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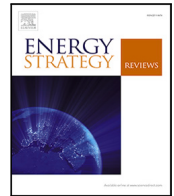
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# Assessing consumer choice projections in energy system models: A heat pump case study

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## ABSTRACT

Consumer adoption of heat pumps is a critical component of uncertainty in load growth forecasts, yet projections of heat pump adoption are rarely a focus of deeper investigation. This paper conducts a case study assessment of the structure, outputs, and performance of a model of U.S. residential heat pump adoption that has been used in multiple buildings sector potential studies and cross-sectoral energy system modeling exercises. The assessment includes model sensitivity testing based on a review of key factors in the heat pump adoption literature. Model projections across a range of scenarios show substantial regional variation in projected heat pump sales shares and sensitivity to input adjustments, with sales shares generally higher and less sensitive to input changes in warmer regions with high existing heat pump penetration, and generally lower and more sensitive in colder regions with a large installed base of fossil- and/or resistance-based heating equipment. Model benchmarking shows good agreement between estimated vs. reported heat pump sales and fuel switching shares in 2020 at the national level, but a tendency to underestimate heat pump sales shares vs. historical benchmarks at the state and regional levels. Key limitations are noted in the coverage and depth of existing historical equipment sales datasets, particularly at the state level. The analysis illustrates the current state of the art in projecting U.S. heat pump adoption and highlights key opportunities for improving confidence in heat pump projections within larger load growth forecasts and energy system modeling efforts.

## 1. Introduction

The rapid growth of U.S. electricity demand, driven by the expansion of data centers, advanced manufacturing, and electrification in the transportation and building sectors, is posing increasing challenges for grid operation and planning [1,2]. Maintaining grid reliability has become a key concern in the United States' efforts to continue advancing new energy-consuming technologies while providing affordable energy to consumers. At the same time, the scale of future electric load growth remains highly uncertain [3,4], reflecting both the rapid pace of technological change and the challenge in understanding what drives the penetration of new sources of electricity demand. Moreover, load growth is expected to vary considerably across regions because of the geographic concentration of data centers and manufacturing facilities, as well as uneven adoption of distributed loads such as electric vehicles and heat pumps [1]. Regions experiencing the fastest demand growth, including the Southeast and Mid-Atlantic, often have limited spare capacity and therefore face higher reliability risks [5]. For policymakers, businesses, and grid operators, reducing load growth uncertainty while

accounting for regional differences is critical for ensuring that sufficient energy resources are available to meet future demand.

This study focuses on the adoption of residential electric heat pump technologies as one major source of uncertainty in the projection of U.S. electricity demand. In 2024, the residential sector accounted for 15% of total end-use energy consumption and 37% of electricity demand in the United States [6]. Together, space cooling and space heating are the largest end-use segments of building energy use, representing 41% of total residential building energy consumption in 2024 [7]. While cooling is currently the primary driver of system peak electricity demand and the majority of heating equipment in the United States is non-electric, electric heating is already prevalent in the Southeast and Northwest and most other regions show recent shifts towards the use of electric heating (Fig. 1). Heat pumps comprise one fifth of total residential heating and cooling consumption [7] and this share is likely to grow as more consumers choose to replace fossil-fired and electric resistance heating units with heat pump systems. As a result, estimating future levels of residential heat pump deployment is a central challenge

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## Nomenclature

### Acronyms

|         |                                                                         |
|---------|-------------------------------------------------------------------------|
| ACS     | American Communities Survey                                             |
| NEMS    | National Energy Modeling System                                         |
| AEO     | Annual Energy Outlook                                                   |
| EIA     | Energy Information Administration                                       |
| BTB     | Buildings Technology Baseline                                           |
| ASHP    | Air Source Heat Pump                                                    |
| COP     | Coefficient of Performance                                              |
| MSHP    | Mini-split Heat Pump                                                    |
| HSPF    | Heating Seasonal Performance Factor                                     |
| GSHPs   | Ground-source Heat Pumps                                                |
| AHRI    | American Heating and Refrigeration Institute                            |
| HARDI   | Heating, Air-conditioning, and Refrigeration Distributors International |
| NYSERDA | New York State Energy Research and Development Authority                |
| NEEA    | Northwest Energy Efficiency Alliance                                    |

### Variables

|                   |                                                                                                                                                       |
|-------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|
| $U_{X,y,m}$       | Unit-level upfront capital costs in year $y$ for competing technology $m$ within set $M$ .                                                            |
| $U_{X,y,k}$       | Unit-level upfront capital costs in year $y$ for competing technology $k$ within set $M$ .                                                            |
| $\psi_{X,y,m}$    | Unit-level annual operating costs in year $y$ for competing technology $m$ within set $M$ .                                                           |
| $\psi_{X,y,k}$    | Unit-level annual operating costs in year $y$ for competing technology $k$ within set $M$ .                                                           |
| $(\beta_1)_{X,y}$ | Beta coefficient from the Annual Energy Outlook Reference Case that weighs the influence of capital cost on market share in the residential sector.   |
| $(\beta_2)_{X,y}$ | Beta coefficient from the Annual Energy Outlook Reference Case that weighs the influence of operating cost on market share in the residential sector. |

for developing accurate load growth forecasts for the US buildings sector.

Policymakers and researchers use energy system models to evaluate how different technology, market, and policy conditions impact long-term emissions, affordability, load growth, and grid reliability. Projection of heat pump adoption is estimated within these larger energy system modeling frameworks (e.g., National Energy Modeling System (NEMS) [10]), but the methods used to represent consumer choice and their validation against real-world data are rarely a focus of the studies that rely on such models. This paper conducts a deeper investigation of one such heat pump adoption projection, from the Scout model of buildings sector energy use. Scout projections have been used in previous studies of buildings sector development scenarios [11–13], grid impacts [12,14], and broader energy system impacts [15]. Moreover, the tool continues to be actively developed for use in similar studies in the future and its code base is public and customizable [16]. Scout is therefore a useful example of an existing adoption modeling framework that would benefit from further testing and evaluation against real-world data.

The case study of Scout's adoption model aims to address the following research questions:

- How does the competitiveness of heat pumps vary regionally under a simple model of economic consumer choice between candidate heating technologies, and what factors drive regional variation?
- How well do heat pump sales shares from this simple choice model correspond to historically-observed shares at national and state levels of aggregation; how sensitive is the model's performance to the addition or subtraction of model input assumptions?
- What gaps in available historical heat pump sales data must be filled in order to further explore and validate model outputs and improve the quality of heat pump adoption projections in the future?

The analysis explores the key characteristics and outputs of Scout's heat pump adoption modeling framework and examines the correspondence of model estimates to available historical heat pump sales datasets. Such model assessments are important for establishing the plausibility of heat pump adoption scenarios embedded within broader estimates of future load growth in energy system modeling frameworks — again, however, focused evaluations of adoption models are not common in the existing buildings sector modeling literature. Moreover, by identifying key gaps in existing data, this paper highlights priorities for subsequent buildings data collection that can improve the understanding of current and possible future trends in buildings sector technology adoption.

## 2. Background

Representations of technology adoption in energy system models often emphasize the role of financial drivers, such as technology capital and operating costs, within economically rational frameworks. However, research has consistently shown that consumer behavior is often “predictably irrational”: rather than processing all available information to maximize utility, individuals rely on simple heuristics because of psychological and situational constraints, such as loss aversion, limited cognitive capacity, and time inconsistency, leading to decisions that are satisfactory rather than economically optimal [17–20]. Rational choice frameworks may under-represent the heterogeneity in consumer preferences, overlooking the potential for technology adoption decisions to be shaped by various household characteristics, experiences, and personal dispositions [21,22]. Consumers may be influenced by intangible, non-economic benefits such as comfort, health, home resilience, and energy independence [22]. Other mechanisms such as human resistance to change, evolving social and cultural norms, institutional dynamics, daily routines, and the diffusion of environmental values across different segments of society may also shape energy-related behavior [18,23,24].

Numerous review studies have identified the limited representation of consumer behavior as a major challenge in current energy system modeling and have called for greater behavioral realism to better capture the nuances of energy transitions. Specifically, researchers argue that models should avoid employing overly-simplified representations of consumers as rational actors who only optimize system costs under uniform decision-making preferences [25–27]. Previous work also suggests that models should reflect how real-life decision-making is driven by bounded rationality, routine habits, and the human tendency to reduce complexity [27,28].

To address these modeling limitations in the context of energy-consuming technology adoption, researchers have proposed incremental modification of existing rational-choice frameworks, which introduces behavioral economics insights, consumer heterogeneity, and non-monetary preferences into established model structures [29,30]. For example, McCollum et al. [31] enhanced MESSAGE-Transport, a global integrated assessment model, by incorporating consumer heterogeneity (e.g., technology attitudes, settlement patterns) and non-cost disutilities (e.g., range anxiety) into light-duty vehicle adoption projections. Their

