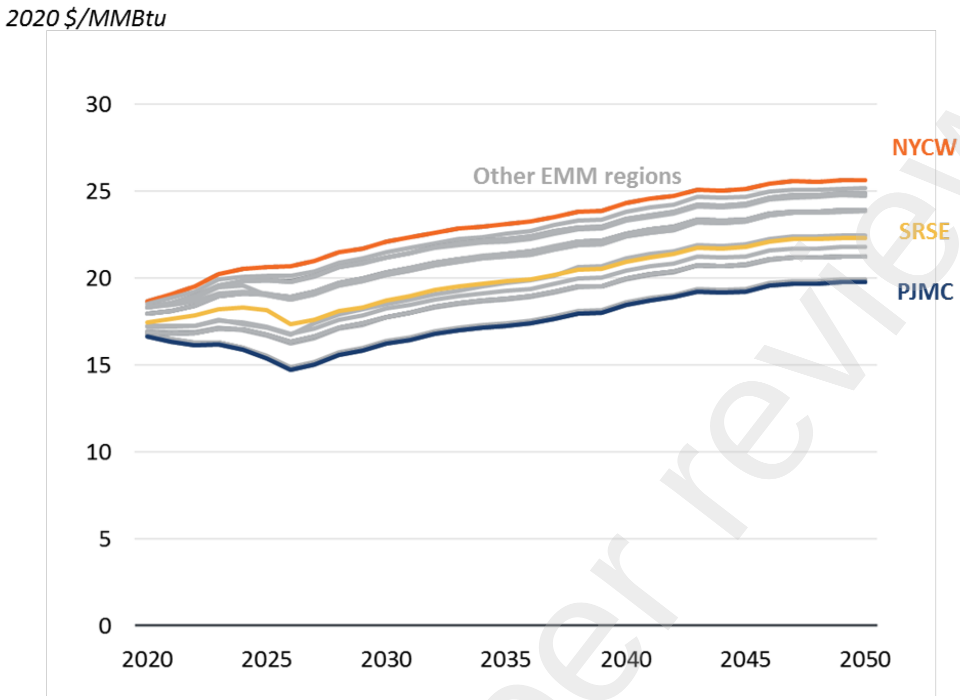

Figure S27: Natural gas fuel price forecasts by EMM region.

2.2.2 Marginal energy and capacity cost outputs

The GridSIM outputs of particular relevance for this study are forecasts of marginal energy and capacity costs. Marginal energy and capacity costs are used to value reductions in overall electricity consumption and in system peak demand attributable to the demand-side measures modeled in this study. Marginal energy costs are estimated using the shadow price on the modeling constraint that requires system load to be fully served by generation in each hour. The shadow price is effectively the per-kilowatt-hour cost associated with a small incremental increase in load. It could include the variable cost of the marginal generator as well as the incremental cost of new capacity (generation or transmission) required to serve new energy needs. Separately, the marginal capacity cost is represented by the shadow price on the modeling constraint that requires that there be enough available capacity online to meet the system's peak demand plus a reserve margin. It represents the cost associated with a small incremental increase in system peak demand.

For each of the modeled grid decarbonization scenarios, years, and modeling regions, GridSIM outputs annual capacity prices in $/MW-year and hourly energy prices in $/MWh (see, e.g., Figure S11). We convert all price input data to hourly estimates in units of $/MWh, and then use the LoadFlex model to value the hourly load impacts of the demand-side measures with time-varying, hourly granularity. To convert capacity prices to $/MWh, we allocate the $/MW-year annual value proportionally across roughly the top 50 to 100 hours per year, depending on the region. To do this, we calculate system net load in each hour and identify a "threshold" net load value for each region, above which the capacity price will be non-zero. We then calculate a "weight" to apply to each net load hour, equal to each net load hour's absolute difference between the threshold value and net load in that hour (the weight is set to zero if net load does not exceed the threshold). We then calculate a weighted average capacity price in each hour, region, and year, based on these weights.

