Title

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Publication Date

1994-05-01

LBL-34046
UC-1330

Lawrence Berkeley Laboratory
UNIVERSITY OF CALIFORNIA

ENERGY & ENVIRONMENT DIVISION

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May 1994

ENERGY & ENVIRONMENT DIVISION

Prepared for the U.S. Department of Energy under Contract Number DE-AC03-76SF00098

LBL-34046
UC-350

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This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Planning and Analysis and Office of Building Technologies, and the Deputy Undersecretary of the Office of Policy, Planning, and Analysis of the U.S. Department of Energy under Contract No. DE-AC03-76SF00098.

ABSTRACT

This report details the data, assumptions and methodology for end-use forecasting of appliance energy use in the U.S. residential sector. Our analysis uses the modeling framework provided by the Appliance Model in the Residential End-Use Energy Planning System (REEPS), which was developed by the Electric Power Research Institute (McMenamin et al. 1992). In this modeling framework, appliances include essentially all residential end-uses other than space conditioning end-uses. We have defined a distinct appliance model for each end-use based on a common modeling framework provided in the REEPS software. This report details our development of the following appliance models: refrigerator, freezer, dryer, water heater, clothes washer, dishwasher, lighting, cooking and miscellaneous. Taken together, appliances account for approximately 70% of electricity consumption and 30% of natural gas consumption in the U.S. residential sector (EIA 1993). Appliances are thus important to those residential sector policies or programs aimed at improving the efficiency of electricity and natural gas consumption.

This report is primarily methodological in nature, taking the reader through the entire process of developing the baseline for residential appliance end-uses. Analysis steps documented in this report include: gathering technology and market data for each appliance end-use and specific technologies within those end-uses, developing cost data for the various technologies, and specifying decision models (both the functional form and equation parameters) to forecast future purchase decisions by households. Our implementation of the REEPS 2.1 modeling framework draws on the extensive technology, cost and market data assembled by LBL for the purpose of analyzing federal energy conservation standards. The resulting residential appliance forecasting model offers a flexible and accurate tool for analyzing the effect of policies at the national level.

The proliferation of models and model parameters and the lack of detailed documentation in the end-use forecasting area have been sources of considerable confusion for practitioners and policy-makers alike. By making explicit the data and assumptions behind our analysis, we seek to clear up some of this confusion and move the energy efficiency debate beyond simply the numerical results of models.

FORWARD AND ACKNOWLEDGEMENTS

This project was undertaken at Lawrence Berkeley Laboratory (LBL) under the direct supervision of Jonathan Koomey, and with the guidance of James E. McMahon and Mark D. Levine. The purpose of this work is to create a well-documented end-use forecasting model for the residential sector, and to use that model to analyze national policies affecting the efficiency and patterns of energy use in the U.S.

The work adopts the modeling framework of the Residential End-Use Energy Planning System (REEPS) developed for the Electric Power Research Institute (EPRI). This report is one of a series of three reports documenting the residential sector end-use forecasting project using EPRI-REEPS 2.1, which is the most recent version of the computer software. The first report in the series summarizes the model framework and inputs, and presents the results of the baseline forecast for each end-use (LBL-34044). The other two reports detail the data, assumptions and methodology for the two distinct groups of end-uses in the residential sector. The second report (LBL-34045) covers the space conditioning end-uses of Heating, Ventilating and Air Conditioning (HVAC) while this, the third report (LBL-34046), covers appliances, including water heating, refrigerators, freezers, clothes washers, clothes dryers, dishwashers, lighting and cooking.

We are grateful for the funding and insights provided by Eric Petersen and David Patton of the Office of Planning and Assessment, Dick Jones of the Office of Building Technologies, and Ted Williams and Jim Kelly in the Office of Policy, Planning, and Analysis of the U.S. Department of Energy.

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Office of Planning and Analysis and Office of Building Technologies, and the Deputy Undersecretary of the Office of Policy, Planning, and Analysis of the U.S. Department of Energy under Contract No. DE-AC03-76SF00098.

