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Energy use of US residential refrigerators and freezers: function derivation based on household and climate characteristics

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Abstract Field-metered energy use data for 1,467 refrigerators and 185 freezers from seven studies conducted between 1992 and 2010 were used to calculate usage adjustment factors (UAFs), defined as the ratio of measured to tested annual energy use. Multiple regressions of UAFs against several household and climate variables were then performed to obtain separate predictive functions for primary (most-used) refrigerators, secondary (second most-used) refrigerators, and freezers, and residual differences between observed and modeled UAFs were fit to log normal distributions. These UAF functions were used to project energy use in the more than 4,000 households in the 2005 Residential Energy Consumption Survey, a statistical representation of US homes. These energy use projections formed the basis of calculating lifecycle energy savings for more efficient refrigerators and freezers, as well as national energy and cost savings. Results were compared with previous published work by the Department of Energy, demonstrating how UAFs impact energy and cost savings. Such an approach could be further improved with additional data and adapted for other appliances in future analyses.

Keywords Refrigerator • Field metering • Usage adjustment factor (UAF)

Introduction

Determining the energy use of devices in buildings, particularly household appliances and miscellaneous plug loads, is an important step in identifying product categories that use significant and, in many cases growing, amounts of energy. In combination with engineering estimates of efficiency improvement potentials, these data can be used to prioritize setting of voluntary and/or mandatory standards and labeling to obtain the largest energy savings. Field energy use data are also important in ensuring that test procedures, which form a critical part of both labeling and standards, properly reflect average energy use of measured products. Finally, variation in energy use among consumers with different behaviors can be very significant in many cases and is an important consideration in setting standards to ensure that consumer subgroups are not disproportionately disadvantaged.

This work arose out of analysis in support of the recent US Department of Energy (DOE) rulemaking process for residential refrigerators, refrigerator–freezers, and freezers, hereafter referred to as "refrigeration products." The energy consumption of all refrigeration products sold in the USA is defined by a test procedure. While the conditions of the test procedure are not very realistic [e.g., refrigerators are empty, the doors are not opened, and the ambient temperature is maintained at 90°F (32°C)] (10 CFR 430, Appendix A1),[1] they are designed to approximate annual energy consumption in actual use.[2]

It has long been recognized that actual energy consumption in homes or businesses ("field energy consumption," FEC) may differ markedly from test energy consumption (TEC). Moreover, FEC can vary strongly with user behaviors, household characteristics, and possibly variation in manufacturing among individual products. This is especially true for refrigeration products, where individual measurements of the ratio of FEC to TEC, known as the "usage adjustment factor" (UAF), has been observed to vary from 0.56 to 1.5 across a range of studies summarized in Appendix 7-A of DOE (2011b). While used in this context, the UAF will vary with the individual unit in a residential setting. According to Meier (1995), the DOE test is unlikely to correctly predict the consumption of an individual unit to closer than about 40%. However, for a population of units, the mean UAF (and its variations) could be used to project energy use across US households under current or future

[1] Full citation: Title 10—Energy, Chapter II—Department of Energy, Part 430—Energy Conservation Program for Consumer Products, Subpart B—Test Procedures, Appendix A1

[2] However, Meier (1995) notes that the success of the DOE test may have been largely fortuitous and that future design changes to refrigerators and freezers may require that the ambient temperature or other conditions of the test procedure be changed to better reflect actual average energy use.

conditions—specifically, after the imposition of new energy efficiency standards.

In order to account for some of the variations in UAFs, DOE has relied on data in the Residential Energy Consumption Survey (RECS) for many recent standards rulemakings. RECS has been published every few years since 1990 and contains a wealth of statistically representative information from about several thousand actual US households. Information such as household size, household income, ages and types of household appliances, and physical properties of the house itself is available for each household in the sample. In addition, RECS provides estimates of the FEC of common household appliances, derived from whole-home monthly energy consumption data through multiple nonlinear regression (described below in further detail).

During the preliminary analysis stage of the rule-making process, RECS data were used to estimate UAFs for several types of refrigerators and freezers, and these UAFs were then used to project energy savings under the assumption that more efficient appliances were to replace current appliances in future years. Results indicated UAFs uniformly higher than 1, varying from 1.08 for bottom-mounted refrigerator–freezers to 1.48 for chest freezers. These calculations contributed to the two main sets of results of DOE efficiency standard analysis, called the life cycle cost (LCC) and national impact analysis (NIA).

After publication of the preliminary analysis, stakeholders expressed concern over the use of RECS-derived UAFs because the data were not actually measured from individual refrigerators but inferred from whole-home measurements. In response to this concern, we developed a new approach for DOE that is described here and summarized in the Notice of Public Rulemaking (NOPR) (DOE 2010a) and in the Final Rule (DOE 2011a). While this analysis retained the use of RECS sample data to provide specific information about each individual household appliance, household characteristics, and climate data, it replaced the use of RECS annual energy consumption data with a UAF function derived from several sets of field-metered electricity consumption data collected for residential refrigeration products over the past 18 years.

Background

RECS regression technique

Refrigerator and freezer electricity use is estimated in RECS from whole-home monthly electricity data. Specifically, electricity use is estimated for space heating, water heating, air conditioning, refrigerators, freezers, and everything else ("plug loads") (similar estimates are separately made for gas and oil consumption monthly data). From a number of other variables also collected as part of RECS, multiple nonlinear regressions are developed to obtain best-fit coefficients (EIA 1993, pp. 195ff.). The most recent available data at the time of this analysis were from 2005.[3] The following variables recorded for each household are used in the nonlinear regression:

- Number of refrigerators
- Number of freezers
- Cooling degree days relative to 65°F (18°C)
- Defrost type (manual or automatic)
  - For each refrigerator:
    - Door style (side-by-side or other)
    - Age (new = 4 years old or less, or old)
    - Usage (used 3 months/year or less, or used more)
    - Size (small = 10 ft^3 or less, medium, or large = 23 ft^3 or more)
  - For freezers:
    - Door style (upright or chest)
    - Age (new = less than 2 year old, intermediate, or old = more than 20 years old)

A best-fit coefficient was determined for each of the above variables and used to predict overall refrigerator electricity use in combination with other major appliances.

Being able to extract meaningful signals from whole-home data is contingent on the temporal pattern of each major component being distinct enough from one another to allow for independent estimation. Space and water heating energy use is expected to be strongly anti-

[3] New data based on a survey conducted in 2009 became available in late 2011 (EIA 2011), but it was too late to be incorporated here.

correlated with outdoor temperature, while air conditioning, refrigerator, and freezer energy use are expected to be strongly correlated. Therefore, it may be difficult to separate these component contributions without individual metered appliance measurements. Moreover, because refrigerators and freezers are usually used all year long, there will also be a constant component that may be difficult to distinguish from the constant component of water heating (also used all year long) and from other plug loads.

Given the obvious limitations of using whole-home data and the improvements described here that were obtained from using field-metered data, we recommend that energy-use metering be incorporated into future RECS efforts for major appliances, such as refrigerators. Ideally, such meters would collect data at sufficiently high resolution (~1 min) to distinguish the various cycles (compressor, defrost, etc.) that occur during the refrigeration process. However, more important would be to collect data over a period of several weeks, even at lower resolution, in order to capture sufficient variation in energy use in response to indoor temperature and user behavior (door openings, etc.). Monitoring of indoor temperature would be a very useful ancillary measurement to include as well.

Previous metered data regression analyses

Proctor and Dutt (1994) Multiple regression of annualized metered electricity consumption of 256 new refrigerators was performed for two efficiency groups in California against a number of predictor variables, including outside temperature, operation of an automatic icemaker, anti-sweat heater operation, number of occupants, refrigerator dial setting, and adjusted volume. While all these variables had a significant statistical correlation, outside temperature was the most important statistical variable and suggested to us that a relationship between inside and outside temperature could be developed for the current study as well.

Pratt and Miller (1998) Analysis of 104 existing and 17 replacement refrigerators was performed for New York City public housing. Multiple regression against individual and combinations of variables was examined: refrigerator age, occupant age (elderly or non-elderly), defrost type (manual or automatic), and temperature of kitchen and refrigerator compartments. While not representative of refrigerators in the general population, the study found a robust age-dependent energy increase of 1.37% per year that has been widely cited in other studies.

Blasnik (2004) This analysis collected time-series data of 156 old refrigerators and 30 new EnergySTAR refrigerators (in the same homes) in Boston over several weeks. Because of the long metering duration, a very robust correlation with indoor temperature was obtained, which was then used to develop a separate proxy relationship with outdoor temperature, modified by the presence of air conditioning and/or the location of the refrigerator unit in an unheated basement. The study also explored approximately two dozen potential predictor variables, settling on the following for the final model: number of occupants, presence of a through-the-door (TTD) icemaker, anti-sweat heater operation, condition of door seal, whether refrigerator was bought used, side-by-side door style, and “flat” (continuously high) energy usage.

Data and methods

Overview

The goal of this analysis was to develop a method for estimating field energy consumption of US residential refrigeration products, based on household, climate, and appliance characteristics. Because each refrigerator/freezer model sold in the USA must report (and comply with minimum efficiency standards for) test energy consumption, the most straightforward way of estimating field energy consumption was to develop a function describing the ratio of field to test energy consumption, defined above as the UAF. It was assumed that this factor would lie, on average, reasonably close to unity, with deviations due mainly to differences in household, climate, and appliance variables (deviations not explained by the above variables were assumed to be real, but unaccounted for; a statistical distribution was developed to capture these residual deviations, discussed below).

An overview of the analysis process is shown in Fig. 1. The items in rectangles repre-

sent data sets, while the items in circles represent major calculation procedures.

The approach for developing a UAF function consisted of the following steps:

1. Gather as much field energy consumption data as possible
2. Filter and/or adjust data as necessary to create a consistent database
3. Where missing, obtain climate data (heating and cooling degree days) from national weather database
4. For each product type (defined below):

(a) Pool applicable data points
(b) Perform a set of multiple regressions on a wide range of potential variables of interest, using a variety of optimization methods, including possible weightings of data
(c) Reduce set of variables to those with greatest statistical significance and/or meaningful physical explanation and choose optimization method which gives best fit to data
(d) Refine multiple regressions using reduced set of variables and optimization method
(e) Obtain final regression coefficients to produce analytic function
(f) From set of differences between actual and calculated UAFs, fit an optimal statistical distribution function (termed residual function)
(g) Add residual function to analytic function to produce final stochastic UAF function

A detailed description of these above steps is covered in the sections below.

Field-metered datasets

After consulting with numerous sources in the US field metering community, seven studies were identified, including about 100 data points that were collected by one of the authors (Greenblatt). A total of 1,967 data points were collected that included units from all representative product classes except compact freezers and spanned a variety of collection years, unit ages, US locations, and household populations, including some units used in commercial settings (e.g., offices and hotels). See Table 1. We made various adjustments to the raw data, including extrapolation to annual electricity consumption where necessary.

