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Using National Survey Data to Estimate Lifetimes of Residential Appliances

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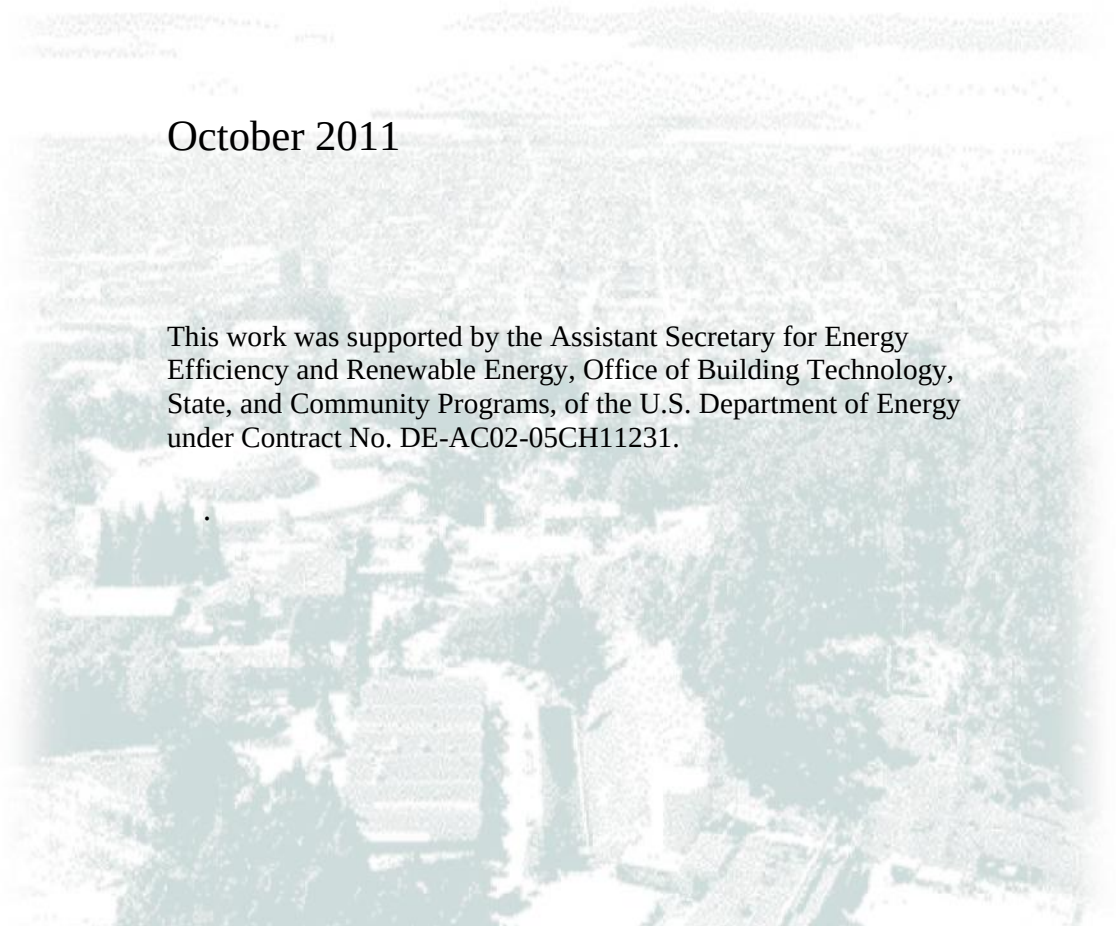

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Using National Survey Data to Estimate Lifetimes of Residential Appliances

ABSTRACT

This article summarizes a rigorous method for estimating the lifetimes of household appliances. The method utilizes data from public surveys regarding appliances in residences combined with manufacturer data on historical shipments. Errors inherent in the survey sampling and analytical methods also are examined. Average lifetimes are estimated for residential central air-conditioners, heat pumps, furnaces, boilers, water heaters, room air-conditioners, refrigrators, and freezers.

INTRODUCTION

Accurate estimates of residential appliance lifetimes are necessary for developing strong regulatory policies and effective voluntary programs. To date, only informal estimates, based on the experiences of manufacturers and installers, have been developed to describe the lifetimes of U.S. residential appliances. This article describes a rigorous method of determining the lifetimes of appliances based on data from public surveys regarding the presence of appliances in residences combined with manufacturer data on historical shipments. This article describes the successful application of the method to estimate lifetimes for residential central air-conditioners, heat pumps, furnaces, boilers, water heaters, room air-conditioners (RACs), refrigerators, and freezers.

