

2020 Residential Energy Consumption Survey: Consumption and Expenditures Technical Documentation Summary

May 2025



Independent Statistics and Analysis U.S. Energy Information Administration www.eia.gov U.S. Department of Energy Washington, DC 20585

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# Introduction

We conduct the *Residential Energy Consumption Survey* (RECS) periodically to provide detailed information about energy usage in U.S. homes. RECS is a multiyear project consisting of a household survey, data collection from household energy suppliers, and end-use consumption and expenditures estimation. The 2020 RECS, the 15<sup>th</sup> iteration of the study, was the largest in program history, with 18,496 household survey respondents.

The *Household Survey* (HS), a voluntary survey, collects data on energy-related characteristics and usage patterns from a representative sample of homes that are occupied as a primary residence. We selected the sample to provide statistically reliable energy-use estimates at the national, regional, division, and state levels. The *Energy Supplier Survey* (ESS), a mandatory survey, collects data from energy suppliers on how much site electricity, natural gas, propane, and fuel oil were consumed in the sampled homes during the reference year. The ESS also collects data on actual dollar amounts spent on these energy sources. We use models (energy engineering-based models in the 2015 and 2020 survey) to produce consumption and expenditures estimates for heating, cooling, refrigeration, and other end uses in all homes occupied as a primary residence in the United States using the data collected from the HS and ESS. Wood-use estimates are also included as part of RECS.

The scope and purpose of RECS differ slightly from similar EIA products that report residential energy data. For RECS, we sample homes occupied as a primary residence, which excludes secondary homes, vacant homes, military barracks, and common areas in apartment buildings. As a result, RECS estimates are not comparable with sector-level totals defined in other EIA products. They are best suited for comparison across different characteristics of homes within the residential sector. These RECS estimates represent the site energy consumption for occupied, primary homes, which excludes accounting for losses in generation and transmission of electricity.

This document provides methodological descriptions for three parts of the overall RECS process:

- Energy Supplier Survey (ESS), which provides details on billing data collection, coverage rates, response rates, and billing data editing and quality
- **Consumption and Expenditures Annualization and Imputation**, which provides details on the consumption and expenditures estimation for calendar year 2020 using the ESS billing and delivery data
- **End-use Estimation Modeling and Calibration**, which provides details on the consumption estimation of household end uses and method changes from previous years

The methodology for the RECS Household Survey and household energy-related characteristics, including sampling and weighting, is provided in a separate document called *Residential Energy Consumption Survey (RECS) 2020 Household Characteristics Technical Documentation Summary.* 

We collaborated with Leidos and Westat to conduct the RECS ESS.

## **Data products**

We release a variety of RECS products on our website across survey cycles tailored to a wide range of data users. These products include:

- Detailed tables of household energy-use estimates across key geographic, structural, and demographic variables
- Topic-specific articles and reports
- Today in Energy articles
- Data-user webinars
- Public-use Microdata files and User Guide
- Survey methods documentation

Although we release similar products across survey cycles, we change these products from one cycle to the next to adapt to changes in the residential energy sector and apply new dissemination methods and tools.

RECS products from previous cycles are available on each survey cycle's *Data* page or in the archived *Analysis and Projections* pages.

RECS data are also used as critical inputs for our sector-level projections, such as the *Annual Energy Outlook* and for energy program analysis.

# **Revisions and changes across cycles**

### Within-cycle data revisions

We executed a series of survey data cleaning, editing, imputation, and coding steps to ensure RECS data and estimates met our quality standards. We released preliminary RECS household characteristics results at the end of the RECS HS phase. After this release, we performed additional quality-control steps to reconcile household characteristics data with energy billing data collected as part of the RECS ESS. This additional quality control resulted in revisions to the preliminary household characteristics estimates, particularly for main-heating fuel and equipment and water-heating fuel. Differences between preliminary and final main space heating equipment and fuel estimates are discussed in Appendix A of the 2020 RECS Household Characteristics Technical Documentation Summary.

### Methodological and content changes across survey cycles

RECS is a cross-sectional study with updates to questionnaire content, statistical methods, and dissemination strategies from the previous cycle. We do not currently conduct a longitudinal household energy-demand study. Each RECS cycle, however, shares content and design elements across survey cycles. The unit of analysis for every RECS cycle is occupied, primary housing units. The sample is designed using geographic and other stratification methods and an address-based housing unit frame. Most survey questions are carried forward from one cycle to the next. Although we encourage RECS users to use caution when drawing analysis-based conclusions across RECS cycles, many comparisons are valid and statistically sound.

Major changes to methods or questionnaire content from one cycle to the next are highlighted in technical documentation reports, special-topic reports (for example, the end-use modeling changes for 2015), and survey form specifications.

# **Energy Supplier Survey**

## **Overview**

We ask RECS Household Survey (HS) respondents to report energy characteristics about their homes, energy-consuming equipment, and energy-related behavior, but we do not collect their energy consumption and expenditures. To capture complete and accurate energy usage information, we conduct a second data collection, the Energy Supplier Survey (ESS). Although the HS is a voluntary data collection for sampled households, the ESS is mandatory for energy suppliers. The ESS collects billing data from electricity and natural gas suppliers and delivery data from propane and fuel oil suppliers for households that responded to the HS. The ESS energy usage and cost data form the basis of RECS annualized consumption and expenditures estimates for the 2020 calendar-year reference period.

## **Survey frames**

For the 2020 RECS ESS data collection, we used responses from the HS combined with staff research to construct the ESS frames. We used two types of frames for the ESS: a household frame, including a list of RECS responding households with their corresponding energy suppliers for each of the reported fuels used, and a supplier frame, including a list of all the unique energy suppliers from the household frame. To populate the ESS household frame, the final section of the 2020 RECS HS asked respondents to report energy supplier names and customer account numbers. We then created a list of records from the combination of the household cases with their corresponding energy suppliers for each reported fuel. Therefore, a household case in the frame can have more than one record when the household reported using at least two fuels (for example, electricity and natural gas).

Out of all HS respondents, 82% provided one or more energy supplier names. The remaining 18% either did not know the name of their energy suppliers or chose not to report them to us. When the electricity or natural gas supplier names were missing, we determined the likely suppliers based on regulated service territory information. When the propane or fuel oil supplier names were missing, we could not determine which propane and fuel oil delivery company serves a particular address because they do not have defined and mutually exclusive service territories. In addition, we did not pursue household billing or delivery data when RECS household respondents indicated that they did not directly pay their energy costs (for example, when an apartment's electricity costs are included in the monthly rent).

In total, the ESS household frame covered 29,941 of the 32,882 (91%) household energy accounts identified in the HS.

## Data collection, response rates, and coverage rates

The 2020 RECS ESS data collection occurred between July 2021 and March 2022. A secure ESS data collection website offered energy suppliers two preferred reporting options: an interactive data collection web page for manual data input or an Excel spreadsheet that suppliers could download, populate, and submit online. We provided suppliers with the addresses and account numbers (where available) of the customers for which we were requesting data.

The data request covered energy usage and cost information that occurred between March 2019 and February 2021. For electricity and natural gas, the supplier typically submitted 24 billing periods of data

per household. The frequency of bulk fuel deliveries varied; for propane and fuel oil, the average was about four to six deliveries per household during the 24-month period.

Unlike the RECS HS, which is voluntary, we have a legal requirement to conduct the ESS as a mandatory data collection, which ensures high coverage and data quality for sampled households. Almost all inscope suppliers responded to the ESS (94%), but some had difficulty finding every requested address in their records. We worked closely with suppliers to locate all requested energy data, which included confirming addresses and account numbers and re-assigning household addresses to a different energy supplier if appropriate. Most household-level nonresponse occurred when a supplier could not locate the address in their records or when the energy supplier could not be determined.

At the end of ESS data collection, we contacted more than 2,500 electricity, natural gas, fuel oil, and propane suppliers, requesting billing data for nearly 30,000 household energy accounts.

Although many surveys report one response rate, we used three metrics to evaluate the success of the ESS data collection and the overall coverage of household consumption and cost data.

- Supplier-level response rate: Percentage of in-scope energy suppliers that responded to the ESS with at least one period record of energy data—94% (2,427 out of 2,587)
- Household-level response rate: Percentage of household energy accounts included in the ESS frame where at least one period record of energy data was received—92% across all energy sources (Table 1, ESS response rate). Each energy source had a response rate of at least 85%, with higher rates for electricity at 94% and natural gas at 90%.
- Household-level coverage rate: Percentage of all RECS household energy accounts where at least one period record of energy data was received—84% across all energy sources (Table 1, *ESS coverage rate*). The coverage rates for propane and fuel oil were about 50%, compared with at least 80% for natural gas and electricity. We could not identify the accurate supplier for bulk fuels when a supplier name was reported incorrectly or was missing.

These response rates and coverage rates of ESS data collection, before data editing and data quality control steps, are described in this section (Table 1). In some cases, we received energy data as part of the ESS that we could not use for RECS. For example, if a supplier provided electricity billing data for an entire apartment building instead of a specific apartment unit, we considered the electricity data for that household to be unusable and deleted it.

			Households with		
	Household uses		any ESS data	ESS	ESS
	energy source	Included in ESS	received	response rate	coverage rate
Energy source	(a)	(b)	(c)	(c/b)	(c/a)
Electricity	18,496	17,891	16,869	94%	91%
Natural gas	11,154	10,029	9,065	90%	81%
Propane	1,999	1,255	1,067	85%	53%
Fuel oil	1,233	766	670	87%	54%
Total	32,882	29,941	27,407	92%	84%

#### Table 1. ESS response rate and coverage rated by energy source before data editing, 2020 RECS

Data source: U.S. Energy Information Administration, *Residential Energy Consumption Survey* (RECS) Note: ESS=Energy Supplier Survey

## **Editing and data quality**

Similar to the RECS HS process, we used a multi-phased approach for quality control of supplier billing and delivery data. We built a limited number of critical edit checks into the system to ensure respondents completed and appropriately formatted required fields when they submitted data through the interactive web page (for example, characters were not allowed in numeric fields). When respondents submitted data using Excel or another electronic format, we manually checked the submission against a short list of acceptance criteria to ensure all required variables were present and formatted to allow for standard data processing. In some cases, we contacted suppliers to resubmit or verify data.

We performed comprehensive data editing on the cases failing edit specification criteria. We designed these criteria to review data inconsistencies, incomplete responses, outliers, and supplier comments. During this editing phase, we made a limited number of changes to the ESS data, including fixing typos in dates, fixing minor errors in reported costs, and removing unusable data. Overall, we changed about 5.1% of the in-scope household cases during this stage, and less than 1% of the cases had all their ESS data deleted (Table 2). Natural gas data had the highest edit change rate, 7.7% of cases, and the other energy sources were at about a 4% edit change rate.

After completing this ESS editing phase, we performed an additional round of editing to reconcile inconsistencies between HS responses and ESS data. We introduced this reconciliation editing phase starting with the 2015 RECS. This phase includes reviewing potential disagreement between a household's reported fuels and end uses and its observed ESS energy usage. For example, a response of *electricity* for main heating fuel on the HS was revised to *natural gas* where ESS data indicated strong winter seasonal use in utility-reported natural gas bills for that household and an absence of such seasonality in their reported electricity bills. We also looked for vacancies or other gaps in reported energy data, including non-household energy use (for example, for an attached commercial business), or excluding some household energy costs. These processes improve the overall quality and consistency of information within and across the HS and ESS phases, which improved the modeled estimates of space

heating and other end uses. Our housing characteristics technical documentation provides additional information on the reconciliation process.

Another review step during this final editing phase was examining the ESS electricity data submitted for RECS households that reported on-site solar generation. Because RECS estimates all site household energy consumption, we reviewed the ESS data for these homes to ensure that both consumption from on-site solar generation as well as electricity delivered from the grid were included in the reported ESS data. For more than 60% of these homes, the reported consumption data included only net-delivered electricity, so we considered it unusable for RECS. For these cases, we removed the consumption data and imputed the total site generation. We retained the reported ESS expenditures data to reflect the actual cost of the supplier-provided electricity to the home.