In addition to metered electricity use, the data sets included some identifying information about each unit (such as brand, model number, year manufactured, door style, presence/absence of through-the-door ice service, and interior volume), which allowed us to classify each measurement by DOE product class (see Table 2), as well as some household characteristics and geographic location. We omitted about 16% of the data points due to missing information and/or data quality issues. The data were pooled into four categories: primary refrigerators, secondary refrigerators (defined, in the case

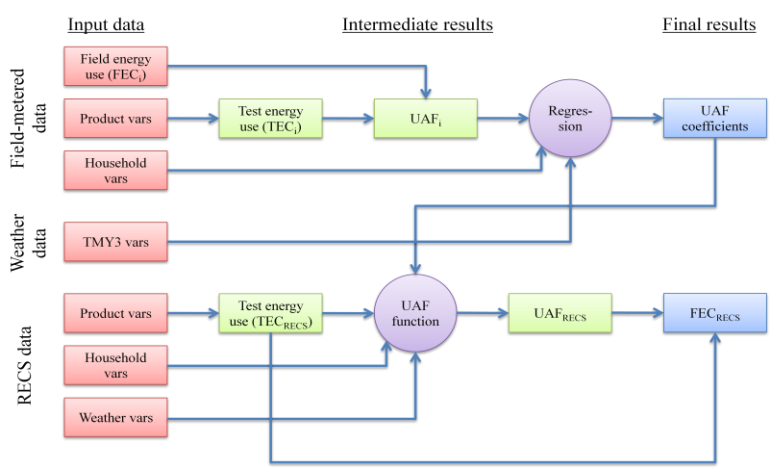

Fig. 1 Flowchart for determining field energy consumption

Table 1 Field-metered datasets

							Number of data points				
Institution	**Reference**	**Population**	**State**	**Period metered**	**Average duration**	**Average unit age (years)**	**Standard-sized refrigerator-freezers**		**Standard-sized freezers**	**Compact refrigerators**	**Total**
							Primary units	Secondary units			
Proctor Engineering Group	Proctor and Dutt (1994)	New rebated units	CA	1992-1993	8 months	0.5	129	0	0	0	129
ComElec	CSG (2010)	General	MA	1995-1996	2.2 h	9.2	802	93	52	0	947
Dalhoff & Associates	Dalhoff (2000)	Low-income	IA	1998-1999	10 days	5.3	44	2	10	0	56
Energy Center of Wisconsin	Pigg and Nevius (2000)	Single-family homes	WI	1999	2.4 h	7.4	204	17	123	0	344
Energy Center of Wisconsin	Pigg and Price (2005)	Renters	WI	2003	2.0 h	7.9	186	0	0	0	186
NSTAR (and others)	Blasnik (2004)	General	MA + RI	2003-2004	21 days	14.4	141	41	0	0	182
LBNL	Data from authors	Offices/ hotels	CA	2009-2010	8 days	6.5	27	0	0	96	123
Total							1,533	153	185	96	1,967
Total used for analysis							1,358	109	185	0	1,652

where more than one refrigerator was present, as a unit other than the one most frequently used), freezers, and compact refrigerators. For compact refrigerators, all 96 data points were analyzed but we decided not to use the resulting fits in the final analysis due to a concern that the data were not sufficiently representative.

The test (or rated) energy consumption for each unit in the analysis was determined by a two-tiered process. First, we looked up the recorded model number of each study unit in several published databases of test results. Data sources included the California Energy Commission, the Federal Trade Commission, the Environmental Protection Agency, and a compilation database hosted by Home Energy Magazine. Given the possibilities of typographical errors in the recorded model numbers and the use of wildcard values by manufacturers within model numbers, a fuzzy string– matching algorithm was employed to identify the closest matches to each reported model number. These matches were then checked based on product class, volume, and year of manufacture in addition to manual inspection. This process resulted in confirmed matches for 63% of all units: 1,235 of the total 1,967. The overall matching rate was 70% for the analysis sample (since some units were omitted) and 76% for the primary refrigerators.[4]

For units that could not be matched based on the recorded model number, the Federal efficiency standard for the year of manufacture was used as the estimate, calculated based on product class, adjusted volume, and year of manufacture. As some units might have consumed less than the minimum standard, this provided a lower limit to the UAF ultimately calculated. For units manufactured prior to the 1990 standards, the 1990 standards values were multiplied by year-specific efficiency factors from the Association of Home Appliance Manufacturers (AHAM) (see Appendix 7-B in DOE 2011b). Since the efficiency standard is a maximum value for energy use, it may over-estimate the actual rated use of the units. The extent of the over-estimation was assessed by comparing reported values for matched units to the standards. This analysis found that the average unit built in 1990 or later was rated to use 6.1% less than the Federal standard. For units built prior to 1990 that included a vintage multiplier, the actual rated use averaged just 0.7% less than this estimate. However, in neither case was the rated energy use results scaled or altered. Figure 2 shows FEC for standard-sized primary refrigerators, secondary refrigerators, and freezers, and Fig. 3 shows the observed UAF derived from FEC and TEC data for the same sets of measurements.

Climate data

Average daily outdoor temperature data during the metering was included with most of the datasets of refrigerator energy use. If needed, historical weather data from NCDC was used to fill in values based on nearby weather station data. Typical year weather data were extracted from TMY3 data files (Wilcox and Marion 2008).

Regression approaches

Typically, a set of data is analyzed assuming the dependent variable(s) (in this case, the UAF) can be explained by a linear combination of independent variables, so that an optimal set of coefficients is obtained using ordinary least-squares minimization. However, the use of several sets of data, obtained by a variety of methods for different purposes over various time period and geographic regions, creates a more challenging situation where alternative regression methods might be required. In this case, a number of alternatives were explored and many retained for the final regressions:

- Weighted least-squares regression (with various ways to define the statistical weighting)

[4] We note that there is also an issue of production variability that can affect the TEC. Although for a well-managed manufacturing facility we expect this variability to be small, it is a contributing factor that will add another degree of "noise" to the measured FEC if test data for the specific unit measured are not available, which was the case for all units in our dataset.

Table 2 Product classes of residential refrigerators and freezers, along with approximate sales and market share in 2008 and number of field measurements

Product Class		Approximate shares in 2008		Number of field measurements
No.	Definition	Sales (thousands)	Market share (%)	
Standard-Size Refrigerator-Freezers				
1 + 1A	Refrigerators and refrigerator-freezers with manual defrost	39	0.3	2
2	Refrigerator-freezers—partial automatic defrost	15	0.1	0
3 + 3A	Refrigerator-freezers—automatic defrost with top-mounted freezer without through-the-door ice service	4,710	32.8	1,409
3A-BI	Built-in all-refrigerators—automatic defrost	19	0.1	0
4	Refrigerator-freezers—automatic defrost with side-mounted freezer without through-the-door ice service	77	0.5	78
4-BI	Built-in refrigerator-freezers—automatic defrost with side-mounted freezer without an automatic icemaker	75	0.5	0
5	Refrigerator-freezers—automatic defrost with bottom-mounted freezer without through-the-door ice service	1,168	8.1	28
5-BI	Built-in refrigerator-freezers—automatic defrost with bottom-mounted freezer without an automatic icemaker	89	0.6	0
5A	Refrigerator-freezers—automatic defrost with bottom-mounted freezer with TTD ice service	531	3.7	0
6	Refrigerator-freezers—automatic defrost with top-mounted freezer with through-the-door ice service	9	0.1	28
7	Refrigerator-freezers—automatic defrost with side-mounted freezer with through-the-door ice service	2,508	17.5	107
7-BI	Built-in refrigerator-freezers—automatic defrost with side-mounted freezer with through-the-door ice service	72	0.5	0
Standard-Size Freezers				
8	Upright freezers with manual defrost	0	0.0	17
9	Upright freezers with automatic defrost	999	7.0	63
9-BI	Built-in upright freezers with automatic defrost without an automatic icemaker	22	0.2	0
10	Chest freezers and all other freezers except compact freezers	1,047	7.3	102
10A	Chest freezers with automatic defrost	0	0.0	0
Compact Refrigerator-Freezers				
11 + 11A	Compact refrigerators and refrigerator-freezers with manual defrost	2,060	14.3	93
12	Compact refrigerator-freezers—partial automatic defrost	145	1.0	0
13	Compact refrigerator-freezers—automatic defrost with top-mounted freezer	22	0.2	0
13A	Compact all-refrigerators—automatic defrost	198	1.4	0
14	Compact refrigerator-freezers—automatic defrost with side-mounted freezer	8	0.1	0
15	Compact refrigerator-freezers—automatic defrost with bottom-mounted freezer	8	0.1	0
Compact Freezers				
16	Compact upright freezers with manual defrost	273	1.9	0
17	Compact upright freezers with automatic defrost	164	1.1	0
18	Compact chest freezers	109	0.8	0
	TOTAL	14,367	100.0	1,957

Source of 2008 sales data: residential refrigerator/freezer NOPR analytical tools, National Impacts Analysis spreadsheet (DOE 2010c)

- Changing the way variables are combined (e.g., products of variables, nonlinear exponents, etc.)

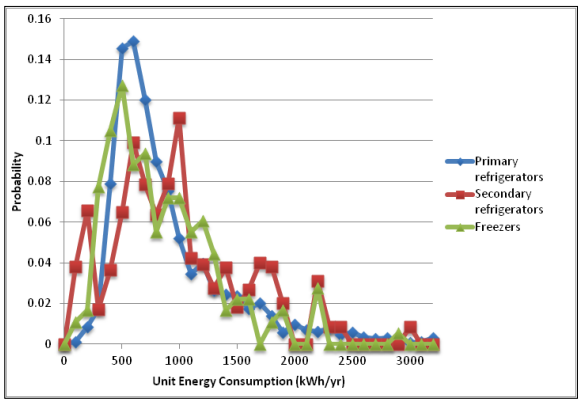

Fig. 2 Field energy consumption (kilowatt hours per year) for standard-sized primary refrigerators, secondary refrigerators, and freezers

- Fitting absolute field energy consumption (kilowatt hours per year) rather than relative energy consumption (UAF)
- Robust regression: A "robust" regression procedure was employed that reduces the influence of outliers on the model fit. The specific procedure used was the "rreg" command in the Stata™ statistics package. This procedure performs an initial screening of the data to remove extreme outliers based on Cook's distance and then performs a series of regression fits downweighting the remaining outliers based on the Huber and biweight approaches as suggested by Li (1985) (see also Stata 2009, p. 1645)

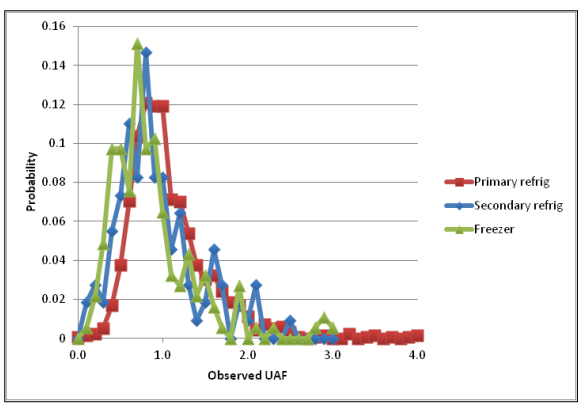

Fig. 3 Observed usage adjustment factor for standard-sized primary refrigerators, secondary refrigerators, and freezers

- Least absolute values regression
- UAF outlier cutoffs were used for one dataset with a few extreme outliers that were almost certainly data errors

All analysis was performed using the Stata™ statistical software package. The statistical models were compared and assessed based on a combination of standard statistical measures of fit and on the physical/engineering interpretability of the coefficients— for models with comparable fits to the data, the one with the most sensible physical interpretation was selected.

RECS household data

We developed household samples for refrigeration products from the 2005 RECS (EIA 2008). The survey, which sampled 4,382 housing units, was constructed to represent the household population throughout the USA.

RECS results indicate whether a household uses a standard-size refrigerator or freezer. For households that have a standard-size refrigerator, RECS specifies whether the freezer is top- or bottom-mounted or is side-mounted. Units in the sample that have top-mounted freezers (product class 3) cannot be distinguished from those having bottom-mounted freezers (product class 5). Therefore, we used the same household sample for product classes 3 and 5. For a household's primary (or "first") refrigerator, RECS specifies whether there is TTD ice service. For households that have standard-size freezers, RECS specifies whether the unit is upright or a chest type. With the above data, we were able to assign each product class considered for potential new efficiency standards to a set of household records (Table 3). For each of the representative built-in product classes, we used the sample that corresponds most closely to the type of built-in product (e.g., for product class 3A-BI, we used the sample for product class 3).