GENERAL METHODOLOGY AND ASSUMPTIONS

The method described here applies a survival function to the number of appliances shipped in a given past year in order to estimate the number of appliances still in use in a future year. The parameters of the survival function are chosen so that the calculated number of appliances still in use matches the number of appliances reported as being in use in a survey performed that year. Suppose, for example, that manufacturers report having shipped 100,000 furnaces between 1980 and 1990. If a 2000 survey indicates that 80,000 households have a furnace that is between 10 and 20 years old (corresponding to the 1980–1990 shipment period), then 80% of furnaces aged 10–20 years are still in use, and 20% have been retired.

Data Sources

The method described in this article relies on publicly available data about appliance shipments and the numbers of in-use appliances in stock. Shipments data were obtained from the Association of Home Appliance Manufacturers and the Air-Conditioning, Heating and Refrigeration Institute. Information on the number of appliances in use in various years was derived from the Energy Information Agency's (EIA) Residential

Energy Consumption Survey (RECS 1990, 1993, 1997, 2001, 2005) and the Census Bureau's American Housing Survey (AHS 1991, 1993, 1995, 1997, 1999, 2001, 2003, 2005, 2007).

Assumptions

The following assumptions are necessary to evaluate the survival characteristics of an appliance.

1. The survival function appropriate to an appliance type does not change over time.
2. The survival function is independent of other household factors (such as household size or region).
3. RECS survey respondents accurately estimate the ages of their appliances.
4. AHS accurately represents the stock of in-use appliances.
5. The historical shipments data are accurate.

By combining household survey results with historical shipments data, the fraction of appliances of a given type and age that remain in operation can be estimated. This survival function provides an average and median appliance lifetime.

The Weibull Distribution

The Weibull distribution (Weibull 1951) is a probability distribution function of wide applicability that was introduced more than five decades ago. Weibull states that the reasoning behind the development of the distribution function "may be applied to the large group of problems, where the occurrence of an event in any part of an object may be said to have occurred in the object as a whole, e.g., the phenomena of yield limits, statical or dynamical strengths, electrical insulation breakdowns, life of electric bulbs, or even death of man, as the probability of surviving depends on the probability of not having died from many different causes" (pg. 293). Over time, this equation has been applied to estimates ranging from the fatigue-life of steel to the sensory shelf-life of ready-to-eat lettuce (Araneda et al. 2008). The Weibull distribution is often used in analyses of lifetime and reliability of mechanical and electronic equipment (Mahzar et al. 2007). The distribution is capable of fitting a broad range of shapes of data. Many common distributions, such as normal, exponential, or Rayleigh, are exact or approximate matches of special forms of the Weibull distribution (Abernethy 2006). In the context of appliance survival rates, a Weibull distribution function has been used successfully instead of normal or linear distributions (Welch and Rogers 2010; Young 2008; Fernandez 2001). This article uses a Weibull distribution as the appropriate survival function to describe lifetimes of residential appliances. An important innovation here is using data from several surveys across many years.

The cumulative Weibull distribution takes the following form:

$$P(x) = e^{-\left(\frac{x-\theta}{\alpha}\right)^{\beta}}, \quad (1)$$

where

P(x) is the probability that the appliance is still in use at age *x*;
x is the appliance age;
α is the scale parameter, which corresponds to the decay length in an exponential distribution;
β is the shape parameter, which determines the way in which the failure rate changes through time; and
θ is the delay parameter, which provides for a delay before any failures occur.

When β = 1, the failure rate is constant through time, producing a cumulative exponential distribution. In the case of appliances, β commonly is greater than 1, reflecting an increasing failure rate as appliances age. An example of such a survival curve is shown in Figure 1.