Across all phases of ESS editing, about 8.2% of the in-scope household energy accounts had edits; natural gas had the highest rate, at 9.6%. For about 3% of the households, we removed the data because they were unusable; we imputed energy consumption and expenditures data for these households, as described in the *Annualization* section in this report. We performed quality control at all stages to ensure we performed the editing and processing consistently and correctly.

Energy source	Households with at least one record	Percentage flagged for editing	Percentage edited before reconciliation	Percentage edited after reconciliation	Percentage deleted before reconciliation	Percentage deleted after reconciliation
Electricity	16,869	17.7%	3.9%	7.7%	1.0%	3.0%
Natural gas	9,065	20.5%	7.7%	9.6%	0.7%	2.6%
Propane	1,067	31.3%	3.7%	8.2%	0.2%	3.0%
Fuel oil	670	25.5%	3.8%	4.6%	0.6%	1.9%
Total	27,671	19.3%	5.1%	8.2%	0.9%	2.9%

#### Table 2. Statistics for ESS analyst editing and reconciliation by household

Data source: U.S. Energy Information Administration, Residential Energy Consumption Survey (RECS)

Note: ESS=Energy Supplier Survey

# **Consumption and Expenditures Annualization and Imputation**

## **Overview**

Annualization for the 2020 RECS estimated the energy consumption and expenditures for households from January 1, 2020, to December 31, 2020, using ESS billing data. Most of the billing records we received from the energy suppliers did not correspond exactly with this time period and required some processing to yield a total for 2020. In most cases, the billing records completely spanned 2020, but in other cases, the suppliers reported consumption and expenditures for only part of the year. For households with bill sets that completely covered 2020, we prorated bills spanning the beginning and ending of 2020. For households with only partial coverage of 2020, we imputed consumption for the missing periods based on modeled values of the expected consumption. More information about these models is provided in the *End-Use Estimation* section of this report.

We considered a set of billing records complete if it covered all of calendar year 2020. For electricity and natural gas, we defined a complete set of billing records as having a series of monthly bills that covered the 366 total days from January 1 to December 31, 2020. Unlike electricity and natural gas, propane and fuel oil are delivered and billed irregularly. Therefore, identifying the true billing data completeness for households using these fuels was more difficult. We considered the billing records for a household using propane or fuel oil to be complete if at least one delivery was reported from each of the calendar years 2019, 2020, and 2021.

	Household has complete billing data	Household has partial billing data	Household does not have billing data
Energy source	(n/percentage)	(n/percentage)	(n/percentage)
Electricity	15,290 (83%)	675 (4%)	2,531 (14%)
Natural gas	8,424 (76%)	399 (4%)	2,331 (21%)
Propane	565 (28%)	331 (17%)	1,103 (55%)
Fuel oil	490 (40%)	136 (11%)	607 (49%)

#### Table 3. Consumption data completeness for electricity, natural gas, and fuel oil by household

Data source: U.S. Energy Information Administration, Residential Energy Consumption Survey (RECS) Note: Expenditures data completeness was not identical to consumption completeness but had only minimal differences.

The methodology we used to perform annualization varies by fuel type, and more details are provided in the following sections. For households with no billing data, we imputed the annual total using statistically adjusted modeling expectations, a process detailed in the *Imputation* section.

In addition, we provide a few examples in Appendix A to illustrate the annualization and imputation procedures.

# **Electricity and natural gas annualization**

For households with complete billing data for electricity and natural gas, we summed the bills covering days in 2020. We prorated bills covering the beginning or end of 2020 according to how many days fell

within calendar year 2020. The annualized consumption total was the sum of the bills that were entirely within 2020 and any prorated bills. We used the same approach for expenditures.

For households with partial billing data, we imputed the missing data to fill out the consumption for calendar year 2020. In general, we used two approaches for imputation for households with partial data: we used one approach for any bills missing either the consumption amount or the energy cost, and we used a different approach for bills missing both the consumption amount and the energy cost.

For any bills missing either the consumption amount or the energy cost, but not both, we calculated a representative energy price from the billing data we received and then used the energy price to calculate the missing consumption amount or energy cost from that. If a particular household was missing a bill, and we had at least six bills, we used the bills we had to find the representative price for the missing bill. If we had fewer than six bills, we calculated a representative energy price from all of reported bills for the energy supplier or used a state-wide average. Once we found the price, we divided the reported energy cost by the average price to yield an imputed consumption amount. We used this approach for 155 households for electricity and 196 households for natural gas.

Households with bills missing both the consumption and the energy costs required a different approach for imputation. For these cases, we imputed the missing bills using our energy modeling expectations of how much energy the household would consume, scaled to match the billing data we received. After we determined the consumption, we imputed the missing expenditures from the imputed consumption using each household's representative energy price, which we determined using the same method described earlier in this section. We then determined the household's energy usage using the same procedure that we used for homes with complete data by adding all of the consumption that occurred within calendar year 2020 plus any prorated bills. The process to handle households with no reported consumption is documented in the *Imputation* section.

If the HS respondent reported the home was vacant for one or more months during 2020 and the energy supplier's records did not cover all of 2020, then we did not impute the consumption for any missing periods. We assumed that the information was not missing but rather that no consumption occurred during that time period.

### Propane and fuel oil annualization

The nature of propane and fuel oil (bulk fuel) usage and deliveries prompted different annualization procedures. Unlike monthly electricity and natural gas billing records, bulk fuels are often delivered at irregular intervals and require different annualization procedures. A large gap between deliveries would not necessarily mean that a time period had missing data. In addition, a delivery occurs on a specific date, but the time period during which the fuel is consumed is less certain. For RECS, we assumed that a delivery would refill a storage tank, replacing fuel that had been consumed since the last delivery.

To annualize a household's bulk fuel consumption, we first chose the subset of deliveries that included as much of the 366 days in 2020 as possible. In some cases, this subset included all of 2020, plus some extra days in 2019 or 2021. In other cases, this subset may have excluded some days at the beginning or end of calendar year 2020. In either case, we summed the total fuel delivered for the time period that was included in the chosen deliveries and then prorated to match calendar year 2020. We used our

energy models to prorate: for each household, we scaled our modeled fuel total for 2020 by the ratio of the total delivered fuel to the modeled fuel use over the same period that the deliveries occurred. More detail about our energy modeling is available in the *End-Use Estimation* section.

As with electricity and natural gas, consumption for unreported time periods was not imputed if the HS respondent reported a vacancy. Because we could not determine vacancy based on the pattern of deliveries, we used the electricity billing records to determine the time periods when a household was vacant. The process to handle households with no reported bulk fuel consumption is documented in the *Imputation* section.

The annualized expenditure for bulk fuels used the same procedure as the annualized consumption when complete billing data is present. If bulk fuel billing data did not include a complete record of expenditures, we calculated the missing expenditures as the annual total consumption multiplied by an annual average price.

### Imputation

When no billing or delivery data were available for a household, we fully imputed the annual consumption using estimates derived from energy end-use models. These models provide expectations for energy consumption based on a household's housing characteristics data and its weather data. The sum of modeled end-use energy expectations is our best estimate of what a home with no billing data would have consumed in 2020. For households needing full imputation, we started with the modeled energy expectations, then incorporated a bias correction based on our statistical calibration methods. More detail about energy modeling and the calibration process is available in the *End-Use Estimation* section.

The imputation used the calibration corrections to the modeled end-use energy expectations as variables in a regression model. We fit separate regression models for various combinations of housing types and Building America climate zones. A representative imputation model for electricity in a particular housing type in a particular climate zone is:

$$C_{elec} = \sum_{g=1}^{12} \beta_g \times E_g$$

where

 $C_{elec}$  is the imputed annual electricity consumption  $\beta_g$  are the regression model coefficients for the particular housing type and climate zone  $E_g$  is the end-use model output for end-use grouping g

Electricity has 12 end-use groupings, including two groupings which vary by the type of heating equipment:

• Space cooling

- Space heating Heat pumps (including central and ductless heat pumps)
- Space heating All other space heating equipment
- Secondary space heating
- Water heating
- Refrigerators and freezers
- Lighting
- Pools and hot tubs
- Furnace fans and boiler pumps
- Fans, dehumidifiers, and humidifiers
- Electric vehicle charging
- All other end uses combined into a large *base* category

For natural gas and propane, we used six groupings because many of the electricity categories do not apply to these fuels; even fewer apply for fuel oil. No households in the sample had consumption within all of these groupings. The resulting coefficients  $\beta_g$  of the regression models were applied on a case-by-case basis to the modeled end-use values of households that had no reported billing data.

The total consumption for a household was equal to the sum of the modeled terms and their corrections plus one additional term. This additional term captures the uses of energy that are present in homes that our household survey failed to capture. During the calibration process, we occasionally found that we needed to introduce a term to represent *unknown* end-use consumption. These cases arise when the annualized billing data totals are much larger than our modeling expectations. More detail about the unknown end use is available in the *End-Use Estimation* section.

We calculated the expenditures as the imputed total consumption multiplied by an average price. The average prices were calculated separately for each household energy account undergoing imputation using the submitted billing data for the 10 homes closest to each other geographically within the same state, in the survey.

This method is an update to the 2015 method, which was a major change from the 2009 methodology. The 2009 methodology used a purely statistical model to estimate total consumption and end uses without first evaluating end-use models.

## **Estimating wood consumption**

For electricity, natural gas, propane, and fuel oil, we rely on energy suppliers to provide most of the information we used to estimate annual household fuel consumption. For wood consumption, however, we relied only on household respondent reports of wood use. For the 2020 RECS, we asked for wood consumption to be reported in cords of wood or tons of wood pellets. For the RECS, a cord of wood is a pile of stacked wood with a volume of 128 cubic feet.

For households who reported their wood consumption in cords, wood consumption was reported categorically. For each category, we assumed a lower and upper bound of consumption. For example, the category *About two cords* was assumed to correspond to any value between 1.5 cords and 2.5 cords. All households within a category were placed into 10 groups of approximately equal size according to their modeled end-use wood consumption. Cord consumption was calculated based on the decile group

and the assumed bounds of the reported category and then converted to British thermal units (Btu)<sup>1</sup>. For households that reported wood consumption in bags of pellets, we made a direct conversion from number of bags to Btu.

For households that reported using wood but did not report a consumption amount, we had to impute their consumption based on their modeled wood consumption. We created regression models for final wood consumption estimates based on modeled wood consumption using the households that reported their wood consumption, and we applied these models to the homes needing imputation. Separate regressions were run based on whether a respondent reported using cords or pellets as well as their reported end uses.

We do not include the final wood consumption estimates in total or average household energy consumption estimates. Instead, we present wood consumption estimates as special tabulations in Tables CE7.1 and CE7.2.

<sup>&</sup>lt;sup>1</sup> We used the assumptions that one cord of wood consists of 20,000,000 Btu of energy content and that one 40-pound bag of pellets is 330,000 Btu.

# **End-Use Estimation**

# **Overview**

For the RECS program, an energy end use is a particular need, appliance, or device in a home that consumes energy. Because direct measures of energy end uses—which often require installing special devices in homes—are rare, national estimates of energy consumption by end use must rely on modeling. The RECS HS collects characteristics about a household's end uses, and the annualized ESS data measure how much total energy the household used for each fuel. End-use estimation is done using both HS and ESS data, combined with publicly available weather data.

End-use estimation includes two main steps:

- A suite of energy end-use models is used to estimate the expected consumption of each end use present for a particular fuel.
- The known annualized total consumption for the fuel is used to calibrate the modeled end-use values.

Each step is applied, in order, to each household in the RECS. The calibration step ensures that the final end-use estimates for each particular fuel sum to the annualized fuel totals while preserving the distributional information provided by the end-use models. We updated the end-use models and the calibration procedures for the 2020 RECS. We updated individual end-use models to bring them up to date with recently published literature and recently enacted efficiency standards. For electricity and natural gas calibration, we extended the optimization approach that we introduced for the 2015 RECS to operate at the billing-level for the 2020 RECS (in other words, about monthly), as opposed to working only with annual billing totals.