The relative standard errors associated with the subsamples that contain specific product classes are not considered so large as to affect the validity of the derived results presented in this chapter. Specifically, the relative standard error of a sample of size N is approximated

Table 3 Refrigeration products in households by product class

Product Class	Number of Household Records [a]	Percent of Total Household Records	Relative Standard Error Due to Sampling
3. Refrigerator-freezer: automatic defrost with top-mounted freezer and no TTD† ice service	2,303	52.6%	2.1%
5. Refrigerator-freezer: automatic defrost with bottom-mounted freezer and no TTD ice service			
7. Refrigerator-freezer: automatic defrost with side-mounted freezer and TTD ice service	1,026	23.4%	3.1%
9. Upright freezer with automatic defrost	248	5.7%	6.4%
10. Chest freezer and all other freezers except compact models	369	8.4%	5.2%

TTD through the door

[a] From the Energy Information Administration's 2005 Residential Energy Consumption Survey

closely by $1/\sqrt{N-1}$. For the full 2005 RECS sample, the associated relative standard error due to sampling is 1.5%. For the subsamples containing product classes 9 and 10, the associated relative standard errors are 5–6%. Although the standard error for the smallest subsample is more than four times the error for the entire 2005 RECS, it still is less than 10%, a relative standard error considered small enough to yield meaningful results. Therefore, we believe the results generated from the household samples for refrigeration products are representative of US households using those appliances.

Income weighting adjustments to RECS data

We made adjustments to the statistical weightings of RECS samples for product classes 3 and 5 based on relationships between income and product class ownership provided by AHAM (2010, personal communication).
Therefore, even though the same RECS households are used to represent both product classes 3 and 5, the statistical contribution of these households to the economic analyses differed. Table 4 provides the resulting shares by income group. For built-in products (product classes 3A-BI, 5-BI, 7-BI, and 9-BI), we used a single relationship between income and built-in ownership provided by AHAM to weight the RECS ownership of each built-in product class, shown in Table 5.

Results

Regressions

Temperature regressions

Because of the primary role that temperature plays in refrigerator/freezer electricity use, it was desirable to obtain correlations of energy use with ambient (indoor) temperature. From thermodynamics, the energy required to maintain a temperature gradient is proportional to that gradient, so assuming a 30°F (17°C) difference between ambient and interior unit temperatures [e.g., 68°F (20°C) ambient and 38°F (3°C) interior], we expect about a 3% impact on electricity use per 1°F (0.6°C) change in ambient temperature. Previous studies that

Table 4 RECS shares of top-mount and bottom-mount refrigerator-freezer

		Values Used in NOPR and Final Rule (this analysis)	
Annual Income	Values Used in Preliminary Analysis for Top- and Bottom-Mount Refrigerator-Freezers	Top-Mount Refrigerator-Freezers (Product Class 3)	Bottom-Mount Refrigerator-Freezers (Product Class 5)
<$25,000	36.9%	40.1%	25.1%
$25,000-$49,000	29.4%	31.1%	30.0%
$50,000-$99,999	24.2%	21.5%	28.7%
$100,000-$119,999	3.9%	3.1%	6.6%
$120,000+	5.6%	4.2% [a]	9.6% [a]
Sum	100.0%	100.0%	100.0%

examined the dependence of energy use on ambient temperature found similar sensitivities (e.g., Meier 1995).

However, such ambient temperature data were only available for a limited number of data points. By contrast, heating and cooling degree days were readily available for all data from a historic US weather database and are already included in RECS data. Previous work, such as the Proctor and Dutt (1994) and Blasnik (2004) studies, have found a consistent relationship

Table 5 Ownership fraction of built-in refrigeration equipment

Annual income	Ownership fraction of built-ins (%)
<$25,000	2
$25,000-$49,000	2
$50,000-$99,999	2
$100,000-$119,999	3
$120,000+	6[a]

between indoor and outdoor temperatures that varies with whether space conditioning is needed and used. At outdoor temperatures below approximately 60°F (16°C), average indoor temperature decreases by about 0.02 to 0.05°F per outdoor °F (0.02 to 0.05°C per outdoor °C), whereas above 70°F (21°C), average indoor temperature increases by about 0.1 to 0.4°F per outdoor °F (0.1 to 0.4°C per outdoor ° C) depending on the use of air conditioning. In the range of about 60 to 70°F, indoor temperature tends to more closely follow outdoor temperature variations as space conditioning is often not used and windows may be open.

Given these relationships between weather, indoor temperature, and refrigerator energy use, we decided to model refrigerator energy use using three climate variables: heating degree days base 59°F (15°C) (HDD59), average outdoor temperature [minus 65°F (18°C) to approximately center the values], and cooling degree days base 70°F (21°C) (CDD70). However, RECS provided only heating and cooling degree days calculated with base of 65°F (HDD65 and CDD65, respectively), which unfortunately falls right in the middle of the sensitive portion of the indoor–outdoor temperature relationship. Therefore, we developed a model to convert HDD65 and CDD65 values into estimates of HDD59 and CDD70. The average outdoor temperature was also easily obtained from the difference between HDD65 and CDD65.

The estimation of CDD70 and HDD59 from CDD65 and HDD65 was based on calculating each of these four values for each of the 1,020 weather stations included in the Typical Meteorological Year 3 weather datasets produced by the National Renewable Energy Laboratory (Wilcox and Marion 2008). Regression models of HDD59 and CDD70 were developed that included HDD65, CDD65, and the square roots of each of these values. The resulting regression models provided an excellent fit to the data with *R*-squared values of 0.9957 for CDD70 and 0.9995 for HDD59. See Table 6. These equations were then used with the RECS data on HDD65 and CDD65 to model the weather impacts of the units. Note that

[a] Because AHAM data only provided ownership fractions in two bins ($100,000–$149,999 and $150,000+), ownership for the $120,000+ income level was calculated by weighting data from these above two bins by data from the 2005 American Housing Survey (US Census Bureau 2005) indicating the fraction of households in each bin (62% between $100,000–$149,999 and 38% at $150,000 or above)

Table 6 Temperature parameters

	Symbol	Coefficient	Standard deviation (1σ)	T value
HD59 (°F) parameters				
Constant	α_H	−2.30145	0.057953	−39.7
HD65 (°F)	b_H	1.1933	0.003702	302.3
CD65 (°F)	c_H	−0.21377	0.008593	−24.9
$\sqrt{\mathrm{HD65(°F)}}$	d_H	−1.32905	0.028216	−47.1
$\sqrt{CD65(°F)}$	e_H	1.500784	0.027742	54.1
CD70 (°F) parameters				
Constant	α_C	−1.714641	0.0502549	−34.1
HD65 (°F)	b_C	−0.0977721	0.0032106	−30.5
CD65 (°F)	c_C	1.038835	0.0074511	139.4
$\sqrt{\mathrm{HD65(°F)}}$	d_C	0.8797741	0.0244682	36.0
$\sqrt{CD65(°F)}$	e_C	−1.008089	0.0240571	−41.9
Average outside temperature (T_{out})−65°F parameters				
Constant	α_T	0	Not applicable	
HD65 (°F)	b_T	−1	Not applicable	
CD65 (°F)	c_T	1	Not applicable	

heating and cooling degree days (per year) were converted to heating or cooling degrees (denoted by HD or CD, respectively) by dividing the quantity by the average number of days in a year. Regressions are shown in Figs. 4 and 5.

Formulas:

$$\mathrm{HD65(°F)} = \mathrm{HDD65(°F\ days)}\ /\ 365.25\ \mathrm{days} \quad (1)$$

$$\mathrm{CD65(°F)} = \mathrm{CDD65(°F\ days)}\ /\ 365.25\ \mathrm{days} \quad (2)$$

$$\mathrm{HD59(°F)} = \alpha_H + b_H \bullet \mathrm{HD65(°F)} + c_H \bullet \mathrm{CD65(°F)} + d_H \bullet \sqrt{\mathrm{HD65(°F)}} + e_H \bullet \sqrt{CD65(°F)} \quad (3)$$

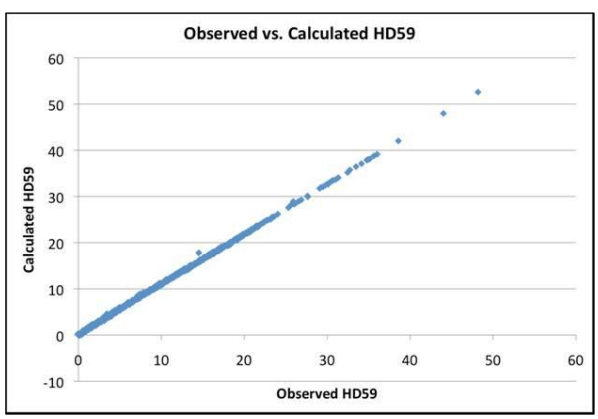

Fig. 4 Observed vs. calculated HD59

$$\mathrm{CD70(°F)} = \alpha_C + b_C \bullet \mathrm{HD65(°F)} + c_C \bullet \mathrm{CD65°F} + d_C \bullet \sqrt{\mathrm{HD65(°F)}} + e_C \sqrt{\mathrm{CD65(°F)}} \quad (4)$$

$$T_{\mathrm{out}} - 65(°\mathrm{F}) = \alpha_T + b_T \bullet \mathrm{HD65(°F)} + \mathrm{CD65(°F)} = \mathrm{CD65(°F)} - \mathrm{HD65(°F)} \quad (5)$$

UAF regressions

In the discussions that follow, statistical significance is usually defined as the ratio of the value of the coefficient to the standard error, also known as the *t* score (Wikipedia 2011a).

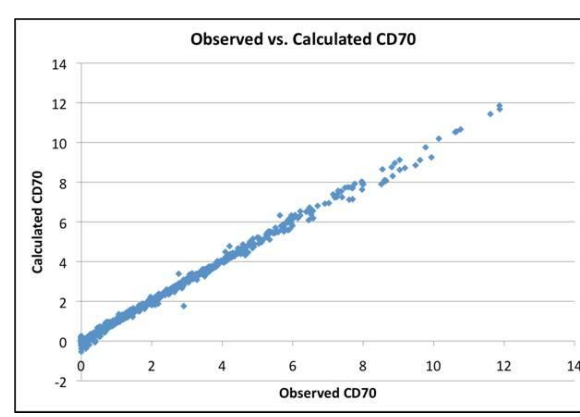

Fig. 5 Observed vs. calculated CD70

Typically, good statistical significance is indicated by | *t* |>2, that is, the absolute value of the

coefficient is larger than twice its standard error. In some limited cases, variables were retained in the regression despite having $|t|<2$, but these variables were retained due to either practical/engineering considerations or to reduce potential confounding.