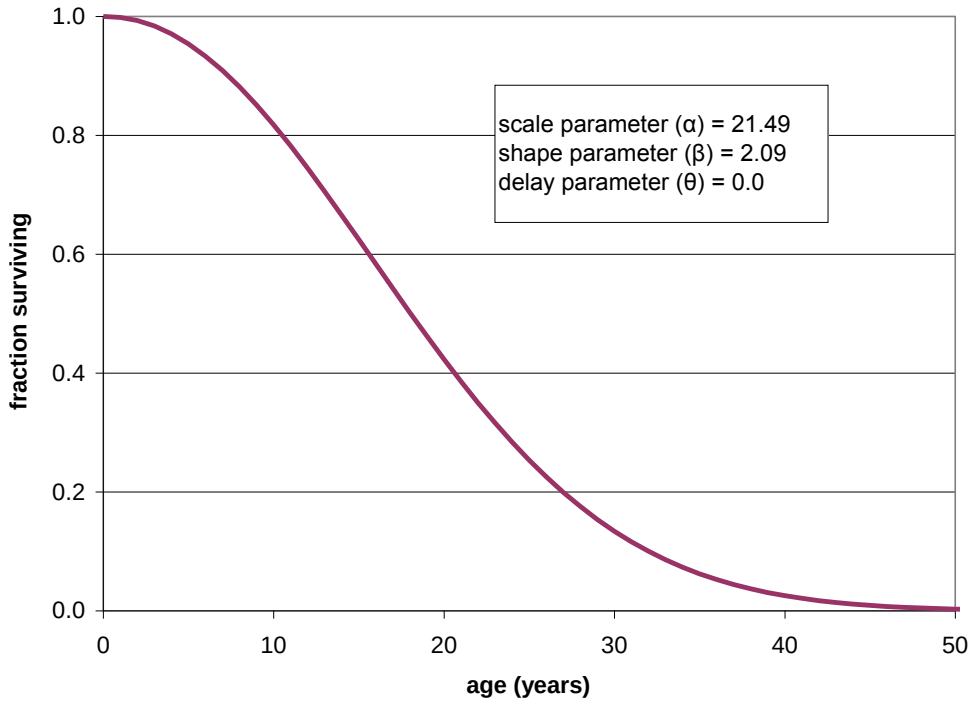

Figure 1. Sample Weibull survival curve.

PREPARING THE DATA

RECS asks residents of occupied primary housing units about the presence of various appliances and the age, within a range, of each appliance. For all of the appliances discussed in this article, RECS asks respondents to place the appliance's age in one of five or six bins. Table 1 shows RECS data taken from the 2005 RECS survey combined with shipments data for central air-conditioning systems.

Table 1. Data on central air-conditioning systems (RECS 2005).

Age of unit	Corresponding year shipped	Number of households represented	Number of units shipped
< 2 years	2004–2005	9,103,214	10,890,900
2 to 4 years	2001–2003	11,103,845	13,724,151
5 to 9 years	1996–2000	16,586,980	21,690,627
10 to 19 years	1986–1995	17,028,647	27,634,578
Over 20 years	1985 or prior	6,825,340	31,203,337
As old as the home	N/A	5,214,930	

Based on the 2005 RECS, in that year, the U.S. housing stock contained 65,862,956 central air-conditioning units of various ages. By comparing those numbers to shipments data that correspond to each age bin, five data points are obtained about appliance replacement rates. Using RECSs conducted in 1990, 1993, 1997, 2001, and 2005, 25 data points are obtained for each appliance considered.

Scaling Data for Number of Households

RECS has been conducted every three or four years for the past several decades. AHS, conducted every odd year, samples more U.S. households (56,650 in 2005, compared to 4,382 for RECS). AHS does not record appliance age, however, but provides the total number of housing units (including unoccupied homes and second homes) that contain a given appliance type. Therefore, RECS data, excluding unoccupied homes and second homes, were scaled to match the number of households AHS reports as having a particular appliance. Including appliances in vacant or second homes enables the calculation to more closely match total recorded shipments.

Scaling Data for Different Time Frames

AHS is conducted in the middle of a year, RECS is scaled to July of the survey year, and shipments data are provided for a calendar year. These differing time frames are corrected for by adjusting the surveys to align with calendar-year shipments data. For appliances that are installed directly in new construction, such as central air-conditioners and heat pumps, units are added to the youngest age bin in RECS to represent homes constructed in the latter half of the survey year. The number of newly constructed units from U.S. Census data are obtained, and they include only new construction known to have installed the appliance type in question. Because RECS data for the youngest age bins tend to have a large scatter relative to the shipments in those years, the first two appliance age bins are combined.

Because it is unusual for appliances to fail during their first years, combining bins should not affect the shape of the distribution.