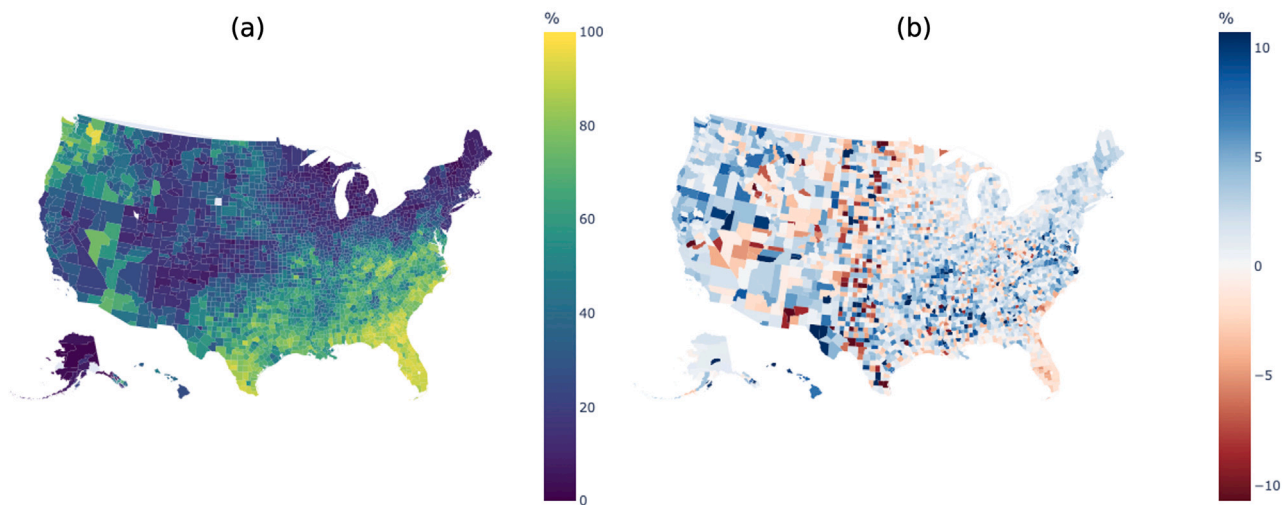


**Fig. 1.** Share of households in each US county that reported using electricity for space heating in the American Communities Survey (ACS) in 2024 (a), and the change in that share between 2020 and 2024 (b) [8,9].

results show that adding these behavioral dimensions significantly affects projected market shares, leading to more gradual adoption trajectories for low-emission transportation technologies compared to the conventional model and highlighting the importance of behavioral realism for robust climate and energy policy analysis. To date, however, no analogous case study exists for U.S. residential heat pump adoption.

The state of the literature on modeling residential heat pump adoption in the U.S. context is relatively sparse, and empirical insights are often inconclusive [30]. Nevertheless, some key findings can be drawn from the available studies. Contextual conditions, including local energy prices, incentive structures, and climatic suitability, are important in influencing the adoption of heat pumps. Rebates have been found to be more effective than low-interest loans in stimulating uptake [32]. Local climate and electricity/natural gas prices are important factors because they directly impact operating costs and effectiveness [33]. Housing characteristics, particularly building vintage, insulation, and home size, can also affect heat pump adoption by influencing both installation cost and convenience and the performance of the heat pump once installed.

On the other hand, evidence on the impact of socio-demographics (e.g., age and gender) on heat pump adoption is more mixed as such factors may serve as observable proxies for other unobserved behavioral attributes [34]. Findings on psychological factors, such as environmental awareness and attitudes, are inconclusive. Some studies report no significant correlation between environmental awareness and heat pump adoption [32,35], while others find empirical links between sustainable lifestyles, climate concern, and heat pump adoption [36]. Social influence can also play a role; for example, neighborhood effects for heat pump adoption in rural Vermont exceeded those observed for solar panels and electric vehicles [37], though the lower visibility of heat pumps may limit their “conspicuous conservation” value and the associated social capital benefits [36].

Overall, the current literature indicates that heat pump adoption is primarily driven by economic and contextual factors, with certain housing and household characteristics also influencing consumers’ heat pump adoption decisions. Other non-economic factors, such as the consumer awareness of the technology and trust in suppliers or installers, are more challenging to quantify within existing modeling frameworks but nonetheless play a role in accelerating market uptake [38,39].

Drawing from both model reviews and the heat pump adoption literature, the current analysis identified a set of variables to be implemented in Scout to test how using alternate adoption assumptions and/or incorporating more granular representation of consumer characteristics might influence projected heat pump uptake. These variables

were selected based on their relevance and feasibility, as suggested in Galster et al. [40], and they align with an incremental improvement pathway that builds on existing model structures and available data. The details of these additional adoption factors are presented in Section 3.3, following an overview of the Scout tool and its reference approach for modeling residential heat pump adoption.

### 3. Methods

To anchor this study in practical modeling needs, a focus was placed on the representation of heat pump adoption in the Scout model of buildings sector stock and energy use, beginning with the representation of technology adoption currently employed in the Scout modeling framework and introducing additional model inputs to test their effects on model outputs and performance vs. available historical data.

Fig. 2 outlines the steps in the analysis workflow — from choosing a case study model, to testing and benchmarking it. The following sections further detail these steps.

#### 3.1. Overview of Scout

Scout is a hybrid [41] building stock modeling framework that estimates the short- and long-term annual impacts of energy efficiency, flexibility, and fuel or technology switching measures on building energy use at regional and national scales. The Scout framework combines a technological-econometric model of building and technology stocks with an end-use distribution model of energy use per unit stock.<sup>1</sup> The tool has been under active development for over a decade [16]; as mentioned, it has been utilized in several studies of U.S. buildings sector impact potential [11–15,43,44].

Scout analyses begin with bottom-up representation of U.S. building technology stock and annual energy use segments. Baseline estimates for building technology stock evolution, per-unit energy service demand and consumption, and energy prices are currently drawn from the 2025 Annual Energy Outlook (AEO) Reference Case [7]. Scout represents scenario-driven changes in baseline technology stock, energy use, and costs at the level of individual building technology measures. Each Scout measure is applied to particular segments of the baseline building technology stock during the year range in which the measure is available to energy consumers. Market share adjustments account for economic competition between multiple measures that provide the

<sup>1</sup> The specific version of the Scout code used in this study is available [42].

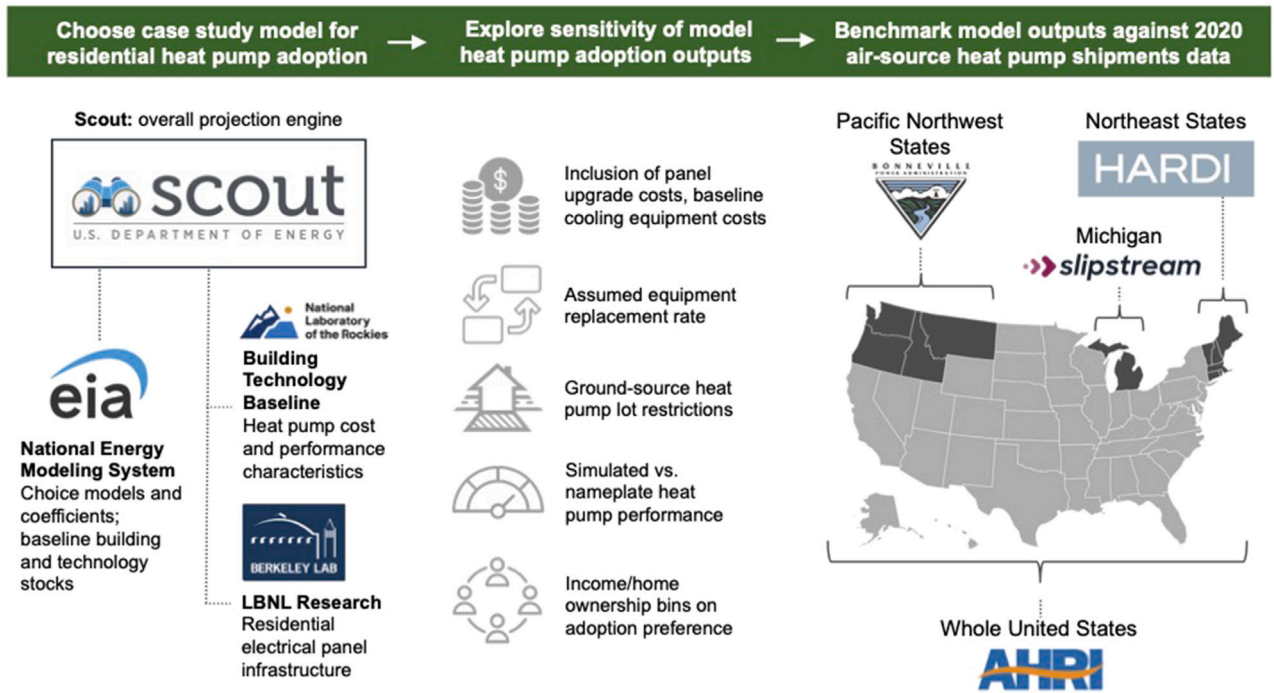


Fig. 2. The methodological approach uses the Scout model as a case study for exploring the sensitivity of residential heat pump adoption projections to model input perturbations and for benchmarking projected heat pump adoption against historical shipments datasets at the national and state or regional levels.

same energy service, as further detailed in the next section. Finally, measure-level stock, energy, and cost results for each scenario are aggregated into annual, portfolio-level series by state across the modeling time horizon, which is set to 2020–2050 for this work.

Additional details about Scout's primary modeling steps are available in the Experimental Procedures of Langevin et al. [12] and in the tool's documentation [45].

### 3.2. Reference approach for modeling heat pump adoption in Scout

The representation of technology adoption potential in Scout is primarily affected by two factors: (1) the speed with which a technology could penetrate a baseline market, which depends on the collective rate of new home additions, existing technology stock replacements, and early technology retrofits, and (2) the economic competitiveness of a technology from a consumer perspective with other technologies that provide the same energy service, which determines a market share adjustment for each technology. The current study focuses on comparing estimated technology market shares in Scout against historical data; therefore, this section details the basis for determining those market shares (see [12] for additional details on how stock turnover is represented in Scout).

