7. Estimation and Sampling Error

This chapter includes sections on the weighting procedures used to develop sample estimates, the model-based procedures for allocating total consumption of each fuel to specific end uses, and the estimation and presentation of information about sampling errors of the estimates. Each section begins with a description of the procedures used in the 1993 RECS. Information about current procedures is followed by an account of procedural and design changes aimed at improving the quality of the estimates that have been introduced since the first survey (NIECS) in 1978.

Sample Weighting Procedures

Weighting Procedures for the 1993 RECS

The sample weighting procedures used in RECS closely parallel those used in other U.S. national household surveys, such as the Census Bureau's Current Population Survey. Figure 7.1 provides an overview of the sample weighting procedures that were used to produce estimated totals for the 1993 RECS target population from the sample data, following completion of all editing operations and imputation for item nonresponse.

The overall weight assigned to each household is equal to the product of the weighting factors assigned to it in the four steps shown in Figure 7.1.

Figure 7.1. RECS Sample Weighting Procedures: 1993

Step	Description	Purpose	Auxiliary Data
1	Apply sampling weights	Reflect sample selection probabilities	None
2	Adjust for unit nonresponse	Reduce effects of nonresponse bias	None
3	Ratio estimate, Stage 1	Reduce between-PSU sampling variance	Uses data from 1990 Census
4	Ratio estimate, Stage 2	Reduce mean square error	Uses Current Population Survey estimates as control totals

Source: Energy Information Administration, *Housing Characteristics* (1993).

Step 1: Application of Sampling Weights. Each household record is assigned a weight equal to the reciprocal of its overall probability of selection. The overall probability of selection is the product of the selection probabilities at all stages of sampling: selection of primary sampling units (PSU's), selection of secondary sampling units (SSU's), selection of listing segments within SSU's, and selection of addresses from the listings. In some instances, the selection probability at one or more stages can be one, as in the case of large metropolitan area PSU's that are selected with certainty.

Sampling weights vary across SSU's for two reasons. The first is that the allocation of sample SSU's to Census divisions is not directly proportional to the number of households by division. Proportionately more sample SSU's are assigned to divisions with fewer households in order to ensure that estimates of acceptable reliability can be made for each division.

The second source of variation in sampling weights is oversampling of targeted population groups. In the 1993 RECS, two groups of special interest were oversampled: low income households and new houses. For the first group, oversampling was accomplished by using higher sample selection rates in SSU's determined by interviewers to be in low-income areas, especially in areas where the main heating fuel was something other than natural gas. For the second group, a supplemental sample of SSU's was selected from Census tracts or block groups with a high percentage of units constructed in the 6-year period prior to the 1990 Census.

In the 1993 RECS, for the first time, sampling weights could also vary within SSU's. Housing units judged to be new by field workers during the listing operation were sampled at a higher rate than other units.

Step 2: Adjustment for Unit Nonresponse. The basic procedure for 1993 was to form a set of weight-adjustment cells consisting of sample households with similar attributes. For each cell, an adjustment factor was calculated by dividing the total number of assigned sample households, including households not interviewed, by the number of interviewed households. If the factor was greater than 2.0, similar cells were collapsed, according to predetermined rules, to form a cell for which the weighting factor was 2.0 or smaller.

The variables used to form the weight-adjustment cells for the 1993 RECS were as follows:

Geographic Domains. These included the nine Census divisions, with Alaska and Hawaii treated as separate domains. Within the four largest Census divisions, the large metropolitan areas that had been selected with a probability of one were also treated separately.

Weighting Classes. Within the geographic domains, subdomains were formed consisting of SSU's and individual housing units that had the same basic sampling weights. As noted previously, basic weights varied primarily because of procedures for oversampling newly constructed housing units and those in low-income areas.

Weather Zones. These domains were based on long-term heating and cooling degree-day averages for counties.

Housing Unit Type. Individual housing units were grouped by type of structure: single family detached, single family attached, multifamily with two to four housing units, and multifamily with five or more units.

A large number of weight-adjustment cells were formed on the basis of these four characteristics. When collapsing was necessary, it was done in the reverse order of the characteristics listed above, that is, starting with the combination of cells representing different housing unit types.

Step 3: Stage 1 Ratio Adjustments. The stage 1 ratio adjustment factors for the 1993 RECS were based on 1990 Census data for the PSU's in strata that were not self-representing; that is, they did not consist of a single PSU that was selected with certainty. A separate adjustment factor was created for each of 36 groups of non-self-representing strata, defined by the 4 Census regions and 9 space-heating fuel categories. The adjustment factor for each group was the ratio of the 1990 Census count of households for all PSU's in the group to an estimate of that count based only on the sample PSU's in the group.

A restriction was placed on the calculation of the adjustment factor that if the denominator, that is, the estimate of Census households in a region and fuel category, was less than 1 million, that fuel category had to be combined with one or more other categories so that the denominator of the calculated adjustment factor was at least 1 million.

Each of the adjustment factors was applied to the weights for all RECS sample households in the corresponding region and space-heating fuel category or categories. Adjustment factors for the 1993 RECS varied from 1.1688 for natural gas in the Northeast Region to 0.7897 for LPG in the Midwest Region.

In sampling terminology, the goal of the first-stage ratio adjustment is to reduce the between PSU component of the sampling variance by using Census information on heating fuels that is available for all PSU's. It can be looked at as a method of compensating for chance factors that may lead to the selection of samples of PSU's whose proportion of households using specified heating fuels at the time of the 1990 Census was higher or lower than the corresponding proportion for all PSU's. Since the distribution of households by heating fuel does not change rapidly, one can expect that these samples of PSU's would deviate in the same direction with respect to the distribution at the time of the survey.

Step 4: Stage 2 Ratio Adjustments. For the 1993 RECS, the second-stage ratio adjustments consisted of four separate steps. In each of these steps, the sampling weights were ratio adjusted so that the sum of the weights for specific categories agreed with the control totals obtained from the Current Population Survey (CPS). Because estimated household counts are available only from the March CPS each year, the control totals for the survey reference month (July 1993 for the 1993 RECS) were derived by linear extrapolation from the CPS estimates for March 1992 and March 1993. The first of the stage 2 ratio adjustment steps started with the weights resulting from Step 3 (stage 1 ratio adjustments). The next three steps in stage 2 started with the weights resulting from the previous step.

The rationale for these adjustments is the expectation that the mean square error of the RECS estimates can be reduced by benchmarking them to the more precise estimates available from the CPS. The CPS estimates are believed to be more precise than the RECS estimates prior to benchmarking for two reasons: the CPS uses a sample of households that is roughly 10 times the size of the RECS sample, and the CPS sample estimates have themselves been benchmarked to post-censal projections of Census household counts. There is considerable evidence from the CPS and other surveys that survey coverage, especially for some population subgroups, is significantly below the coverage of the population that is obtained in the decennial censuses (for further discussion of this point, see Cox, 1995).

The four steps in the stage 2 ratio adjustments were as follows:

Step 4.1 Weights derived from Steps 1 to 3 were adjusted so that their sum equalled the extrapolated CPS household counts for each of 4 large States--California, New York, Texas and Florida--and for each of the 9 Census divisions.

Step 4.2 Weights derived from Steps 1 through 4.1 were adjusted so that their sum equalled the extrapolated CPS counts for 12 categories defined by the 4 Census regions and 3 "MSA (metropolitan statistical area) status" classifications: central city of MSA, remainder of MSA, and non-MSA.