REGRESSION ANALYSIS

To determine the Weibull function parameters, a least-squares fit of the surviving stock is used, given by the data from RECS or AHS, to the modeled surviving stock, which is derived from the shipments data and the survival function.

To control for the differences in sample size between the RECS and AHS, each residual is weighted by the inverse of its variance, which results in the following expression for the sum of squares of the errors:

$$S = \sum_{i,y1} \frac{\left(RECS_{i,y1} - Surv_{i,y1}\right)^2}{\sigma^2_{i,y1RECS}} + \sum_{y2} \frac{\left(AHS_{y2} - Surv_{y2}\right)^2}{\sigma^2_{y2,AHS}}, \quad (2)$$

where

i is the identifier for an age bin from a single RECS year;
y1 is the identifier for a RECS year;
y2 is the identifier for an AHS year;
$RECS_i$ is the number of appliances reported by RECS in bin *i;*
AHS_y is the total installed stock of appliances as measured by AHS in year *y;*
$Surv_{i,y}$ is the number of surviving appliances in bin *i* and year *y* predicted by the Weibull distribution (defined by α, β, and θ), applied to historical shipments data;
$\sigma_{i,y1,RECS}$ is the statistical standard error due to sampling (square root of the variance) of the RECS data point for bin *i* in year *y1*; and
$\sigma_{i,y2,AHS}$ is the standard error of the AHS data point for year *y2.*

Then the parameters α, β, and θ are determined by minimizing the sum of the squares of the errors as calculated by Equation 2. One limit is placed on the parameters: that the delay θ must be greater than or equal to zero. Restricting the delay to be zero or greater allows us the matching of the boundary condition that shipments equal sales (and therefore the stock at age zero). It is noted that the lifetime calculating using this method is the appliance lifetime from the standpoint of the physical object, rather than the lifetime of an appliance purchase from a consumer's standpoint. From the consumer's standpoint, an appliance that fails at a very young age will commonly be replaced under warranty, so economic calculations from their standpoint (such as life-cycle cost calculations) should use a lifetime function with zero possibility of failure before the end of the warranty period. Appliances replaced under warranty are included in the manufacturer shipments used in this article, so by allowing the delay parameter in the fits to be zero, the physical lifetime of each appliance is consistently chosen for evaluation rather than the consumer's economic lifetime.

In this regression analysis, the sampling error is used to weight the RECS and AHS residuals, which results in assigning more weight to the AHS survey because of its larger sample size. See the "Error Modeling and Nonsampling Errors" section for a discussion of nonsampling errors.

Survival Function and Parameters

Based on Equation 1, the median age *M* can be written as

$$M = \theta + \alpha\left(\ln(2)\right)^{1/\beta} \tag{3}$$

and the mean as

$$Mean = \alpha\Gamma\left(1+\tfrac{1}{\beta}\right) . \tag{4}$$

In these equations, as in Equation 1, α is the Weibull scale parameter and β is the Weibull shape parameter. Γ is the Gamma function.

By substituting Equation 3 into Equation 1, the survival function can be defined in terms of the more practical parameters of the distribution: delay θ, shape β, and median *M*, as done in the rest of this article. In this case,

$$P(x) = e^{-Ln(2)\left(\frac{x-\theta}{M-\theta}\right)^{\beta}} . \tag{5}$$

One advantage of this formulation is that it simplifies the estimation of the standard error in the median *M*, as described below.

Least-squares fitting produces estimate of the value of the parameters of the curve fit to the data. By varying the values of the parameters slightly away from the best-fit values and examining the resulting change in the residuals, the sensitivity of the fit to each parameter can be evaluated. This process, in turn, reveals the best estimate of the variance in the best-fit parameter values. It can also reveal covariance between pairs of parameters.

The function to which survey data are fit, Equation 5, is nonlinear in its parameters, so the Jacobian must be used first to build a linear approximation around the best-fit parameters. The Jacobian takes the form of a matrix of constants having a number of rows equal to the number of observations to be fit (and therefore the number of residuals) and a number of columns equal to the number of parameters (three in this case). Each entry J_{ij} in the Jacobian is defined as

$$J_{ij} = -\frac{\partial r_i}{\partial \pi_j} , \tag{6}$$

Where r_i is the *i*th residual, and π_j is the *j*th parameter.