Residential market shares are calculated in Scout with a logistic regression model, adopting the approach used in the U.S. Energy Information Administration (EIA) NEMS modeling for the 2025 AEO to allocate market shares across equipment efficiency levels within a given technology class [10]. Specifically, the market share estimate,  $\theta_{X,y,m,M}^{\text{mkt}}$ , reflects a trade off between a technology's capital and operating costs:

$$\theta_{X,y,m,M}^{\text{mkt}} = \frac{\exp((\beta_1)_{X,y} U_{X,y,m} + (\beta_2)_{X,y} \psi_{X,y,m})}{\sum_{k=1}^M \exp((\beta_1)_{X,y} U_{X,y,k} + (\beta_2)_{X,y} \psi_{X,y,k})} \quad (1)$$

where  $U_{X,y,m}$ ,  $U_{X,y,k}$ ,  $\psi_{X,y,m}$ , and  $\psi_{X,y,k}$  are the unit-level upfront capital and annual operating costs in year  $y$  for competing technologies  $m$  and  $k$  within set  $M$ , respectively, and  $(\beta_1)_{X,y}$  and  $(\beta_2)_{X,y}$  are choice coefficients from the AEO Reference Case that weigh the influence of capital and operating costs, respectively, on market share in the

residential sector [46]. The ratio of these choice coefficients, which is interpreted as an implicit discount rate, is held constant at 6.5% for all end uses in AEO 2025. The value of the coefficients are calibrated by efficiency level to ensure that modeled equipment purchase shares align with historical shipment data.

In this study, equipment capital costs ( $U_{X,y,k}$  and  $U_{X,y,m}$  in Eq. (1)) were drawn from the 2024 Buildings Technology Baseline (BTB) dataset [47]. All costs were drawn from the year 2023 in the Reference case. Capital costs were regionally-adjusted to account for geographic differences in construction costs, using the RSMeans City Cost Index for the largest city in each state [48]. Per-unit energy costs ( $\psi_{X,y,k}$  and  $\psi_{X,y,m}$ ) are based on the AEO 2025 Reference Case [7]. Specifically: AEO-forecasted fuel prices for a given segment were multiplied by total forecasted fuel consumption for the same segment to project aggregate segment energy costs from AEO data; the result was divided result by the forecasted number of units in the segment to reach the per-unit energy costs of Eq. (1).

Additionally, beta coefficients  $(\beta_1)_{X,y}$  and  $(\beta_2)_{X,y}$  were used that reflect the tiered coefficient structure introduced in AEO 2025, where coefficient estimates are conditional on equipment energy performance level. For heating equipment, the tiered coefficient estimates were developed by first determining the share of total equipment in a given class that meets ENERGY STAR performance requirements (ca. 2024) (considered a proxy for "high efficiency") using historical ENERGY STAR and American Heating and Refrigeration Institute shipment data (see more coverage of these sources in Section 3.4.1). Coefficients were then estimated that reproduce these historical shares of high efficiency heating equipment as closely as possible.<sup>2</sup> When calculating market shares in Eq. (1), any equipment that meets or exceeds the ENERGY STAR performance requirements uses one set of coefficients, while equipment that is below this threshold uses another set of coefficients.

Scout's handling of consumer switching across equipment classes (e.g., conversions from existing fossil-based or resistance heating to

<sup>2</sup> Understanding based on correspondence September 17th, 2025 with EIA NEMS modeling team member Rosalie Dubbohlke.

heat pumps) is an important area of distinction between the tool's modeling approach and that of AEO/NEMS. Whereas the latter represents switching on the basis of a life cycle cost comparison and imposes caps on the percentage of units that can switch away from the baseline technology class in a given year [10], Scout's calculations allow competition among technologies within *and across* equipment classes on the basis of Eq. (1), effectively assuming that coefficients that were fit based on sales data particular to a given equipment class generalize to the assessment of competing options from outside that equipment class that provide the same energy service. Subsequent sections will demonstrate the degree to which fuel switching rates produced with this simplifying assumption are consistent with inferred rates of fuel switching from historical heating equipment sales data.

### 3.3. Changes to reference adoption model to test sensitivities

The reference Scout model of residential technology choice in Eq. (1) serves as an example of a simple rational-choice framework that could benefit from the incremental addition of behavioral drivers, as suggested in Section 2. Six changes to the reference Scout technology choice modeling framework were introduced to demonstrate the model's sensitivity to additional inputs and test the degree to which each input improves the model's correspondence to historical benchmarks for heat pump adoption.

#### 3.3.1. Nameplate vs. simulated heat pump performance

Scout typically defines competing building technology performance characteristics — and energy costs, by extension — based on nameplate (rated) equipment efficiency. The actual performance of heat pumps may vary from the nameplate value, particularly in outdoor conditions that differ significantly from the conditions in which the unit is tested.

Using state-level annual mean heating performance results for air-source heat pump (ASHP) units from the ResStock Standard Data Release 2025.1 [49],<sup>3</sup> simulated unit performance was calculated and used in lieu of the nameplate performance when assessing ASHP energy cost savings and competitiveness against alternative types of heating equipment.<sup>4</sup>

Specifically, simulated ASHP heating coefficient of performance values compare the ResStock-simulated ASHP performance in each state to nameplate performance to develop a state-resolved simulated vs. nameplate performance ratio.<sup>5</sup> The calculation draws data from all ResStock baseline dwelling units with air source or mini-split heat pumps (MSHPs). Simulated heating COPs are a weighted average of the delivered heating energy (`out.load.heating.energy.delivered.kbtu`, converted from kBTU to kWh) vs. consumption, including electric resistance backup heating and electricity consumed by air distribution fans or circulating pumps (`out.electricity.heating.energy.consumption.kwh + out.electricity.heating.hp.backup.energy.consumption.kwh + out.electricity.heating.hp.backup.fan.energy.consumption.kwh`). This simulated heating COP value for each state was divided by the nameplate heating COP, calculated by dividing the rated heating seasonal performance factor (HSPF) by 3.14, to obtain the ratio that was then applied to the Scout COP value to reflect a simulated performance adjustment in the modeling.

#### 3.3.2. Treatment of electrical infrastructure upgrade costs

When representing fuel switching from fossil-fired heating equipment to all-electric heat pumps, Scout adds the cost of installing a

dedicated circuit for the new electric equipment in all homes [47] as well as the cost of an electrical panel upgrade in a significant portion of homes.<sup>6</sup>

Two alternate cases were tested in which: (1) all homes are assumed to incur the additional electrical panel costs, or (2) none of these additional costs are represented, in order to obtain upper and lower bounds on the estimates.

#### 3.3.3. Scope of comparable baseline costs

Scout assumes that consumers considering a switch from separate heating and cooling equipment (e.g., a gas or electric resistance furnace with separate central air conditioning) assess heat pump installed and operating costs against the combined installed and operating costs of the separate heating and cooling units, since heat pumps replace both of those energy services.

An alternate case was tested in which the full installed cost of a heat pump and the heat pump's operational heating costs were competed against only the baseline heating equipment's installed and operating costs, while the avoided costs from replacing the separate cooling equipment and any cooling consumption savings were not counted in the competition calculations.

#### 3.3.4. Consideration of adopter income level and home ownership characteristics

The choice coefficients used in the Scout adoption model are representative of an average consumer and do not account for heterogeneity in consumer income level and home ownership status, which literature suggests may influence the weight assigned to upfront vs. operating costs.<sup>7</sup>

An alternate case was tested in which Scout's market segments were further segmented by income bin (low vs. high) and tenancy status (renter vs. owner). Income and tenancy data were obtained from ResStock outputs, which are derived from data from the American Community Survey. Low-income households are defined as those that are below the federal poverty level, using the 2019 U.S. federal poverty level guidelines, which varies by household size and location. Tenancy options included owner, renter, and unoccupied; homes tagged as unoccupied assumed the same shares of low-income residents as for the occupied units. Homes with missing tenancy and income data were excluded when determining shares [49].<sup>8</sup>

Each sub-segment was then assigned a unique set of technology choice coefficients. Specifically, Scout's reference implicit discount rate for heating equipment of 6.5%<sup>9</sup> was doubled for low-income renters (i.e., they were assigned a relatively higher weight for capital costs than in the reference model, since typically owners make the purchasing decisions and do not pay the energy costs [54]) and was halved for high-income owners (i.e., they were assigned a relatively lower weight

<sup>6</sup> The share of homes that require a panel upgrade when switching heating equipment classes is estimated across baseline equipment fuel types for existing single family homes only, based on previously-developed methods for determining existing panel ratings and the need for upgrades to accommodate new equipment in the ResStock data [50].

<sup>7</sup> For example, lower-income consumers have less cash on hand to cover a large up-front investment in higher-performing technology that generates more cost savings over time, and renters may face additional constraints on their ability to install new equipment [51–53].

<sup>8</sup> Federal poverty level depends on household size and region. For the contiguous United States, the levels for household sizes between 1 and 8 are between \$12,490 and \$43,430. For households with over 8 people, the limit is \$4420 per additional person.

<sup>9</sup> The implicit discount rate is the ratio of the capital cost beta coefficient to operating cost beta coefficient in Eq. (1). Per the NEMS documentation [10], the implicit discount rate value results from exogenous adjustment of beta coefficients such that modeled equipment purchases mimic shares of historical equipment sales for the given equipment type.

<sup>3</sup> The values are based on ResStock national result "upgrade\_0".

<sup>4</sup> The focus here was on ASHPs given availability of both ResStock simulation and sales state-level data to compare results against.

<sup>5</sup> This is done for the ASHP nameplate COP that is closest to that used in the Scout modeling, which is 2.58 for the typical Scout ASHP.

**Table 1**  
Scenarios tested, including base Scout adoption model and additional sensitivity cases.

| # | Description and abbreviation                                                        |
|---|-------------------------------------------------------------------------------------|
| 1 | Reference Scout adoption model (base)                                               |
| 2 | Ignore cooling equipment capital and operation costs (no_cool_costs)                |
| 3 | Ignore electrical infrastructure upgrades when tech. switching (no_elec_infr_costs) |
| 4 | All homes receive electrical upgrades when tech. switching (all_elec_infr_costs)    |
| 5 | Increase rate of existing equipment replacement (early_retro)                       |
| 6 | Restrict GSHP applicability to lots >1 acre (gshp_lots)                             |
| 7 | Use simulated vs. nameplate COPs for HPs (hp_perf)                                  |
| 8 | Account for income and rent vs. owner status (income_rent)                          |
| 9 | Combination of 5–8 (lots_perf_income_retro)                                         |

to capital costs than in the reference model). The two remaining bins of consumers (high-income renters and low-income owners) were assigned the 6.5% implicit discount rate.