Step 4.3 Weights derived from all preceding steps were adjusted so that their sum equalled the extrapolated CPS counts in three categories: one-person households occupied by males, one-person households occupied by females, and all other households.

Step 4.4 Step 4.1 was repeated, so that the final weights resulted in exact agreement with the CPS-based household counts for the four large States and nine Census divisions.

Step 4, with its series of successive adjustments to different sets of marginal totals, can be regarded as a raking procedure designed to minimize differences between RECS and CPS estimates of the distribution of households by geographical and other classifiers.

Changes in Sample Weighting Procedures

The basic structure of the sample weighting procedures, as shown in Figure 7.1, has been the same for all survey years. However, there have been several changes in the details, aimed mostly at improving the precision of the survey estimates.

The basic sampling weights (Step 1 in Figure 7.1) have varied as necessary to reflect the specific sample selection procedures used in each survey year. Oversampling of households in low-income areas occurred in the 1981, 1984, 1987, and 1993 survey years. Oversampling of new housing units occurred for the first time in 1993.

Because of the procedures used to oversample new housing units, 1993 was the first survey year for which it was possible for an SSU to have households with different basic sampling weights. This change led to a significant revision of the procedure for calculating the factors used to adjust for unit nonresponse. In all prior survey years, a separate adjustment factor was calculated for each SSU by dividing the total number of assigned sample households in the SSU by the number for which interviews had been completed. If the factor was greater than 2.0, the effect of the adjustment was spread across other SSU's in the same PSU. As noted above, for the 1993

RECS, the initial weight-adjustment cells were formed across SSU's, combining housing units with the same basic sampling weights from a group of SSU's with similar characteristics. This procedure also made it possible to take account of another characteristic of individual housing units, namely type of structure, in deriving the nonresponse adjustment factors.

The stage 1 ratio adjustment (Step 3 in Figure 7.1) has been essentially the same for all survey years, with minor changes made to conform with changes in the space heating fuel categories used in the most recent Census of Population and Housing. The stage 2 ratio adjustment procedure (Step 4 in Figure 7.1) has been modified to make use of a successively larger number of control totals from the CPS.

For survey years 1978 through 1982, a single set of adjustments was made to 12 geographic control totals consisting of CPS estimates of housing units for the 4 Census regions and 3 location categories--central city, remainder of metropolitan statistical area, and nonmetropolitan. Examination of the resulting RECS estimates of the number of one-person households for these years showed that they were consistently about 3 percent below comparable CPS estimates (Response Analysis Corporation 1983). Consequently, for the 1984 RECS, an intermediate ratio adjustment was introduced using national CPS estimates as controls for the number of households in three categories: one-person, male; one-person, female; all others. One more stage was introduced in the 1993 RECS. As explained above, the first step was based on CPS estimates for four large States and the nine Census Divisions, and this step was repeated following the intermediate steps, ensuring exact agreement between RECS and CPS estimates for these geographic domains.

Application of the second-stage ratio estimate procedures is dependent on the availability of the control totals from CPS. Because of uncertainty as to whether March 1991 CPS estimates would be adjusted for undercoverage in the 1990 Census, the necessary CPS data were not available when the 1990 RECS weights were first developed in September 1991. Consequently, the control totals for the survey reference month, November 1990, were developed by forward extrapolation from the March 1989 and March 1990 CPS estimates. In November 1991, the March 1991 CPS estimates were released and revised second-stage ratio adjustments were developed by interpolation between March 1990 and March 1991. For most of the 12 region/location cells, the change in the RECS estimates was 1 percent or less, but the RECS estimates in the Northeast Region increased by 3 percent for the central city metropolitan domain and by 2 percent for the nonmetropolitan domain (Battles 1991b).

Special Estimation Procedures for New Homes

Initial estimates of average energy consumption per household by year built from the 1990 RECS showed a striking reversal of a previously consistent trend for newer homes to consume less energy. The estimated average consumption for homes built in the 1988-1990 period was 103.1 million Btu, 53 percent above the estimate of 67.6 million Btu for homes built in the 1985-1987 period. Both estimates were based on relatively small samples of households, 225 for 1985-1987 and only 138 for 1988-1990 (EIA 1993a, Table 11, p.28).

In an attempt to better understand the factors associated with the apparent trend reversal, data from the Census Bureau's Survey of Construction and Survey of New Mobile Home Placements were used as ancillary data to produce new estimates of average consumption per household for new homes. Two different estimation procedures were developed: a *post-stratification procedure* and a *ratio-adjustment procedure*. They are described in detail in the *Consumption and Expenditures Report* for 1990 (EIA 1993a, pp. 173-181).

The post-stratification procedure used nine strata defined by a combination of Census region, type of home, and main space-heating fuel. The post-stratified estimate was a weighted average of the RECS estimates of average consumption per household for the nine strata, with the weights being the Census Bureau estimates of the proportion of housing units in each stratum. The ratio-adjustment procedure was based on Census Bureau estimates of the distribution of new homes by Census region and the increase in average heated floor space by region for homes built in 1988-1990 compared with those built in 1985-1987. Ratio-adjusted RECS estimates of average consumption per household were based on adjustments that eliminated or reduced RECS-Census differences for these two characteristics.

Both of the revised estimates showed a substantially smaller increase in average energy consumption for homes built in 1988-1990 compared with those built in 1985-1987:

Estimate	Average Consumption (millions of Btu)		Percent Increase
	1985-87	1988-90	
Original RECS estimate	67.6	103.1	53
Post-stratified estimate	74.5	89.7	20
Ratio-adjusted estimate	70.6	90.3	30

Standard errors of the post-stratified estimates were appreciably smaller than those of the original RECS estimates for both periods (Latta 1993, p.14). Standard errors were not computed for the ratio-adjusted estimates.

The estimation procedures used in this instance were designed to improve the precision of a specific class of RECS estimates, and it is doubtful whether their application across the board for all estimates would be feasible or desirable. However, they illustrate the potential for using post-stratification and allied techniques for improving estimates used in specific kinds of analyses.

Special Weighting Procedures for Buildings

Appendix B to the *Consumption and Expenditures 1990* report presented, for the first time, some tabulations of RECS data that used the building, rather than the household or housing unit, as the unit of analysis (EIA 1993a, Table B6, p.152). Additional data on residential buildings were presented in a 1995 EIA report, *Buildings and Energy in the 1980's* (EIA 1995b). According to the building definition used in EIA's Commercial Buildings Energy Consumption Survey, most housing units correspond to separate buildings; however, this was not the case for units in multiunit apartment buildings.

Estimates of the number of buildings were obtained by dividing the sampling or base weight for each RECS sample housing unit in a multiunit building by the total number of housing units in that building. This information had been collected in the Household Survey for sample housing units in buildings with five or more housing units, but had not been collected for sample households in buildings with two to four housing units. Therefore, for the latter group, a constant divisor was used in each Census region, based on data from the 1990 Census of Housing and Population.

RECS estimates of the number and total floorspace of residential buildings are subject to two kinds of biases:

- The number of buildings is underestimated because RECS interviews are not conducted in vacant housing units. The amount of underestimation is likely to be similar to the housing unit vacancy rate, which was estimated by the Census Bureau's American Housing Survey to be about 9 percent in 1989.

- The size of multiunit buildings is understated because the floorspace of common areas, such as hallways, stairwells, elevators, and lobbies is not accounted for.