In RECS cycles before 2015, the end-use models were statistical and operated through nonlinear regression using the ESS data. In the 2015 and 2020 RECS studies, the end-use models follow an engineering approach that depends only on the collected housing characteristics and homes' weather data. The change in approach from 2009 to 2015 was substantive, and although many of the 2020 models have been updated from the 2015 versions, the approaches and coverage of the end-use models are very similar in both studies.

Each RECS before 2015 also used a simple normalization approach to calibrating modeled end-use outputs to annual billing and delivery fuel totals. This approach prorated the difference between the annualized ESS total and the modeled sum for a given home over all end uses in the home. In practice, every individually modeled end-use value for a given home was multiplied by the same factor—the ratio of the ESS total to the sum of modeled end uses.

Additional details on the previous end-use estimation methodology are available in the 2009 RECS Enduse models FAQs.

In the 2015 and 2020 RECS studies, the end-use models follow an engineering approach, and the calibration is based on the relative uncertainties of, and correlations between, the end uses being estimated. Also, the 2020 RECS published results include more end-use estimates than in previous RECS

cycles, including electric-vehicle charging and the third-most-used television. The sections below describe the updated methodology and provide further details on the modeling approaches for each of the published end-use estimates.

## **Energy end-use modeling**

Energy end-use models might best be thought of as *expert* models. Instead of estimating unknown parameters and interpreting their solution values, as is done in statistical modeling, the engineering models improve upon statistical models by drawing on existing studies to construct physically principled models using published values for parameters, such as estimates for unit energy consumption (UEC). Unlike the statistical models, engineering models do not rely on the ESS data, which allows us to obtain the modeled end-use estimates without having to wait for the ESS data to become available. Another benefit of this independence is that we can use the initial modeled estimates in the data editing process to detect any inconsistences between the household data and the ESS data (described in the *Editing and data quality* section).

The complexity of the end-use models depends on the end uses and how much information about them we collect in the HS. Some models are simple, such as the expected energy consumption for a toaster oven. Respondents are asked whether a toaster oven is present and used at least once a week, and no other specific usage information is collected. If the response is *yes*, the engineering model estimate is the average UEC value found from published sources and zero otherwise. Other models are moderately complex, such as the expected energy consumption for a refrigerator. The model assigns an effective UEC value<sup>2</sup> based on the reported configuration, size, and age of the unit, as well as whether a through-the-door ice maker is present. Further adjustments are made based on average ENERGY STAR<sup>®</sup> prevalence for that kind of refrigerator and the estimated temperature of the space in which the refrigerator is stored (for example, reported thermostat set points). Finally, a few models are complex, such as space heating and space cooling. Each of these follows an approach of first estimating an underlying conditioned load based on building characteristics and weather or climate variables and then estimating how much energy is required to meet that load given the efficiency of the equipment and fuel used in the home (for example, a natural gas furnace that is 10 to 14 years old).

A new feature introduced into the 2020 RECS end-use models is that all models now produce daily modeled consumption outputs for each end use. For some simple end-use models, the daily output was calculated by dividing the annual total by 366 calendar days; however, some end-uses are seasonal and required additional analysis to produce daily outputs. These end uses include:

- Space conditioning
- Refrigerators and separate freezers
- Water heating
- Lighting
- Pools and hot tubs
- Fans

<sup>&</sup>lt;sup>2</sup> UEC values are calculated based on U.S. efficiency standards for refrigerators, sales-weighted ENERGY STAR<sup>®</sup> data for refrigerators, an aging degradation factor, and expected changes in consumption due to the ambient space temperatures.

- Dehumidifiers and humidifiers
- Electric vehicle charging

The models are described in more detail in Appendix B. For example, space conditioning end uses depend on temperature, and we produced daily estimates for end-use consumption by modeling estimates of heating or cooling load, using daily weather records instead of annualized values.

In addition to the explicitly modeled end uses, each fuel has the possibility of an *unknown* source of energy consumption, a feature introduced in the 2015 RECS. Historically, the consumption from end uses not asked about in the RECS had been absorbed into the consumption total from the explicitly modeled end uses during calibration. In the 2015 and 2020 RECS, we can identify cases needing an *unknown* end use based on large differences between their expected energy use and their annualized billing totals. In principle, carrying through the possibility for an *unknown* end-use component should allow for more accurate estimation of the explicitly modeled end uses. More detail about the unknown end use and how this component is treated in the calibration step is provided in the *Unknown Consumption* section.

Reported vacancy was preserved as a characteristic of households as described above in the *C&E Annualization and Imputation* section, another feature introduced in the 2015 RECS. Modeled engineering totals were prorated to reflect only the consumption from occupied periods.

## Minimum variance estimation calibration procedure

Although end-use modeling provides information about how the end-use consumption is distributed across the end uses in a home, the model outputs for a home rarely equal the home's annualized billing total. We used a calibration procedure to preserve the distribution of a fuel's consumption across its end uses while ensuring the sum of end-use estimates equal the known billing total. In general, a calibration procedure evaluates the difference between a known billing quantity and the modeled sum of all end-use consumption over the corresponding billing period. If the billing quantity is the annualized total, then the billing period is the whole year, but a calibration procedure can also compare the billing totals and modeled totals for individual billing periods. Either way, the evaluated difference is a *target value*: if the *target value* is positive, then a calibration procedure must increase the modeled end-use estimates to match the billing total; if the *target value* is negative, then a calibration procedure must reduce the modeled end-use estimates. Either way, the calibration procedure can be seen as correcting the initial modeled end-use estimates.

In RECS studies before 2015, the calibration procedure used was simple normalization, where every individually modeled end-use value for a household was multiplied by the same factor to ensure the scaled estimates summed to the billing total. In the 2015 RECS, we introduced a new calibration method, known as *minimum variance estimation*, which uses estimates of the models' likely errors, or uncertainties, to produce unique factors for each end use. Because models vary in complexity and use of RECS data, the various model outputs have varying levels of uncertainty. Further, certain end-use pairs are also likely to be correlated. For example, households that use clothes washers more than average are likely to use clothes dryers more than average. The uncertainties associated with the end-use

estimates and the correlations between certain end-use pairs were used to make the calibration adjustments information-based and internally consistent.

Mathematically, if the set of initially modeled end uses in a given home is x, a column vector that has the same number of components as the home has end uses, then the calibration procedure corrects each end-use estimate,  $\Delta x$ , so that the final, corrected estimates are  $x + \Delta x$ . The uncertainties and correlations are used to define a weighting matrix, a variance-covariance matrix, P, whose inverse can be used in a cost function, J, which is a quadratic form that assigns a scalar cost to each possible vector of corrections:

$$J(\Delta x) = \frac{1}{2} \Delta x^T \boldsymbol{P}^{-1} \Delta x$$

The optimal—or most likely—set of corrections is found as the vector that minimizes the cost function is subject to two types of constraints. First, the final estimates cannot be negative or zero, because negative consumption is unphysical, and zero consumption would effectively erase a reported end use from a home. So,  $x_i + \Delta x_i > 0$ , with the subscript *i* indexing each end use present. Second, to satisfy the calibration goal, all of the corrections must sum to the target value,  $\Delta Y$ , which is the difference between the initial modeled sum of end-use consumption and the known annualized billing total:  $\sum_i \Delta x_i = \Delta Y$ .

A new feature introduced into the 2020 RECS is the ability to calibrate at the billing level, as opposed to relying on annualized billing totals and modeled annual totals for end uses. As described in the previous section, a requirement for this approach is to have modeled end-use values for billing periods of arbitrary lengths. We extended our end-use models to give daily outputs, which could be summed to give values for any billing period within 2020. The complementary requirement on the calibration side was extending the variance-covariance matrix, **P**, to include representations of each end use over each billing period. More detail on these correlations is in the *Estimating correlations* section.

We only applied billing-level calibration for end-use estimates of electricity and natural gas because the bills indicate when the fuels were consumed, as opposed to with the bulk fuels where the fuels can be consumed anytime after delivery. Within the RECS cases with electricity or natural gas bills, in two scenarios, we did not attempt billing-level calibration: homes that heat their swimming pools with natural gas and homes with any bills showing negative consumption amounts due to bill corrections by the supplier.

Regardless of whether the problem is prescribed for the annual level or at the billing level, minimizing the involved cost function under the stated constraints is a standard problem in quadratic programming, and it is easily solved in many software packages. Defining the uncertainties and correlations to use in the weighting matrix (described in the next section) is more challenging.

## **Estimating uncertainties**

The general approach to estimate the uncertainty associated with the output from each end-use model is to separate each model into its most basic components, both inputs and assumptions, and try to ascribe a reasonable uncertainty estimate to each component. The total uncertainty of the model output then comes from classic error propagation. Model inputs introduce uncertainty based on likely response errors in the HS. Model assumptions introduce uncertainty based on the accuracy of approximations made in the models, including how well an underlying regression is expected to work, how believable a stated effect size is, and how plausible the published estimates are.

Estimating the uncertainty for every end use present in every home in the RECS sample is impractical. An implementable approach assumes that the uncertainty of an end use in any home can be effectively represented by an average value of *relative uncertainty* across all homes. Relative uncertainty is framed as plus or minus a percentage of the estimate value. For example, if an end use is estimated to have 20% relative uncertainty, then a modeled estimate of 1,000 kWh has resulting absolute uncertainty of ±200 kWh, whereas a modeled estimate of 200 kWh has resulting uncertainty of ±40 kWh. Both have ±20% uncertainty, but their absolute uncertainties are quite different (200 vs. 40). Working with relative uncertainty makes the prospect of ascribing uncertainty to each engineering model output manageable.

As a simple example of assessing the uncertainty of a model's output, consider the RECS end-use model for clothes washers, which only models the machine energy use of the appliance, not the energy used to heat water. Functionally, the model can be written as:

$$\begin{array}{l} \textit{Output} = \textit{OperatingEnergy} + \textit{StandbyEnergy} \\ &= \frac{366}{7} \\ &\cdot \left(\textit{LoadsPerWeek} \cdot \textit{EnergyPerLoad} + \left(168 - \textit{LoadsPerWeek} \cdot \frac{\textit{MinutesPerLoad}}{60}\right) \\ &\cdot \textit{StandbyWattage} \end{array}\right) \end{array}$$

where the model *Output* is the total energy required by a particular clothes washer with a given efficiency, *EnergyPerLoad*, to do a reported *LoadsPerWeek* of clothes washing.

Both *EnergyPerLoad* and *LoadsPerWeek* are uncertain. Some clothes washers also have standby consumption, depending on their age, and the actual standby wattage is also uncertain, as is the assumed duration of a single load of wash. However, the consumption from standby mode is so small compared with the active consumption that the uncertainty of the end-use model is really just determined by:

$$Output = \frac{366}{7} \cdot (LoadsPerWeek \cdot EnergyPerLoad)$$

We can provide some background on these terms:

LoadsPerWeek: We collect this housing characteristics data item within the HS, variable =
WASHLOAD. It is an integer, numeric variable over the range 0–99, and its main uncertainty
comes from whether the respondent accurately characterized their average weekly usage. For
example, if the respondent has seasonal variation in their usage but they respond based on their
usage in the particular season in which they complete the survey, then the value may be
inaccurate.

 EnergyPerLoad: This is an assumed efficiency value within our end-use model. Its value depends on whether the respondent answered that the unit is a top-loading washer or front-loading washer. Also, the values we assume are an average of efficiencies for washers that qualify for ENERGY STAR<sup>®</sup> and those that do not, weighted by their relative sales data over calendar year 2020.

When the two sources of potential uncertainty are assumed to be uncorrelated, then classic error propagation dictates that the square of the relative uncertainty of the *output* is equal to the sum of squares of each term's own relative uncertainty:

$$\left(\frac{\Delta Output}{Output}\right)^{2} = \left(\frac{\Delta LoadsPerWeek}{LoadsPerWeek}\right)^{2} + \left(\frac{\Delta EnergyPerLoad}{EnergyPerLoad}\right)^{2}$$

To evaluate these, we have to estimate the likely level of uncertainty in survey responses for WASHLOAD, and we have to estimate the likely level of uncertainty in an assumed efficiency value for a clothes washer. Although we cannot know the true uncertainties of these, we can probably estimate decent values, yielding a representative overall uncertainty value for the model output for our end-use model. For example, if survey respondents reported WASHLOAD values within ±20% of the actual value, and if we assumed values for energy consumption per wash load were within ±25% of the actual value, then these would imply an overall uncertainty for the model output of

$$\sqrt{(0.20)^2 + (0.25)^2} \sim \pm 32\%$$

Under these assumptions, a model output of 100 kWh consumption from using a clothes washer in 2020 would be interpreted as likely being within the range of 68 kWh to 132 kWh.