### 3.3.5. Additional restrictions in technology applicability

This analysis represents potential technology switching from fossil and resistance heating to either air- or ground-source heat pumps (GSHPs), also known as geothermal heat pumps. GSHPs with horizontal ground loops, the most common configuration for residential buildings, require a large lot around the home to accommodate trenching for long ground loops, which can reach hundreds of feet per ton of capacity. Vertically-drilled systems require less space, but have higher upfront costs due to additional drilling costs.

An alternate case was tested where all GSHPs are assumed to be horizontal systems that require a single family home with at least one acre of lot space.<sup>10</sup> This excluded multifamily and mobile homes and single family homes with less than 1 acre of space from adoption, further restricting the potential for technology switching to GSHPs. Lot size data were obtained from the 2023 American Housing Survey [56].

### 3.3.6. Increased stock turnover rates

The rate at which existing baseline equipment stocks are assumed to turn over can affect total estimated market shares by increasing or decreasing the influence of existing equipment replacements on the total number of heating equipment sales (e.g., in new homes as well as in existing homes), given that installation costs differ between the new and existing contexts [47].

An alternate case was tested with rates of existing HVAC equipment replacement that were slightly higher than reference stock turnover rates — which are based in Scout on the inverse of equipment lifetimes — to make the rates consistent with those implied by HVAC retrofit data from the American Housing Survey [57]. These additional early retrofit rates have been used as a stock turnover sensitivity parameter in previous work [13].

## 3.4. Modeling scenarios and measures

By toggling the reference Scout adoption model with the integration of the additional sensitivity inputs described in Section 3.3, a suite of nine total scenarios was developed — including the reference, or “base” case — that span a wide range of potential factors impacting heat pump adoption. Table 1 describes key scenario attributes.

A consistent measure set was competed across all scenarios that represents the typical<sup>11</sup> equipment available on the market in each equipment class, such that there is one technology option per class in the competition. Equipment classes cover all potential options for residential heating and cooling service, including oil and gas furnaces

and boilers with central air conditioners or no cooling, electric resistance heating with central air conditioners or no cooling, and air- and ground-source heat pumps. Shares of households with no existing cooling equipment were resolved by Building America climate zone using RECS 2020 data [58].<sup>12</sup>

As mentioned, all equipment options were openly competed in the scenario runs, allowing switching across adopted technology classes when economically beneficial from a consumer perspective. Notably, in cases where consumers switch from fossil-based to electric equipment, they were assumed to retire the old equipment completely rather than to use it in a backup or “dual-fuel” configuration. This has important implications for results, since such measures may lower the initial cost of heat pump installation and therefore encourage greater adoption.

### 3.4.1. Model performance benchmarking approach and data

To benchmark the correspondence between Scout-projected and historically-reported heat pump adoption, several potential equipment stock and sales databases were reviewed. Table 2 summarizes these datasets.

The datasets are of both national and state-level scope. They vary in their coverage of equipment types — in particular, many do not cover GSHPs or electric resistance furnaces explicitly. Some of the datasets inventory the total installed base of equipment stock, while others track the number or share of sales of a given equipment type in a given year. Not all of the datasets are made publicly available.

Since the current study focuses on estimating heat pump market penetration, only those datasets that report equipment sales (vs. stocks) were chosen. This isolated heating equipment competition to a given year and removed the influence of the already-installed base of heating equipment from penetration shares. Furthermore, the focus was on sales shares rather than absolute sales figures to remove the influence of building and technology stock turnover assumptions on the outcomes (stock turnover rates determine the overall number of heating units that will need to be replaced and/or purchased for new construction in a given year). Finally, only datasets that are publicly available were used.

These criteria resulted in the use of five datasets for benchmarking: (1) American Heating and Refrigeration Institute (AHRI) heat pump manufacturer sales (or “shipments”) data at the national level, (2) Heating, Air-conditioning, and Refrigeration Distributors International (HARDI) data on historical heat pump sales in New York and New England made public by the New York State Energy Research and Development Authority (NYSERDA), (3) a heat pump market penetration report from Massachusetts utility program administrators, (4) HVAC sales data from the Northwest Energy Efficiency Alliance (NEEA), covering Washington, Oregon, Idaho, and Montana, and (5) a heat pump market characterization report from Michigan.

<sup>10</sup> This lot size requirement is based on the assumption that the minimum lot requirement is 255 square feet per ton for vertical loop systems and 14,520 square feet per ton for horizontal loop systems [55].

<sup>11</sup> Sales-weighted average across efficiency levels within each equipment class.

<sup>12</sup> The specific shares used are defined in each Scout measure definition under the measure's `mkt_scale_fraction` parameter. The measures that were run for this study are found in the folder `./ecm_definitions/ief_t5` [42].

**Table 2**  
Data sources reviewed for adoption model benchmarking purposes.

| Data source                                                              | Geographic scope           | Variables covered                                                                             | Period                                               | Public?                | Used? |
|--------------------------------------------------------------------------|----------------------------|-----------------------------------------------------------------------------------------------|------------------------------------------------------|------------------------|-------|
| AHRI Shipments [59]                                                      | National                   | Sales (air-source heat pumps, fossil heating)                                                 | 2005–2024                                            | Yes                    | Yes   |
| HARDI Distributor Sales Data [60]                                        | All States                 | Sales (air- and ground-source heat pumps, fossil heating)                                     | 2013–2023                                            | Mostly No <sup>a</sup> | Yes   |
| Heat Pump Market Effects Indicators Update PY2023/2024 Final Report [61] | MA                         | Sales and market penetration % (air-source heat pumps)                                        | 2021–2023                                            | Yes                    | Yes   |
| Northwest HVAC Sales Insights [62,63]                                    | Northwest (ID, MT, OR, WA) | Sales (air-source heat pumps, fossil heating)                                                 | 2016–2023                                            | Yes                    | Yes   |
| 2022 Michigan Heat Pump Collaborative Market Characterization [64]       | MI                         | Sales (air-sourced heat pumps, furnace)                                                       | 2013–2021                                            | Yes                    | Yes   |
| Residential Energy Consumption Survey (RECS) [58]                        | National                   | Stock (air- and ground-source heat pumps, fossil heating)                                     | 1987, 1990, 1993, 1997, 2001, 2005, 2009, 2015, 2020 | Yes                    | No    |
| American Housing Survey [56]                                             | National                   | Stock (electric heat pumps, fossil heating)                                                   | 1973–2023 (biennial after 1983)                      | Yes                    | No    |
| ENERGY STAR Shipments [65]                                               | National                   | Sales and market penetration % (ENERGY STAR-rated air- and ground-source HPs, fossil heating) | 2003–2023                                            | Yes                    | No    |
| BRG Annual Shipments [66]                                                | National                   | Sales (air- and ground-source heat pumps, fossil heating)                                     | 2000–2023                                            | No                     | No    |
| NEEA Residential Building Stock Assessment [67]                          | Northwest (ID, MT, OR, WA) | Stock (air- and ground-source heat pumps, fossil heating)                                     | 2011, 2017, 2022                                     | Yes                    | No    |
| California Residential Appliance Saturation Study [68]                   | CA                         | Stock (heat pumps, fossil heating)                                                            | 2003, 2009, 2019                                     | Yes                    | No    |
| NYSERDA Residential Building Assessment [69]                             | NY                         | Stock (air- and ground-source heat pumps, fossil heating)                                     | 2015, 2019                                           | Yes                    | No    |

<sup>a</sup> Available for NY and New England between 2017–2021, via NYSERDA [70].

The national AHRI dataset was used by Malinowski et al. [71] to derive implied rates of conversion from fossil-based heating equipment to heat pumps between 2015 and 2022, which were also used for benchmarking purposes in this study. The derived share for a given historical year is based on the percentage decline in the sales of the gas and oil furnaces in that year relative to what they would have been in 2015, had their share of the heating equipment market remained constant since then. To calculate the percentage of total heating equipment sales in a given year that is due to fossil-based switching to heat pumps, these conversion shares were multiplied by the sales of each type of fossil heating equipment in 2015, and again by the ratio of all heating equipment sales in the given year to those in 2015.

Model benchmarking across these datasets uses a 2020 snapshot year. This is the earliest-available historical year in Scout's projection range. More importantly, 2020 precedes the implementation of many of the more aggressive financial incentives, regulations, and other policies designed to accelerate heat pump adoption at the state and federal levels, including the Inflation Reduction Act (IRA). This meets the intent to assess the performance of the equipment choice framework in reproducing real-world heat pump penetration levels primarily on the basis of economics, before considering the impacts of more aggressive levers for accelerating heat pump deployment.

## 4. Results

This section first explores the range of outcomes produced by the scenarios of adoption assumptions shown in Table 1, examining regional differences in results and in the sensitivity to changes in adoption modeling assumptions.

Next, historical estimates from the model are benchmarked against the national- and state-level sales datasets highlighted in Table 2 and key gaps in the available benchmarking data are discussed.

### 4.1. Interpreting model projections across scenarios

Fig. 3 shows the modeled share of total heating equipment sales<sup>13</sup> in 2020 that is an ASHP, separately for each state and nationally. Here, modeled ASHP sales shares are distinguished by the type of decision that produced the sale: (1) a like-for-like replacement of a heat pump; (2) fuel switching to a heat pump away from gas-fired equipment; (3) fuel switching away from other fossil-fired equipment (e.g., propane, heating oil); and (4) technology switching from electric resistance-based heating.