RECS estimates of energy consumption for multiunit residential buildings are probably also understated because they are made by applying appropriate weights to metered or estimated consumption for individual units in those buildings. Consumption for heating, cooling, and other uses in common areas of these buildings is not accounted for.

No attempt has been made to adjust the published estimates for these sources of bias. Their net effect on estimates of energy intensity (thousand Btu per square foot) is unknown.

End-Use Estimation

Introduction

In addition to knowing the total residential energy consumption for each of the five major fuels--natural gas, electricity, fuel oil, LPG and kerosene--energy analysts and policymakers need information about the allocation of these amounts to different end uses, such as space heating, water heating, air-conditioning, and appliances. However, utility bills, the primary source of data on total consumption, are not broken down by end use, nor is there any practical means by which such information could be obtained directly from each sample household. Consequently, an indirect, model-based nonlinear regression technique is used in RECS to provide estimates of the consumption of each fuel by end use for each sample household. The same technique is used to estimate total consumption for those households and fuels for which no usable utility bill data have been obtained.

There are three main steps in the modeling and estimation process:

1. For each fuel, parameter values in a preliminary model for end-use allocation are estimated by using data only for sample households that used the fuel, have usable billing data, do not have imputed values for key independent variables in the model, and meet other quality requirements. The process is iterated, eliminating (with some exceptions) independent variables whose estimated coefficients do not differ from zero by at least four standard deviations and, if necessary, removing outliers, i.e., households with large differences between estimated and reported consumption, from the data base. Model parameters for natural gas are estimated first, because certain relationships in the natural gas model are carried over to other fuels.

2. The final model from step 1, with estimated parameter values, is used to impute missing values for total consumption for each fuel.

3. For all sample households, the final model is used to estimate total consumption of each fuel by end-use category. For each household, the end-use consumption estimates are "normalized"; that is, they are adjusted proportionately to sum to the reported or imputed value of total consumption.

The RECS end-use estimation techniques have been gradually developed and refined since the first survey in 1978. Through the 1982 RECS, the techniques were considered experimental and the results were published in special reports and articles (EIA 1983c, Thompson 1987). Starting with the 1984 RECS, the estimates of end-use consumption by fuel have been published routinely in the *Consumption and Expenditures* reports (the data for 1984 were published in Volume 2, Regional Data, of the report). However, refinements have continued, as described in more detail below. The nature of the estimation procedure is such that the regression equations used in each survey year are unlikely to be identical to those used in the preceding survey year.

The specific estimation equations for each end use depend on the kinds of information collected in the Household Survey or from other sources that are relevant to that end use. For space-heating, for example, such variables as heating degree-days, type, size, and age of the housing unit, amount of heated space, thermostat settings, type of heating equipment, and amount and type of secondary space heating are all likely to be associated with variations in consumption. While many of these variables are of interest in their own right, the inclusion of questions needed to provide inputs to the end-use estimation equations has always been a major consideration in the choice of content for the RECS Household Survey questionnaire.

Although the full equations used for the 1984 survey were presented in the regional supplement to the *Consumption and Expenditures* report and the full equations for the 1987 and 1990 surveys were presented in the corresponding national *Consumption and Expenditures* reports, data users are cautioned with respect to interpretation of the coefficients that are associated with the independent variables.

As with any large regression, care should be taken in interpreting the individual coefficients in the equations. The variables that are used in the equations may be highly correlated with variables, which are not used in the equations. Thus the value of the coefficients will reflect both the impact of the included variables and the impact of any correlated excluded variables. For instance, the natural gas equations did not contain variables that used the type and R-value of insulation directly, but the impact of the type and amount of insulation is included through variables which indicate the presence of insulation (EIA 1993a, p. 198).

End-Use Estimation for the 1993 RECS

The 1993 end-use estimation model consisted of five nonlinear regression equations: one for each of the major energy sources. In each equation, the dependent variable was the total consumption for that fuel for the survey reference year. The equation expressed total consumption for the fuel as the sum of three or more components, corresponding to the end uses for which separate estimates were to be obtained, plus an error term. Each of these components was expressed, in turn, as a complex nonlinear function of household variables available from RECS.

For each fuel, the estimation equation included a space-heating and water-heating component. For fuel oil, LPG, and kerosene, there was one additional component, called "appliances," covering all other uses of that fuel. For natural gas, there was an additional component for air-conditioners and a residual category for appliances. For electricity, there were additional components for air-conditioners, refrigerators, freezers, lighting, cooking, dishwashers, clothes dryers, and all other appliances.

To illustrate the structure of the nonlinear regression model and its components, Figure 7.2 shows the basic equation used in the 1993 RECS for electricity and the formulation for one of its components, the one covering electricity consumption for freezers. The units of measure in Figure 7.2 are thousands of Btu’s. Although there are many variations in the variables by component and fuel, the basic structure of all components is similar. Typically, a component, such as the electricity freezer component shown in Figure 7.2, consists of a base term and one or more multiplicative adjustment terms. The base term models the energy consumption for a "standard" situation.

For the freezer component, the base term (FZBASE × CDDBASE) is a function of the number of freezers and cooling degree-days. There are four adjustment terms. The first two adjustment terms (MANUADJ and UPRTADJ) are functions of the type of freezer (manual defrost versus frost free and chest versus upright). The third adjustment term (AGEADJ) is a function of the age of the freezer. For the few households with two or more freezers, the adjustment terms are determined by the type and age of the largest freezer. (In effect, the model assumes any additional freezers are of the same type and age as the largest freezer. To save interviewing time, only the type and age of the largest freezer was recorded.)

Figure 7.2. Selected Components of the Nonlinear End-Use Consumption Model for Electricity Used in the 1993 RECS

Regression equation for electricity:

$$Y_{EL} = X_{SH} + X_{WH} + X_{AC} + X_{RFG} + X_{FZ} + X_{LGT} + X_{CK} + X_{DW} + X_{CD} + X_{OTAPL} + e$$

where Y_{EL} = *actual* annual consumption of electricity

X_{SH}, X_{WH}, X_{AC}, X_{RFG}, X_{FZ}, X_{LGT}, X_{CK}, X_{DW}, X_{CD}, and X_{OTAPL} are end-use components for space heating, water heating, air conditioning, refrigerator, freezer, lighting, cooking, dishwashing, clothes dryer, and all other appliances, respectively

and $e = Y^{1/4}_{EL} - \hat{Y}^{1/4}_{EL}$

with $\hat{Y}_{EL}$ being the *estimated* annual consumption of electricity.

Details for the Electricity Freezer Component: 1993 RECS

$$X_{FZ} = \text{FZBASE} \times \text{CDDBASE} \times \text{MANUADJ} \times \text{UPRTADJ} \times \text{AGEADJ} \times \text{TOTADJ}$$

where TOTADJ is an adjustment factor applied to all electricity components, based upon the price of electricity, demographic characteristics of the household, geographic location, and type of housing unit

and	FZBASE	= 2345 × (Number of freezers)
	CDDBASE	= 1 + (0.0170 × $(\text{CDD65})^{1/2}$)
	MANUADJ	= 1 - (0.2019 × MANUFZ)
	UPRTADJ	= 1 + (0.1123 × UPRTFZ)
	AGEADJ	= 1 + (0.2718 × FZ20PLUS) - (0.3203 × FZ4MNUS)

and	CDD65	= cooling degree-days to the base 65 degrees Fahrenheit
	MANUFZ	= 1 if largest freezer is a manual defrost freezer and 0 otherwise
	UPRTFZ	= 1 if largest freezer is an upright freezer and 0 otherwise
	FZ20PLUS	= 1 if largest freezer is 20 years old or more and 0 otherwise
	FZ4MNUS	= 1 if largest freezer is 4 years old or less and 0 otherwise.