3 Sensitivity of results to accounting for fugitive emissions sources

We assess the sensitivity of the emissions results in our benchmark scenarios to accounting of several fugitive emissions sources, including leakage of refrigerants from building HVAC technologies and leakage of methane from the natural gas supply chain. In the former case, installing air conditioning (AC) and heat pump (HP) technologies in both residential and commercial buildings will cause an increase in emissions of fluorinated gases ("F-gases"), which are commonly used as refrigerants in these technologies and, when leaked into the atmosphere, have very high global warming potential (GWP) [23]. In the latter case, replacing natural gas-fired space and water heating equipment with electric technologies will not only reduce direct emissions from on-site natural gas combustion but will also avoid the leakage of methane (CH_4) throughout the oil and natural gas supply chain [24], thus avoiding another high-GWP source of emissions. These two sources of fugitive emissions will counteract one another in scenarios that feature accelerated adoption of HP technologies, but the magnitude of their associated emissions impacts relative to avoided operational emissions under various building decarbonization scenarios has not been studied before at the scale of the U.S. building stock.

We integrate data into our modeling framework on both fugitive emissions sources at the technology level to determine how they impact overall CO_2-equivalent (CO_2-eq) emissions. Figure S28 presents results for our three benchmark scenarios (see Table 4). In general, our results show that increases in CO_2-eq emissions due to refrigerant leakage (shown as negative emissions reductions in the orange bars in the figure) are of a smaller magnitude across scenarios as are further decreases in CO_2-eq emissions due to avoided methane leakage (shown as positive emissions reductions in the blue bars in the figure). In 2030, the impact of refrigerant leakage is around half of that of avoided methane leakage across scenarios. In 2050, we find that avoided methane leakage emissions are greater than refrigerant leakage emissions by 45.9 Mt CO_2-eq in Scenario 1 (around 3.5X), which reflects the constraint of aggressive HP conversions to fuel switching contexts in that scenario (e.g., excluding aggressive replacement of resistance heating/water heating technologies with HPs). We see that when a wider frame of aggressive HP conversions is explored that includes both fuel switching to HPs and replacement of electric resistance heating and water heating with HPs (scenario 3), the difference in impacts of refrigerant leakage and avoided methane leakage are somewhat smaller, though methane leakage still dominates (a ratio of 1.9X), leading to overall CO_2-eq savings that are 33 Mt CO_2-eq higher than in the benchmark for that scenario.

These findings demonstrate important sensitivities to accounting for fugitive emissions sources from refrigerant and methane leakage in building decarbonization analyses. They suggest that the negative effects of aggressive fuel switching to HP technologies in terms of added refrigerant leakage emissions are always offset by concurrent reductions in methane leakage from the natural gas supply, due to reduced demand for gas heating and water heating services under high electrification. Furthermore, our sensitivity analysis assumes that HVAC technologies use typical refrigerants that are used in the HVAC/water heating markets today and/or mandated in the future by existing regulations (see additional methodological details in the following section); if new policies are passed that further regulate the use of higher-GWP refrigerants and thus accelerate the adoption of lower-GWP refrigerants, the avoided methane leakage benefits from fuel switching will further outweigh the influence of added refrigerant leakage emissions in the overall fugitive emissions accounting framework. We identify further sensitivity analysis to the use of lower-GWP refrigerants as an important area of further study for the fugitive emissions topic.