Nationally, the base case ASHP sales share is estimated at 47 percent with a range of 42%–51% across the sensitivity cases; this range encompasses the 2020 sales share observed in the AHRI data, 50%. Examining the state-level results, Florida has the highest ASHP sales share, followed by South Carolina and North Carolina. Notably, the 12 states with the highest ASHP sales share are all either from the Southeast or the South, which are characterized by having relatively low residential electricity prices, low heating loads, high cooling loads, and a high installed base of ASHPs when the model starts competition in 2020. On the other end of the spectrum, Rhode Island has the lowest ASHP sales share, followed by New Hampshire and Massachusetts. States with low ASHP sales shares are generally located in the Northeast and the Midwest, and they are characterized by high heating loads and high electricity prices. States in the Pacific Northwest such as Washington, Oregon, and Idaho, which are characterized by medium

<sup>13</sup> Sales are counted across both new construction and existing building contexts, and the decision types are framed relative to the adoption outcome that would have otherwise occurred in Scout's baseline model run, which is consistent with the AEO 2025 Reference Case.

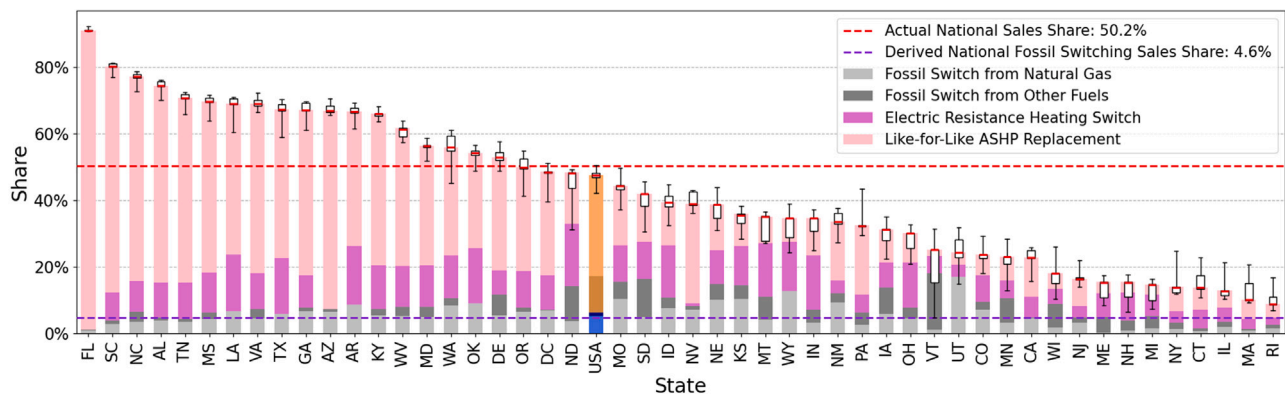


**Fig. 3.** Modeled ASHP sales share in 2020 by state and nationally (labeled “USA”), broken down by type of ASHP adoption decision (like-for-like replacement, switch from resistance-based heating, and switch from gas or other fossil-fired heating). Horizontal lines show historical AHRI shipment data benchmarks for: (top line) share of total heating equipment from heat pumps across decision types and (bottom line) share of total heating equipment sales from heat pumps that were switched from fossil-based equipment. Total heating sales (the denominator in the sales share calculation) includes heat pumps and fossil-based heating equipment. Electric resistance heating equipment is excluded.

heating loads and low electricity prices, lie close to the national sales share.

Fig. 3 also shows that, at the national level, the model estimates that 6% of heating equipment sales are from conversions from fossil-based heating equipment to heat pumps, close to the share derived from the AHRI data, 5%. In the modeled estimates, these switching cases comprise 13% of all ASHP sales. The share of ASHP sales from fuel switching varies widely across different states, however. For instance, while only around one percent of ASHP sales in Florida are from fuel switching, fuel switching makes up the majority of ASHP sales in Vermont and Utah and is also significant in other Northeastern states (Maine, Rhode Island, and New Hampshire) and several Midwestern states (Iowa, Kansas, the Dakotas, Michigan, Minnesota, and Wisconsin). States with higher relative shares of fuel switching tend to have lower installed bases of ASHP stock and higher installed bases of fossil-fuel heating equipment — heating oil in Vermont and natural gas in Utah, for example.

Fig. 4 further details the nature of the sensitivity ranges around base ASHP sales shares in Fig. 3. These results demonstrate the following about model sensitivities:

- Nationally and in each highlighted state aside from Florida, the sensitivity runs that remove consideration for avoided cooling costs lower the sales share (*no\_cool\_costs*). The relative magnitude of this effect is highest in Vermont, where high heat pump installation costs are exacerbated by widespread need for electrical panel upgrades (see Fig. A.1) and electricity prices are among the highest in the nation, increasing the importance of cooling cost savings.<sup>14</sup> In Florida, removing cooling costs has little effect because switching to heat pumps is already economically unfavorable in the baseline case, given that most consumers would be switching away from cheap electric resistance heaters.
- Representing simulated vs. nameplate heat pump performance (*hp\_perf*) lowers the sales share in the highlighted states with high heating demands, which reduce heat pump performance and operational cost savings vs. nameplate conditions (Vermont, Wisconsin; see ratios in Fig. A.2). The effect is particularly stark

<sup>14</sup> This is true for the houses that already have cooling equipment; however, Vermont falls mostly in the “Very Cold” Building America climate zone, where 55% of households do not have existing cooling [58]. For such households, removing cooling from the adoption decision *increases* economic favorability and adoption, since the new cooling cost with a heat pump is no longer accounted for.

in Vermont. Here, a large share of households do not have existing cooling,<sup>15</sup> which makes heat pump economics more sensitive to heating performance and energy cost savings vs. baseline equipment (in Vermont, mostly fuel oil). In highlighted states with lower heating demands, the effect of heat pump heating performance assumptions is minimal.

- Assuming all homes avoid additional electrical infrastructure upgrades (*no\_elec\_infr\_costs*) increases heat pump adoption. The relative magnitude of the increase is greatest in highlighted states where the most homes require a panel upgrade when switching to a heat pump under a baseline scenario (Vermont, Wisconsin; see Fig. A.1).
- Differentiating discount rate by income and tenancy group (*income\_rent*) also generally increases adoption, though the effect is minimal in the highlighted states. The small size of the effect reflects that these states do not have particularly high shares of low income renters or non-low income owners, the two groups that were assigned modified discount rates in the choice model (see Fig. A.3). The positive direction of the effect owes to the fact that significantly more residents fall into the non-low income/owner category (lower discount rate, greater importance of heat pump bill savings) than into the low income/renter category (higher discount rate, reduced importance of heat pump bill savings).
- Relative to the base case, assuming that all homes require electrical infrastructure upgrades (*all\_elec\_infr\_costs*) does not have a meaningful effect on ASHP sales shares. Since the base case already assumes that all homes that switch fuels to a heat pump require a circuit upgrade — regardless of whether they need a new electrical panel — the difference in per-unit heat pump costs between this sensitivity case and the base case is smaller than the other extreme sensitivity tested, where all electrical upgrade costs are removed.
- Similarly, adding consideration for early retrofitting behavior (*early\_retro*) and lot size restrictions for GSHPs (*gshp\_lots* and see Fig. A.4) do not have meaningful effects on ASHP sales shares. Regarding the early retrofit sensitivity, this case produces a very minimal increase in the number of units that a heat pump can compete for in the 2020 benchmark year — an additional 0.5% of the total heating stock, which as noted aligns the HVAC replacement rate with that implied by AHS retrofit

<sup>15</sup> Again, the portion for the “Very Cold” climate zone is 55%, per RECS [58].