## **Estimating correlations**

A calibration procedure should recognize when end uses are correlated so that the initial modeled values can be adjusted according to their expected correlations. As explained above, with the introduction of billing-level calibration, we now have two different types of correlations to consider: correlations between end uses and correlations across bills. Unfortunately, the true correlations we would like to use are inaccessible and immeasurable by any data sets or measurements currently available. As a result, any correlations, including any assumptions that end uses are uncorrelated, are approximations. After experimentation and research, we implemented this general approach for estimating the correlations:

## For correlations between modeled end uses

• Where available, we use the direct correlations between HS data that ask about the frequency of use or behaviors for a given end use, such as weekly usage of clothes washers and dryers, to approximate the correlations between the end uses' energy consumption. We determined that the correlations in usage would account for most, if not all, of the true correlation between the covered end-use pairs. In the clothes washer and dryer example, their strong correlation in consumption is most likely due to their correlation in usage rather than something intrinsic about the installed units in the home.

- We use the outputs from the engineering models across suitably defined subsets of similar homes to estimate the correlations between the three largest end uses: space heating, air conditioning, and water heating. Addressing these end uses is necessary because of their large share of total consumption. After experimentation, we found that the best strategy for defining *similar homes* is based on different climate zones. This strategy offers the best trade-off between dividing cases meaningfully and retaining reasonable sample sizes.
- We combine the first two approaches, when appropriate, to estimate the cross-correlations between end uses with usage variables in the HS and space heating, air conditioning, and water heating.
- Otherwise, we assume correlations between end-use pairs are zero. The assumption of zero correlation between all other end uses was supported by the results of finding the correlations between all of the RECS HS usage variables. Although some of the correlations across these usage variables are notable and non-zero, most of the correlations are very small. Clothes washer use and clothes dryer use are understandably highly correlated—higher than the 0.9 level—as are the usage of the main TV in a home and the second-most used TV in a home—at about the 0.5 level. However, many pairs, like main TV usage and oven usage, correlate empirically at less than the 0.1 level, even with a very large sample size. These results provided further confidence in assuming zero correlation between the many end uses for which no usage information is collected.

### For correlations across bills

- For correlations across bills but within a given end use, we assume that end uses with natural seasonality have smaller correlations than do end uses with no obvious seasonality. So, end uses that are used regularly for only certain seasons within a year (for example, space conditioning) are assumed to have relatively small correlations across bills. End uses with seasonality but that are used throughout the year (for example, water heating) are assumed to have moderate correlations across bills. End uses with no expected seasonality are assumed to have the highest correlations across bills. The unknown end use, described in the next section, is assumed to have no correlations across bills.
- For correlations across bills and between end uses (for example, the correlation between space heating in January and water heating in October), we essentially multiply the three different, related correlations: the between-end-uses correlation, the between-bills correlation of the first end use, and the between-bills correlation of the second end use. Because of this approach, the resulting correlations are typically quite small.

### **Unknown consumption**

Beginning in the 2015 RECS, each household has the opportunity to have a positive end-use estimate for *unknown* consumption. A household can only end up with positive unknown consumption during the calibration process: the initial modeled expectations for unknown consumption is zero for all fuels with zero uncertainty and no correlations to other end uses or to itself across bills. However, during the calibration step, if the billing total is sufficiently larger than the corresponding initial modeled fuel total, then we increase the absolute uncertainty of the unknown, allowing the calibration process to assign some of the large *target value* to the unknown end use. Occasionally, the calibrated value for the

*unknown* end use accounts for most of the unexpectedly large mismatch. We allow for unknown consumption to contain large unexpected differences and prevent them from unrealistically perturbing the consumption estimates for other present end uses.

Most RECS homes are assigned zero unknown consumption estimates. For some homes, we find unexpectedly large differences between the billing data and the initial modeled fuel totals. Large differences can result from household end uses not captured in the HS that consume abnormally high amounts of energy (for example, a tanning bed or a propane greenhouse heater) or from unreported non-household end uses (for example, a farm). Also, large mismatches between the household characteristics and billing data could also result from respondent error that was not detected in the data editing process.

The introduction in the 2020 RECS of billing-level calibration for electricity and natural gas has introduced the possibility of billing-level *unknown* consumption. In general, we attempted billing-level calibration on all RECS households with electricity bills except for homes with a swimming pool or homes with a bill showing negative consumption. Similarly, we attempted billing-level calibration for all homes with natural gas bills except for homes that heated their pools using natural gas. If during the billing-level calibration we detected the need to allow for unknown consumption, we defaulted to a modified version of billing-level calibration that allowed for unknown consumption. In this modified version, we treated each bill independently to remove all correlations across bills. For a case with 12 bills covering 2020, we performed 12 calibrations, one for each bill, and although all 12 calibrations had the potential to realize positive unknown consumption, often only one or a few actually did so.

# **Appendix A. Examples of Annualization and Imputation**

This appendix provides examples illustrating different scenarios for the consumption annualization and imputation processes of an individual home. The procedures for electricity and natural gas were similar, and the procedures for propane and fuel oil were similar.

### Table A-1. Example of complete reported ESS data for a household using natural gas

Billing End Date	Billing Days	Consumption (Ccf)	Notes
12/09/2019		126	Not included as part of 2020 consumption
01/07/2020	29	193	Included 7 days of prorated consumption for January 2020
02/05/2020	29	241	Included as part of 2020 consumption
03/06/2020	30	297	Included as part of 2020 consumption
04/07/2020	32	174	Included as part of 2020 consumption
05/06/2020	29	76	Included as part of 2020 consumption
06/05/2020	30	32	Included as part of 2020 consumption
07/07/2020	32	27	Included as part of 2020 consumption
08/05/2020	29	19	Included as part of 2020 consumption
09/04/2020	30	19	Included as part of 2020 consumption
10/05/2020	31	20	Included as part of 2020 consumption
11/03/2020	29	24	Included as part of 2020 consumption
12/04/2020	31	88	Included as part of 2020 consumption
01/06/2021	33	138	Included 27 days of prorated consumption for December 2020

Data source: U.S. Energy Information Administration, Residential Energy Consumption Survey

Note: ESS=Energy Supplier Survey

Annualization steps for a complete case for electricity and natural gas

- Step 1: Adjusting the consumption amount for the 2020 edge months
  - Adjusting the beginning bill: 7 days in the 1/7/2020 bill fell in 2020, so we prorate the bill's consumption based on the days (the 2020 consumption was 193 × (7/29) = 47 Ccf)
  - Adjusting the ending bill: 27 days in the 1/6/2021 bill fell in 2020, so we prorate the bill's consumption based on the days (the 2020 consumption was 138 × (27/33) = 113 Ccf)
- Step 2: Adding the consumption portions that occurred within 2020, we find the total consumption for this case was 1,177 Ccf

Natural gas requires an additional step for unit conversion. If an energy supplier reported a case's consumption to us in volume units (for example, Ccf, or hundred cubic feet), then we converted the consumption to energy units. The energy contained in a given volume of natural gas depends on several factors, the two most important of which are the inherent heat content of the gas (related to the mix of particular hydrocarbons) and the pressure of the natural gas at which the volume was measured. To account for the varying heat content of natural gas, we used our state-level data on the average heat content of delivered natural gas. To account for varying pressure effects, we opted to account for the

average deviation from sea-level pressure as determined by a home's elevation above sea level. Our conversion follows this form: *energy units* = *volume units* × *state-level heat content factor* × *pressure factor*. In RECS studies before 2015, we performed the conversion by multiplying the volume by a constant national heat content factor. All conversions from electricity to Btu used the standard conversion rate of 3,412 Btu/kWh.

In addition, if a household reported a vacancy, the calculation procedure for the total consumption was the same as above except the consumption of the unreported billing periods was counted as zero.

### Table A-2. Example of complete reported ESS data for a house using propane or fuel oil

Billing End Date	Billing Days	Consumption (gallons)	Notes
04/24/2019	-	63	Not included as part of 2020 consumption
01/08/2020	259	166	Not included as part of 2020 consumption
02/14/2020	37	134	Included as part of 2020
04/09/2020	54	129	Included as part of 2020
12/15/2020	250	89	Included as part of 2020
02/12/2021	59	136	Included as part of 2020
04/22/2021	70	94	Not included as part of 2020 consumption

Data source: U.S. Energy Information Administration, Residential Energy Consumption Survey

Note: ESS=Energy Supplier Survey

### Annualization steps of a complete case for propane and fuel oil

For annualization of bulk fuels, we interpret delivery amounts as a measure of the consumption that occurred in the time since the previous delivery.

- Step 1: We identify a set of deliveries that include as much of 2020 as possible while also getting as close as possible to 366 days, and then we add the delivered fuel over that set.
  - Because the delivery on 2/14/2020 covers the consumption that occurred from 1/9/2020 onward, the set of deliveries from 2/14/2020 to 2/12/2021 covers 400 days of data and happens to include nearly all of 2020. The January 2020 delivery covers fuel consumed mostly in 2019 and so is excluded.
  - These identified deliveries sum to 488 gallons.
- Step 2: We adjust the identified sum of deliveries to better match calendar year 2020 using modeled fuel totals.
  - The end-use models for propane produced expectations that this home would use 525 gallons of propane over this particular 400 day span, which is greater than was actually consumed by the home.
  - The end-use models for propane expected that this home would use 442 gallons of propane within calendar year 2020.
  - So, the final annualized estimate for 2020 consumption is 442 × (488/525) = 411 gallons.

Unlike the annualization procedure for electricity and natural gas, the long duration between the deliveries in April 2020 and December 2020 was not treated as a missing period.

End use	End-use model estimates	Coefficients of imputation model	(End-use model estimates) × (coefficients)
Space heating	5,120	1.046	5,356
Furnace fan - heating	87	1.211	106
Space cooling	2,634	0.941	2,479
Ceiling fan	38	1.033	39
Refrigerators & freezer	1,878	1.040	1,952
Lighting	321	1.113	357
All other end uses	2,140	1.098	2,350

#### Table A-3. Example of a household with no reported ESS data

Data source: U.S. Energy Information Administration, *Residential Energy Consumption Survey* Note: ESS=Energy Supplier Survey

#### Annualization steps for a household with no usable billing data apply to all fuels

The above sample values are from a household in a single-family detached home in the mixed-humid climate zone with the end-use groupings shown for their electricity use in the household.

- Step 1: We collect all the end-use model output for end uses of electricity and form the appropriate end-use groupings for our imputation model.
- Step 2: We collect the appropriate regression coefficients for the specific housing type and climate zone from the imputation model.
- Step 3: We compute each end-use grouping term within the imputation model and sum them. The initial modeled fuel total for electricity consumption was 12,218 kWh (from 5,120 + 87 + 2,634 + 38 + 1,878 + 321 + 2,140), and the final imputed annualized total for this home is 12,639 kWh.

# **Appendix B. Detailed Model Descriptions for Published End Uses**

Below is a description of the engineering models for each end-use estimate of energy consumption published in RECS data tables or the public-use microdata file. Users should consult the microdata file codebook, which contains an indicator for each HS variable used in these models. Note that some published end-use estimates (for example, *TVs and Related*), are actually the sum of separately modeled and calibrated end uses.

The end-use models used in the 2020 RECS were largely based on those used in the 2015 RECS, with updates and improvements. The references below represent the information we used to construct the models as implemented, including any improvements. We consulted additional references to assess and establish the validity of the cited sources shown here. Web links are provided where available, although some of the references used at that time may have since become unavailable.