Primary refrigerator–freezers For standard-sized primary refrigerator–freezers, which contained the largest number of sample points, the following predictor variables were explored:

- Climate variables (various combinations of heating and cooling degree days)
- Presence/absence of a TTD icemaker
- Door style (top-, bottom-or side-mount freezer)
- Number of household occupants
- Unit age
- Year of manufacture ("vintage")
- Short-term (<1-day) metering data only
- Low-income household

Because of the presence of outliers, a number of alternative regression model fitting approaches were explored, including robust regression, weighted least-squares regression, least absolute value regression, and simple UAF value cutoffs. The robust regression appeared to provide more consistent and sensible results compared to ordinary least squares, but after observing that most outliers came from short-term metered data and the <2-h data in particular, we also explored weighted least squares using the metering length as a weighting criterion. This latter approach gave similar results to the robust regression and moreover had a justification for downweighting that was based on measured quantities, rather than simply being an "outlier." As a result, this '

Table 7 Final UAF regression model for primary standard-sized refrigerator-freezers

	Symbol	Coefficient	Standard error (1σ)	*T* value
Parameters				
Constant	α_P	79%	4.33%	16.83
Unit age (years)	b_P	1.60%	0.20%	8.16
Heating degrees base 59°F (15°C) (HD59)	c_P	1.89%	0.54%	3.47
Cooling degrees base 70°F (21°C) (CD70)	d_P	-0.81%	0.89%	-0.91
Average outside temperature (Tout)−65°F (18°C)	e_P	2.00%	0.46%	4.37
Number of occupants ≤3	f_P	12.09%	2.48%	4.87
Through-the-door icemaking (= 1)	g_P [a]	170.5 kWh	43.5kWh	3.92
Residual	r_P	See below		
Dummy parameters (not used in RECS UAF calculations)				
Unit built before 1993 (= 1)	h_P	-12.51%	4.05%	-3.09
Low income (=1)	i_P	16.64%	6.35%	2.62
Short-term (≤1 day) metering (= 1)	j_P	10.25%	2.36%	4.34
Residual function (best-fit log normal parameters)				
Scale	σ_P	0.28771	Not available	
Shape (or location)	μ_P	-0.04393	Not available	

[a] Note that for new refrigerators, rather than this icemaking energy coefficient, the placeholder energy consumption value of 84 kWh/year was used

method was adopted in the final analysis. Regression coefficients and sensitivities are shown in Table 7.

The UAF function was calculated in two stages, using the set of best-fit coefficients. The first stage was based entirely on deterministic variables derived from RECS:

$$\mathrm{UAF_{int}}\,\% = \alpha_{\mathrm{P}} + b_{\mathrm{P}} \bullet \mathrm{AGE} + c_{\mathrm{P}} \bullet \mathrm{HD59} + d_{\mathrm{P}} \bullet \mathrm{CD70} + e_{\mathrm{P}} \bullet (T_{\mathrm{out}} - 65°\mathrm{F}) + f_{\mathrm{P}} \bullet \mathrm{OCCUP3} + (\mathrm{g_P} / \mathrm{TEC_{RECS)}} \bullet \mathrm{TTD} \quad (6)$$

Where:

$\mathrm{UAF_{int}}$	intermediate UAF function for primary refrigerators
AGE	Age of refrigerator in years
HD59	As defined above
CD70	As defined above
T_{out}	As defined above
OCCUP3	Number of occupants up to and including three
TTD	Presence (1) or absence (0)of through-the-door icemaking
$\mathrm{TEC_{RECS}}$	Test energy consumption of unit (kilowatt hours)

The second stage concerned the development of a residual function to fit the remaining mismatch between actual and predicted UAF. This function is introduced at the end of the section and developed in detail in "Residual function."

Regressions with HDD65 and CDD65 climate variables from RECS were statistically very significant (t = 3–4). However, the statistics were improved by using other variables derived from these two; after several iterations, it was determined that using HD59, CD70, and T_{out} —65°F (18°C) gave the best fit to the data and also had the strongest theoretical appeal, see discussion earlier on temperature regressions.

The presence of TTD icemaking was found to be statistically significant. While a percentage energy use model was also considered, we found that slightly better model agreement resulted when TTD icemaking was fitted in absolute (energy) terms, so this variable was treated somewhat differently from the other variables.

The TTD variable is very strongly correlated with the side-by-side door variable (denoting product class 7) and led to the door style variable no longer being statistically significant so door style was not included separately in the final model. The large magnitude of the TTD coefficient (about twice the 84 kWh/year in the new refrigerator– freezer test procedure for automatic icemaking; see DOE 2010d) is indicative of older units but represents approximately 12% of non-TTD icemaking energy consumption as measured by $\mathrm{UEC_{test}}$, consistent with previous estimates of the size of this term (Meier and Martinez 1996).

For some variables (number of household occupants, unit age, and vintage), regressions were explored using both a single variable, as well as multiple independent variables defined over various bins, e.g., $\mathrm{AGE_1}$ = 0–1 years, $\mathrm{AGE_2}$ = 2–4 years, etc. so that

$$\mathrm{UAF} = c_1 \bullet \mathrm{AGE_1} + \mathrm{c_2} \bullet \mathrm{AGE_2} + \ldots + (\text{functions of other variables}) \quad (7)$$

where the coefficients c_1, c_2, etc. are not necessarily the same.

Not all datasets contained data on the number of household occupants. Modeling each household occupancy level separately, we found that the UAF varied almost linearly with the number of occupants up to 3, with strong statistics (t=2.8 to 4.9), but a very weak correlation for larger numbers of occupants (t<0.1). Because the correlation were so linear with the number of occupants up to 3, the regression was repeated with the number of occupants treated as a single variable but truncated at values larger than 3. The resulting regression was very strong (t=4.9), so this approach was retained in the final analysis.

For unit age, the data generally supported the hypothesis that a decrease in performance (e.g., increase in energy use) manifested quickly approximately over the first year and over subsequent years a steady but slower decrease occurred. This type of degradation should be expected due to the degradation in effective R value of the foam insulation. One dataset (Proctor and Dutt 1994) provided a little less than a year of continuous data on 129 newer refrigerators. A

regression analysis of that data found a first year annual degradation rate of almost 9% (t=3.8), but the result varied under differing model specifications. Some long-term data on a smaller sample of refrigerators not included in Table 1 that were provided by BC Hydro (Berrisford 2010, personal communication) revealed an annual degradation rate of about 1% per year for older existing units. Other studies corroborate this general trend; for instance, Meier (1995) reports that Bos (1993) tested 50 older refrigerators collected in a California utility program and found tested energy use generally between 40 and 60% higher than the labeled values, with some over 200% higher. Among these units, about one third were improperly charged with refrigerant, and 18% had some sort of gasket or cabinet damage.

The largest sample size and most consistent estimate of degradation came from analyzing all datasets together. Both single and two-variable age regressions were considered. The two-variable regression suggested a more rapid UAF increase in the first 2 years (about 5% increase per year), followed by a more gradual increase, as seen in the Proctor data, but the t scores were significantly smaller (t<2). It is likely that this unsuccessful fit was due to a lack of metered data from refrigerators between 1 and 5 years old. By contrast, the single-variable regression model resulted in excellent statistics (t=8.2), with a UAF increase of 1.60%/year. This figure is fairly close to the 1.37% estimated by Pratt and Miller (1998).

The UAF proved to be largely insensitive to vintage, with the exception of products built prior to 1993, when the first set of national efficiency standards for refrigerators and freezers went into effect; this factor accounted for a 12.5% decrease in UAF, with t03.1. Even with weighted regression, the short-term metered data had a regression coefficient indicating those measurements were about 10% larger than measurements taken over longer periods. This finding is believed to reflect a real bias of short-term metering, since all such metering occurs during the daytime, when refrigerator use is more frequent as well as the existence of higher average ambient room temperatures, both of which tend to increase energy consumption. This correlation was used to remove the effect from the model, which is intended to estimate long-term average energy consumption.

Units in low-income households [all units in Dalhoff (2000) and some units in Pigg and Nevius (2000) used on average about 17% more energy relative to their rating than those not identified as low income. It was concluded that the bias likely reflects the prevalence in low-income households of units that are bought used and tend to run less efficiently than similarly aged models that were bought new. However, there may have also been a bias in the sample of households metered because the purpose of both metering studies was to identify households with high energy consumption units in order to qualify them for free replacement. Therefore, it was not considered a reliable indicator of energy use bias in a low-income household, irrespective of other factors, and was not used as a general predictive variable.

In summary, for the final model, the following variables were used:

- Unit age
- Climate variables [HD59, CD70, and T_{out}—65°F (18°C)]
- Presence/absence of a TTD icemaker
- Number of household occupants up to 3

All variables except the last one were obtained from the full set of primary refrigerator–freezer data, using weighted least squares with weights proportional to the square root of the metering period. The agreement between observed and predicted annual energy use in kilowatt hours per year is shown in Fig. 6 as a scatter plot and in Fig. 7 as a comparison of two histograms.

While the agreement between actual and predicted UAF is far from perfect, other studies measuring the UAFs of refrigerators have comparable levels of scatter, e.g., on the order of ±60% (around a mean of 0.85) (Meier and Heinemeier 1988; Meier and Jansky 1991). Moreover, application of the above UAF model demonstrably reduces the variability in the observed data, as can be seen in the narrowing of the distribution (particularly on the low end) in Fig. 7.

Another way of viewing the degree of improvement is in Fig. 8, where the observed UAFs (defined as the ratios of FEC to TEC)

along with a quantity we call "residuals," defined as the ratios of FEC to modeled FEC (FEC_{model}),[e] are shown as cumulative probability distributions, with each dataset shifted so that their median values are centered at zero.[f] Thus, each dataset shown in the figure contains the same numerator (FEC) but different denominators. The range in observed UAF values within the central 68% probability distribution—that is, between the 16 and 84% cumulative probability levels, equivalent to twice the standard deviation (σ) of a normal distribution—is 0.80, whereas the range in the residual values is 0.57, a narrowing of 28%. Thus, because the residual distribution is narrower than the observed UAF distribution, it indicates that the regression model (FEC_{model}) is an improvement over the TEC at predicting the observed FEC.

However, despite these positive attributes, the UAF_{int} function clearly did not capture all the observed variability in the metered data, indicating that while the approach is adequate for a large population on average, it may not be very accurate in predicting the energy consumption of individual refrigerators. This point will be revisited in the section on life cycle cost, where a large population of individual households is simulated via Monte Carlo analysis to determine differences in cost savings among consumers.

In order to capture the full range of observed variability in UAFs, therefore it was desirable to model the residual differences that were not accounted for in Eq. 6. Figure 9 shows a distribution histogram of residuals, defined as the ratio of observed to predicted UAF.[g] In order to represent this additional variability, a log normal function was fitted to the residual distribution. We used this function as a probability distribution to sample from and multiplied the resulting scaling factor by the above UAF function:

$$\mathrm{UAF_P}(\%) = \mathrm{UAF_{int}}(\%) \bullet rp \qquad (8)$$

[e] FEC_{model} Is defined by $UAF_{int} = FEC_{model}/TEC$

[f] This was done since the regression obtained a non-zero offset, shifting the median relative to the observed data.

[g] This definition is equivalent to the one given earlier, since $UAF/UAF_{int} = (FEC/TEC)/(FEC_{model}/TEC) = FEC/FEC_{model}$

where:

UAF_P	UAF of primary refrigerators
r_p	Random draw from residual log normal distribution

Parameters for r_p are found in Table 7.Further discussion on residual functions appears in Section 3.2.

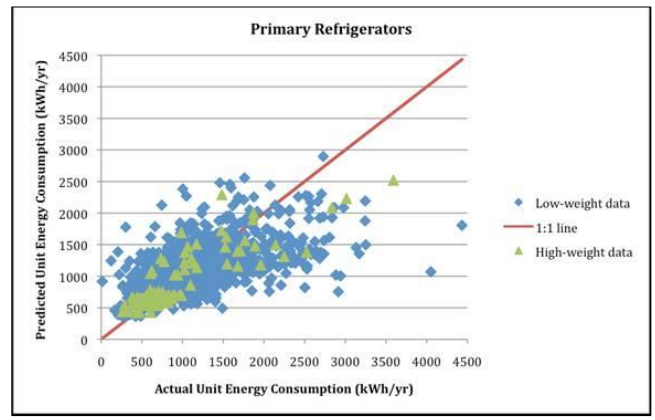

Fig 6. Actual vs. predicted annual energy consumption of primary refrigerator-freezer

Secondary refrigerator–freezers For secondary refrigerator–freezers, the number of statistically significant variables was much smaller, and there was no correlation with number of household occupants. The location of the unit in the home, which is frequently in a room other than the kitchen and often experiences a different mean annual temperature, was found to be statistically important. After exploring a number of alternate models, we chose a model based on the presence of a basement and/or heated space. If a basement exists in the home, the secondary unit was assumed to reside there, with RECS data providing information on whether the basement is heated or not. If no basement exists, a probability of being located in a heated space was used, based on a statistical distribution derived from the metered data.