This partial derivative is calculated numerically by varying each parameter slightly and calculating the change in the values of the residuals. The matrix $J^T W J$ is then constructed,where [*W*] is the matrix of weights assigned to each observation. The weights are, as in the fit itself, the inverses of the variances of the measurements (smaller weights correspond to less certain measurements):

$$W_{ii} = \frac{1}{\sigma_i^2}, \; W_{ij} = 0 \text{ for } i \neq j, \tag{7}$$

where σ_i^2 is the variance for observation *i*, either from RECS or AHS. Only the variance due to sampling error was used because of the difficulty in quantifying the nonsampling error (see the "Error Modeling, Nonsampling Errors" section).

Then the three-by-three matrix $J^T W J$ is inverted to calculate the covariance matrix:

$$\Sigma = \left(J^T W J \right)^{-1} = \begin{bmatrix} V_M & C_{M\beta} & C_{M\delta} \\ C_{M\beta} & V_\beta & C_{\beta\delta} \\ C_{M\delta} & C_{\beta\delta} & V_\delta \end{bmatrix}. \quad (8)$$

From Equation 8, the variance (and therefore the standard error) is determined for each parameter (V_M, V_β, V_δ), as well as the covariance for each pair of parameters ($C_{M\beta}$, $C_{M\delta}$, and $C_{\beta\delta}$).

RESULTS: APPLIANCE LIFETIMES

This section presents lifetimes estimated using the method described above for each type of appliance, along with values for the parameters of the Weibull survival function for that type of appliance.

Central Air-Conditioners

Table 2 shows the parameters of the Weibull survival function that, when applied to total shipments of central air-conditioners, give the best match of the stock of central air-conditioners by age bin in RECS and AHS data. The best-fit survival function is characterized by parameters α = 21.5, β = 2.09, and θ = 0.0. The survival function for central air-conditioners indicates a median lifetime of 18.0 years and a mean of 19.0 years.

Table 2. Results for central air-conditioners.

Number of observations: 29	Best fit	Error
Median	18.04	0.2817
Shape	2.094	0.2706
Delay	0.000	1.8536
Scale	21.49	
Mean	19.03	

A major uncertainity in calculating the lifetimes of central air-conditioners is the fraction of units used in commercial applications, such as small, stand-alone businesses or homes converted to businesses. The method of this study depends on comparing total shipments with the residential stock. If significant shipments are not included in the residential stock, the resulting lifetime estimates could be artificially short. For the central air-conditioner results given above, it was assumed that 95% of the appliance stock is in residential units and, thus, is captured by RECS and AHS. If it was assumed that 100% of the stock was in residential applications, the median lifetime would decrease to 16.5 years; if it was assumed that 90% of the stock is in housing units, the median lifetime

would increase to 19.7 years. This uncertainty is greater than the statistical uncertainty in the best estimate resulting from sampling error and parameter uncertainty in the least-squares fitting process, for which the standard error is estimated to be 0.3 years.

It also is possible that the fraction of shipments to nonresidential applications has changed over time. Lacking any data to support this possibility, however, a simple, fixed fraction was assumed, consistent with the opinions of industry experts.

Heat Pumps

No single realistic survival function easily fits the shipment and stock history for residential heat pumps. Both AHS and RECS show the residential stock of heat pumps virtually unchanging from 1997 to 2003, while annual shipments grew substantially. AHS shows stock ranging from 13.8 million in 1997 to 14.7 million in 2003, followed by a sharp increase to 16.5 million in 2005; RECS reports 10.5 million in 1997, 11.5 million in 2001, and 12.1 million in 2005. During this period, shipments grew from 1.06 million in 1997 to 1.52 million in 2003 and 2.02 million in 2005. If attempting to fit all of these data with a single survival function, unchanging over time, the resulting function is unrealistic, approaching a step function at an age of approximately 15.5 years. While this average age at retirement may be reasonable, this function is dramatically inconsistent with the observed age distribution from RECS alone, which reports significant stock over age 20.

In order to build a consistent survival function that represents current market and consumer choices, the input data was restricted to AHS and RECS only from 2001 to 2007 (the most recent data available). Using these surveys alone, a survival function was calculated with a median age at returement of 14.6 years and a mean lifetime of 16.8 years. The parameters are shown in Table 3.

Table 3. Results for heat pumps.