Space heating: Total energy consumption for a home's space heating is modeled as the energy required by the reported space heating equipment to meet a modeled space heating load. Assumed equipment efficiencies are taken from efficiency standards, adjusted to reflect the performance of ENERGY STAR<sup>®</sup> qualifying units. Space heating load is modeled as a home's total heat loss from three separately modeled mechanisms: conduction through its building envelope, conduction through its foundation, and infiltration exchange with outside air.

Conduction follows a *U-A* approach, multiplying insulation properties (U-factors) by the areas (A) over which conduction occurs. We estimate U-factors based on climate zone and home age relative to state building code adoptions. We calculate areas based on reported square footages, stories, and housing types. Infiltration follows a *normalized leakage* approach. We use heating degree days (HDDs) to approximate the temperature gradients driving conduction and infiltration. The base temperature used for calculating HDDs for a particular home is set by the state where it is located, modified by their reported thermostat setpoints. The state-level base temperatures were estimated using EIA 861M data; most are less than 65°F. Main and secondary space-heating equipment are modeled separately, and can use different fuels, but they work together to meet a home's total space-heating load.

- Air handlers-heating: Total consumption for air handlers in heating equipment is the sum of the energy used by two components: furnace fans in forced-air furnaces and heat pumps and circulation pumps in boilers with radiators. Both of these circulate heat throughout a home, and both always consume electricity. The model for each component is based on the computed total space-heating load from the space-heating model and a home's total heated square footage and parameters, which depend on the housing type and climate zone. This end-use estimate is a separate component from space heating because it consumes electricity even for non-electric space heating (for example, a natural gas furnace).
- Air conditioning: Total consumption for air conditioning (AC) is modeled as the energy used by the reported AC equipment to meet a modeled space-cooling load. Assumed equipment efficiencies are taken from efficiency standards, adjusted to reflect the performance of ENERGY STAR<sup>®</sup> qualifying units. The cooling load is based on heat gain from three separately modeled mechanisms: conduction through the building envelope (for example, U-A calculations), infiltration exchange of sensible heat (for example, temperature), and infiltration exchange of

latent heat (for example, moisture). We used cooling degree days (CDDs) to estimate the temperature gradients driving conduction and sensible heat exchange, and we used a degree day-like quantity based on dew point temperature to approximate the gradients driving latent heat exchange. The base temperature used for calculating CDDs for a particular home is set by the state where it is located, modified by their reported thermostat setpoints and whether large shade trees are present. The state-level base temperatures were estimated using EIA 861M data; most are less than 65°F.

- Air handlers-cooling: This element is the energy consumption used by the air handler or ventilation component of central air conditioning (AC) units and heat pumps run as central AC units in the cooling season. The model is based on the computed cooling load from the space-cooling model and a home's total cooled square footage and parameters, which depend on the housing type and climate zone. Similar to air handlers for space heating, this end-use estimate is a separate component from air conditioning end use.
- **Evaporative coolers**: In the 2020 RECS, *space cooling* is the combination of AC and evaporative coolers, although they are modeled differently. Total consumption for evaporative coolers is modeled as a given wattage for the unit multiplied by the estimated number of days for which cooling is necessary. If a given day has non-zero CDDs, which means the temperature exceeds 65°F, then the unit is assumed to run all day. The number of days a year for which cooling is necessary is modeled based on the CDD total for each home.

References for Space heating, Air conditioning, Air handlers, and Evaporative coolers

- Air Infiltration
  - ASHRAE. 2012. Addendum n to ANSI/ASHRAE Standard 62.2-2010: Ventilation and Acceptable Indoor Air Quality in Low-Rise Residential Buildings. American Society of Heating, Refrigerating and Air-Conditioning Engineers.
    - https://www.ashrae.org/File%20Library/Technical%20Resources/Standards%20and %20Guidelines/Standards%20Addenda/62\_1\_2010\_o\_Final\_09132013.pdf
  - ASHRAE. 2013. 2013 ASRHAE Handbook: Fundamentals. American Society of Heating, Refrigerating and Air-Conditioning Engineers.
  - Chan, W., J. Joh, and M. Sherman. 2012. *Analysis of Air Leakage Measurements from Residential Diagnostics Database.* LBNL-5967E.

https://buildings.lbl.gov/sites/default/files/lbnl-5967e.pdf

- U-Factors
  - DOE, EERE. Building Energy Codes Program. Accessed Sep 2021 (no longer exists). https://www.energycodes.gov/status/residential
  - Huang, J, J. Hanford, and F. Yang. 1999. *Residential Heating and Cooling Loads Component Analysis*. Lawrence Berkeley National Laboratory. LBNL-44636. https://simulationresearch.lbl.gov/dirpubs/44636.pdf
  - IECC. 1998, 2006, 2009, 2012, 2015, and 2018. International Energy Conservation Code. https://energycode.pnl.gov/EnergyCodeReqs/

Ungar, L. 2016. *Take a Ride on the Energy Slide with Building Codes*. ACEEE blog. https://www.aceee.org/blog/2016/02/take-ride-energy-slide-building-codes

Equipment Efficiencies

- AHAM. 2010. *Room Air Conditioners Energy Efficiency and Consumption Trends*. Association of Home Appliance Manufacturers. http://aham.org/
- DOE, EERE. *Federal Register, 10CFR Part 430.32* (Standards). Electronic Code of Federal Regulations. Current:

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-C/section-430.32#p-430.32(b)

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-C/section-430.32#p-430.32(c)

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-C/section-430.32#p-430.32(e)

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-C/section-430.32#p-430.32(i)

DOE, EERE. 2010. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Residential Water Heaters, Direct Heating Equipment, and Pool Heaters.

https://www.regulations.gov/document/EERE-2006-STD-0129-0149

DOE, EERE. 2011. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment. Residential Clothes Dryers and Room Air Conditioners.

https://www.regulations.gov/document/EERE-2007-BT-STD-0010-0053

- DOE, EERE. 2015. Final Rule Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Residential Boilers. https://www.regulations.gov/document/EERE-2012-BT-STD-0047-0070
- DOE, EERE. 2015. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Residential Furnaces. https://www.regulations.gov/document/EERE-2014-BT-STD-0031-0027
- DOE, EERE. 2016. Final Rule Technical Support Document: Energy Efficiency Program for Consumer Products: Residential Central Air Conditioners and Heat Pumps. https://www.regulations.gov/document/EERE-2014-BT-STD-0048-0098
- DOE, EERE. 2015. Working Group Meeting Presentation: CAC and HP ASRAC Working Group Fifth & Sixth Meetings.

https://www.regulations.gov/document/EERE-2014-BT-STD-0048-0052

- Fairey, P., D. Parker, B. Wilcox, and M. Lombardi. 2004. Climate Impacts on Heating Seasonal Performance Factor (HSPF) and Seasonal Energy Efficiency Ratio (SEER) for Air Source Heat Pumps. Florida Solar Energy Center. FSEC-PF-413-04. http://www.fsec.ucf.edu/en/publications/html/FSEC-PF-413-04/
- Guidehouse and Leidos. 2023. EIA Technology Forecast Updates Residential and Commercial Building Technologies Reference Case. Prepared for the U.S. Energy Information Administration.

https://www.eia.gov/analysis/studies/buildings/equipcosts/pdf/appendix-a.pdf

- Navigant Consulting, Inc. 2015. *Residential End Uses: Area 1: Historical Efficiency Data*. Prepared for the U.S. Energy Information Administration. https://www.eia.gov/analysis/studies/residential/pdf/appendix-a.pdf
- Wenzel, T., J. Koomey, G. Rosenquist, M. Sanchez, and J. Hanford. 1997. Energy Data Sourcebook for the U.S. Residential Sector. LBNL-40297. https://www.osti.gov/servlets/purl/585030
- Furnace Fans

DOE, EERE. 2014. Final Rule Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment; Residential Furnace Fans.

https://www.regulations.gov/document/EERE-2010-BT-STD-0011-0111

DOE, EERE. *Federal Register, 10CFR Part 430.32* (Standards). Electronic Code of Federal Regulations. Current:

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-C/section-430.32#p-430.32(y)

• Circulation Pumps

Lutz, J., C. Dunham-Whitehead, A. Lekov, and J. McMahon. 2004. *Modeling Energy Consumption of Residential Furnaces and Boilers in U.S. Homes*. LBNL-53924. http://eaei.lbl.gov/sites/all/files/modeling\_energy\_consumption\_of\_residential\_fur naces\_and\_boilers\_in\_us\_homes\_lbnl-53924.pdf

• Evaporative Coolers

Representative wattage value drawn from the mode of various sources citing unit wattage, including, for example, this list of representative home costs composed by Duke Energy:

http://www.amhomeservices.net/upload/Appliance\_OpCost\_List\_Duke\_v8.06.pdf

• **Ceiling fans**: Total consumption for each fan is modeled as an average unit energy consumption (UEC) value, adjusted based on how reported usage compares with the survey weightedaverage usage. Homes with more than one ceiling fans are assumed to use each additional fan a fraction as much as the previously modeled fan. The model assumes regional variations in average energy consumption for reported use (for example, a home in the South reporting the same use as a home in the Northeast would be assumed to consume more energy based on likely using higher fan speeds or using the fan for more hours per day).

#### Reference for Ceiling fans

DOE, EERE. 2016. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Ceiling Fans. https://www.regulations.gov/document/EERE-2012-BT-STD-0045-0149

Kanter C., S. Young, S. Donovan, and K. Garbesi. 2013. *Ceiling Fan and Ceiling Fan Light Kit* use in the U. S.---Results of a Survey on Amazon Mechanical Turk. LBNL. https://www.osti.gov/biblio/1165855

• **Dehumidifiers**: Total consumption is the sum of the consumption from portable units and whole-home units, which are modeled separately. Each is modeled as a representative UEC, adjusted based on how reported usage compares with an assumed value of base usage, in months. If a home reports using more than one portable units, we assume that all units are operating for equal time if the home has enough square footage to cover; otherwise, we assume that the second and higher units are not used as much as the primary unit.

#### References for Dehumidifiers

Burke, T., H. Willem, C. Ni, H. Stratton, C. Whitehead, and R. Johnson. 2014. Whole-Home Dehumidifiers: Field-Monitoring Study. LBNL. https://www.osti.gov/servlets/purl/1164163

DOE, EERE. 2016. Final Rule Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Residential Dehumidifiers.

https://www.regulations.gov/document/EERE-2012-BT-STD-0027-0046

Mattison, L. and D. Korn. 2012. *Dehumidifiers: A Major Consumer of Residential Electricity*. The Cadmus Group, Inc. http://www.cadmusgroup.com/wp-content/uploads/2012/11/Dehumidifier-Metering-

Study-Mattison-050912.pdf

- Willem, H., T. Burke, C. Whitehead, B. Beraki, J. Lutz, M. Melody, M. Nagaraju, C. Ni, S. Pratt, S. Price, and V. Tavares. 2013. Using Field-Metered Data to Quantify Annual Energy Use of Residential Portable Unit Dehumidifiers. LBNL. https://www.osti.gov/servlets/purl/1164800
- Humidifiers: Total consumption is the sum of the consumption from portable units and wholehome units, which are modeled separately. Each is modeled as a representative UEC, adjusted based on how reported usage compares with an assumed value of base usage, in months. Homes with more than one portable units are assumed to use each additional humidifier a fraction as much as the previously modeled humidifier.

#### **Reference for Humidifiers**

- EPA, ENERGY STAR. 2012. Market & Industry Scoping Report Residential Humidifiers. https://www.energystar.gov/sites/default/files/asset/document/ENERGY\_STAR\_Scopin g\_Report\_Residential\_Humidifiers.pdf
- Water heating: Total consumption for water heating is modeled as the total energy needed to deliver domestic hot water (DHW) to a home divided by the thermal efficiency associated with the fuel used to heat the water. The total energy needed to deliver DHW is sum of the energy required to meet a home's demand for DHW and the standby energy losses incurred by storing a tank full of hot water. Demand for DHW is modeled primarily based on the number of household members in the home and the inlet ground water temperature. Energy losses for a storage tank water heater are based on the size and insulation of the tank, inferred from federal efficiency standards, and the temperature difference between the tank's heating setpoint and the ambient temperature of the space where the tank is located in a home. A further correction to the losses is based on whether the household uses an insulating blanket around its water heater. For homes with more than one water heater, the water heating load is split by an assumed fraction to determine the load that must be met by the reported main and secondary water-heating equipment.