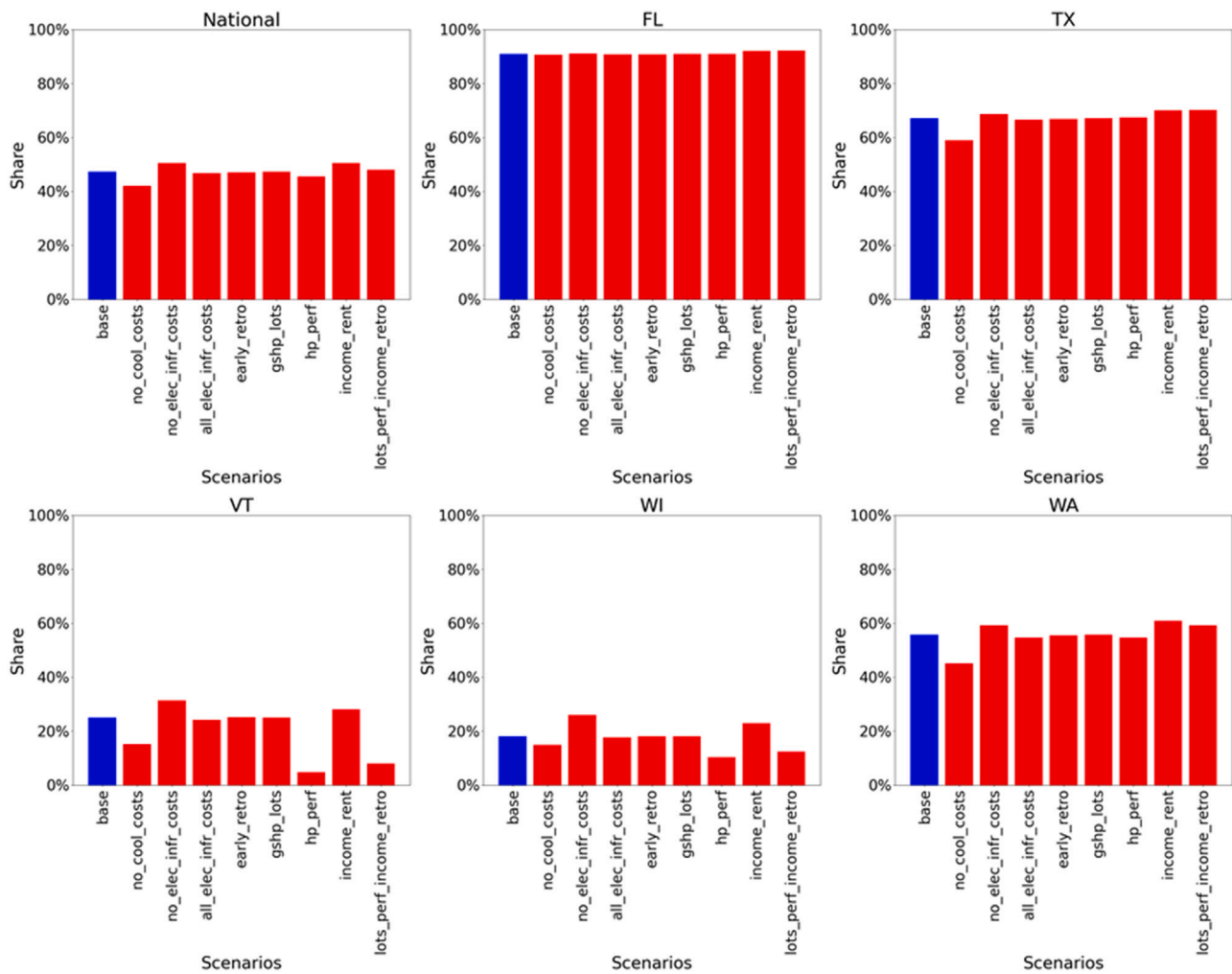


**Fig. 4.** Modeled share of total heating equipment sales in 2020 that are from ASHPs, nationally and in Florida, Texas, Vermont, Wisconsin, and Washington state. Results are shown for all 9 modeled scenarios, including the base Scout adoption model run (left-most bar in each plot) and the 8 additional sensitivity cases outlined in Table 1. Total heating equipment sales (the denominator in the sales share calculation) includes heat pumps and fossil-based heating equipment.

data [12,57]. In the lot size sensitivity case, GSHPs already have very low adoption in the base case, so adding further restrictions on their application has minimal effect.

#### 4.2. Assessment against historical data

Fig. 5 compares the model-estimated share of ASHP sales in 2020 to national and state-level sales data from that year. The figure also includes model and benchmarking data for years after 2020 when available for reference; however, comparisons in those years are not the primary focus since model and measure conditions were set up to align with a 2020 snapshot and several heat pump programs and incentives were introduced in subsequent years at both the state and national levels that are not represented in the Scout modeling assumptions.

As noted previously, the model gets close to the national heat pump sales share in 2020 (47% penetration in the base adoption model vs. 50% in the historical AHRI data) and to the derived fuel switching share for the same year (6.3% of total heating equipment sales in the base adoption model vs. 4.6% inferred from the AHRI data).<sup>16</sup>

<sup>16</sup> A study from Malinowski et al. [71] finds that there are 10% and 11% declines in gas furnace and oil furnace sales respectively relative to what they would have been, had their share of the heating equipment market stayed constant since 2015. The historical 2020 ASHP sales from fuel switching is

Sub-nationally, correspondence between modeled and historical values differs by region, suggesting that nationally-aggregated estimates obscure both under- and overestimation of heat pump adoption at the state level. In the Northwest, the 2020 modeled estimate is well-aligned with the actual sales share (at 47% in historical shipment and between 40 to 50% across different scenarios). In the Northeast, however, there are notable gaps between the modeled results and the historical HARDI data for New York, HARDI data for the rest of New England, and market report data specific to Massachusetts. In these cases, modeled ASHP penetration shares are generally around half of the penetration level shown in the historical datasets. Specifically, while historical ASHP share data for New York, New England, and Massachusetts are 33%, 47%, and 25% respectively, the modeled results reach up to roughly 20% in the most optimistic scenario where electrical infrastructure upgrade costs are avoided. Such discrepancies may reflect limitations in the model's ability to capture key drivers of the overall sales trend in such regions — including the degree to which fuel switching is attractive to consumers, for example — or the discrepancies may reflect

derived from the sum of 10% and 11% of historical 2015 sales of gas furnace and oil furnace respectively, multiplied by the ratio between 2020 to 2015 total heating equipment sales. This represents around 313,000 of ASHP sales in 2020, which represents 4.6% of total heating equipment sales when excluding electric resistance heating units.

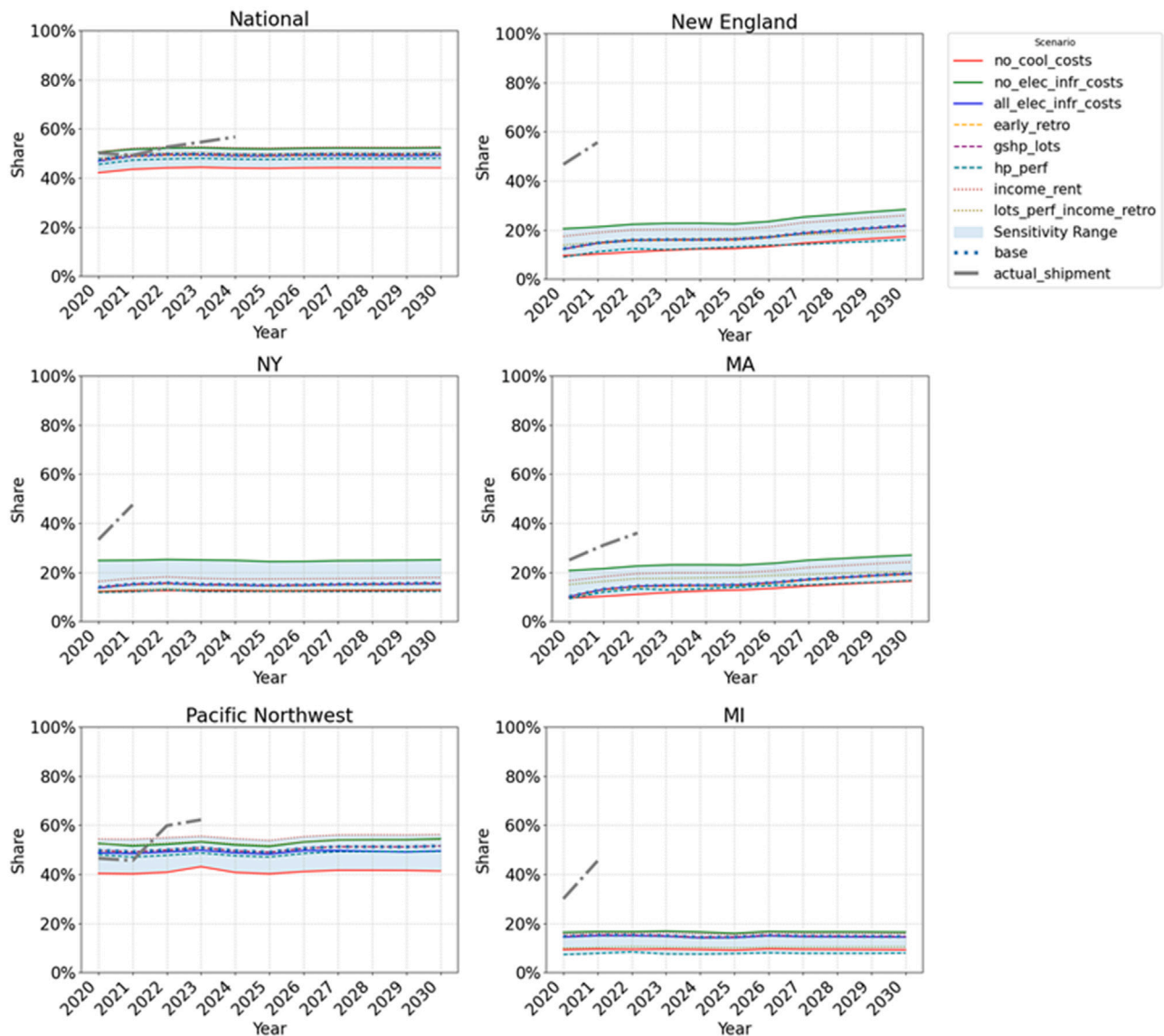


**Fig. 5.** Comparison of trend in modeled ASHP sales shares from 2020–2030 across all scenarios (shaded range) vs. reported historical sales shares in 2020 and any other years available in the reported data. Comparisons are shown nationally (top left) and in the regions/states for which historical benchmark data are available — Michigan, New England, New York, Massachusetts (separate from the rest of New England), and the Pacific Northwest. Total heating sales (the denominator in the sales share calculation) includes ASHPs and fossil-based heating equipment, but excludes electric resistance heating. Sales data from AHRI (national); HARDI (New England and NY); Heat Pump Market Effects Indicators Update (MA); Northwest HVAC Sales Trends and Insights (Pacific Northwest); and Heat Pump Collaborative Market Characterization (MI).

issues with the interpretation of state-level historical benchmark data. Both possibilities are addressed further in the Discussion.

#### 4.3. Key data gaps

Current datasets for benchmarking heat pump adoption models are limited in the following ways: (1) few state-level sales datasets are publicly available; (2) available data lack resolution about adopted and replaced equipment types; and (3) there is a lack of reporting standardization across datasets.

The previous section underscores that publicly-accessible sales data are only available for a handful of states in the Northeast, Northwest, and Midwest regions of the United States. Notably, these data limitations extend to most of the nine states that set aggressive targets for heat pump sales shares through the U.S. Climate Alliance, [72] despite the need for such data to demonstrate progress towards reaching such targets. Modeled sales in states with available benchmark data

collectively represent just 7% of modeled 2020 ASHP national sales in the base case run. This percentage is slightly higher when considering only modeled sales that represent fuel switching behavior — about 10% of modeled fuel switching heat pump sales occur in states with available historical benchmarking data — yet, none of the state-level benchmarking datasets isolate the share of heat pump sales that is from fuel switching.