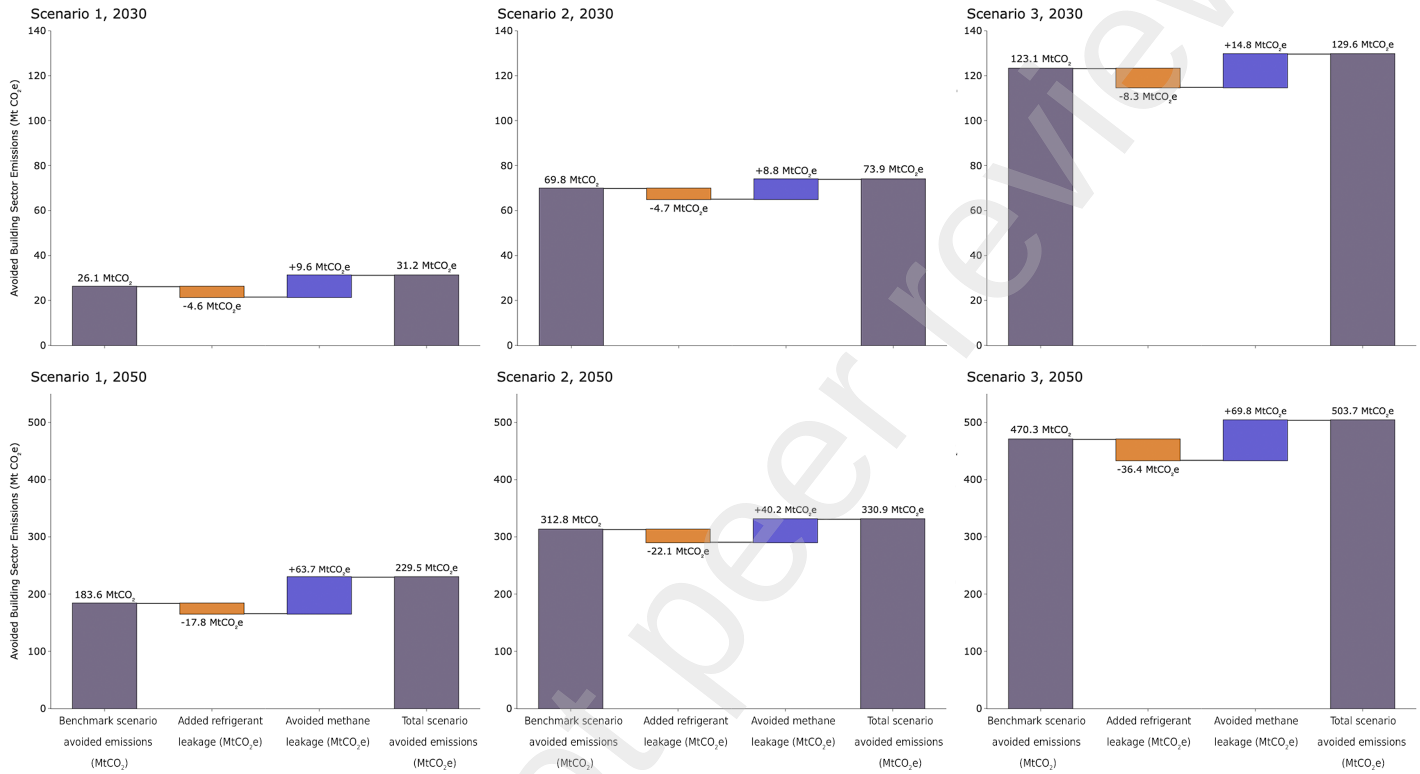

Figure S28: Sensitivity of benchmark scenario emissions reductions to fugitive emissions impacts in 2030 and 2050. Total avoided CO_2 emissions for each benchmark scenario are calculated both with and without accounting of additional impacts from fugitive emissions sources, including leakage of refrigerants from building HVAC technologies and leakage of methane from the natural gas supply chain. Figure bars show initial benchmark scenario avoided emissions, increases in emissions due to refrigerant leakage, decreases in emissions due to reductions in methane leakage from the natural gas supply chain, and total benchmark scenario avoided CO_2-eq emissions after accounting for fugitive emissions.

3.1 Fugitive emissions assessment methodology

3.1.1 Refrigerant emissions data and analysis approach

To assess CO_2-eq emissions from refrigerant leakage over the lifetimes of both HP and AC technologies, we use a modified version of the *total equivalent warming impact (TEWI)* equation [25] to calculate the direct emissions from refrigerant leakage and end-of-life recovery losses, as in:

Table S3: Summary of data used to calculate fugitive emissions from refrigerant leakage.

Sector	Equipment	L_{annual} (%)	n (yr)	m (kg)	Typical Refrigerant	GWP-100	Low-GWP Refrigerant	GWP-100
Residential	Room AC	2	18	0.7				
	ASHP	5.8	15.5	3.59	R-410A	2088	R-32	675
	GSHP	5.8	15.5	3.59				
	Central AC	5.8	18	2.95				
	HPWH	2	13	4.7	R-134a	1430	R-1234yf	<1
	Refrigeration	0.3	17	0.275				
Commercial	Scroll chiller	8.5	20	995	R-410A	2088	R-32	675
	Centrifugal chiller	8.5	25	995				
	Reciprocating chiller	8.5	20	995	R-134a	1430	R-1234ze	7
	Screw chiller	8.5	20	995				
	Central AC	5.8	21	2.95				
	GSHP	5	18	141.4		2088	R-32	675
	Rooftop ASHP	5	21	141.4				
	Rooftop AC	5	21	141.4	R-410A			
	Wall-window room AC	2	10	0.7		1430	R-1234yf	<1
	Refrigeration - large	22.5	10	2000		3900	R454C	148
	Refrigeration - small	22.5	10	2000	R-134a	1430	R-1234yf	1
	HPWH	2	15	60.5				

$$TEWI = (GWP \times m \times L_{\text{annual}} \times \mathbf{n}) + (GWP \times m \times EOL)) \quad (15)$$

where:

- GWP = global warming potential of refrigerant, relative to CO_2 (GWP = 1);
- L_{annual} = leakage rate per year (%);
- n = system operating life (years);
- m = refrigerant charge (kg); and
- EOL = end-of-life emissions as a percentage of initial refrigerant charge (%)

For each technology type modeled in Scout, data are collected from existing sources on typical refrigerants, refrigerant charges, and end-of-life refrigerant leakage [26, 27]; typical refrigerant leakage rates [28, 29], and system operating lifetimes. GWP-100 values from the IPCC Fourth Assessment Report [30] are used to convert refrigerant emissions to CO_2-eq In our analysis, if a conventional refrigerant in use today is subject to regulation that would prohibit the use of that refrigerant in a future year (e.g., the U.S. EPA's Final Rule 21 [31] prohibits the use of R-410a for chillers as of January 1, 2024), we represent that via a phase-out year after which the conventional refrigerant is substituted with a low-GWP alternative. Additional rule-making from the EPA is anticipated under the American Innovation & Manufacturing (AIM) Act that will establish lower GWP limits for a wide variety of HVAC and refrigeration applications [32]. While we do not reflect such anticipated rules in this analysis, our framework is developed in such a way that new rules that affect phase-out years for existing refrigerants can be incorporated as they enter into force.

Table S3 shows the input data used for each Scout technology type (EOL refrigerant leakage for all equipment types is assumed to be 15% [28].) Values from equation 15 are formulated at the level of individual technology stock units in Scout, thus facilitating their attachment to Scout stock estimates in the same manner that per-unit operation-phase CO_2 emissions terms $I_{X,y}^{\text{euse}-\text{alt}}$ and $I_{X,y,m,mt}^{\text{euse}-\text{alt}}$ are in equations 2 and 4, respectively.

3.1.2 Supply chain methane emissions data and analysis approach

To assess the CO_2-eq emissions of methane leakage from the oil and natural gas supply chain, we incorporate data on leakage rates across various segments of the natural gas industry to calculate methane leakage rate factors for consumption of natural gas. These factors are used to calculate fugitive methane emissions from baseline building sector natural gas consumption as well as avoided methane emissions when reducing natural gas consumption through efficiency or removing it entirely via fuel switching to electricity.

Previous assessments of emissions from methane leakage throughout the oil and natural gas supply chain find that the U.S. EPA's Greenhouse Gas Inventory (GHGI) has historically underestimated the degree of leakage. Alvarez et al. [33] find in a recent bottom-up assessment of methane emissions across all oil and natural gas industry segments that emissions are especially underestimated for the production segment. Given the geospatial resolution of Scout and the variability of methane leakage rates across different oil and natural gas production basins in the U.S., we incorporate data on methane leakage rates at the state-level using recent work from Burns and Grubert [34]. Their study uses basin-level estimates of production-stage methane emissions in combination with data on natural gas production, consumption, and trade to attribute production-stage methane emissions to individual states. Figure S29 shows the state-level leakage rates from Burns and Grubert, and Table S4 shows estimates of average leakage rates for the other oil and natural gas industry segments from Alvarez et al.