#### **References for Water heating**

DOE, EERE. *Federal Register, 10CFR Part 430, Appendix E to subpart B* (Test Procedure). Electronic Code of Federal Regulations. As of Jan 2004 and Apr 2015. Current:

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-B/appendix-Appendix%20E%20to%20Subpart%20B%20of%20Part%20430

DOE, EERE. *Federal Register, 10CFR Part 430.32* (Standards). Electronic Code of Federal Regulations. As of Jan 2004 and Apr 2015. Current: https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-

C/section-430.32#p-430.32(d)

- DOE, EERE. 2011. Final Rule Technical Support Document. https://www.regulations.gov/document/EERE-2006-STD-0129-0149
- Hendron R. and J. Burch. 2007. *Development of Standardized Domestic Hot Water Event Schedules for Residential Buildings*. NREL/CP-550-40874. https://www.nrel.gov/docs/fy08osti/40874.pdf
- Lutz, J., Renaldi, A. Lekov, Y. Qin, and M. Melody. 2011. Hot Water Draw Patterns in Single-Family Houses: Findings from Field Studies. LBNL-4830E. https://eta.lbl.gov/sites/all/files/publications/hot\_water\_draw\_patterns\_in\_singlefamily\_houses\_findings\_from\_field\_studies\_lbnl-4830e.pdf
- Clothes washers: Consumption is modeled as an assumed energy use-per-wash load, which is based on whether the unit is top- or front-loading and is adjusted to reflect ENERGY STAR<sup>®</sup> sales data. The energy use-per-load is multiplied by the reported average number of loads per week; each load is assumed to last for an hour and multiplied by 52 weeks per year. The time when the washer is not actively running leads to standby-use consumption. Estimates are only for washer operation and do not include any energy needed to heat water. The example in the *Estimating uncertainties* section provides more detail.

References for Clothes washers

- AHAM. 2010. *Clothes Washers Energy Efficiency and Consumption Trends*. Association of Home Appliance Manufacturers. http://aham.org/
- DOE, EERE. 2012. Direct Final Rule Technical Support Document. https://www.regulations.gov/document?D=EERE-2008-BT-STD-0019-0047
- DOE, EERE. 2012. Energy Conservation Program: Energy Conservation Standards for Residential Clothes Washers.

https://www1.eere.energy.gov/buildings/appliance\_standards/pdfs/rcw\_direct\_final\_ru le\_5\_14\_2012.pdf

- EPA, ENERGY STAR. Unit Shipment and Sales Data Archives. Accessed Jan 2022. https://www.energystar.gov/partner\_resources/products\_partner\_resources/brand\_o wner resources/unit shipment data/archives
- Korn, D. and S. Dimetrosky. 2010. Do the Savings Come Out in the Wash? A Large Scale Study of In-Situ Residential Laundry Systems. The Cadmus Group, Inc. http://www.washingtonelectric.coop/wp-content/uploads/2011/08/hobo-news\_dryerstudy.pdf
- **Clothes dryers**: Consumption is modeled as active-use energy consumption, which is derived from responses to a usage question. Active-use consumption is the product of the annual number of loads, an assumed value of one hour per dryer load, and the energy use per dryer

load, which varies based on the dryer fuel. Dryers manufactured in 2016 or later have their assumed energy-use-per-load value adjusted to reflected reported ENERGY STAR<sup>®</sup> sales data. The model also calculates standby energy use (always electric) based on the inactive hours of use through the year and an assumed standby-use power draw. For the electric clothes dryers end use, the standby-use consumption is combined with the active-use consumption, but for natural gas and propane dryers, the standby use is included in the *not elsewhere classified* total.

**References for Clothes dryers** 

- DOE, EERE. 2011. Clothes Dryer Direct Final Rule Technical Support Document. https://www.regulations.gov/document?D=EERE-2007-BT-STD-0010-0053
- EPA, ENERGY STAR. Unit Shipment and Sales Data Archives. Accessed Jan 2022. https://www.energystar.gov/partner\_resources/products\_partner\_resources/brand\_o wner\_resources/unit\_shipment\_data/archives
- KEMA. 2010. 2009 California Residential *Appliance Saturation Study*. Prepared for the California Energy Commission. http://www.energy.ca.gov/appliances/rass/

Northwest Energy Efficiency Alliance and Northwest Power and Conservation Council. 2010. Comment submitted in Federal Register. EERE-2011-BT-TP-0054. https://www.regulations.gov/contentStreamer?documentId=EERE-2011-BT-TP-0054-

0021&attachmentNumber=1&contentType=pdf

Lighting: Indoor and outdoor lighting are modeled separately, and within each category—
incandescent, CFL, and LED—lighting is modeled separately. Total consumption is the sum of
these six possible components. For indoor lighting, the model first estimates the total number of
bulbs and lamps in a home, regardless of bulb or lamp type and then models how this total
count is distributed over four usage categories: 0–1 hr/day, 1–4 hr/day, 4–8 hr/day, and 8–24
hr/day. These distributions are informed by the reference and results from previous RECS
studies. The model then estimates the fractional share of bulbs and lamps that are
incandescent, CFL, and LED, based on survey responses. Finally, using assumed values for
representative bulb wattages, the model multiplies these values by the daily usage of each bulb
and lamp type in the home and sums the consumption over a year. The outdoor lighting model
is similar, but the usage is only divided into two categories: lights left on all night and lights that
are not left on all night.

#### **Reference for Lighting**

Navigant Consulting, Inc. 2017. 2015 U.S. Lighting Market Characterization. Prepared for DOE, EERE.

https://www.energy.gov/sites/prod/files/2017/12/f46/lmc2015\_nov17.pdf

• **Refrigerators**: Primary and secondary refrigerators are modeled separately, but any additional refrigerators beyond the second are modeled as a group. Total consumption for the primary refrigerator is modeled as an adjusted UEC value. A base UEC value is assigned according to federal efficiency standards, based on the reported configuration, size, and age of the refrigerator, plus whether ice is available through the door. We include an aging *degradation* factor in efficiency. We applied adjustments based on reported ENERGY STAR<sup>®</sup> sales data, as well as the estimated ambient temperature of the space where the refrigerator is located.

Modeling for the secondary refrigerator proceeds similarly, except we make assumptions about having ice service through the door (for example, only models with side freezers have ice service). For additional refrigerators in the home, we model them based on the reported type and age as the secondary refrigerator, although we assume each successive refrigerator is one category smaller than the previous. We do not apply corrections to these additional refrigeratoral ambient temperature.

• Freezers: The primary freezer is modeled separately, but any additional separate freezers beyond the first are modeled as a group. Total consumption for the primary freezer is modeled as an adjusted UEC value. A base UEC value is assigned according to federal efficiency standards, based on the reported configuration, size, age, and defrost mechanism (for example, manual vs. automatic). We include an aging *degradation* factor in efficiency. Adjustments are then applied based on reported ENERGY STAR<sup>®</sup> sales data, as well as the estimated ambient temperature of the space where the separate freezer is located, which we assign based on other survey responses about having a second refrigerator, a basement, or an attached garage. For additional separate freezers in the home, we model them based on the reported type and age as the primary freezer, although we assume each successive freezer is one category smaller than the previous. We assume all additional freezers are manually defrosted, and we do not apply corrections based on their locational ambient temperature.

#### References for Refrigerators and Freezers

DOE, EERE. *Federal Register, 10CFR Part 430.32* (Standards). Electronic Code of Federal Regulations. As of Jan 2001 and Sep 2014. Current: https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-

C/section-430.32#p-430.32(a)

- DOE, EERE. 2021. Energy Conservation Program: Test Procedures for Refrigeration Products. https://www.federalregister.gov/documents/2021/10/12/2021-21663/energyconservation-program-test-procedures-for-refrigeration-products
- EPA, ENERGY STAR. *FAQs > Appliances/Electronics/Lighting > Refrigerators*. Accessed Jan 2022.

https://energystar-mesa.force.com/ENERGYSTAR/s/article/Can-I-put-a-refrigerator-inan-uninsulated-garage-which-is-subject-to-winter-and-summer-extreme-temperatures-1600088469650

EPA, ENERGY STAR. Unit Shipment and Sales Data Archives. Accessed Jan 2022. https://www.energystar.gov/partner\_resources/products\_partner\_resources/brand\_o wner\_resources/unit\_shipment\_data/archives

Pratt, R.G. and J.D. Miller. 1998. The New York Power Authority's energy-efficient refrigerator program for the New York City Housing Authority -- 1997 savings evaluation. https://www.osti.gov/servlets/purl/296886

• **Cooking**: Ranges, separate ovens, and separate cooktops are all modeled separately. Total consumption for each component is modeled as an adjusted UEC value. A base UEC value is specified based on home type and then adjusted based on how reported usage compares with the survey weighted-average usage. Homes with more than one cooking appliance (for example,

two separate ovens) are assumed to use their additional units a fixed fraction of their primary unit use.

**References for Cooking** 

- DNV GL Energy Insights USA, Inc. 2021. 2019 California Residential Appliance Saturation Study. Prepared for the California Energy Commission. http://www.energy.ca.gov/appliances/rass/
- DOE, EERE. Energy Conservation Program: Test Procedure for Cooking Products. EERE–2012– BT–TP–0013.

https://www.federalregister.gov/documents/2022/08/22/2022-15725/energyconservation-program-test-procedure-for-cooking-products

DOE, EERE. Energy Conservation Program: Energy Conservation Standards for Residential Conventional Ovens. EERE–2014–BT–STD–0005.

https://www.energy.gov/sites/prod/files/2015/06/f22/residential\_ovens\_nopr.pdf

DOE, EERE. Energy Conservation Program: Energy Conservation Standards for Consumer Conventional Cooking Products. EERE–2014–BT–STD–0005.

https://www.federalregister.gov/documents/2023/02/01/2023-00610/energyconservation-program-energy-conservation-standards-for-consumer-conventionalcooking-products

Sweeney, M., et al. 2014. *Induction Cooking Technology Design and Assessment*. EPRI. https://www.aceee.org/files/proceedings/2014/data/papers/9-702.pdf

• **Microwaves**: Total consumption is modeled as the sum of active-use consumption and standbyuse consumption. Active-use consumption is the product of the reported daily number of microwave uses (cycles), an assumed value of average cycle length, 366 days in the year, and an assumed active use wattage. Standby-use consumption is the product of an assumed standby wattage and the remaining (inactive) time in 2020.

References for Microwaves

DOE, EERE. Energy Conservation Program: Energy Conservation Standards for Standby Mode and Off Mode for Microwave Ovens. EERE–2011–BT–STD–0048. https://www1.eere.energy.gov/buildings/appliance\_standards/pdfs/mwo\_final\_rule.pd f

DOE, EERE. 2022. Energy Conservation Program: Test Procedure for Microwave Ovens. https://www.federalregister.gov/documents/2022/03/30/2022-06451/energyconservation-program-test-procedure-for-microwave-ovens

Greenblatt, J.B., et al. 2013. *Field data collection of miscellaneous electrical loads in Northern California: Initial results.* LBNL-6115E. https://www.osti.gov/servlets/purl/1172006

Williams, A., et al. 2012. *Surveys of Microwave Ovens in U.S. Homes*. LBNL-5947E. https://www.osti.gov/servlets/purl/1172657 • **Dishwashers**: Total consumption is the sum of active-use energy consumption and standby-use energy consumption, although units at least 15 years old are assumed to have no standby energy use. Active-use consumption is calculated for a year based on multiplying an assumed power draw and length of cycle by the reported average number of uses per week. If applicable, the standby use is calculated for a year based on multiplying the inactive hours per year by an assumed standby energy draw. Estimates are only for dishwasher operation and do not include the energy needed to heat water.