State-level heat pump sales and market penetration data that do exist are limited in their coverage of the full suite of heating systems consumers can choose between. This is most evident for the GSHP category, which is not directly broken out in any of the benchmarking datasets. While GSHPs have historically had low penetration due to high upfront costs and site specificity, perhaps explaining their exclusion as a sales reporting category, their future penetration will be important to track alongside advances in drilling techniques that reduce costs and innovative models for financing equipment and/or sharing the cost of equipment across a thermal energy network. Beyond GSHPs,

few of the reviewed datasets include electric resistance heating as a separate category of heating sales, either.

Finally, there is currently no industry-wide guideline for reporting sales data. Each of the benchmarking datasets reviewed uses different data dissemination formats, different equipment categories, and different definitions of what constitutes a “shipment”, and includes different levels of the documentation needed to verify the quality and representativeness of the available data. This makes it challenging to compile and compare across different data sources, which in turn limits confidence in the veracity of any single source of available data.

## 5. Discussion

This case study generated actionable insights about the economic competitiveness of residential heat pumps, the factors that may increase or decrease competitiveness, and the degree to which modeled adoption of heat pumps is verifiable against real-world evidence. Key insights and their policy implications are further highlighted here.

### 5.1. Regional variation in heat pump adoption

First, there is significant regional variation in the nature of heat pump adoption under a purely economic model of consumer technology choice. In the Southeast, for example, where significant electric heating penetration has already occurred (see Fig. 1a), modeled heat pump sales in 2020 are already the majority of overall heating equipment sales and are overwhelmingly driven by like-for-like ASHP replacements. By contrast, colder states dominated by fossil-fired heating equipment see much lower modeled heat pump sales as a share of overall heating equipment sales, particularly in states with high electricity prices and high penetration of gas-fired heating with relatively low operating costs (e.g., the Upper Midwest). States with high penetration of more expensive fuel oil heating, such as Vermont, New Hampshire, and Maine, see heat pump sales driven much more by fuel switching decisions.

For policymakers, the regional variation in modeled outcomes underscores the importance of tailoring programs designed to encourage heat pump adoption to their geographical context. In areas with significant existing gas heating and high heating needs, for example, a focus on designing electricity rates that accurately reflect the potential costs and benefits of additional heat pump demand on the grid while mitigating bill increases may be especially important for ensuring that fuel switching to heat pumps is an affordable option [73]. In places where the economics of heat pumps are already favorable — e.g., in warmer climates where existing electric resistance heating penetration is high and electricity rates are also high — it may be more important for programs to address non-economic barriers to adoption, such as bolstering installer networks and consumer awareness. Reducing the upfront costs of heat pump equipment everywhere will increase the competitiveness of these systems with fossil- or resistance-based heating alternatives; however, this focus may be particularly important in states with larger shares of low-income residents, who can least afford the added upfront costs of heat pump upgrades when compared to conventional heating equipment costs.

### 5.2. Key modeling sensitivities

Out of the modeled scenarios, estimated shares of heat pump sales are most sensitive to assumed electrical infrastructure upgrade costs, differences in simulated vs. nameplate heat pump performance — particularly in northern states with large shares of homes that do not have existing cooling — and crediting of avoided cooling equipment investment and operating costs in equipment switching contexts (e.g., resistance or gas furnace plus AC to heat pump). Sales are sensitive to a lesser degree to the representation of differences in choice preferences according to adopter income and tenancy status. As with

overall heat pump penetration rates, the relative degree of sensitivity to scenario assumptions is variable across states, with greater sensitivity in states with higher heating demands, such as in the Northeast and Upper Midwest.

Since heat pump adoption sensitivities explored in this study remain largely limited to economic decision variables, the relative influence of these factors suggests the highest-leverage places that policy makers can focus program resources to improve the overall economic competitiveness of heat pumps. Based on this study's findings, for example, programs may do well to focus on reducing the soft costs of heat pump installation — such as the supporting electrical upgrade work — which can comprise a significant proportion of the overall upfront cost [74]. In Northern states, normalizing cold climate heat pump models, which minimize backup resistance heating that drives degradation in actual vs. rated performance, will increase consumer confidence in operational cost savings. Programs could also further stress the cost and convenience advantages of heat pumps replacing existing heating and cooling services simultaneously, which avoids the costs and time needed to separately upgrade heating and cooling systems in the future. Lastly, marketing campaigns and financial assistance instruments could be tailored to particular consumer segments to address the influence of consumer heterogeneity on decision preferences.

### 5.3. Model validation and benchmarking challenges

Modeled shares of overall heat pump sales and sales due to fuel switching in 2020 compare favorably against national sales data. In the few comparisons available at the state-level, however, the model's 2020 estimates underestimate heat pump penetration in states in the Northeast and Midwest, while accurately estimating penetration in Northwestern states. These regions are quite different in the makeup of their existing heating stock — mostly electric heating in the Northwest, vs. mostly heating oil with some natural gas in the Northeast and mostly natural gas in the Midwest — and there are differences in heating demand patterns and intensity as well, particularly given the Marine conditions of the coastal Northwest. While such differences may help explain the regional inconsistencies in model performance, additional data on the drivers of sales in each region — including breakouts of fuel- and technology-switching cases vs. like-for-like replacements, are needed to dig deeper on where the model is erring in its representation of regional heat pump adoption.

Moreover, the scope and accuracy of the state-level benchmarks is difficult to determine given the absence of multiple data sources to cross-reference estimates with. In the New York benchmark, for example, NYSEDA estimates that the HARDI contractor network represents only 5%–25% of the New York State market depending on product category [75]. Definitional issues may also play a role. Benchmarking data generally distinguish between ductless and ducted ASHPs, for example, while Scout reports a single ASHP category. In cases where multiple ductless units are required to replace a single existing heating unit (e.g., replacing a boiler system without existing duct work), Scout estimates may under count added heat pump sales and penetration. Furthermore, the sales recorded in a given state may not always represent the final installed location of the equipment (e.g., they sometimes represent a “ship-from” vs. “ship-to” address [75]). This could overstate the level of heat pump sales penetration in the state's benchmarking data. Finally, differences may be attributable to incomplete information — missing state-level incentives in the cost modeling, for example — or may relate to non-economic factors that are not represented at all in the model structure.

Action by industry and policy stakeholders is needed to expand access to existing heat pump sales datasets, which would help address such validation and benchmarking challenges. This point is further discussed in the subsequent section on future work.

#### 5.4. Study limitations

Several limitations should be considered when interpreting the results of this study. First, although this work aims to improve the behavioral realism of residential heat pump adoption modeling, the analysis remains grounded in an economic choice framework. The modeled scenarios extend Scout by refining economic and structural assumptions, such as upfront costs, consumer segmentation, and contextual influence, rather than explicitly representing broader non-economic drivers identified in the literature, including consumer awareness, installer trust, social influence, supply-chain constraints, and workforce availability [21,22]. Hence, the additional modeling factors presented here should be viewed as incremental extensions to a rational-choice framework rather than a comprehensive representation of household decision-making processes.

The simplicity of the underlying adoption model and lack of direct representation of non-economic adoption drivers limits the degree to which this paper's findings may be generalized to geographical contexts beyond the United States. Furthermore, model outputs are evaluated only against historical adoption data, providing evidence of the model's ability to reproduce past adoption patterns but offering limited insight into its predictive performance for future technology uptake in which new drivers of adoption are introduced. The analysis framework is better suited to evaluating the relative influence of adoption factors on technology uptake than to predicting how adoption behavior may evolve under emerging technologies, policies, and market conditions. Indeed, the intent of this work is not to provide definitive answers about which adoption model configuration will make the best predictions across applications. Rather, the paper seeks to show how the buildings sector technology adoption models typically used in larger energy system modeling exercises can be interrogated and benchmarked against real-world evidence. Such an approach is needed to build transparency about the use and limitations of these models, while identifying key areas for improvement in model design and in the data that are available for continuous model refinement and reassessment over time.

Furthermore, this analysis did not explicitly represent a dual-fuel system option, in which households retain existing fossil-fueled heating systems alongside a heat pump and switch between systems depending on outdoor temperature, energy prices, or comfort preferences. Dual-fuel systems may represent an important transitional pathway for households that are not suitable to fully electrify space heating, particularly in colder climates or in homes where existing equipment has not yet reached end-of-life. Excluding this pathway may underestimate the extent to which households adopt heat pump technologies; therefore, such measures have been incorporated in subsequent Scout modeling work [76].

As already discussed, additional limitations relate to the availability and consistency of empirical benchmarking data. Existing public datasets on heat pump sales and installations remain limited, especially at the sub-national level. Uncertainty in geographic coverage, incomplete information on incentive programs, inconsistent reporting standards, and limited visibility into fuel-switching behavior all complicate efforts to rigorously validate modeled adoption outcomes. As a result, discrepancies between modeled and observed adoption patterns may reflect a combination of missing explanatory variables, data uncertainty, and structural limitations within the model itself.

#### 5.5. Future research and data needs

Future work could place a deeper focus on particular states of interest to further investigate the nature of differences between modeled and observed historical adoption trends in that state. Ideally, such efforts would focus on states where data on fuel and technology switching prevalence and the consumer preferences that affect adoption decisions has already been collected. Such data can fill key gaps in the understanding of what type of decisions are driving overall heat pump sales

and can address missing components of the economic choice framework that may help explain discrepancies with real-world adoption trends.

Expanding researchers' access to existing heat pump sales datasets is also critical for improving the ability to track real-world heat pump adoption and benchmark model projections. Expanded market data collection at the state, regional, and national levels could leverage existing survey frameworks and relationships with HVAC equipment suppliers but place greater emphasis on characterizing equipment sales (vs. stock) and on harmonizing reporting conventions to allow greater comparability across sources/regions.<sup>17</sup> At the national level, for example, RECS survey forms could incorporate new questions about recent equipment upgrades, including information about what systems were upgraded to and from. Recurring state-level surveys such as the California Residential Appliance Saturation Survey and the Residential Building Assessments in New York and Northwest could consider similar expansions to the survey frame. To bolster these expanded data with additional industry evidence, researchers could develop standard data-sharing agreements with groups like AHRI and HARDI that enable broader access to sub-national sales data for research purposes. Such agreements would need to establish a level of data granularity that goes beyond current, national-level breakouts of product sales while still ensuring anonymity for product suppliers who report into the datasets.