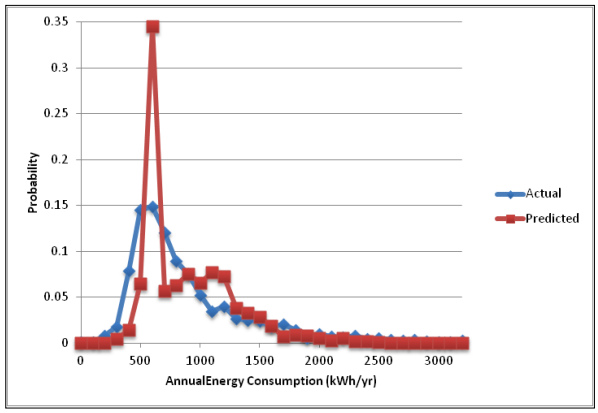

Fig 7. Actual and predicted annual field energy consumption histograms of primary refrigerator-freezers

The UAF function was calculated from the set of best-fit coefficients shown in Table 8 and multiplied by a residual scaling factor obtained independently for secondary refrigerator–freezers:

$$\mathrm{UAF_S}(\%) = [\alpha_S + b_S \bullet (T_{out} - 65°\mathrm{F}) + c_S \bullet (T_{out} - 65°\mathrm{F}) \bullet \mathrm{BASEMENT} + d_S \bullet \mathrm{HEATED}] \bullet r_S \quad (9)$$

where:

$\mathrm{UAF_S}$	UAF of secondary refrigerator
T_{out}	as defined above
BASEMENT	presence (1) or absence (0) of a basement
HEATED	heated space, defined as follows: if BASEMENT=1, defined as 1 if basement is heated, 0 if unheated. If BASEMENT=0, probability of 1 is 75% (random draw)
r_S	Random draw from residual log normal distribution (see Table 8)

The agreement between observed and predicted annual energy use in kilowatt hours per year is shown in Fig. 10 as a scatter plot and in Fig. 11 as a comparison of two histograms.

Standard-sized freezers For standard-sized freezers, we found very few variables with statistical significance, and only a single heated space variable was used in the final model. The heated space variable was treated similarly to that for secondary refrigerator–freezers, but with a different probability for being in a heated space if not in a basement (again based on the metered data).

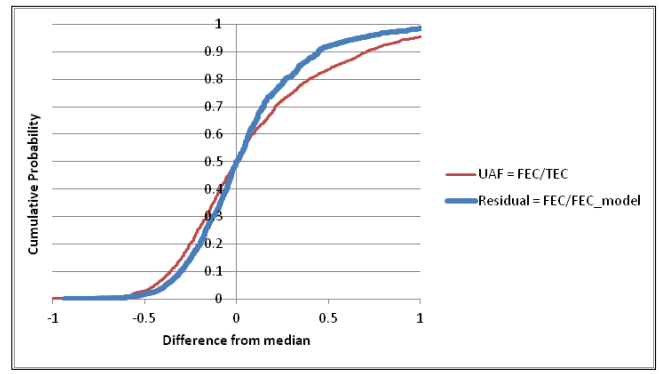

Fig 8. Comparison of observed UAFs and residuals (defined in the text) for primary refrigerator-freezers

The UAF function was calculated from the set of best-fit coefficients shown in Table 9 and

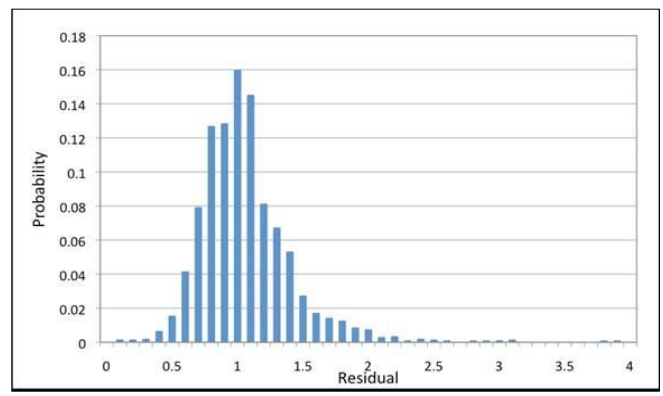

Fig. 9 Residual UAF histogram of primary refrigerator-freezers

multiplied by a residual factor obtained for freezers:

$$\mathrm{UAF_F}(\%) = (\alpha_F + b_F \bullet \mathrm{HEATED}) \bullet r_F \quad (10)$$

where:

$\mathrm{UAF_F}$	UAF of freezer
HEATED	heated space, defined as follows: if basement exists (=1), defined as 1 if basement is heated, 0 if unheated. If basement is not present (=0), probability of 1 is 46% (random draw) random draw from residual log normal distribution (see Table 9)

r_F random draw from residual log normal distribution (see Table 9)

The agreement between observed and predicted annual energy use in kilowatt hours per year is shown in Fig. 12 as a scatter plot and in Fig. 13 as a comparison of two histograms

Residual function

The residual distributions (ratios of observed UAF to modeled UAF), as illustrated for primary refrigerators in Fig. 9, were significant for all three product grouping and had to be included in order to represent the full range of variability observed in the UAF data. While the approach taken could have been to draw a custom distribution directly from these residuals, the statistical noise of the residual distributions, especially for secondary refrigerators and freezers, was substantial, so the use of a smoothed distribution was preferable.

Initially, a simple least-squares optimization using a Weibull distribution function was employed and gave visually satisfactory results for all product groupings; see
Figs. 14, 15, and 16 (Weibull distribution fits). These fits were used in the published NOPR results (DOE 2010a, b, c).

However, the mean value of the residual distributions did not match the actual distributions closely for any product grouping, differing by between −7.8% (primary refrigerators) and −17.5% (freezers); see Table 10, Fit 1, though the medians differed from the data less, by between −1.1% (primary refrigerators) and −4.2% (freezers). Also, close inspection revealed that for primary refrigerators and freezers, the Weibull function under-predicted the probability for arguments between about 1.5 and 2 (for primary refrigerators) and between 2 and 3 (for freezers), i.e., the data exhibited a slight“shoulder” that was not well-matched by the Weibull function in this region (see Figs. 14 and 16). This was more apparent when comparing between data and model in the cumulative distributions: In all cases, the Weibull fits approached 1 more quickly than the data did (see Figs. 17, 18, and 19).

While all the above disagreements raised concerns, the differences in mean were considered to be the most important shortcoming, as they affect the mean UAF obtained from the RECS data and hence the estimate of overall energy consumption. Therefore, two alternative approaches were explored, and ultimately combined, to form the solution used in this analysis, which not only largely rectified the problem with the means but also satisfactorily addressed the other concerns.

Table 8 Final UAF model for secondary standard-sized refrigerator-freezers

	Symbol	Coefficient	Standard deviation (1σ)	*T* value
Parameters				
Constant	α_S	100.5%	7.5%	13.5
Average outside temperature-65°F (18°C)	b_S	0.76%	0.36%	2.13
Average outside temperature-65°F (18°C) x Basement (=1)	c_S	-0.32%	0.39%	-0.82
Heated space (=1)[a]	d_S	21.5%	9.4%	2.29
Residual	r_S	See below		
Residual function (best-fit log normal parameters)				
Scale	σ_S	0.44544	Not available	
Shape (or location)	μ_S	-0.12201	Not available	

[a] See Eq. 9

Alternative optimization algorithm: Kolmogorov–Smirnov test

When comparing two probability distributions, an improvement over least-squares optimization is the Kolmogorov–Smirnov (K–S) test (Press et al. 2007, pp. 334 ff. and 736 ff.; Wikipedia 2011b).

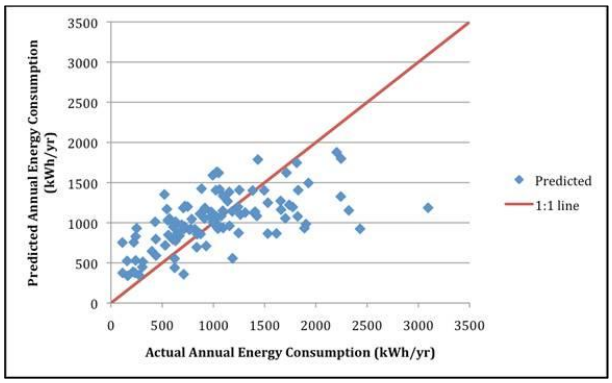

Fig. 10 Actual vs. predicted annual energy consumption of secondary refrigerator-freezers

The K–S test quantifies the distance D between two distribution functions (specifically, their cumulative distribution functions), defined as the maximum absolute value of the differences between the two functions:

$$D = \max_{-\infty < x < \infty} |S(x) = P(x)| \qquad (11)$$

where:

S(x) cumulative probability distribution of observations at *x*

P(x) cumulative probability distribution of model at *x*

The probability that the two distributions are the same is calculated by the function Q_{ks} and can be computed from *D* and the number of data observations *N:*

$$Q_{ks}(z) = 1 - \frac{\sqrt{2\pi}}{z} \sum_{j=1}^{\infty} \exp\left(-\frac{(2j-1)^2\pi^2}{8z^2}\right) \qquad (12)$$

$$Q_{ks}(D \bullet f_N) = \text{probability that } D > \text{observed} \qquad (13)$$

$$f_N = \sqrt{N} + 0.12 + 0.11 / \sqrt{N} \qquad (14)$$

(the approximation in Eq. 14 becomes asymptotically accurate as N becomes large and is already quite good for N>3, which is the case for all the data analyzed here).

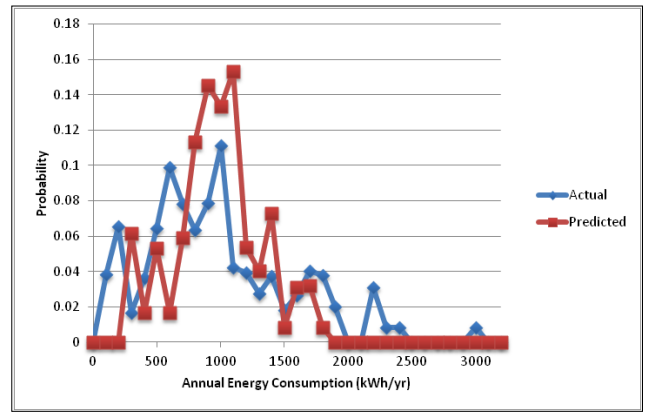

Fig. 11 Actual and predicted annual energy consumption histograms of secondary refrigerator-freezer

A value of Q_{ks} close to 1 signifies an excellent model fit, while a value of 0.05 or less indicates marginal fit (>95% probability that the two distributions are not the same). It is important to point out, however, that Q_{ks} is a very sensitive indicator of a matched statistical distribution and a low Q_{ks} does not necessarily mean that the fit to the data is useless, only that

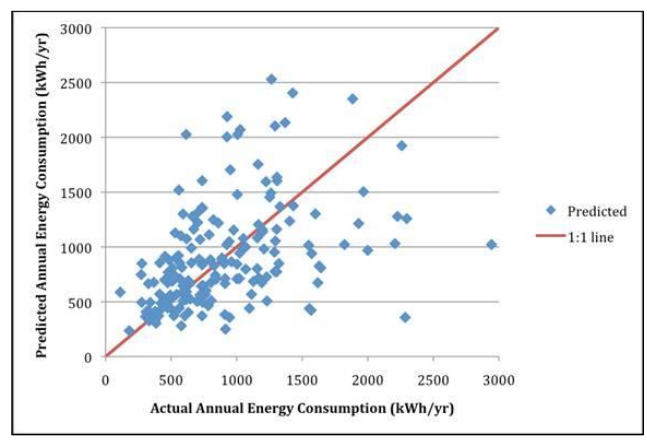

Fig. 12 Actual vs. predicted annual energy consumption of freezers

it is not statistically equivalent. This is especially evident in large datasets (e.g., for primary refrigerator, with 1,358 points).