The last adjustment term (TOTADJ) is used for all components in the electricity model. It includes variables that should have an effect on all electricity components. Examples of this are the price of electricity, the family income level, and other demographic characteristics of the household. The model assumes that the effect of variables used in TOTADJ is the same for all components. For instance, high income may imply bigger homes with bigger freezers, bigger appliances of other kinds, and more appliances. Thus, high income may be associated with higher electricity consumption for all end-uses.

Using a nonlinear formulation of the model, the freezer component requires the estimation of only six coefficients to model the effect of climate (number of cooling degree-days), type of freezer, and age of freezer on the electricity consumption of freezers. The model assumes that factors interact proportionally. For example, the effect of the age of a freezer on its electricity consumption is proportionally the same for all freezer types and for all climates. The resulting equation projects that, for freezers of the same type located in the same climate, the newest freezers use 32 percent less electricity than freezers in the next age group, while the oldest freezers use 27 percent more.

The model-fitting procedure was designed to minimize the sum of the squared error term over all households included in the analysis for each fuel. For the 1990 and 1993 RECS, as shown in Figure 7.2, the error term was equal to the difference between the fourth root of the actual consumption and the fourth root of the estimated consumption. The error term defined in this way was found to be more nearly normally distributed with a constant variance than alternative formulations of the error term, such as the simple difference or the difference between logarithms or square roots of the actual and estimated consumption.

Because the regression equations are nonlinear, the parameter values cannot be estimated with standard multivariate linear regression techniques. They were estimated by using a nonlinear regression procedure in the statistical computer package, SAS.[1]

As noted in the introduction to this section, the regression analysis for each fuel was based on a subset of the sample households using that fuel. Households were excluded from the analysis for many reasons, the principal ones being: they did not pay the supplier directly for all uses of the fuel (so that usable billing data were not available); other problems with the consumption data, such as data covering only part of a year or inclusion of nonresidential uses in the billing data; or imputed values of key independent variables, such as occurred for many variables when the Household Survey data were obtained by mail.

Table 7.1 shows the number and percents of sample households used in the regression analysis for each fuel type in the 1990 RECS. Of the households using each fuel, the proportion included in the analysis varied from slightly less than one-half for fuel oil to about two-thirds for electricity. A draft Technical Note on the 1990 regression analysis (Harrison 1993) provides additional detail on the data sets included in the analyses by housing unit type and major end-use category. That report identifies several fuel/end-use categories for which the number of sample households used was small, for example, natural gas air-conditioning (only eight observations were available), use of all fuels as secondary fuels for water heating, and use of fuel oil or kerosene for any purpose other than heating. Although separate models were not developed for each housing type (adjustment terms were developed to model differences by housing type), the report also notes that "Because there were more observations for households living in single-family detached homes, the regression analysis should give the best estimates for [these households]."

This relatively brief description has covered the highlights of the complex nonlinear regression models used in the 1993 RECS to allocate consumption of each fuel to end-use categories and to impute total consumption of the fuel when necessary. Substantial additional detail, including the equations used for each fuel and end use, is provided in: Appendix D, "End-Use Estimation Methodology," of the *Consumption and Expenditures 1990* report (EIA 1993a); Appendix C, "End-Use Estimation and Methodology," of the *Consumption and Expenditures 1993* report (EIA 1995d); and in the Technical Note cited above (Harrison 1993).

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[1] Statistical Analysis System (SAS) (Cary, NC).

Table 7.1. Number and Percent of Sample Households Used in Regression Analyses, by Fuel Type: 1990 RECS

Category	Fuel Type									
	Nat. Gas		Electricity		Fuel Oil[b]		LPG		Kerosene	
	No.	Pct.	No.	Pct.	No.	Pct.	No.	Pct.	No.	Pct.
Households Using Fuel	3,255	100.0	5,094	100.0	700	100.0	461	100.0	278	100.0
Used in Analysis	1,917	58.9	3,392	66.6	336	48.1	257	55.7	163	58.6
Not Used, by Reason[a]										
Didn't Pay for Some Used Directly	612	18.8	356	7.0	145	20.7	26	5.6	1	0.4
Quality of Consumption Data Not Acceptable	506	15.5	1,028	20.2	161	23.0	152	33.0	81	29.1
Key Independent Variables Imputed	220	6.8	318	6.2	50	7.1	22	4.8	15	5.4
Other[c]	NA	NA	NA	NA	8	1.1	4	0.9	18	6.5

[a]Each household not used is counted under the first applicable reason.
[b]Data for Model A only, see Source, p. 45.
[c]Did not purchase or, for kerosene only, did not use for space heating.
NA = Not Applicable.
Source: Latta, *Poststratification Estimation* (May 1993).

Changes in End-use Estimation Methodology: 1978-1993

The RECS energy consumption end-use estimation procedures and models have never been precisely the same from one survey to the next. Changes occur for several reasons. First, there have been many changes in the content of the Household Survey questionnaires and hence in the data items available for use as independent variables in the regression analyses. Many of the questionnaire changes have been motivated by the desire to collect new information that could be used either to reduce the size of the error term in the basic equations or to introduce new end-use categories for which separate estimates could be made. In the 1990 RECS, the appliance category for electricity was subdivided into refrigerators, freezers, and other appliances.

In the 1993 RECS, the addition of new questions on lighting and electric appliances made it possible to further subdivide the appliance category for electricity to provide separate end-use estimates for lighting, cooking, clothes dryers, and dishwashers.

Second, even if the questionnaire content and the model specification were to remain unchanged from one survey to the next, the estimates of the model parameters would change, due in part to sampling variability of the estimates and in part to real changes in the underlying relationships of the independent variables. It is also possible that some parameter estimates that met the basic test for significance in one survey year might not qualify in a subsequent survey year. However, the initial significance test criterion has been loosened somewhat, in order to improve comparability of end-use estimates over time and to avoid eliminating variables that appear to have intrinsic validity as part of the model.

Third, there have been some basic changes in the structure of the model used for end-use allocation of energy consumption. A major change occurred in the 1984 RECS when the linear model used in prior surveys, for which parameter values could be estimated by standard multivariate least squares regression, was replaced by a nonlinear model requiring a different estimation method. The decision to adopt a nonlinear model was reached after extensive experimentation with and evaluation of both linear and nonlinear models and associated procedures to estimate end-use consumption by fuel, using data from the initial survey years (see following subsection on "Evaluation of End-use Estimation Procedures").

There were three major reasons for the change to a nonlinear model: (1) the ability to formulate a more realistic model; (2) the ability to formulate the model in a way that avoids negative estimates for households that have a combination of factors all pointing to lower energy consumption; and (3) the ability to formulate the error term in a way that results in its distribution being approximately normal, with a constant variance.

To understand these advantages, it may be useful to consider a possible linear formulation of one component of the nonlinear model now in use. Figure 7.3 shows a linear formulation of the model for electricity and its freezer component. Like the nonlinear formulation, the linear one uses actual annual consumption of electricity as the dependent variable. The error term for the linear model, following the usual practice, is the difference between actual and estimated annual electricity consumption. The coefficients for the terms of the freezer component--a_1, a_2, a_3, a_4, a_5, and a_6--would be estimated using linear regression. Knowledge of the characteristics of freezers gives the expectation that a_1, a_2, a_4, and a_5 would be positive and that a_3 and a_6 would be negative.