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1. INTRODUCTION

This report details the data, assumptions and methodology for end-use forecasting of appliance energy use in the U.S. residential sector. Our analysis uses the modeling framework provided by the Appliance Model in the Residential End-Use Energy Planning System (REEPS), which was developed by the Electric Power Research Institute (McMenamin et al. 1992). In this modeling framework, appliances include essentially all residential end-uses other than space conditioning end-uses. The space conditioning end-uses include Heating, Ventilating and Air Conditioning (HVAC) and are discussed in a separate report (Johnson et al. 1994). For appliances, REEPS allows the user to define a distinct appliance model for each end-use based on a common modeling framework provided in the software. Each appliance model can then be configured for a given end-use with its own structure, data, and functional relationships. This report details our development of the following appliance models: refrigerator, freezer, dryer, water heater, clothes washer, dishwasher, lighting, cooking and miscellaneous. Taken together, appliances account for approximately 70% of electricity consumption and 30% of natural gas consumption in the U.S. residential sector (EIA 1993). Appliances are thus important to those residential sector policies or programs aimed at improving the efficiency of electricity and natural gas consumption. The baseline forecast using the REEPS model described here is presented in a separate report (Koomey et al. 1994a).

Engineering-economic models such as REEPS offer a means of assessing future trends in energy consumption at the end-use level under differing assumptions, scenarios or policies. Such models attempt to characterize the long-term structure and patterns of energy consumption in homes and are also called end-use forecasting models because they generally include considerable end-use detail. They rely on data regarding the building stock, the equipment available for supplying energy services, and historical patterns of end-use energy consumption in homes. For the analysis of appliances, which is the focus of this report, engineering data on energy-using equipment are combined with economic parameters regarding purchase and usage of the equipment. At the national level, these end-use forecasting models facilitate the analysis of energy conservation programs and policy initiatives that are widely applicable and broad in their scope such as residential appliance standards (US DOE 1989, US DOE 1990, US DOE 1993b) and national energy policy initiatives (EIA 1990). Utilities rely on end-use forecasting models in order to assess market trends for new technologies (McMenamin et al. 1992) and in the development of Demand-Side Management (DSM) programs (Hummel and McMenamin 1992).

The report details the supporting data, model parameters, and methodology for appliance models developed for use with REEPS 2.1. In Section 2 we outline the modeling framework provided by REEPS and the end-use structure and assumptions we adopted for this analysis. In Section 3, we discuss the structure and methodology we have adopted for the decision models that are used to forecast appliance purchases. In Section 4, we define the structure, data and model parameters for refrigerators, freezers, and dryers. In Section 5, we define appliance models for the three end-uses associated with water consumption, including water heaters, dishwashers, and clothes washers. Section 6 details the model structure and baseline data development for the lighting end-use. Section 7 provides a brief outline of the cooking and miscellaneous end-uses, which are characterized in a reduced-form representation. In Section 8, we discuss the technology data for those appliance models that we have characterized with specific technology options, including the refrigerator, freezer, water heater, clothes washer, dishwasher, and dryer models. In Section 9, we describe the historical stock of appliances and our methods for forecasting changes to that stock in future years. In Section 10, we outline areas for future work in the end-use forecasting of appliances that could not be included in the model due to data and time limitations. In Section 11 we summarize and conclude the report.

2. MODEL STRUCTURE AND ASSUMPTIONS

In this section of the report we outline the REEPS modeling framework and the assumptions and data structure we have adopted in configuring the appliance models. In Section 2.1, we briefly describe the general features of residential end-use forecasting and the particular features of the REEPS modeling framework, with special reference to those aspects which relate to appliances rather than HVAC. In Section 2.2, we detail the major steps in model execution and the general functional relationships among the various algorithmic components. In Section 2.3, we describe the end-use structure and conventions we adopted in configuring the appliance models. In Section 2.4, we provide an overview of the data sources we used to develop the structure, inputs and parameter estimates for the appliance models. In Section 2.5, we discuss some of the potential applications of the model in analyzing impacts of government policies, utility programs, changes in technology development and adoption, and economic scenarios.