# **References for Dishwashers**

DOE, EERE. 2012. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Residential Dishwashers. https://www.regulations.gov/document/EERE-2014-BT-STD-0021-0029

DOE, EERE. Appendix C1 to Subpart B of Part 430—Uniform Test Method for Measuring the Energy Consumption of Dishwashers. Electronic Code of Federal Regulations. Accessed 2014.

https://www.ecfr.gov/current/title-10/chapter-II/subchapter-D/part-430/subpart-B/appendix-Appendix%20C1%20to%20Subpart%20B%20of%20Part%20430

- TVs and related: This category is the sum of all TVs, video game consoles, set-top boxes, internet streaming devices, Blu-ray players, DVD players, VCRs, and home theater and audio systems.
  - TVs: First-, second-, and third-most-used TVs are modeled separately, and any additional TVs beyond the third are modeled as a group. Total consumption for a TV is the sum of active-use consumption and standby-use consumption. An assumed value for active-mode power draw is based on the reported type and size of the TV. Standby power draw is assumed to be a constant wattage for all TV models. The active consumption is calculated by multiplying the active power draw by the total active hours in a year, which is based on separately reported usage for weekends and weekdays. The standby-use consumption multiplies the standby power draw by the total number of inactive hours in a year, the complement of the active hours in a year.
  - Video game consoles: Total consumption is modeled based on an assumed UEC, and households can have multiple reported units.
  - Set-top boxes: Cable and satellite boxes, separate DVRs, and combination DVRs are modeled separately. Each type of set top box has its own representative UEC value, and households can have multiple reported units of each type.
  - **DVD and Blu-ray players and VCRs**: These electronics have their own representative UEC values, and homes can have multiple reported units of each type.
  - Internet streaming devices: Total consumption is modeled based on an assumed UEC, and households can have multiple reported units. Examples include AppleTV, Google Chromecast, Slingbox, or Roku.

 Home theater and audio systems: Total consumption is modeled based on an assumed UEC, and households can have multiple reported units. Reference for TVs and related

Urban B., K. Roth, and J. Olano. 2021. Energy Consumption of Consumer Electronics in U.S. Homes in 2020. Fraunhofer USA. https://shop.cta.tech/collections/research/products/energy-consumption-ofconsumer-electronics-in-u-s-homes-in-2020

- **Pool pumps**: Total consumption is modeled as the energy consumption from the sum of activeuse and standby-use. The active-use consumption comes from a pool pump's active power draw multiplied by its assumed time duration in active mode. We model a pool pump's active power draw from an assumed horsepower rating, an assumed service factor, and an assumed efficiency. We model its time in active use as a fixed proportion of the reported duration of seasonal use from the HS. We model a pool pump's standby-use consumption very similarly, with an assumed standby wattage and the time spent in standby mode defined by the total duration less the active-use time. Our assumed parameter values were informed by the references. For respondents reporting variable-speed pool pumps, we multiply their total consumption by a set fraction.
- **Pool heaters (natural gas)**: Total consumption is modeled as the energy needed for heating equipment with an assumed efficiency to meet a home's pool heating load. The load is assigned based on a home's state, and each state's load profile has its own assumed duration of months. The home's energy consumption is prorated relative to the state's assumed duration, based on the respondent's reported months of pool use.
- Hot tub pumps: Total consumption is modeled as an annual UEC (representing 12 months of usage), prorated over the reported number of months in use.
- Hot tub heaters (electric and natural gas): Total consumption is modeled as an annual UEC (representing 12 months of usage), prorated over the reported number of months in use.

References for Pools and Hot tubs

Association of Pool & Spa Professionals (APSP). 2014. *American National Standard for Portable Electric Spa Energy Efficiency*.

https://efiling.energy.ca.gov/GetDocument.aspx?tn=74378&DocumentContentId=1314

Consortium for Energy Efficiency (CEE). 2013. CEE High Efficiency Residential Swimming Pool Initiative.

https://library.cee1.org/system/files/library/9986/CEE\_Res\_SwimmingPoolInitiative\_01J an2013 Corrected.pdf

DOE, Energy Saver. Gas Pool Heaters. Accessed in 2022.

https://www.energy.gov/energysaver/gas-pool-heaters

- DOE, EERE. 2015. Technical Support Document: Energy Efficiency Program for Consumer Products and Commercial and Industrial Equipment: Pool Heaters. https://www.regulations.gov/document/EERE-2015-BT-STD-0003-0009
- EPA, ENERGY STAR. 2012. ENERGY STAR Pool Pumps: Draft 1 Specification, Draft 2 Test Method, Connected Functionality: Stakeholder Webinar. https://www.energystar.gov/sites/default/files/specs//ENERGY%20STAR%20Pool%20Pu mps%20Draft%201%20Spec%20Webinar%20%20Final%202012-09-28.pdf
- Hunt, A. and S. Easley. 2012. *Measure Guideline: Replacing Single-Speed Pool Pumps with Variable Speed Pumps for Energy Savings.* NREL/SR-5500-54242. https://www.osti.gov/servlets/purl/1046268

Mass Save. 2017. Plunge into Savings with these Pointers on Pool Pumps. Accessed in 2022. https://www.masssave.com/blog/residential/pool-pumps

• Electric vehicle charging: Total consumption for electric vehicle (EV) charging is modeled as the energy used to recharge an EV's battery when the vehicle is parked at home. Daily consumption is calculated as the product of a vehicle's efficiency (kWh/mile), utility factor, daily mileage, and reported proportion of at-home charging. The model also applies temperature adjustments, which are daily multiplicative adjustments that we calculated based on the daily average temperatures at homes with EVs. A vehicle's year, make, and model information is used to find the vehicle's respective city-highway combined efficiency. A respondent's reported daily mileage is assumed to be a respondent's weekly mileage divided by 7. For plug-in hybrids (PHEVs), a utility factor (proportion of miles driven on electricity) is calculated from a respondent's reported mileage, the vehicle's rated electric range, and vehicle age. The utility factor is assumed to be 1 for battery-electric vehicles (BEVs). The annual estimate is calculated by summing up all the daily estimates in 2020.

# References for Electric vehicle charging

DOE (EERE) and EPA. www.fueleconomy.gov, the official U.S. government source for fuel economy information. Accessed in 2022.

https://www.fueleconomy.gov/feg/download.shtml

Geotab. 2020. *What 6,000 EV batteries tell us about EV battery health*. Accessed in 2022. https://www.geotab.com/blog/ev-battery-health/

Geotab. 2020. *To what degree does temperature impact EV range?* Accessed in 2022 (blog post updated in Feb 2023).

https://www.geotab.com/blog/ev-range/

- Yuksel, T. and J.J. Michalek. 2015. *Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States*. https://www.cmu.edu/me/ddl/publications/2015-EST-Yuksel-Michalek-EV-Weather.pdf
- Not elsewhere classified: Each fuel has an end-use category called *Not Elsewhere Classified*, which represents the energy consumption from end uses within a home that are not explicitly classified within the other published end uses. This list of the end uses covers the *Not Elsewhere Classified* category for each fuel:.
  - Electricity

- Desktop computers, laptop computers, monitors, network equipment, and peripherals such as printers, fax machines, and copiers
- Smart speakers, tablets, and smartphones
- Floor fans, attic fans, and whole-house fans
- Coffee makers, toasters, toaster ovens, slow cookers, pressure cookers, rice cookers, blenders, wine chillers, and declared *other* small kitchen appliances
- The standby electric consumption from natural gas and propane dryers, but only for dryers with some reported usage
- Pool heaters
- Assumed amount of *baseload* consumption, which the HS does not capture, such as always-on loads (for example, wired smoke detectors), widely used end uses for everyday purposes (for example, vacuum cleaners and hair dryers), and other common end uses without dedicated questions in the HS (for example, sump pumps and well pumps)
- Unknown consumption assigned during calibration
- Natural Gas
  - Outdoor grills
  - Unknown consumption assigned during calibration
- Propane
  - Pool heaters
  - Hot tub heaters
  - Unknown consumption assigned during calibration
- Fuel Oil
  - Pool heaters
  - Hot tub heaters
  - Unknown consumption assigned during calibration

# References for Not elsewhere classified

DNV GL Energy Insights USA, Inc. 2021. 2019 California Residential Appliance Saturation Study. Prepared for the California Energy Commission. http://www.energy.ca.gov/appliances/rass/

DOE, EERE. 2011. Clothes Dryer Direct Final Rule Technical Support Document. https://www.regulations.gov/document?D=EERE-2007-BT-STD-0010-0053

# Duke Energy. 2013.

http://www.amhomeservices.net/upload/Appliance\_OpCost\_List\_Duke\_v8.06.pdf EPA, ENERGY STAR. 2012. Market & Industry Scoping Report Coffee Makers.

https://www.energystar.gov/sites/default/files/asset/document/ENERGY\_STAR\_Scopin g\_Report\_Coffee\_Makers.pdf

- Kwatra, S., J. Amann, and H. Sachs. 2013. Miscellaneous Energy Loads in Buildings. Report Number A133. American Council for Energy-Efficient Economy. http://aceee.org/sites/default/files/publications/researchreports/a133.pdf
- Parker, D. S. 1992. *Measured natural Cooling Enhancement of a whole House Fan*. Florida Solar Energy Center. FSEC-PF-273-92.

http://www.fsec.ucf.edu/en/publications/html/FSEC-PF-273-92/index.htm

- Parker, D. S. 2005. Literature Review of the Impact and Need for Attic Ventilation in Florida Homes. Florida Solar Energy Center. FSEC-CR-1496-05. https://www.fsec.ucf.edu/en/publications/pdf/FSEC-CR-1496-05.pdf
- Urban B., K. Roth, and J. Olano. 2021. Energy Consumption of Consumer Electronics in U.S. Homes in 2020. Fraunhofer USA.

https://shop.cta.tech/collections/research/products/energy-consumption-of-consumerelectronics-in-u-s-homes-in-2020

West, Tristam. 2003. Oak Ridge National Laboratory. https://www.ornl.gov/news/fourth-july-no-picnic-nations-environment

# Extending end-use models to give daily outputs

As described in the *Energy end-use modeling* section, a new feature we added for the 2020 RECS was extending the end-use models to give optional daily outputs. In this section, we briefly describe how we attained this capability for each model.

# Space conditioning and air handling

These models were easily adapted to provide daily output. Although most model parameters were constant throughout the year (for example, insulation, square footage, equipment efficiency), the models rely on weather inputs, which vary from day to day, and these daily variations in HDDs, CDDs, soil temperatures, and dew point temperatures naturally impart daily variations in the expected consumption for these end uses. By construction, the daily outputs sum exactly to the models' annual outputs.

#### Fans, dehumidifiers, and humidifiers

These models were adapted to provide daily outputs by first evaluating the annual end-use consumption expectations, and then *placing* that consumption within the 2020 calendar year. For ceiling fans, dehumidifiers, and humidifiers, the HS collects categorical usage information (for example, *use only during summer months to stay cool*), but for floor fans, attic fans, and whole-house fans, we had to assume a duration of usage within the year. For the given duration of use, we apportion the expected annual consumption total over the corresponding number of days (for example, 60 kWh annual distributed over 60 days would yield 1 kWh/day). We then assign the continuous daily usage to the period within 2020 where some weather quantity is maximized, so for instance, for fans, we find the continuous stretch of specified duration where the home experienced the hottest average temperatures; humidifiers and dehumidifiers are instead assigned days on the least or most humid stretch within 2020 (potentially wrapping around from December to January). Last, to help the billing-level calibration process, we smoothed the edges of this period to extend a smaller portion of daily consumption beyond the nominal duration of the usage period (for example, a six-month period extends further beyond six months, but with lower consumption at the edges than in the central portion's peak usage).

#### Water heating

This model was easily adapted to providing daily output, because one of its inputs is the inlet water temperature, which we model based on estimates of soil temperature from National Oceanic and Atmospheric Administration (NOAA) at each home. Because the soil temperatures have an annual cycle, so do the daily outputs of our water-heating model. Also, one improvement to the end-use model for the 2020 RECS was to allow standby energy losses to depend on the ambient temperature of the space where a storage tank is stored, and the ambient temperature can also vary throughout the year. Depending on the location of the water heating within the home, we estimate the ambient temperature based on either thermostat setpoints, a modulated basement temperature, a modulated garage temperature, or the outdoor temperature. By construction, the daily outputs add exactly to the model's annual outputs.