We reran our fits of the residual distributions to a Weibull cumulative distribution function optimized using the K-S test and found significantly better results; see Fit

Table 9 Final UAF model for standard-sized freezers

	Symbol	Coefficient	Standard Deviation (1σ)	*T* value
Parameters				
Constant	α_F	80.2%	3.8%	21.1
Heated space (=1)*	b_F	14.3%	7.7%	1.86
Residual	r_F	See below		
Residual log normal parameters				
Scale	σ_F	0.47022	Not available	
Shape (or location)	μ_F	-0.02309	Not available	

* See Eq. 10

3 in Table 10. The differences in means varied from –3.4% (primary refrigerators) to –8.4% (freezers), an improvement over the least-squares optimization results. The differences in medians relative to the data, however, were not much improved. Q_{ks} was above 0.8 for secondary refrigerators and freezers; however, for primary refrigerators, Q_{ks} was 0.02, indicating a marginal fit with the Weibull function. While the fits were not very different in gross appearance, the shoulder mentioned above, while still present, was less noticeable.

By comparison, calculating the Q_{ks} for the initial least-square optimizations (Fit 1) revealed worse fits. For primary refrigerators, Q_{ks} was vanishingly small (1×10^{-7}), while for freezers, it was marginally acceptable (0.05). Only secondary refrigerators had an acceptably large Q_{ks} (0.36), but still less than half the value as for the K–S optimization results. These results confirmed our initial assessment that the fits were far from optimal.

As a final check, we considered the effect of using least squares to minimize the cumulative Weibull distribution, rather than the probability Weibull distribution, as this is the function optimized in the K–S test. See Fit 2 in Table 10. To our surprise, the results were not too different from those obtained using the K–S test, with similar differences for means and medians and comparable (though slightly smaller) Q_{ks} results. Thus, the improvement in fit may be more due to optimizing the fit to the cumulative, rather than the probability, distribution function, and not due to the optimization method used.

Alternative fitting function: log normal

Since the most important product class grouping, primary refrigerators, had an unsatisfactorily small Q_{ks} using a Weibull function regardless of optimization approach used and a significant difference in the mean relative to the data, an alternative functional form was sought which might give a better inherent fit. It turns out that the log normal
function is often used to describe a probability distribution that arises from a product of independent random factors, of which the residual function is assumed to be composed (Wikipedia 2011c). It also has a shape similar to that of the Weibull function, but importantly, declines less rapidly than a Weibull as the argument increases above 1. These considerations suggested that a log normal function might provide for a better fit to the residual distributions for primary refrigerators and freezers, and after some investigation, it was confirmed that this is indeed the case.

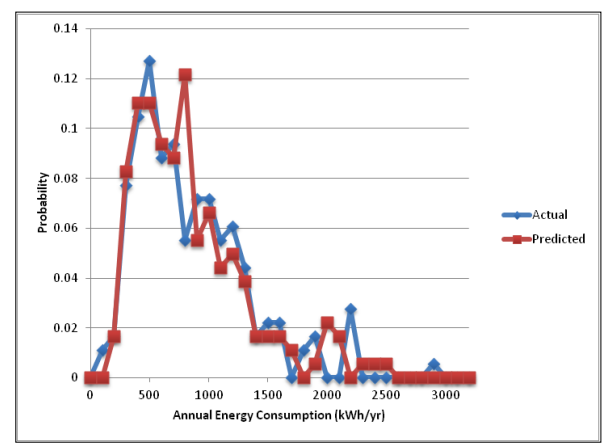

Fig 13. Actual and predicted annual energy consumption histograms of freezers

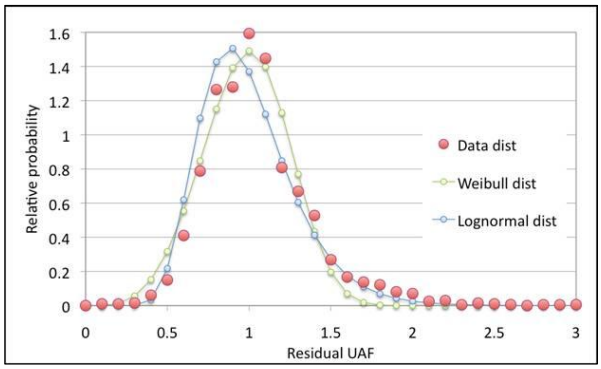

Fig. 14 Comparison of primary refrigerator residual probability distribution data using least-square Weibull and Kolmogorov-Smirnov lognormal optimazation

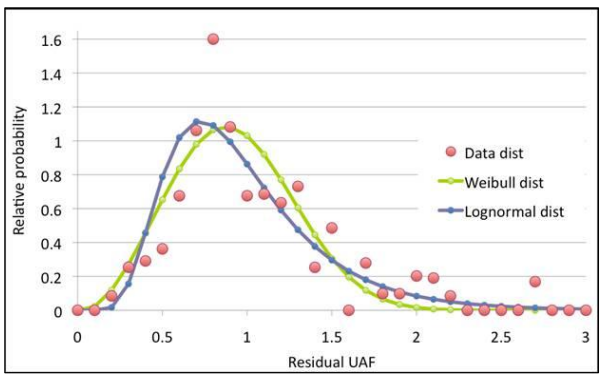

Fig 15. Comparison of secondary refrigerator residual pobability distribution data using least-squares Weibull and Kolmogorov-Smirnov lognormal optimizations

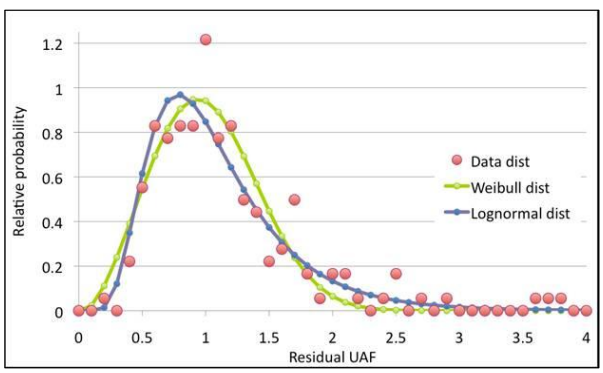

Fig. 16 Comparison of freezer residual probability distribution data using least-squares Weibull and Kolmogorov-Smirnov lognormal optimzations

The new function was fit to the data using the same set of optimizations as for the Weibull function discussed above; results are shown in Table 10, Fits 4 through 6. It was found that the mean differences from the data were uniformly closer to zero than the corresponding fit using the Weibull function and that for those fits to the cumulative distribution function, the median differences and Q_{ks} parameters were improved, significantly so for primary refrigerators.

In all cases, the fit in the vicinity of the shoulder at 1.5 to 2 for primary refrigerators and 2 to 3 for freezers was much improved. This was confirmed visually in the cumulative distributions (see Figs. 14, 15, and 16) where the fits to the data were significantly better than for the Weibull fits.

It appeared to make little difference to most parameters whether the least-squares or K–S optimization was used on the cumulative distribution function, and results from both optimizations were very good, though Q_{ks} for primary refrigerators was noticeably higher using K–S optimization. For this latter reason, the K–S optimization on the cumulative distribution function (Fit 6) was chosen for the final results.

Sensitivities

As a final check, we examined how the choice of bin boundaries affected the results. Three alternative sets of fits were performed, with bin boundaries shifted by 0.025, 0.05, and 0.075 units, respectively, compared to the base analysis (bin size 0.1 units in all cases). The standard deviations among the four bin runs can be interpreted loosely as the standard deviation of the parameters themselves. No significant differences in mean or median were found for any of the fits, with standard deviations of 1% or less. The standard deviation of the scale parameter had a similar magnitude (less than 2%). Only the log normal shape parameter (also called μ) exhibited larger variability (about 6–8% for refrigerators and 14% for freezers), indicating it was not as well constrained by the data as the other parameters.

We also checked whether the bin size affected the results, by rerunning the optimizations with a bin size of 0.05 units, half of the base case bin size. We found that for all but Fit 4 (log normal L–S probability), the resulting mean and median were different by less than 1.1%, and with the exception of secondary refrigerators, the scale and shape parameter were different by less than 2.6%. These deviations were only marginally larger

Table 10 Fits of residual functions for primary refrigerators, secondary refrigerators, and freezers

	Data	Fit 1	Fit 2	Fit 3	Fit 4	Fit 5	Fit 6
Fitting function		Weibull			Log normal		
Distribution type		Probability	Cumulative		Probability	Cumulative	
Optimization		Least squares		K-S	Least squares		K-S
Primary refrigerators							
Scale parameter		1.0234	1.0779	1.0765	0.2716	0.2971	0.2877
Shape parameter		4.034	3.824	3.733	0.0121	-0.0437	-0.0439
Mean	1.006	0.928	0.974	0.972	1.050	1.000	0.997
Median	0.946	0.935	0.979	0.976	1.012	0.957	0.957
Mean difference from data		-0.078	-0.032	-0.034	0.044	-0.006	-0.009
Median difference from data		-0.011	0.033	0.030	0.066	0.011	0.011
K-S test (Q_{ks})		1×10^{-7}	0.01	0.02	2×10^{-8}	0.49	0.83
Secondary Refigerators							
Scale parameter		0.9809	1.0685	1.0587	0.3937	0.4553	0.4454
Shape parameter		2.677	2.381	2.460	-0.0580	-0.1203	-0.1220
Mean	0.980	0.872	0.947	0.939	0.980	0.984	-0.977
Median	0.872	0.855	0.916	0.912	0.944	0.887	0.885
Mean difference from data		-0.108	-0.033	-0.041	-0.040	0.004	-0.003
Median difference from data		-0.017	0.044	0.040	0.072	0.015	0.013
K-S test (Q_{ks})		0.36	0.86	0.92	0.26	1.00	1.00
Freezers							
Scale parameter		1.0787	1.1879	1.1841	0.4447	0.4895	0.4702
Shape parameter		2.554	2.258	2.357	0.0206	-0.0253	-0.0231
Mean	1.133	0.958	1.052	1.049	1.127	1.099	1.091
Median	0.976	0.934	1.010	1.014	1.021	0.975	0.977
Mean difference from data		-0.175	-0.081	-0.084	-0.006	-0.034	-0.042
Median difference from data		-0.042	0.034	0.038	0.045	-0.001	0.001
K-S test (Q_{ks})		0.05	0.65	0.81	0.75	1.00	1.00

than found for the bin boundary sensitivity study above. For secondary refrigerators, there was a difference of 3–7% in the log normal shape parameter (μ). For primary refrigerators