2.1. REEPS Modeling Framework

The basic assumptions and structure of residential end-use forecasting are quite similar across both different modeling frameworks and different end-uses (Johnson et al. 1992). The household is considered the fundamental unit for energy consumption. The physical housing stock is defined by its thermal properties, while energy-using equipment is described by variables such as size (or capacity) and efficiency. Macroeconomic and demographic variables that change over time include the housing stock, household size, fuel prices and household income. Technology data characterize the existing and/or future stock of equipment and allow the formulation of functional relationships to use in the forecast. Consumer data describe ownership patterns for equipment and appliances, generally segmented by housing type. Consumer attitudes toward energy efficiency investments are typically characterized by parameters that represent economic tradeoffs between purchase price and operating cost. Market shares are estimated for each technology or fuel for a given end-use and the models adjust these market shares over time as households retire and purchase equipment.

The EPRI-REEPS model is one of several prominent end-use forecasting models that have been developed since the mid-1970s. One of the earliest residential end-use forecasting models was developed at Oak Ridge National Laboratory (Hirst and Carney 1978). This model was later modified at the Lawrence Berkeley Laboratory (McMahon 1987) for the analysis of residential appliance standards. REEPS has been used since the early 1980s both as a tool for national policy analysis and subsequently as an analytical tool for electric utilities to forecast long-term residential energy demand (EPRI 1982). The first version of the model, REEPS 1.0, relied on an econometric/micro simulation approach to estimate energy consumption for a given sample of households (Cowing and McFadden 1984). The newest version of the model, REEPS 2.1, is quite different in that it provides the user with a generalized modeling framework rather than attempting to simulate a particular set of households. As a result, REEPS 2.1 does not have the theoretical foundation and household-specific data enumeration offered by the micro simulation approach in REEPS 1.0 (Cowing 1992).

This latest version of REEPS incorporates the basic features of residential end-use forecasting into a generalized modeling framework in which the user has considerable control over the algorithms and model structure (McMenamin et al. 1992). All REEPS users work within a common software framework, which allows them to focus on the substantive aspects of the analysis and avoid potential programming errors introduced by changes in the software source code. This framework provides greater flexibility compared to traditional models which are "hardwired" for particular formulations of residential sector energy use. Rather than relying on a fixed set of equations and/or parameters, the user can precisely specify the equations used to forecast future appliance and housing characteristics. Both the functional form and parameters included in these equations are open to modification by the user. This enables modeling of a wide range of scenarios and policies, at varying levels of disaggregation, without ever changing the computer program itself. This improved modeling flexibility, however, brings with it considerably more responsibility on the part of the user in configuring the input data. Each distinct set of data and parameters results in a different model, with the result that there can be considerable variation in the forecast results even when exogenous variables remain the same. In effect, the "model" consists of the structure, data, and algorithms developed by the user, with the REEPS computer program itself as a modeling shell that imparts a higher level structure and consistency to the analysis.

The REEPS 2.1 Appliance Model[1] forecasts future purchases and energy consumption of appliances, using the modeling framework described above. the individual appliance end-use models in REEPS derive their higher-level structure from other input variables shown in Figure 2.1. Exogenous variables include macroeconomic projections such as income and household size, along with other external parameters needed by the model. Fuel price projections are implemented as exogenous time series for each fuel and rate class used in the model. Households data allow the user to forecast changes to the housing stock based on separate decay rates for each housing type and vintage block. Demographic segmentation divides the appliance market into different segments based on household characteristics such as income or household size, allowing purchase decisions to be differentiated between the segments. These other input sets precede the specification of the appliance models themselves because they define important elements of appliance model structure, such as the housing types specified in the Households module. Data from these input sets are used as drivers in forecasting the size, characteristics, and usage of the appliance stock. In general, REEPS uses data in the form of an average value within a market segment (house type, income, etc.), rather than a distribution of values that would more closely approximate the actual situation. This data structure could potentially introduce aggregation bias into the forecasts, which the user may attempt to minimize by dividing the market into smaller segments (thus the average values input to REEPS represent fewer houses).

2.2. Appliance Model Flow and Execution

The REEPS 2.1 Appliance Model is a vintaged capital stock or stock flow-adjustment model that maintains accounts of appliances by vintage year. REEPS 2.1 uses a state-based approach to forecasting in which purchase decisions are explicitly modeled at the household level and depend upon the "state" (or characteristics) of the household and its existing appliance ownership status. This means that for each housing class a prototypical or average house is specified and purchase decisions for this house are assumed to apply to all houses in that class, additionally, the decision model may change based on the characteristics of this average house (Section 3 describes the various decision models in more detail). The state-based approach differs from a saturation approach to appliance modeling, in which the saturations or market shares are forecast as a function of population characteristics and the difference from the current ownership patterns are attributed to appliance purchases (EPRI 1990, p. A-3).