The model in Figure 7.3 does not include interaction terms for the climate, type, and age of the freezers. Interaction terms could be added. The model does not include terms for the effects of the price of electricity or the family income on the freezer component. (Lower electricity prices and/or higher income could be associated with larger freezers.) Again, interaction terms could be added.

The use of many interaction terms in the linear model may result in a formulation that looks more realistic, but the actual estimated coefficients may result in unrealistic estimates for some combinations of type of freezer, age of freezer, climate, income level, and electricity price. Some estimates could even be negative. The use of a nonlinear model allows the formulation of a more realistic model using far fewer terms than would be needed with a linear model. The use of fewer terms in the model reduces the possibility of unrealistic estimates for some combinations.

Analysis of the residual terms from the linear model previously used shows that the error terms were not normally distributed with constant variance. In fact, the error terms were skewed in the positive direction and the variance of the error terms increased as the projected energy consumption increased. The use of weights can alleviate the effect of trends in the variance of error term with either linear or nonlinear regression. However, weights alone do not alleviate the effect of the skewness of the error terms.

Figure 7.3. An Alternative Linear Formulation of the Model Components Shown in Figure 7.2

Regression equation for electricity:

$$Y_{EL} = X_{SH} + X_{WH} + X_{AC} + X_{RFG} + X_{FZ} + X_{LGT} + X_{CK} + X_{DW} + X_{CD} + X_{OTAPL} + e$$

where Y_{EL} = *actual* annual consumption of electricity

X_{SH}, X_{WH}, X_{AC}, X_{RFG}, X_{FZ}, X_{LGT}, X_{CK}, X_{DW}, X_{CD}, and X_{OTAPL} are end-use components for space heating, water heating, air-conditioning, refrigerator, freezer, lighting, cooking, dishwashing, clothes dryer, and all other appliances, respectively

and $e = Y_{EL} - \hat{Y}_{EL}$

with $\hat{Y}_{EL}$ being the *estimated* annual consumption of electricity.

Details for the Electricity Freezer Component: 1993 RECS

$$\begin{aligned} X_{FZ} = \; & a_1 \times (\text{Number of freezers}) \\ & + a_2 \times (\text{Number of freezers}) \times (\text{CDD65})^{1/2} \\ & + a_3 \times (\text{Number of freezers}) \times \text{MANUFZ} \\ & + a_4 \times (\text{Number of freezers}) \times \text{UPRTFZ} \\ & + a_5 \times (\text{Number of freezers}) \times \text{FZ20PLUS} \\ & + a_6 \times (\text{Number of freezers}) \times \text{FZ4MNUS} \end{aligned}$$

where CDD65 = cooling degree-days to the base 65 degrees Fahrenheit
MANUFZ = 1 if largest freezer is a manual defrost freezer and 0 otherwise
UPRTFZ = 1 if largest freezer is an upright freezer and 0 otherwise
FZ20PLUS = 1 if largest freezer is 20 years old or more and 0 otherwise
FZ4MNUS = 1 if largest freezer is 4 years old or less and 0 otherwise.

The error term adopted for the nonlinear model introduced in 1984 was the difference between the logarithms of actual and estimated consumption. This error term was closer to being normally distributed, but its variance was still not constant for all energy and household types. This problem was dealt with by using a weighted regression method in which households in categories with high error variances were given lower weights. For example, for natural gas a weight of 1.0 was given to most households, but a weight of 0.2 was assigned to households using natural gas which:

1. Did not use it as a main space-heating or water-heating fuel.

2. Did not use it as a main water-heating fuel, did use it as a main space-heating fuel, and the main equipment was a natural gas floor furnace, wall furnace, pipeless furnace, or room heater.

In the 1990 RECS, the logarithmic error term used in 1984 and 1987 was replaced by the one shown in Figure 7.2--that is, the difference between the fourth roots of actual and estimated consumption of each fuel. Investigation of four alternative error terms--linear, logarithmic, square root, and fourth root--had shown that the last of these came closest to meeting the basic requirements for normality and constant variance. With the introduction of the new error term, the weighted regression procedures used in 1984 and 1987 were no longer necessary.

There have also been some conceptual changes involving the definition of certain end-use components of the model. In the 1984 RECS, electricity used to run fans for central forced-air heating systems was assigned to the space-heating component for electricity. In subsequent survey years, electricity used for this purpose was assigned to the appliance component rather than the space-heating component. This change was made so that households which did not use electricity for space heating would not have any consumption of electricity assigned to the space-heating component. A similar change was made for electricity used to operate whole-house fans, ceiling fans, window fans, and evaporative (swamp) coolers. In 1984, electricity used for these purposes was included in the air-conditioning component; since 1987, it has been included in the appliance component.

Evaluation of End-Use Estimation Procedures

In recent years, new technologies have made it possible to measure the consumption of electricity for individual appliances and other uses within the home, a process often referred to as submetering (Windell 1986). Conceivably, similar technologies could also make it possible to measure amounts of natural gas used for space heating, hot water heating, cooking, and other uses. An ideal means of evaluating the RECS end-use estimation models for electricity and natural gas would be to measure end-use consumption of these fuels in a subset of RECS sample households and compare these direct measurements with estimates generated by the nonlinear regression models for the same households. However, there are two obstacles to such a project: the high cost per household of installing the monitoring equipment and the difficulty in enlisting an acceptably high proportion of households in a national probability sample to agree to participate in such a study. Consequently, efforts to evaluate the RECS end-use estimation procedures have so far relied on less direct methods. Three studies that have been undertaken are described in this subsection.

As noted earlier in this section, end-use allocation for the first five survey years, 1978 through 1982, was based on a linear model, with the nonlinear model being introduced in the 1984 survey. The independent variables included in the linear model varied during the five survey years for which it was used, as new items were added to the Household Survey questionnaire.

Following the 1984 RECS, an exploratory study was undertaken to examine the effects on the end-use estimates of using different models (Carroll 1987). The study also looked at the effects of the models on estimates of total consumption for each fuel, because the same models were being used to impute total consumption for households for fuels for which direct data were not available. For the survey years 1978, 1980, 1981, 1982, and 1984 (the 1979 survey was not included in the study), estimates of total consumption and consumption by end use were developed by using two different nonlinear models: one (called the NIECS-based model) using only those variables, which were available from all five surveys, and the other (called the 1984 RECS-based model) using all of the variables available from the 1984 RECS, with substitution of proxy variables for those for which data were not collected in earlier surveys. For example, the study report states that "Income dummy variables proved to be effective proxies for the [unavailable air-conditioning] use data in the 1978 and 1980 surveys."

The only results available from this study are from a preliminary report which does not include all of the basic tabulations. Some of the author’s conclusions were as follows:

- Compared to the linear models, the nonlinear models consistently allocated more consumption to space cooling and less to appliances.

- The overall predictive power of the NIECS-based nonlinear model (which included fewer independent variables) was slightly lower than that of the 1984 RECS-based nonlinear model, accounting for 10 percent less of the total variance. However, there was relatively little difference in mean consumption amounts estimated by the two models.

- Differences between the end-use allocations estimated by the NIECS-based and RECS-based nonlinear models were small, except for space cooling.