Number of observations: 12	**Best fit**	**Error**
Median	14.64	0.884
Shape	1.525	0.525
Delay	0.000	3.734
Scale	18.62	
Mean	16.77	

The challenge of finding a realistic single survival function for heat pumps illustrates some of the difficulties faced when applying this lifetime-calculation technique in the face of data indicating more complex consumer behavior. The large discrepancy between the reported stock of heat pumps between AHS and RECS (AHS reports more than 30% more heat pumps than RECS in some years) indicates either systematic differences between the two surveys or a large stock of heat pumps in housing units that are not primary residences. Lacking reliable data regarding the split of shipments between residential and commercial applications, and how that split may have changed over time, prevents the reaching of conclusions regarding the possibility of a change in consumer

behavior (or mechanical lifetime) between 1995 and 2005, which could explain the sharp rise in shipments while the stock remained almost constant.

Gas Furnaces

Table 4 shows the best-fit parameters for the Weibull survival function of gas furnaces. The best-fit survival function is characterized by parameters α = 26.7, β = 2. 22, and θ = 0.0. The survival function for residential gas furnaces indicates a median lifetime of 22.6 years and a mean of 23.6 years.

Table 4. Results for gas furnaces.

Number of observations: 29	Best fit	Error
Median	22.61	0.326
Shape	2.218	0.320
Delay	0.000	2.542
Scale	26.68	
Mean	23.63	

Gas Boilers

Table 5 shows the best-fit parameters for the Weibull survival function of gas boilers. The best-fit survival function is characterized by parameters α = 25.3, β = 1.00, and θ = 0.0. The survival function for residential furnaces indicates a median lifetime of 17.5 years and a mean of 25.3 years.

Table 5. Results for gas boilers.

Number of observations: 29	Best fit	Error
Median	17.54	0.721
Shape	1.000	0.148
Delay	0.000	2.188
Scale	25.31	
Mean	25.31	

Gas and Electric Storage Water Heaters

Table 6 and 7 show the best-fit parameters for the Weibull survival function of gas and electric storage water heater, respectively. The best-fit survival function is characterized by parameters α = 11.6, β = 1.31, and θ = 3.2 for gas storage water heaters and α = 13.2, β = 1.17, and θ = 0.0 for electric storage water heaters and. The survival function for gas storage water heaters indicates a median lifetime of 12.0 years and a mean of 13.9 years. The survival function for electric storage water heaters indicates a median lifetime of 9.6 years and a mean of 12.5 years.

Table 6. Results for gas water heaters.

Number of observations: 29	Best fit	Error
Median	11.99	0.117
Shape	1.307	0.061
Delay	3.196	0.436
Scale	11.64	
Mean	13.93	

Table 7. Results for electric water heaters.

Number of observations: 29	Best fit	Error
Median	9.65	0.068
Shape	1.174	0.020
Delay	0.000	0.020
Scale	13.19	
Mean	12.48	

Shorter lifetimes for electric water heaters compared to gas water heaters is somewhat unexpected, as electric water heaters have fewer mechanical components to fail. Possible explanations of this difference might be due to houses with electric water heaters having poorer water quality or using different amounts or temperatures of hot water.

RACs

One specificity of room air-conditioners (RACs) is that units are shipped to both the commercial and the residential sectors. Because the Commercial Building Energy Consumption Survey (CBECS 2003), also performed by the EIA, does not ask businesses how many RACs they have or the age of the units, several assumptions must be made to calculate the number of RACs shipped to commercial enterprises. Based on CBECS data about the total commercial square footage that is cooled by RACs, and assuming an average cooling capacity of 2.9 kW and an average cooling load of 1 kWh/m^2, shipments are found to be split 88% for residential applications and 12% for commercial. Investigation of previous CBECSs produced similar results.

For RECS, only the age of the most used RAC in a household is recorded. For this study, it is assumed that any additional units in a household were acquired at the same time as the most used unit.

The results for RACs, based on the above assumptions, are given in Table 8.

Table 8. Primary results for (RACs).

Number of observations: 30	Best fit	Error
Median	11.08	0.089
Shape	1.442	0.040
Delay	0.000	0.279
Scale	14.29	
Mean	12.96	

The results in Table 8 were generated using AHS survey data from 1989 to 2007 and RECS survey data from 1990 to 2005. Although the overall agreement between the model and the data is good, having a coefficient of correlation of 94%, the number of RACs calculated to be installed for 2007 is about 30% higher than the 2007 AHS survey data. This overestimation of the stock begins with the 2003 AHS and occurs in the 2005 RECS as well (for which the model overestimates the reported stock by 18%). This result led to the conclusion that the apparent lifetime of RACs has changed in recent years. As observed from RECS, most of the stock fits in the age bins of one to eight years. Based on the stock ages, it is estimated that the change in longevity happened in the late 1990s. Tables 9 and 10 give the resulting fits if data collected before 2000 and those collected after 2000 are seperated.