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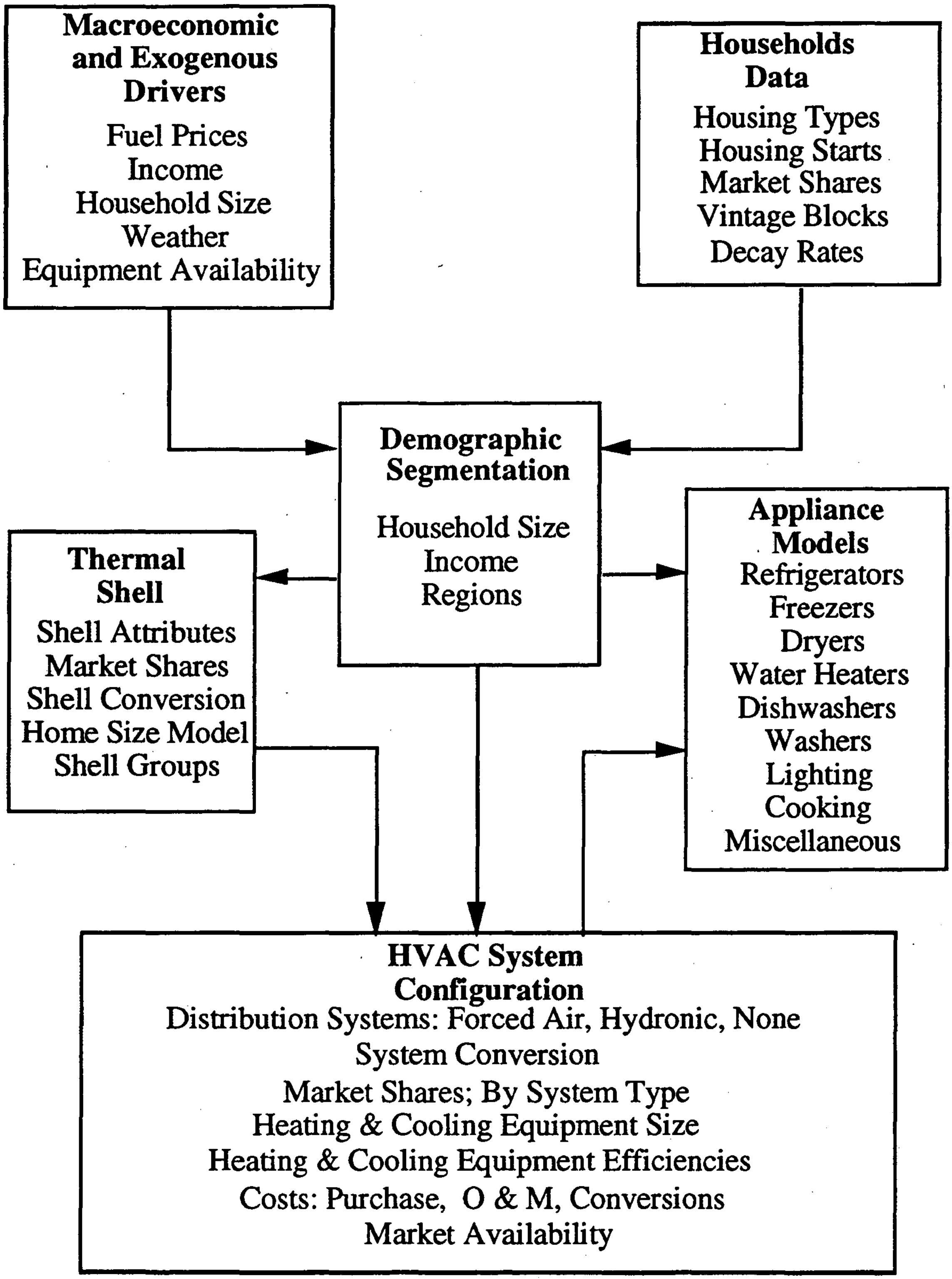
[1] We sometimes refer to the REEPS Appliance Model and other times to a particular appliance model. References to the former are capitalized in this report. The REEPS Appliance Model refers to the basic modeling structure provided to the user, and this structure is the same for all end-uses or appliances. A particular application of this Appliance Model for, say, refrigerators, results in a refrigerator appliance model. This distinction is quite important because REEPS allows the user considerable control over the structure, data, and functional equations. This means that a different input set can describe a completely different appliance model rather than simply differing only in the control data or in particular parameters.