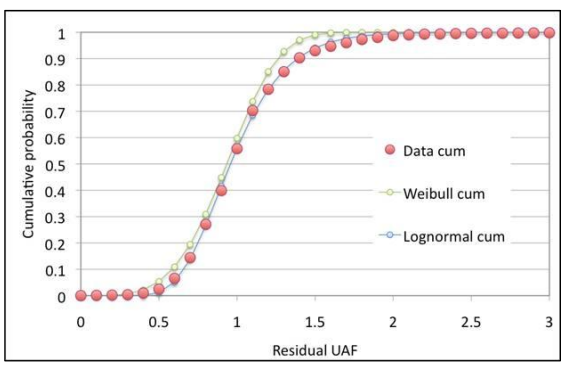

Fig. 17 Comparison of primary refrigerator residual cumulative distribution data using least-squares Weibull and Kolmogorov-Smirnov lognormal optimizations

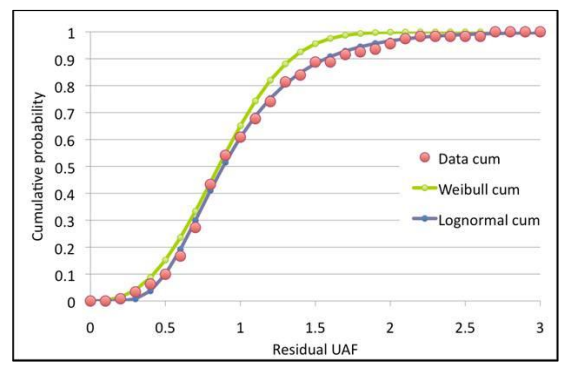

Fig. 18 Comparison of secondary refrigerator residual cumulative distribution data using least-squares Weibull and Kolmogorov-Smirnov lognormal

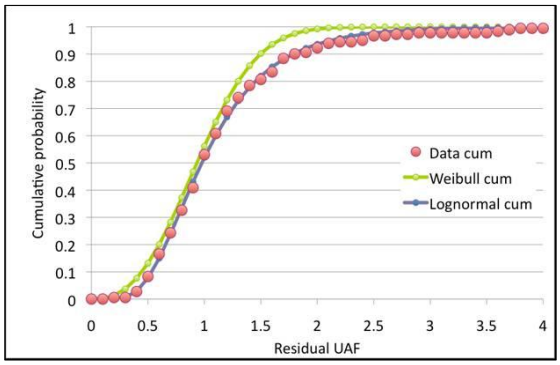

Fig. 19 Comparison of freezer residual cumulative distribution data using least-squares Weibull and Kolmogorov-Smirnov lognormal optimizations

and freezers, Fit 4 exhibited larger differences in the mean and median (up to 2.6%) and the scale parameter by up to 3.7%, while the log normal shape parameter exhibited larger variability, as for the bin boundary sensitivity above. Overall, the choices of bin boundary and size were deemed unimportant to obtaining a reliable fit to the data for all three datasets examined.

Discussion

Through this experimental fitting process, it was learned that the combination of cumulative distribution optimization and a log normal distribution function were required to acceptably fit the residual distributions of primary refrigerators. While this combination also produced superior results for secondary refrigerators and freezers, neither was actually necessary (according to the Q_{ks} >0.05 criterion), though the use of either approach significantly improved the fit for freezers, and the use of cumulative distribution optimization alone improved the fit of secondary refrigerators, regardless of the function used. The K–S optimization produced slightly better results for primary refrigerators, and the Q_{ks} was a useful way to assess the goodness of fit to the data. In the remainder of this paper, the residual functions fitted using a log normal function with K–S optimization were used.

Calculating field energy consumption from RECS data

Standard-size refrigeration products

In order to generate a US nationwide statistical estimate of residential refrigeration product energy use, including its variability across households, we used the UAF functions developed above in conjunction with RECS data to produce an estimate of the field energy consumption for each RECS household.

Conversion to secondary refrigerators When a household purchases a new refrigerator, some first units become second units. Chapter 8 of DOE (2010b, 2011b) discusses how the conversion of refrigerators from first to second units was modeled. A second refrigerator, generally located in a basement or garage, enters a new operating environment and may be used less than year-round. For those units that become a second refrigerator, therefore, the annual energy consumption changes, presumably remaining at the new level for the rest of its lifetime.

The UAF over a refrigerator's lifetime can be expressed in the following manner:

$$\mathrm{UAF}(y) = \begin{cases} \mathrm{UAF_P}(y), y < y_{\mathrm{conv}} \\ \mathrm{UAF_S}(y) \geq y_{\mathrm{conv}} \end{cases} \quad (15)$$

where:

UAF(y)	overall usage adjustment factor (year-dependent)
$\mathrm{UAF_P}(y)$	usage adjustment factor for primary refrigerator phase (year-dependent)
$\mathrm{UAF_S}$	usage adjustment factor for secondary refrigerator phase (year-independent)
y_{conv}	year of conversion from primary to secondary refrigerator

Test energy consumption of standard-size products in RECS households

It was necessary to develop a unique $\mathrm{TEC_{RECS}}$ value for each RECS household because we assumed that the new refrigeration product has the same characteristics as the product sampled in 2005 with respect to total interior volume (also referred to as "size"), door style, and presence of TTD ice service. The latter two items determine the product class and hence the formula to calculate test energy consumption. The size is a variable in the formula, which is determined by a method described in detail in

Table 11 Energy conservation standards for refrigeration products under new test procedure

Product Class	2001 standard	2014 standard[a]
3. Top-mount refrigerator–freezers without TTD ice service	9.80AV+276.0	8.04AV+232.7
5. Bottom-mount refrigerator–freezers without TTD ice service	4.6AV+459.0	8.80AV+315.4
7. Side-by-side refrigerator–freezers with TTD ice service	10.10AV+406.0	8.50AV+431.1
9. Upright freezers with automatic defrost	12.43AV+326.1	8.62AV+228.3
10. Chest freezers	9.88AV+143.7	7.29AV+107.8
3A-BI. Built-in all-refrigerators without TTD ice service	9.80AV+276.0	7.55AV+215.1
5-BI. Built-in bottom-mount refrigerator–freezers without TTD ice service	4.6AV+459.0	9.35AV+335.1
7-BI. Built-in side-by-side refrigerator–freezers with TTD ice service	10.10AV+406.0	9.07AV+454.3
9-BI. Built-in upright freezers with automatic defrost	12.43AV+326.1	9.24AV+244.6

TTD through the door, *AV* adjusted volume in ft^3
[a] DOE (2011a)

Chapter 7 of DOE (2010b, 2011b). The size was then converted to an adjusted volume through a linear equation, which differed by product class, also described in Chapter 7 of DOE (2010b, 2011b). From this information, the maximum allowable kilowatt hours per year was calculated from a linear function of adjusted volume (AV), shown in Table 11.

UAF distributions

Table 12 shows average overall UAFs, as well as UAFs in year 1 and year 20 (for refrigerator–freezers), by product class and analysis performed. Large decreases in all product classes are apparent between the DOE preliminary analysis and the NOPR analysis, due to the change from using RECS to field-metered data to estimate UAFs. Between the NOPR and Final Rule analysis, uniform increases are observed, due to the change in the residual function.

Figure 20 shows the distribution of UAFs for the RECS households in the subsample for product class 3 (top-mount refrigerator–freezers) in year 1 using the residual function used in the NOPR analysis (year 20 is very similar). Each figure shows the distribution of UAFs used for the LCC analysis. For other standard-size product classes, the UAF distributions also appear very similar. Similarly, for the residual function developed in this paper, results appear almost identical but shifted to higher mean value.

Figure 21 shows the distribution of UAFs for the RECS households in the subsample for product class 9 (upright freezers), using the residual function used in the NOPR. Note that the function is the same for all years. The UAF distribution for product class 10 (chest freezers) is almost identical, as it is when using the residual function developed in this paper.

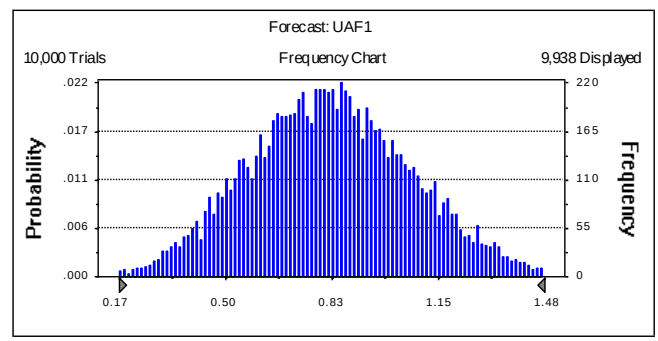

Fig. 20 Product class 3, top-mount refrigerator-freezers: distribution of UAF in the first year of the refrigerator, using DOE NOPR analysis residual function

Figure 22 shows the average UAF by year for product class 3, using the new residual function developed in this paper. These functions vary little with product class.

While the use of the residual functions clearly adds additional uncertainty to the predicted UAFs of individual household units, this uncertainty is important to include in the overall US distributions because the LCC analysis is designed to capture the full range of

Table 12 Comparison of usage adjustment factors among DOE preliminary, NOPR, and Final Rule analyses

Analysis		DOE Final Rule (this analysis)	DOE NOPR	DOE preliminary
Optimization method		K-S	Least squares	N/A
Optimized distribution		Cumulative	Probability	N/A
Residual function		Lognormal	Weibull	N/A
Product Class	RECS sample size	Mean UAF[a]	Mean UAF[a]	Mean UAF
3. Top-mount refrigerator–freezers without TTD ice service	2,303	0.996 (0.880 to 1.108)	0.933 (0.825 to 1.037)	1.227
5. Bottom-mount refrigerator- freezers without TTD ice service	2,303	0.988 (0.874 to 1.096)	0.917 (0.813 to 1.015)	1.077
7. Side-by-side refrigerator–freezers with TTD ice service	1,026	1.014 (0.903 to 1.110)	0.941 (0.839 to 1.033)	1.437
9. Upright freezers with automatic defrost	248	0.969	0.849	1.370
10. Chest freezers	369	0.960	0.893	1.479

TTD through the door

[a] Averages are based on lifetime distribution and include conversion to second refrigerators. Ranges for product classes 3, 4, and 7 indicates average UAF in year 1 (minimum) and year 20 (maximum)

variability encountered in US households. In the future, better data may allow researchers to abandon the residual approach in favor of a more predictive function that adequately captures the variability in energy use seen in real households.

Annual energy consumption

An important assumption of the UAF approach was that it is affected only by household and climate variables, not properties of the refrigerator or freezer itself. That is, if the efficiency of the refrigerator/freezer were to change, the field energy consumption would scale proportionally, so that the UAF remains constant.[8] Thus, using the UAF derived for each RECS household, we assumed that the UAF would be the same for products that meet some future energy efficiency standard as it is for their current appliance, using the following equation:

$$\begin{aligned} \mathrm{FEC_{EL}} &= \mathrm{FEC_{RECS}} \bullet (1 - R_{\mathrm{EL}}) \\ &= \mathrm{UAF_{RECS}} \bullet \mathrm{TEC_{RECS}} \bullet (1 - R_{\mathrm{EL}}) \end{aligned} \quad (16)$$

where:

$\mathrm{FEC_{EL}}$	new refrigeration product's field energy consumption at a given efficiency level
$\mathrm{FEC_{RECS}}$	new refrigeration product's field energy consumption at baseline efficiency level
R_{EL}	reduction in energy consumption (expressed as fraction) due to efficiency improvements at a given efficiency level
$\mathrm{UAF_{RECS}}$	usage adjustment factor specific to RECS household
$\mathrm{TEC_{RECS}}$	maximum allowable test energy consumption for the new baseline refrigeration product

Note that for standard-size refrigerator–freezers,

[8] This is admittedly a large assumption and one that was noted earlier in the discussion of the possible need for future changes to the DOE test procedure. However, in the absence of a detailed model of how a more efficient refrigerator or freezer would change its response to household and/or climate variables, we felt that assuming a constant UAF for each household was the most straightforward approach to project future energy use.