## 6. Conclusion

A case study was conducted of the structure, outputs, and performance of a model of U.S. residential heat pump adoption. The analysis revealed substantial regional variation in projected heat pump sales shares and sensitivity to input adjustments, with sales shares generally higher and less sensitive to input changes in warmer regions with high existing heat pump penetration, and generally lower and more sensitive in colder regions with a large installed base of fossil- and/or resistance-based heating equipment. Model benchmarking against historical data showed generally good agreement between estimated vs. reported heat pump sales and fuel switching shares in 2020 at the national level and varying degrees of agreement with state and regional data. Importantly, the effort to benchmark the model demonstrated key limitations in the coverage and depth of existing historical equipment sales datasets, particularly at the state level. Given the present-day policy focus on load growth and the large influence that heat pump adoption can have on future demand for electricity, energy system modelers must seek to improve the transparency of their technology adoption projections while advocating for more comprehensive public datasets that can support the validation of their models.

#### Declaration of competing interest

The authors declare no competing interests.

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#### Appendix. Scenario input values

See Figs. A.1–A.4.

<sup>17</sup> Reporting standards for building operational data are a useful existing example of where this has been done in the buildings area [77,78].

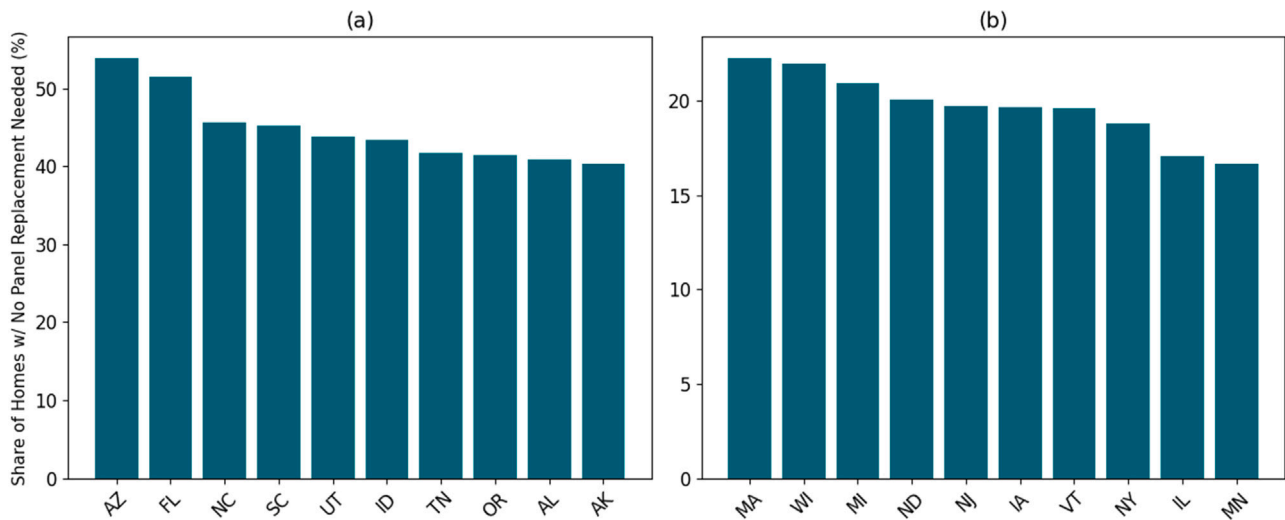


**Fig. A.1.** The 10 states with the highest (a) and lowest (b) shares of homes that *do not* require an electrical panel upgrade when switching from gas equipment to heat pumps.

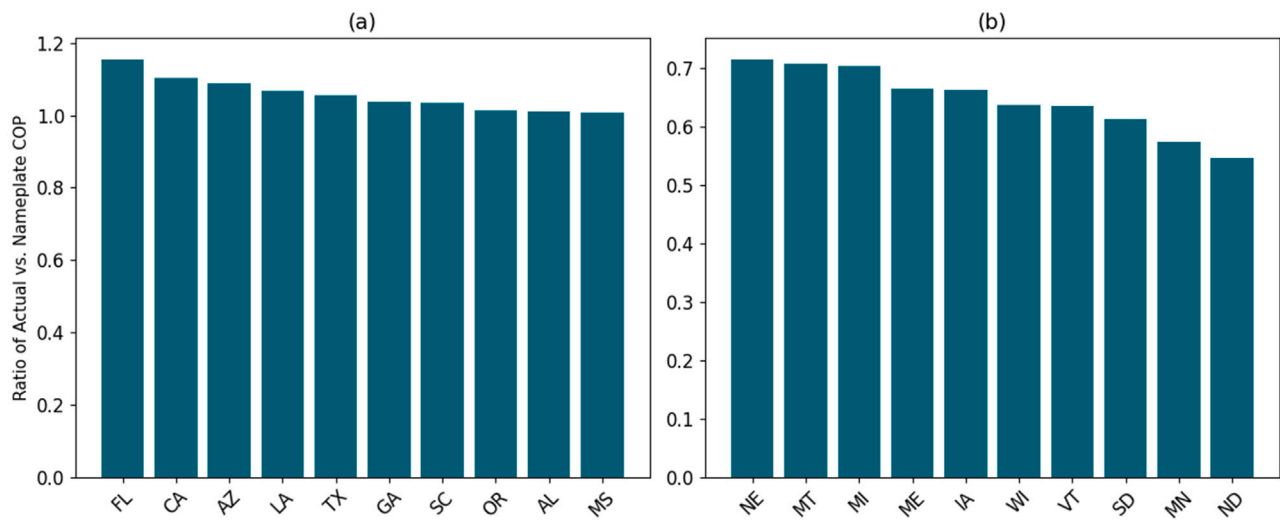


**Fig. A.2.** The 10 states with the highest (a) and lowest (b) ratios of ResStock-simulated vs. nameplate heat pump COP.

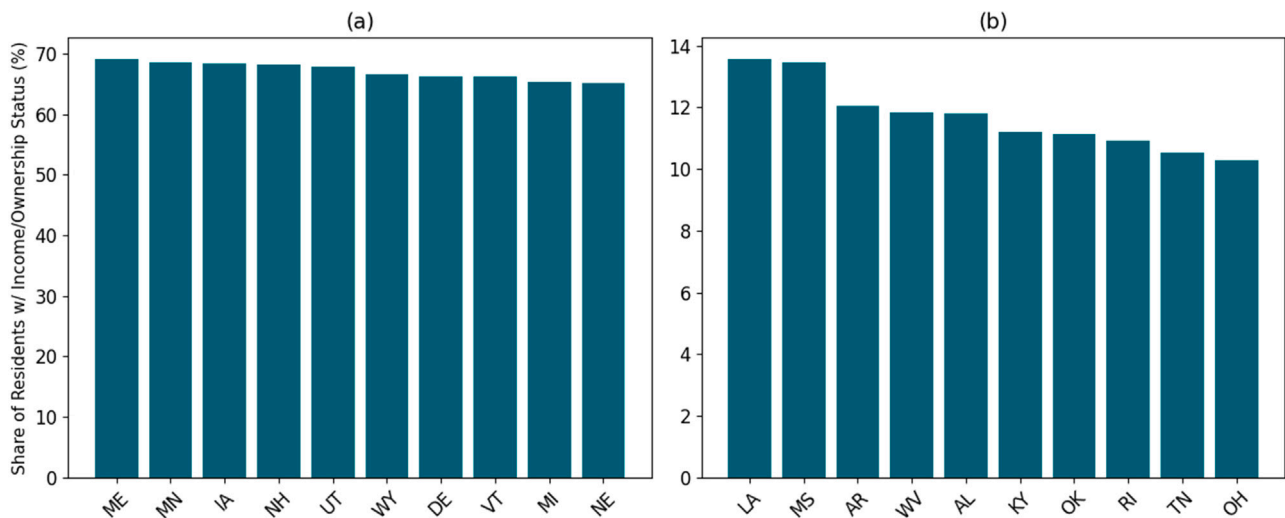


**Fig. A.3.** The 10 states with the highest share of residents that are (a) non-low income owners and (b) low income renters.

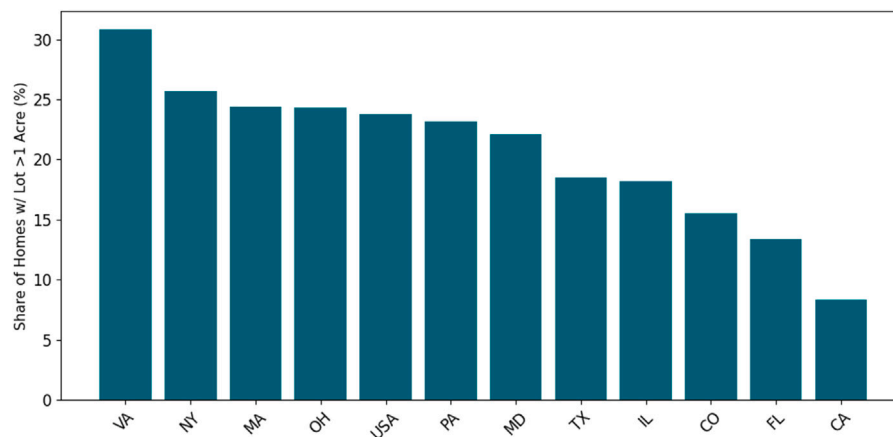


Fig. A.4. Share of homes with greater than 1 acre of space available to install ground-source heat pumps.

## Data availability

Data will be made available on request.

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