The other two studies were about end-use allocation of residential consumption of electricity, and both of them made use of residential submetering data collected by electric utilities. Battles (1990) reports on a comparison of nonlinear model-based estimates of electricity consumption by end use from the 1987 RECS with estimates based on submetering data collected for various studies by eight electric utilities. The comparisons covered four end uses of electricity: space heating, room air-conditioning, central air-conditioning, and water heating. The method of comparison for each of the eight utilities was to select a subset of RECS sample households from the same Census division that matched as closely as possible on known characteristics of the households for which the utility had obtained submetering data. All households in the study were in single family housing units. Other characteristics taken into account for all or some of the utilities were heating and cooling degree-days, tenure, floor area, and the use of certain appliances. The RECS end-use estimates for this subset of sample households were then compared with the corresponding estimates for the households that had been submetered by the utility, taking into account the sampling errors associated with the RECS estimates.

Given the large sampling errors associated with the RECS estimates and the fact that the households studied by the utilities did not constitute a probability sample of the same population, the results of the comparisons can only be roughly indicative of possible biases in the RECS model-based estimates. Battles concluded that the RECS model-based estimates were "reasonable estimates" when compared to the utilities’ submetered estimates. However, she stated that:

> This study does, though, reveal some areas where further investigation may be warranted. All of the submetered estimates for both air-conditioning and space heating are lower than the RECS CDA [conditional demand analysis] comparative estimates and all water-heating submetered estimates are higher than the RECS CDA comparative water-heating estimates. The consistency in differences is important. (Battles 1990, p.12)

The other study that made use of submetered data on consumption of electricity (Response Analysis Corporation 1992c,d) compared the utility data with RECS estimates of end-use consumption based on the model used in the 1990 RECS. As explained earlier in this section, the 1990 RECS was the first to use an error term based on the fourth roots of estimated and actual consumption, as opposed to the logarithmic error term used in 1984 and 1987. The study used submetering data and information on household and demographic characteristics that had been obtained for samples of households by five utilities. Only those households for which both kinds of information were complete were included in the study: sample sizes by utility varied from 13 for the City of Austin to 182 for Pacific Gas and Electric. All of the utilities provided end-use load data on water heating and all provided data on one or more of the following: central air-conditioning, room air-conditioning, space heating, total HVAC (heating, ventilation and air-conditioning), refrigerators, and total appliances.

Because the utilities did not collect all of the household and demographic information that is available for RECS sample households, a separate modified end-use estimation model was developed for each of the five utilities, making use only of the variables that were available for that utility. The submetered end-use data for that utility were then compared with three sets of estimates:

1. Estimates for the utility's sample households based on the modified RECS model

2. Estimates for a selected set of RECS sample households, similar in their characteristics to the utility's sample households, based on the modified RECS model

3. Estimates for the same set of RECS sample households, based on the full RECS model.

Assuming that estimates based on the modified RECS model do not differ significantly from those based on the full model, the comparison of the submetered data with set 1 provides the best indicator of how well the statistical end-use model allocates consumption. In some instances it appeared that the assumption was not valid, so adjustments were made to the estimates in set 1 on the basis of the relationship between sets 2 and 3.

Table 7.2 shows the percentage differences between the submetered end-use data and the *adjusted* model-based estimates for the same households (set 1). The findings for four of the five utilities were consistent with the indications from the previous study that the RECS end-use estimation model might be overestimating consumption for central and room air-conditioning and space heating and underestimating consumption for water heating. Findings for the Bonneville Power Administration were in the opposite direction. The authors of the report suggest that the RECS end-use models might be improved by developing a separate model for each region, on the grounds that the factors that determine space-heating and air-conditioning consumption in different climates may be quite different.

Table 7.2. Percentage Difference[a] Between Modeled and Submetered End-Use Estimates

End-Use Estimate	Utility				
	Austin	BPA[b]	PGE[c]	Santee Cooper	SCE[d]
Central Air-Conditioning	40%	NA	370%	13%	33%
Room Air-Conditioning	NA	NA	17%	NA	69%
Space Heating	54%	-10%	NA	33%	NA
HVAC	84%	-22%	NA	27%	NA
Water Heating	-25%	4%	-23%	-8%	NA
Refrigerators	NA	-23%	0%	NA	18%
Appliances	-27%	5%	NA	-1%	NA

[a]Percent difference = $\frac{\text{(Modeled estimate - Submetered estimate)}}{\text{Submetered estimate.}} \times 100$

[b]Bonneville Power Administration.
[c]Pacific Gas and Electric.
[d]Southern California Edison.
NA = Not Available.
Source: Response Analysis Corporation (1993).

Sampling Errors

The sampling error of each published statistic is estimated by using the balanced half-sample replication method. The estimated sampling errors are used to check the validity of statements made in the text of survey reports and as the basis for suppressing estimates whose relative standard errors are 50 percent or more. Due to space limitations, the estimated sampling errors for the individual table cells are not published, but the estimates provide the basis for the derivation of generalized variance functions, which are published and permit users to compute an approximate relative standard error for each published estimate.

This section describes the procedures used for the estimation and publication of sampling errors in the 1993 RECS, followed by information about changes in the methodology used in earlier surveys. The section concludes with a discussion of the accuracy of sampling error estimates and the extent to which RECS has achieved its goals for the precision of key estimates of energy consumption. Readers who would like additional detail about the derivation and use of sampling errors in RECS may refer to the introductions and appendices of the *Housing Characteristics* and the *Consumption and Expenditures* reports for each survey year--for example, pp. 18-20 and 231-236 in the *Housing Characteristics* report for 1993 (EIA 1995a).

Estimation of Sampling Errors for the 1993 RECS

The half-sample replications were formed from 78 "super strata," each containing pairs of sample households:

- Thirty-eight of the super strata consisted of pairs of non-self-representing strata from the same Census Division. Strata from the four most populous States (California, New York, Texas, and Florida), which had been formed so as not to cross State lines, were always paired with other strata from the same State. Within Census Divisions and also within the four most populous States, strata for Metropolitan Statistical Areas (MSA's) were paired with other MSA strata and non-MSA strata were paired with other non-MSA strata. The pairs in each of the 31 super strata consisted of the sample households in the primary sampling units selected from each of the two strata.

- Thirty-one of the super strata consisted of large metropolitan areas that had been selected with certainty. The pairs consisted of sample households in two sets of the secondary sampling units that had been selected from the metropolitan area.

- The nine remaining super strata each consisted of a single non-self-representing stratum. The pairs consisted of sample households in two sets of the secondary sampling units that had been selected from the sample PSU in that stratum. These non-self-representing strata were not combined with other non-self-representing strata because of restrictions on combining strata with differing attributes, for example, strata in different Census divisions.

Ninety-six half samples were formed from the 78 super strata by selecting, in each instance, one of the pairs of sample households from each super stratum. The selection was balanced--that is, it was carried out in such a way that each pair member from a super stratum was included in 48 of the 96 half samples. To produce sample estimates from each of the 96 half samples, the sampling weights were ratio-adjusted upwards so that the sum of the weights was equal to the control totals (housing-unit counts derived from the Current Population Survey) for each of the nine Census divisions and four States--California, New York, Texas, and Florida.

The estimated variance for each sample estimate was the mean squared deviation of the 96 half-sample estimates from the full sample estimate. Because the ratio adjustments to control counts were applied to each half sample, the estimated housing-unit counts for the nine Census divisions have zero variance. For estimates of housing-unit counts that are close to the control counts, such as the number of housing units using electricity or the number with refrigerators, the sampling errors are very small.