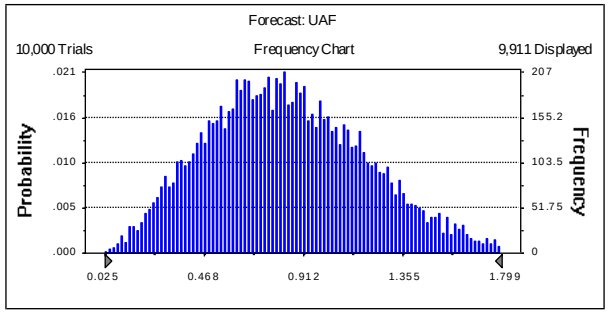

Fig. 21 Product class 9, up-right freezers: distribution of UAF, using DOE NOPR analysis residual function

UAF_{RECS} and hence FECRECS and FECEL are functions of time, e.g., age of the refrigerator–freezer.

Table 13 shows the considered efficiency levels and corresponding average annual energy consumption for product class 3 as an example. The choice of UAF function has a potentially large effect on the overall energy use. Table 14 shows the effect of this choice for all modeled product classes, along with the percentage change. "This analysis" shows results using the revised residual function developed above. "NOPR analysis" shows results as depicted in the published NOPR. "No residual" shows results without any residual function.

To better assess the degree of change arising from each choice of UAF function, Table 14 also shows the change in energy use between the NOPR and this analysis. We see that the new residual function developed in this paper results in an increase in the UAF of about 7–8% for standard-size refrigerators, 14% for upright freezers, and about 8% for chest freezers. Since these results were so significant, we decided to propagate the results through the main stages of the efficiency standard rulemaking analysis, described in the next section below.

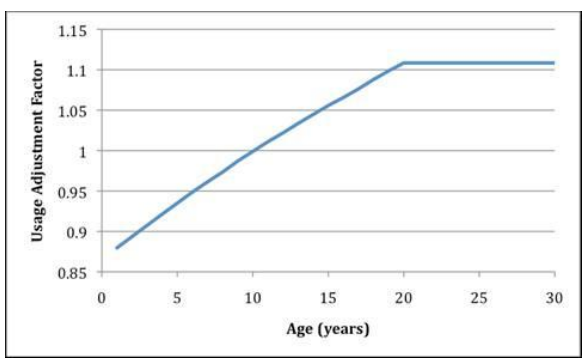

Fig 22. Product class 3: UAF as a function of age, using DOE Final Rule residual function

Life cycle cost and national impacts analyses

Life cycle cost analysis

DOE's method and metrics for analyzing the economic impacts on individual consumers of potential energy efficiency standards for refrigeration products are described in Chapter 8 of DOE (2010b, 2011b). Impacts include a decrease in operating cost and a change (usually an increase) in product cost. The most important metric for determining these effects is the LCC, defined as the total cost consumers incur during the life of an appliance, including purchase and operating costs (including energy expenditures). DOE discounted future operating costs to the time of purchase and sums them over the lifetime of a product. Because the calculation is run in a Monte Carlo fashion on a wide range of US households representing differences in geography, demographics, energy use, interest rates, etc., the percentage of consumers who benefit (and incur a cost) from the standard is also calculated.

Table 15 shows results at the Final Rule standard level for product class 3 (top-mount refrigerator–freezers, 25% better than current baseline) and 9 (upright freezers, 30% better than current baseline) for three variants of the UAF function on some key quantities: average

Table 13 Average annual energy use by efficiency level for top-mount refrigerator-freezers

Efficiency level (% less than baseline energy use)	Top-mount refrigerator-freezers (product class 3) (kWh/year)[a]	
	DOE Final Rule (this analysis)	DOE NOPR
Baseline	536	501
1(10)	482	451
2(15)	456	426
3(20)	429	401
4(25)	402	376
5(30)	375	351
6(36)	345	323

[a] Average energy use calculated over the lifetime of the product

Table 14 Baseline energy use by product class and choice of UAF function

Product class	Baseline energy use (kWh/year)			Change from DOE NOPR to this analysis (%)
	This analysis	DOE NOPR analysis	No residual function	
3. Top-mount refrigerator–freezers without TTD ice service	536	501	541	+6.8
5. Bottom-mount refrigerator–freezers without TTD ice service	658	613	658	+7.3
7. Side-by-side refrigerator–freezers with TTD ice service [a]	828	768	830	+7.9
9. Upright freezers with automatic defrost	685	600	626	+14.1
10. Chest freezers	398	370	370	+7.5

TTD through the door
[a]Icemaking energy not included

LCC savings, fraction of households experiencing a net benefit and cost, and median payback period. Results for other product classes are very similar. Comparing results of this analysis to the NOPR analysis, at a given efficiency level, one finds higher LCC savings, a shift toward more households experiencing a net benefit, and a shorter payback period, though overall changes are fairly modest. The effect of using no residual function gives even larger shares of households experiencing a net benefit and slightly smaller payback periods than found with this analysis, but the effect on average LCC savings is mixed: higher savings for product class 3, but lower savings for product class 9. This emphasizes the importance of using a distribution of UAFs, rather than a single value, in evaluating LCC savings.

National impacts analysis

We evaluated the following impacts over the 30-year analysis period (2014–2043) for the NIA (DOE 2010b, 2011b, Chapter 10): (1) national energy savings (NES) attributable to each possible standard, (2) monetary value of those energy savings to consumers of the considered products, (3) increased total installed cost of the products because of standards, and (4) net present value (NPV) of energy savings (the difference between the value of energy savings and increased total installed cost). DOE discounted future operating costs to the time of purchase, using two prescribed discount rates (3 and 7%/year). Other quantities were calculated as well, including the monetized savings from reductions in pollutants (CO2, NOx, and Hg) arising from energy savings, but these are not reported here.

We determined both the NES and NPV for all the efficiency levels considered for residential refrigeration products for all product classes. Table 16 shows a comparison of the NES and NPV for standard-size refrigerator–freezers at the Final Rule standard level (25% for top- and side-mount units and 20% for bottom-mount units) using the UAF function used in this analysis and in the NOPR[9]. Table 17 shows the same comparison of the NES and NPV for standard-size freezers at the Final Rule standard level (30% for upright freezers and 25% for chest freezers). An additional 0.35 quads for standard-size refrigerator– freezers plus freezers are expected using the new UAF function, an increase of almost 9%. Total expected NPV for standard-size refrigerator–freezers plus freezers increases by between $1.57 billion (at 7% discount rate) and $4.10 billion (at 3% discount

[9] While the UAF function used in this analysis is identical to that in the Final Rule, the method of calculating NPV savings in the Final Rule differed from that in the NOPR, unrelated to changes in the UAFs. Therefore, in order to make a direct comparison of the effect of the change in UAFs function on the NPV results, the NOPR method was retained here.

rate), representing significant increases in expected savings—61 and 22%, respectively (differences in NES and NPV for built-ins are not shown because total savings are very small using either UAF function. For this analysis, total savings are 0.06 quads and −$0.40 billion at 3% discount rate or −$0.31 billion at 7% discount rate).

Table 15 Comparison of results across residual function choice at Final Rule standard level

	This analysis	DOE NOPR analysis	No residual function
Product class 3 (Final Rule standard level = 25%)			
Average LCC savings ($)	30	22	33
Households experiencing a net benefit (%)	48.2	45.1	52
Households experiencing a net cost (%)	51.8	54.9	48
Median payback period (years)	10.5	10.9	10
Product class 9 (Final Rule standard level =30%)			
Average LCC savings ($)	183	148	158
Households experiencing a net benefit (%)	85.8	81.1	93.8
Households experiencing a net cost (%)	14.0	18.7	5.9
Median payback period (years)	5.9	6.2	5.8

Table 16. Standard-size refrigerator-freezers: cumulative national energy savings and net present value at the Final Rule standard level (25% for top- and side-mount units and 20% for bottom-mount units)

	Top-mount refrigerator-freezers	Bottom-mount refrigerator-freezers	Side-mount refrigerator-freezers	Total standard-size refrigerator-freezers[a]
	Product classes 1, 1A, 2, 3, 3A, 3I, and 6	Product classes 5, 5A, and 5I	Product classes 4, 4I, and 7	
National energy savings (quads)				
NOPR analysis	2.08	0.09	0.88	3.05
This analysis	2.22	0.10	0.95	3.27
Difference	0.14	0.01	0.07	0.22
National net present value (2009$ billions) at 3% discount rate				
NOPR analysis	6.10	0.78	3.62	10.49
This analysis	7.75	0.86	4.45	13.06
Difference	1.65	0.08	0.83	2.57
National net present value (2009$ billions) at 7% discount rate				
NOPR analysis	-0.29	0.27	0.46	0.44
This analysis	0.35	0.30	0.79	1.44
Difference	0.65	0.03	0.33	1.00

[a] Does not include built-in refrigerator-freezers.

Table 17 Standard-size freezers: cumulative national energy savings and net present value at the Final Rule standard level (30% for upright freezers and 25% for chest freezers)

	Upright freezers	Chest freezers	Total standard-size freezers[a]
	Product classes 8 and 9	Product classes 10 and 10A	
National energy savings (quads)			
This analysis	0.75	0.38	1.14
NOPR analysis	0.66	0.36	1.01
Difference	0.09	0.03	0.13
National net present value (2009$ billions) at 3% discount rate			
This analysis	5.42	2.37	7.78
NOPR analysis	6.58	2.73	9.31
Difference	1.16	0.33	1.53
National net present value (2009$ billions) at 7% discount rate			
This analysis	1.57	0.54	2.12
NOPR analysis	2.01	0.68	2.69
Difference	0.43	0.14	0.57

[a] Does not include built-in freezers

Conclusions

The use of a UAF function based on field-metered data played a critical role in estimating energy use from residential refrigeration products. In comparison to UAF estimates based on RECS data used in the efficiency standards Preliminary Analysis, results were dramatically lower, reducing energy use estimates accordingly. We believe that these field-metered results are a significant improvement, however, over the RECS data, because they were estimated from actual energy measurements of refrigeration products, rather than whole-house energy measurements.

The subsequent refinement of the function that was used to fit the residual differences between observed and modeled UAF data played a minor but not insignificant role in improving the analysis since the publication of the NOPR. UAF estimates increased by between 7 and 14% depending on product class. Over the 30-year analysis period, this results in an increase of 0.35 quads in the energy savings expected for standard-size refrigerator–freezers plus freezers (an increase of 9% over the NOPR estimate). Moreover, the increase in expected national net present value is between $1.57 (7%discount rate) and $4.10 billion (3% discount rate), an increase of 61 and 22%, respectively. While these changes to the analysis have no direct impact on actual energy and monetary savings, they represent an important refinement in our estimation of savings resulting from increased efficiency standards.

While more difficult to implement, the demonstrated advantage of using a multiple regression approach on field-metered data with several household and climatic variables has hopefully been made clear. However, improvements over the methods presented here will undoubtedly allow future estimates of actual energy use to be more accurate. For instance, collection of field data using identical methodology, including an accurate recording of model numbers so that test energy consumption can be definitively determined, as well as recording of temperatures both

interior and exterior to the unit, would greatly improve the analysis. Performing data collection in the same year across a statistically valid sample of US demographic—and particularly, geographic—variables would provide more comprehensive coverage of household and climate variation. Moreover, improvements in the test procedure to more accurately reflect field energy use, perhaps by replacing the closed-door test with one that more realistically simulates real conditions (e.g., door openings, introduction of warm foods, etc.) would also improve the estimation of the actual energy use of refrigeration products.

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