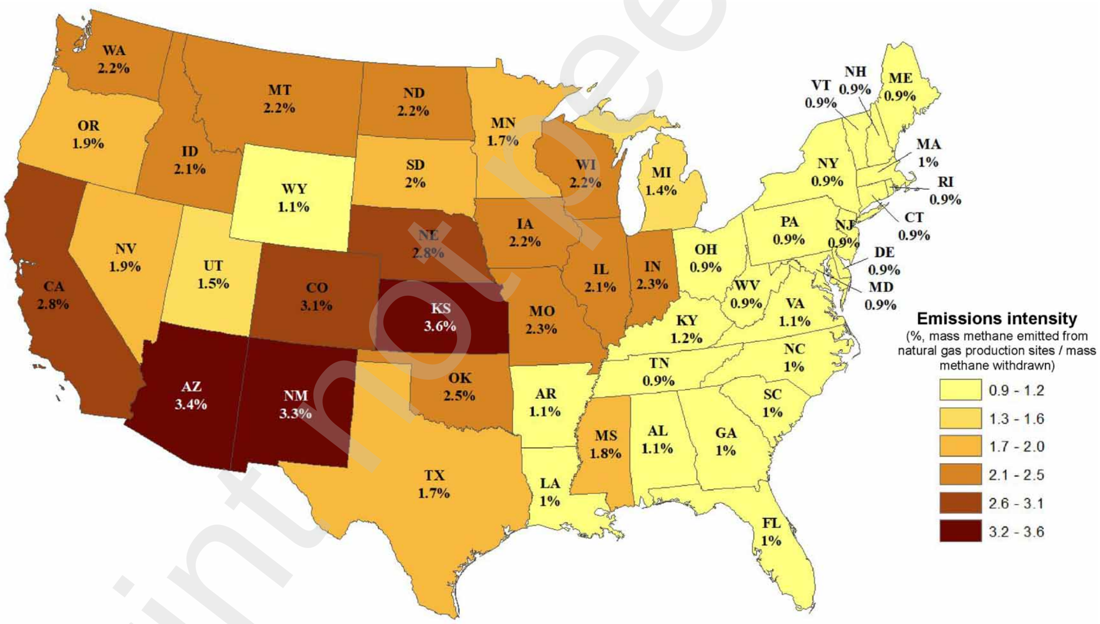

Figure S29: Estimated consumption-normalized production-stage methane emissions for natural gas consumed in each state, adapted from [34].

In our analysis, we add state-level production-stage leakage rates to U.S. national averages for the remaining oil and natural gas industry segments, which we assume decrease proportionally with production-stage decreases, to calculate total methane leakage factors by state, as in:

Table S4: Estimates of non-production-stage methane emissions across oil and natural gas industry segments and converted leakage rates used to assess fugitive emissions in Scout.

Industry Segment	Alvarez et al. estimate of 2015 CH_4 (Tg/yr)	Converted methane leakage rate†
Gathering	2.6	0.46%
Processing	0.72	0.13%
Transmission & Storage	1.8	0.32%
Local Distribution	0.44	0.08%
Oil Refining and Transportation	0.034	0.01%

† Based on estimated 2015 total natural gas production of 565 Tg[33]

$$L_{\text{s}} = L_{\text{p,s}} + L_{\text{g,US}} + L_{\text{pr,US}} + L_{\text{ts,US}} + L_{\text{ld,US}} + L_{\text{ort,US}} \tag{16}$$

where:

- L_{s} = total state methane leakage rate per year (%);
- $L_{\text{p,s}}$ = production-stage leakage rate specified by state (%);
- $L_{\text{g,US}}$ = national average gathering leakage rate (%);
- $L_{\text{pr,US}}$ = national average processing leakage rate (%);
- $L_{\text{ts,US}}$ = national average transmission and storage leakage rate (%);
- $L_{\text{ld,US}}$ = national average local distribution leakage rate (%); and
- $L_{\text{ort,US}}$ = national average oil refining and transportation leakage rate (%)

After determining state-level leakage rates based on this approach, we apply these to reference case and alternate scenario estimates of energy consumption where the fuel type f is natural gas (see main text equations 1 and 7). Given that the leakage rates apply to volume of methane leaked from natural gas production, we convert natural gas consumption in MMBtu to volume using a conversion factor of 1.037 MMBtu = 1,000 ft^3 [35]. We then apply the state-level leakage rates mapped to the EMM region set [1] to calculate volume of methane leaked, which we then convert to mass using the specific volume of methane at 70 degrees Fahrenheit, 1 atmosphere of pressure (20.2 g/ft^3). Finally, we use the GWP-100 value of methane (28) to convert to CO_2-eq emissions that we add to reference and alternate case emissions estimates in equations 2 and 8.

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