Table 9. Results for RACs (Based on Surveys Between 1989 and 2000).

Number of observations: 18	Best fit	Error
Median	12.91	0.130
Shape	1.067	0.090
Delay	8.000	0.562
Scale	6.92	
Mean	14.75	

Table 10. Results for RACs (Based on Surveys After 2000**).**

Number of observations: 12	Best fit	Error
Median	8.36	0.17
Shape	1.08	0.06
Delay	0.00	0.51
Scale	10.27	
Mean	11.27	

The tables indicate that the apparent mean lifetime decreased by 3.5 years between the two periods. The reduction in lifetimes could have many causes, from technical

failure to consumer behavior or replacement programs. The methodology here does not enable the identification of the factors that may induce changes in calculated lifetimes. The conclusions are limited to what can be observed by comparing the shipments data to the surveyed stocks.

This case is an example of a challenge to our assumption of constant lifetime through the period of study (see "Discussion" section).

Refrigerators and Freezers

Refrigerators follow more complex lifetime trends than do many other residential appliances. AHS records only whether a housing unit contains a refrigerator, not whether it has more than one unit. Therefore, it is difficult to compare total stock as recorded by AHS to calculated stock. In addition, AHS may record a housing unit as containing a refrigerator when it contains a compact, rather than standard-sized, appliance. RECS, on the other hand, provides the age and volume of both first and second refrigerators. These factors led to the use of AHS data only to scale the number of houses with standard-sized primary refrigerators found in RECS. AHS data was not used to develop a separate set of data points. Unlike the appliances discussed previously, most refrigerators are not installed during construction. Therefore, the content of the bins were adjusted for half a year of retirements and replacements (to account for survey timing) but do not assume that new homes completed in the latter half of a year contain installed refrigerators.

Table 11 shows the parameters of the Weibull survival function that, when applied to total shipments of refrigerators, give the best match of the stock of refrigerators by age bin in the RECS data. The Weibull distribution is characterized by parameters α = 11.7, β = 1.27, and θ = 8.87. This distribution indicates a mean refrigerator lifetime of 19.8 years and a median lifetime of 17.7 years.

Table 11. Results for refrigerators.

Number of observations: 20	Best fit	Error
Median	17.68	0.357
Shape	1.272	0.187
Delay	8.874	1.141
Scale	11.75	
Mean	19.77	

The same methodology was applied to standard-sized stand-alone freezers. The best-fitting Weibull distribution is characterized by parameters α = 17.9, β = 1.89, and θ = 6.46. This distribution indicates a mean freezer lifetime of 22.4 years and a median lifetime of 21.2 years. The parameters for freezers are shown in Table 12.

Table 12. Results for freezers.

Number of observations: 20	Best fit	Error
Median	21.21	0.706
Shape	1.885	0.730
Delay	6.459	4.746
Scale	17.92	
Mean	22.36	

The process by which first refrigerators are converted to second refrigerators was also modeled as a Weibull process. Rather than comparing second refrigerators to shipments, they are compared with the total installed stock of refrigerators of a certain age, as measured by RECS.

That is, this Weibull distribution models not a "survival function" but a "conversion function," for which an offset at time zero was added. The offset considers the fraction of refrigerators bought for use as second refrigerators as having been converted from first to second units immediately at purchase. To the extent that this consumer behavior exists, it appears as a nonzero offset. The conversion function is shown in Equation 9:

$$C(x) = \varphi + (1-\varphi) \times e^{-\left(\frac{x}{\alpha}\right)^{\beta}}, \quad (9)$$

where

$C(x)$ is the probability that the refrigerator has been converted to a second refrigerator at age x;
x is the refrigerator age;
α is the scale parameter, which corresponds to the decay length in an exponential distribution;
β is the shape parameter, which determines the way in which the conversion rate changes through time; and
φ is the offset parameter, which is the fracton of refrigerators that are purchased to be second refrigerators.