#### Lighting

This model was adapted to provide daily outputs by first evaluating the annual end-use consumption expectations and then imposing a sinusoidal (that is, a sine wave) seasonal cycle throughout the calendar year. We assume that lighting consumption varies within the year as the length of daylight changes. To build this into the model, we construct a sinusoid of how many hours of daylight are expected each day of the year, based on the solar declination angle throughout the year and a home's latitude (capped at 60°N). The daily expected consumption is the average daily consumption, based on the home's expected annual total, modulated by this sinusoid, which gives minimum lighting consumption on the summer solstice and maximum consumption on the winter solstice.

#### **Refrigerators and freezers**

These models were extended to give varying daily outputs by way of an end-use model improvement, which links consumption to the ambient temperature of the space where the appliance is stored. Refrigerators and freezers consume more electricity when working within a warmer space, and the ambient temperature can vary throughout the year. We estimate the ambient temperature depending on the location of the appliance within the home. We assume all primary refrigerators are stored within a home's main living space, and so the ambient temperature is determined by a home's thermostat set points. The HS asks respondents where their second refrigerator is located in the home, and we estimate the ambient temperature based on either thermostat setpoints, a modulated basement temperature, a modulated garage temperature, or the outdoor temperature. We have to make assumptions about where any separate freezers are located in the home, and we assume they are located in the same space as a second refrigerator, if one exists.

#### Electric vehicle charging

As described above, this model is new for 2020, and it evaluates daily values for charging throughout the year and then sums the daily values to arrive at the annual value. Charging is temperature dependent, because vehicle efficiency is temperature dependent; driving the same mileage in very cold or very warm weather leads to more frequent charging, and so greater electricity consumption.

#### **Pools and hot tubs**

We were unable to adapt our models for these end uses to produce daily varying values, because in the *Minimum variance estimation calibration procedure* section, we determined uncertainty exists as to when within the calendar year homes are actively using their pools and hot tubs, especially homes in warmer climates. So, these end-use models still only produce annual consumption expectations.

#### All other end uses

The models for all other end uses, including laundry appliances, cooking appliances, small kitchen appliances, and consumer electronics, do not have expected seasonal variations. As such, their daily outputs are trivial, just dividing their annual totals by 366 calendar days.

# **Appendix C. Monthly Estimates of Consumption and Expenditures for Electricity and Natural Gas**

As described in the *Consumption and Expenditures Annualization and Imputation* section, we generate annual estimates for electricity and natural gas consumption. As described in the *End-Use Consumption* section, we also generate annual estimates for electricity and natural gas consumption by end use. Appendix C describes our process for generating monthly estimates for electricity and natural gas consumption by end use.

As detailed in the *Consumption and Expenditures Annualization and Imputation* section, our annualization process produces our estimates for the annual consumption and expenditures of electricity and natural gas. We received complete coverage of energy consumption during calendar year 2020 from the collected bills for electricity and natural gas for a large majority of RECS cases (Table 3). For these cases, the annualization process adds the reported billing totals over the year and prorates the calendar's *edge bills* —that is, any bills that cover portions of two different calendar years—to estimate just their coverage of 2020.

Most electricity and natural gas bills are issued monthly. Even though energy providers issue bills on nationally uncoordinated billing cycles that do not always align with the beginning and end of calendar months, *monthly* bills allow us to produce *monthly* consumption and expenditures (C&E) estimates at the national and sub-national level. Also, we are now able to derive end-use consumption estimates for electricity and natural gas at the monthly level, because of the methodology improvements explained in the *End-Use Estimation* section—in particular, the shift to performing the calibration at the billing level. To produce monthly estimates, we prorate the monthly billing totals or billing-level end-use estimates to get them all on regular, monthly intervals, a process we term *calendarization*. Once we synchronize the data, we can apply survey weights and calculate monthly C&E estimates where data users will know, for example, a *June estimate* accounts for the C&E only over June 1 to June 30, 2020.

While the annualization process leads to annual estimates, the calendarization process leads to monthly estimates; both processes rely on proration. However, proration's relative importance to the calendarization process is much greater than to the annualization process. Consider that to produce annual estimates, we sum a year's worth of bills and need only prorate the edge bills. One annual estimate typically comes from prorating 2 out of 13 bills. But for monthly estimates, *each* of the 12 estimates in a year typically comes from prorating two bills. So, the accuracy of the monthly estimates depends on the accuracy of the proration to a much greater extent than for the accuracy of annual estimates.

Appendix A provides an example of how the annualization process goes from a case's set of natural gas bills to an annual estimate of its total consumption in 2020. In that example, we explain how the proration of the edge bills was based on the relative coverage of calendar days within 2020 and outside of it. This is equivalent to assuming the same daily consumption throughout a billing period. We decided this was accurate enough for forming annual totals, particularly because we knew we would be adding random noise to the consumption totals as a disclosure avoidance measure. However, when producing monthly estimates, we use *model-guided proration* for increased accuracy: we use our end-use models to provide an estimate of the *shape* of the consumption within a billing period.

Below explains how we leveraged monthly estimates and have now issued monthly C&E estimates of electricity and natural gas, including some major end uses. Because of the irregular delivery schedules of the bulk fuels, we are unable to produce monthly C&E estimates for those fuels or for wood or total energy (that is, the RECS variable "TOTALBTU").

# Monthly estimates for electricity and natural totals

# Model-guided proration

We collect billing data for electricity and natural gas consumption by household directly from energy suppliers, and the billing data spans the full base year (2020) with several months of coverage in the adjoining years. Billing cycles are typically about one month in duration but often straddle neighboring months and can sometimes straddle multiple months. To convert from billing cycle data to produce calendar month estimates, we begin with the end-use models described in the section *End-Use Consumption* to provide expectations of the *daily* use of electricity and natural gas. The daily expectations are then scaled so that integrated billing cycle totals match the reported billing data we collected. The scaled daily expectations are then aggregated by calendar month. This application of *model-guided proration* thus achieves our desired calendarization process.

End-use model expectations are desirable to use in the proration because they are based on the daily weather experienced by households, which drives variations in the energy used for space conditioning. Also, the models account for how much consumption is due to end uses that are sensitive to daily weather variations (for example, space conditioning) and how much is due to end uses that are insensitive to weather (for example, cooking). Having expectations based on weather and end-uses reported by households produces the *shape* of energy consumption within a month, and knowing the shape can lead to more accurate proration of billing totals.

We would never expect our modeled expectations to match our billing data exactly; however, we believe they can provide an appropriate trend through time over a billing period. To preserve the expected shape of consumption, we employ a simple scaling parameter, one per billing period. These scaling parameters force the scaled, daily modeled expectations to abide by the collected billing cycle totals.

The value of the end-use model-guided approach increases as the billing period duration increases, since the longer the billing period is, the less likely it is for constant daily use of a fuel to be a good approximation of what actually occurred throughout the billing period. So, proper model-guided proration is especially valuable for cases with bimonthly billing or cases with randomly appearing long gaps in their billing record.

# Handling cases with incomplete billing coverage of 2020, including no coverage

For some households in the ESS portion of RECS, we received either incomplete billing coverage or no billing coverage at all (Table 3), and some amount of imputation is required to produce the final annual C&E estimates for these cases. For households with incomplete billing coverage, imputation was applied

at the billing level as necessary. After the imputation was performed, we treated the imputed values as if they had been collected and proceeded with the calendarization process by way of the model-guided proration approach described above. For households for which we received no billing data, all the consumption is imputed by applying estimated imputation coefficients to the expectations set by the end-use models. The imputation coefficients are applied to the daily modeled values and aggregated into monthly values. Table A-3 shows an example of the imputation coefficients and imputed end-use estimates for different end uses.

# Monthly estimates for major electricity and natural gas end uses

As explained in detail in the *End-Use Estimation* section, for electricity and natural gas in the 2020 RECS, we calibrated at the billing level. We implemented this improvement in the 2020 RECS to attain more accurate annual end-use estimates, but a natural byproduct of this approach is producing individual end-use estimates at the billing level. As with the reported billing totals from ESS, these billing-level end-use estimates may be input to the calculation of monthly end-use consumption estimates.

For the 2020 RECS, we produced estimates of monthly electricity and natural gas end-use consumption. All monthly end-use consumption estimates must satisfy three constraints:

- **Non-negativity.** No monthly end-use estimates may be negative, except for the few rare energy bills that we purposefully allowed through editing with negative fuel totals (due to bill corrections by the supplier)
- Monthly Consistency. All monthly end-use estimates for a month must sum to the corresponding fuel total for that month (the monthly fuel estimation process is described in the previous section of this appendix)
- End-Use Consistency. All monthly end-use estimates for an end use must sum to its published annual estimate (the annual end-use estimation process is described in the *End-Use Estimation section*).

For publishing monthly estimates, we have begun with the *major end uses* of electricity and natural gas that exhibit seasonality, namely space conditioning and water heating. In the 2009 RECS and earlier, we defined the major end uses to be space heating (SPH), space cooling (COL), water heating (WTH), refrigerators (RFG), and other (OTH). Natural gas has only SPH, WTH, and OTH. Here the OTH end use is a catch-all for all other end uses of a fuel not already listed explicitly. Our approach to finding the monthly values of these end uses is to treat OTH as a slack variable. We proceed with model-guided proration for the first four major end uses, and then within each month, we subtract their sum from the monthly fuel totals to recover the appropriate OTH values. If we find that any of the inferred OTH values are negative, then we must apply an adjustment process of all the monthly end-use values to satisfy the three constraints listed above.

Fortunately, most cases underwent billing-level calibration, which means the end-use consumption estimates are guaranteed to add to the fuel totals in each billing period. This means that OTH will never be negative for these cases. However, as described in the *Minimum variance estimation calibration procedure* section, there was a subset of cases for which we were not able to perform billing-level calibration, namely for cases with pools (or cases that heat their pools with natural gas) or cases with

any negative billing amounts. For these cases, we had to default to performing the same annual calibration we performed in the 2015 RECS. Annual calibration is based solely on annual totals, whereas billing-level calibration has access to the individual bills, which introduces time dependence to the process. When using annual calibration, there is no guarantee that the modeled shapes of end-use consumption will abide by the shapes of the billing totals, even once the modeled shapes are scaled so that they sum to the final annual calibrated estimates. For example, we may not be sure in which months a household uses its pool, even if we have produced a good estimate of its annual energy consumption. So, we need an adjustment process to eliminate the negative OTH values and ensure that the totals within months and across months still sum to their targets.

*The end-use estimate adjustment process for cases having undergone annual calibration* If a case underwent annual calibration instead of billing-level calibration, then we do not have calibrated values for the major end uses from a billing-level process, and therefore we do not know how their consumption should be distributed throughout the year. However, we know the most about SPH, COL, WTH, and RFG, because the survey asks the most information about these end uses, and we have principled end-use models for those. Therefore, we take the approach of beginning with the estimated monthly fuel totals (which we will refer as TOT), and then inferring the shape of OTH based on the scaled, modeled monthly values of the other four end uses: OTH = TOT - (SPH + COL + WTH + RFG). If OTH is ever calculated to be negative, then we aim our reshaping process at those months with negative OTH.

The first step of reshaping is to add consumption to the OTH end use in those months where it is negative to make OTH zero. To ensure compliance with the second constraint above (*monthly consistency*), adding consumption to OTH necessitates decreasing the consumption for the remaining end uses in those months. Then, to ensure compliance with the third constraint above (*end-use consistency*), if we add consumption to OTH in the months where it is inferred to be negative, we must subtract consumption from OTH from the remaining months (where OTH is positive) and increase consumption for the remaining end uses in those same months. Because this process is applied as stepwise process, it is sometimes possible that it must be applied a second time, as the adjustments in other months can cause the values of OTH to become negative in months where it was inferred to be positive initially. Because the annual end-use estimates sum to the annual fuel total, a feasible solution for the monthly estimates is guaranteed, and this adjustment process has proven to converge in every case thus far.