Generalized Variances

Showing the estimated sampling error for each published statistic would roughly double the space required for publication of tabulations. As an alternative, generalized variance functions, which permit users to determine an approximate value of the relative standard error (RSE) for each table cell, are included in the publications. Figure 7.4 shows an example of a 1990 RECS publication table with "row and column factors" which can be used as shown in the example to determine the relative and absolute standard errors and a confidence interval for any cell in the table.

Figure 7.4. Example of the Use of RSE Row and Column Factors to Derive Approximate Standard Errors

Characteristics	Major Energy Sources	Electricity	Natural Gas	Fuel Oil	Kerosene	Liquified Petroleum Gas	RSE Row Factors
RSE Column Factors	0.9	0.8	0.7	0.7	1.5	1.9	
Total U.S. Households	12.0	23.6	5.6	7.8	9.4	11.2	1.3
Urban Status							
Urban	11.9	24.6	5.7	7.8	9.5	11.4	1.7
Central City	11.2	24.3	5.8	7.3	9.8	14.3	3.1
Suburban	12.4	24.8	5.6	8.0	9.2	11.2	1.8
Rural	12.2	20.8	5.2	7.8	9.4	11.0	2.6
Climate Zone							
Under 2,000 CDD and Over 7,000 HDD	10.2	21.6	5.0	7.7	9.5	10.1	3.5
5,500 to 7,000 HDD	10.1	24.6	5.3	7.9	9.2	11.2	2.8
4,000 to 5,499 HDD	12.0	23.5	6.3	7.8	9.9	11.2	3.6
Under 4,000 HDD	13.8	24.3	5.8	8.0	9.0	11.5	2.5
2,000 CDD or More and Under 4,000 HDD	15.9	23.0	5.9	Q	10.3	12.9	5.2
Type of Housing Unit							
Single-Family	11.9	23.3	5.5	8.0	9.5	11.0	1.5
Detached	11.8	23.2	5.4	8.0	9.5	11.0	1.6
Attached	12.9	24.5	6.1	8.1	9.8	Q	3.6
Mobile Home	13.0	21.6	5.3	8.2	9.4	11.7	2.9
Multifamily	11.9	25.6	6.1	7.2	8.5	13.5	3.8
2 to 4 Units	10.7	26.5	6.1	8.1	Q	13.1	4.3
5 or More Units	13.4	24.9	6.0	5.9	Q	Q	3.3

Row Factor (Urban) = 1.7
Column Factor (Electricity) = 0.8

Approximate RSE (Average Electricity Expenditure in the Urban Area) = (1.7) * (0.8) = 1.36 percent.

Approximate Standard Error (Average Electricity Expenditure in the Urban Area) = (.0136) * (24.6) = 0.33 Dollars per Million Btu.

Approximate 2 Standard Errors (95 percent confidence interval) = (1.96) * (0.33) = 0.6 Dollars per Million Btu.

Therefore, with 95 percent confidence, the average electricity expenditure in the Urban area is between 24.0 and 25.2 Dollars per Million Btu (24.6 ± 0.6).

Source: Energy Information Administration, Office of Energy Markets and End Use, 1990 Residential Energy Consumption Survey.

The publication also explains how to use the RSE's for the appropriate table cells to determine the RSE's for percentages based on household counts and for the ratios and differences of two statistics (under the assumption that they are independent). The row and column factors for each publication table are derived by using the estimated RSE's for the table cells to estimate the parameters of a log-linear model,

$$\log(RSE_{ij}) = m + a_i + b_j.$$

The row factor for the ith row is the geometric mean of the RSE's in that row and the column factor for the jth column is an adjustment factor with geometric mean equal to one. Special procedures are used for cells with very large or very small RSE's or missing values.

The row and column factors are derived separately for each publication table. Consequently, an estimate that appears in more than one table may have different RSE's arrived at by using different sets of row and column factors. Any of these values should provide a useful approximation to the relative standard error for that item as estimated by the replication method (EIA 1986b).

Estimates of Change Between Surveys

When comparing statistics between survey years, assuming independence of the estimates from different surveys will, in most instances, lead to an *overestimate* of the sampling error of a difference or ratio of estimates of the same variable for different years. This occurs because the samples for different years are not in fact fully independent. For most survey years, the sample PSU's have been the same as those used in the previous survey year, and even in those years when new samples of PSU's were selected, the selection procedure was designed to maximize the overlap between the old and new samples. In addition, the samples for survey years 1982 through 1990 included longitudinal components, so that in each of these years approximately one-half of the sample housing units had also been included in the sample for the preceding survey year (except for 1982, when the overlapping units had been included in the 1980 survey). For most survey variables, one would expect estimates for different years from these overlapping samples to be positively correlated, leading to reductions in the sampling errors of their differences or ratios.

Better estimates of the sampling error of change between survey years under these conditions are possible with the balanced half-sample replication method, provided that the same sets of half samples are used for the two years in question and the differences are estimated from each half sample. Sampling errors were estimated by this method and compared with sampling errors estimated under the assumption of independence for selected variables and pairs of survey years from 1978 through 1984 (EIA 1987c, pp. 217-225). Some of the results are shown in Table 7.3. For virtually all of the variables and pairs of years shown, the more precise estimates of sampling errors of differences (Method 2) are substantially smaller than sampling errors calculated under the assumption of independence (Method 1). The reductions for the 4-year interval, 1980 to 1984, are less than those for either of the 2-year intervals, 1980 to 1982 and 1982 to 1984. The reasons for these smaller reductions are not entirely clear, because the pattern of sample overlap for these periods was relatively complicated. However, a reduction in the correlation over time for longer intervals may have been a contributing factor.

Table 7.3. Comparison of Standard Error of Difference Estimated by Two Methods for Changes in Average Consumption per Household Between Survey Years

Years and Fuel	Average Consumption[a]			Standard Error		
	Year 1	Year 2	Difference[b]	Method 1[c]	Method 2[d]	Percent Difference[e]
1980 and 1982						
All fuels	114.2	102.9	-11.2	2.3	1.2	49
Electricity	30.1	28.9	-1.2	1.0	0.4	59
Natural gas	95.7	88.1	-7.6	2.2	1.4	36
Fuel oil/kerosene	100.8	73.4	-27.0	3.5	2.0	42
LPG	47.6	39.4	-8.2	3.4	2.1	38
1982 and 1984						
All fuels	102.9	104.7	1.7	2.2	1.1	48
Electricity	28.9	28.8	-0.2	0.9	0.5	49
Natural gas	88.1	89.9	1.8	2.1	1.4	32
Fuel oil/kerosene	73.4	71.9	-1.5	3.4	2.7	22
LPG	39.4	40.1	0.7	3.3	2.6	21
1980 and 1984						
All fuels	114.2	104.7	-9.5	2.3	1.7	25
Electricity	30.1	28.8	-1.4	0.8	0.4	45
Natural gas	95.7	89.9	-5.8	2.2	1.8	20
Fuel oil/kerosene	100.8	71.9	-28.9	3.4	3.4	1
LPG	47.6	40.1	-7.5	3.4	3.2	6

[a]Average consumption per household using fuel, in millions of Btu.
[b]Due to rounding, may not be consistent with values shown in table for Years 1 and 2.
[c]Assumes estimates for Years 1 and 2 are independent.
[d]Reflects correlation between estimates for Years 1 and 2.
[e]Percent reduction from using Method 2. Due to rounding, may not be consistent with values shown for Methods 1 & 2.
Source: Energy Information Administration (1987).