Here AHS is not used to scale or adjust RECS, because AHS provides no data on the number of households that have more than one refrigerator.

Table 13 shows the best fit of conversion to second refrigerators for a Weibull distribution. The best-fit Weibull parameters are α = 53.5, β = 1.83, and φ = 0.049. The offset parameter indicates a direct conversion rate of 5% upon purchase. Close to 14% of surviving refrigerators are converted to second refrigerator status before they reach age 15.

Table 13. Results for second refrigerator.

Number of observations: 20	Best fit	Error
Scale	53.449	4.424
Shape	1.827	0.160
Offset	0.049	0.004
Median	41.96	

The high median age at conversion is a reflection of the fact that conversion of first refrigerators to second refrigerators does not happen regularly. Many first refrigerators do not survive long enough to be converted to a second refrigerator.

ERROR MODELING AND NONSAMPLING ERRORS

RECS utilizes a complicated survey method that engenders numerous possible errors beyond statistical sampling error. For the proposed method to produce rigorous results, several assumptions are made regarding those additional errors. First, it is assumed that the additional sources of errors do not lead to bias in the estimation method. Second, it is assumed that those errors that do not scale with the sample size in the same way that the statistical error does are small. If the nonsampling errors scale with sample size in the same way that sampling errors do, then they do not affect the relative weighting of RECS bins, and the same Weibull distribution is the best fit. Such errors would, however, change the error estimates for the Weibull parameters (see "Survival Function and Parameters" Section).

Because the AHS data display a relatively small variance, and thus a smaller expected error, than do the RECS data, the AHS data are weighted more heavily. As with RECS, the estimates of statistical sampling error from AHS are used to account for the sample size. AHS, like RECS, encompasses various sources of error that are not captured by the sampling error alone, and the same assumptions are made regarding those errors as for the RECS data.

DISCUSSION

The analysis described herein yields predictions that align reasonably with what one might expect regarding normal consumer behavior and typical appliance lifetimes. It differs considerably, however, from long-standing estimates of appliance lifetime established by industry consensus. *Appliance Magazine*'s Annual Portrait of the U.S. Appliance Industry (2009) includes estimates of various appliance lifetimes based on a wide-ranging survey of appliance manufacturers, including engineers, designers, and product managers. These lifetime estimates have been generally accepted for policy purposes and are used for example in the lifecycle cost calculations by the U.S. Department of Energy for appliance energy efficiency standards (DOE 2007). The results of that survey are given in Table 14 and compared with the results obtained using the method of this study.

Table 14. Comparison of estimated appliance lifetimes.

Product	*Appliance Magazine*	Median from this Study	Mean from this Study	Difference*
Freezer	11	21.21	22.36	103%
Refrigerator	12	17.68	19.77	65%
Water Heater, Electric	13	9.65	12.48	-4%
Water Heater, Gas	11	11.99	13.93	27%
Room Air-Conditioning	9	8.36	11.27	25%
Central Air-Conditioning	11	18.04	19.03	73%
Boiler, Gas	20	17.54	25.31	27%
Furnace, Gas	15	22.61	23.63	58%
Heat Pump	12	14.64	16.77	40%

* Percent change between Appliance Magazine and mean from this study.

Table 14 shows that for most of the appliances outside of electric water heaters, a longer lifetime is found than what is usually accepted by consensus. This means that inefficient old appliances are staying in the stock longer than expected and, therefore, that energy efficiency policies have a lower impact than previously assumed.

In order for others to use the results of this article, the lifetime is described by a constant function over time. As seen in the case of RACs, this is not always the case. A component of time variability could have been added to the equation to take into account these observations, even though there is less confidence in predicting these effects in the future.

SUMMARY AND CONCLUSIONS

The analysis described herein has been successfully used to estimate the survival function for several residential appliances. The analysis rests on several important assumptions. The first is that a Weibull distribution is the correct distribution to use for appliance lifetimes. Although the Weibull is the standard distribution used for analyzing lifetimes, there is no guarantee that it reflects actual consumer behavior. The second assumption is that consumer behavior and appliance lifetimes have not changed through time. That is, data from the 1990 and 2005 RECS or the 1991 and 2005 AHS can be compared as equals. Limiting the analysis to only recent surveys would result in least-squares fits based on only a handful of data points. Assuming unchanging appliance lifetimes expands and enriches the available data.

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