Changes in Methodology

The same basic method of estimating sampling errors, balanced half-sample replication, has been used in all survey years. There have been several changes in estimation procedures and the methods of presenting information about sampling errors in RECS publications:

- The number of half samples used has varied. From 1978 through 1982, 32 half samples were used, except in 1979, when there were 72. In the 1984, 1987, and 1990 surveys, 128 samples were used and, as noted earlier, 96 were used in the 1993 RECS.

- In the 1978 NIECS, the same overall weights were used for each half sample, so that the effects of nonresponse adjustments and ratio estimates to control totals were not reflected in the estimated sampling errors. In the following year and subsequently, separate weights were developed for each half sample.

- The composition of the "super strata" used to form half samples has varied, mainly because of changes in the design of the RECS sample. In the first three surveys, all non-self-representing strata were paired to form super strata. Subsequently, it was decided that certain restrictions should be placed on pairing, such as not pairing strata from different Census divisions. Non-self-representing strata that could not be paired under these restrictions were treated as separate super strata, with the half samples being formed from two sets of secondary sampling units in the sample primary sampling unit for each super stratum.

- In the 1978, 1979, and 1980 survey reports there were two separate sets of tables, one containing the sample estimates and the second containing the estimated sampling errors corresponding to many of the estimates shown in the first set. Various methods were suggested for estimating sampling errors not shown in the second set of tables. Tables of individual sampling errors were dropped from the reports after 1980 and a series of procedures, based on various methods of estimating generalized sampling errors, was provided in one of the appendices to each report. The *Consumption and Expenditures* report for 1984 introduced the method of showing row and column factors in the data tables, and this approach has been followed since then.

Limitations of Sampling Error Estimates

Estimates of sampling error are themselves subject to sampling error. Their sampling error would be minimized if all possible half samples were used in the balanced half-sample replication estimates, but the cost of doing so would be prohibitive, so a subset is used. The larger the subset, the closer the estimated sampling errors will be to the value obtained by use of all possible half samples.

For the super strata formed by collapsing non-self-representing strata, sampling errors are overestimated because the reduction in sampling error resulting from stratification is not fully reflected. On the other hand, sampling errors for the super strata that consist of a single non-self-representing stratum are underestimated, because the estimates do not reflect the between primary sampling unit component of the variance for these strata. No data are available on the net effect of these biases, which are inherent in the estimation of sampling errors for a sample design that selects a single primary sampling unit from each stratum.

Sampling errors for estimates of energy consumption and expenditures by end use are understated, because the parameters of the nonlinear end-use allocation model are not estimated separately for each half sample. Thus, the estimated sampling errors do not reflect the error of estimation of the model parameters. Sampling errors for the 1990 end-use estimates were calculated, but not published, for this reason. Sampling errors or row and column factors have been published for 1984, 1987, and 1993. In the *Consumption and Expenditures* report for 1993 (EIA 1995d), the row and column factors for end-use estimates were footnoted to indicate that they were underestimates.

The generalized estimates of sampling errors that have appeared in the published RECS reports since 1984 are approximations to the values estimated directly for published data cells. As noted above, the direct estimates were presented only for selected items in the 1978, 1979, and 1980 RECS reports and have not been published in subsequent reports. A detailed analysis of the differences between the direct estimates of sampling error and the approximations based on row and column factors was undertaken for the 1983 Nonresidential Buildings Energy Consumption Survey (EIA 1986b, pp. 200-203). The measure of accuracy chosen for that analysis was the root mean square, along a table column, of differences of the base-10 logarithms of the approximate and direct estimates of the relative standard errors. For most table columns, these values were found to correspond to percentage differences between 20 and 60. The differences from the direct estimates were fairly evenly distributed between positive and negative values.

Sampling Error Targets for Key Estimates

The 1993 RECS sample was designed to produce estimates of average energy expenditures with sampling errors no greater than specified target levels: 1.25 percent for the national estimate, 2.75 percent for estimates by Census region and 4.50 percent for estimates by Census division. As shown in Table 7.4, actual sampling errors, whether estimated directly or by using the appropriate row and column factors, were all below these target values. Achievement of values that were well below the targets in some instances resulted in part from the supplementation of the 1993 core sample with special samples designed to strengthen sample coverage of newly constructed housing units and low income households.

Design Effects

Notwithstanding best efforts to develop a sampling frame consisting of heterogeneous clusters, the sampling errors of estimates based on a complex multistage cluster sample like the one used in RECS are usually greater than the sampling errors that would have been obtained if a simple random sample of the same size had been used. The cluster design is, of course, preferred, because it can produce the desired level of reliability at a lower cost than a simple random sample can.

A recent analysis of the RECS sample design produced estimates of the optimum number of primary sampling units (PSU's), secondary sampling units per primary sampling unit, and households per secondary sampling unit for several categories of RECS variables (EIA 1994). Table 7.5 shows the design effects, expressed as the ratio of the variance or standard deviation to the variance or standard deviation for a simple random sample of the same size, for the optimum size clusters and for those actually used in the 1993 RECS. Number of PSU's and cluster sizes for the optimum designs were based on core samples of 5,095 housing units. As the table shows, the design effects on the standard deviation ranged from 1.21 to 1.26 for the designs using optimum cluster sizes and from 1.39 to 1.60 for the actual 1993 sample design. Design effects for estimates of consumption and expenditures were somewhat higher than those for other types of variables.

Table 7.4. Sampling Errors for Estimates of Average Consumption per Household: 1993 RECS

Area	Relative Standard Error (Percent)		
	Target	Approximation[a]	Direct Estimate
United States	1.25	1.04	1.08
Census Region			
Northeast	2.75	1.92	2.61
Midwest	2.75	1.84	2.24
South	2.75	2.00	2.10
West	2.75	2.08	2.19
Census Division			
New England	4.50	3.28	4.23
Middle Atlantic	4.50	2.32	3.14
East North Central	4.50	2.00	3.04
West North Central	4.50	3.68	2.88
South Atlantic	4.50	2.80	3.16
East South Central	4.50	3.44	3.83
West South Central	4.50	3.68	4.17
Mountain	4.50	3.44	3.89
Pacific	4.50	2.64	2.72

[a]Approximate values based on row and column factors.
Sources: Energy Information Administration, *Consumption and Expenditures* (1993a); Energy Information Administration (1994).

Table 7.5. Design Effects for RECS, Using Optimum and Actual Cluster Sizes

Sample Design and Type of Variable	Number of PSU's m	SSU's per PSU $\bar{n}$	Housing Units per SSU[a] q	Design Effect on	
				Variance[b]	Standard Error
Optimum Design					
Consumption and Expenditures	201.2	16.83	1.50	1.586	1.259
Housing Unit Characteristics	152.8	23.10	1.44	1.472	1.213
Appliances	92.9	30.60	1.79	1.492	1.221
Demographic	94.6	31.14	1.73	1.480	1.217
Actual 1993 Design					
Consumption and Expenditures	116	13.88	3.06	2.558	1.599
Housing Unit Characteristics	116	13.88	3.06	2.337	1.529
Appliances	116	13.88	3.06	1.937	1.392
Demographic	116	13.88	3.06	1.974	1.405

[a]For actual 1993 design, includes only the base sample.
[b]DEF = $h_1 \bar{n} q + 1 + h_2 (q - 1)$ where h_1 = within PSU measure of homogeneity.
h_2 = within SSU measure of homogeneity.
Source: Energy Information Administration (1994).