Figure 2.1: Relationships among REEPS Input Sets



The decision models determine the value of four key variables for a particular appliance type throughout the course of the forecast: Size, Efficiency, Usage, Market Share. These variables, when combined with an exogenous forecast of the number of households, determine the residential-sector energy consumption for that specific appliance type. The five variables are related through the fundamental energy demand identity used in REEPS:

$$E_g = \sum_h \sum_s \frac{(\text{Usage}_{h,s,g})\,(\text{Size}_{h,s,g})}{(\text{Efficiency}_{h,s,g})}\,(\text{Share}_{h,s,g})(\text{HH}_{h,s,g}) \tag{2.1}$$

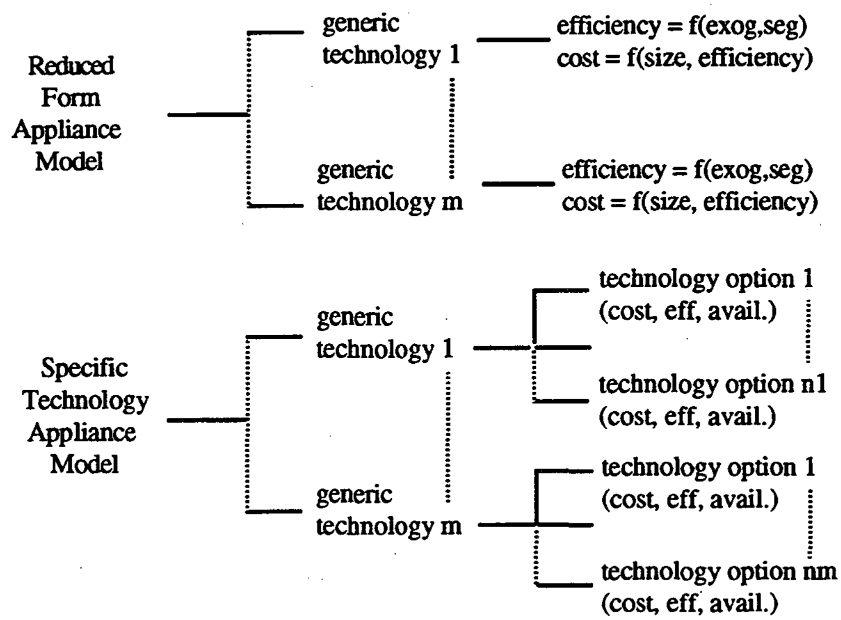
where E is the total sectoral energy consumption, g is the generic technology, h is the housing type, s is the demographic segment, *Usage* is the intensity of use of the appliance (e.g., loads/yr.), *Size* is the appliance capacity, *Efficiency* is the level of end-use services delivered per unit of energy input, *Share* is the ownership share (saturation), and *HH* is the number of households in a particular market segment. Appliance size, efficiency and usage are defined by the user in the units and values appropriate for a given end-use and/or appliance. The number of households is exogenous to the Appliance Model, having been derived in the Household Data module shown in Figure 2.1.

The user specifies the characteristics of the existing stock of appliances so that Equation 2.1 can be evaluated in the base-year of the forecast. The characteristics include appliance efficiency, size and market share. The result of Equation 2.1 (without the "HH" term) is then compared to a known value of Unit Energy Consumption (UEC) as a check for input errors and to calibrate the model to empirically-observed trends. The user also specifies equipment lifetimes and optional vintage blocks to differentiate efficiencies across appliance vintages and to facilitate proper accounting for decay and replacement of appliances over time.

The energy use characteristics of the appliance stocks are primarily affected by the efficiency of the new stock additions. The level of energy consumption for an appliance may also change as a result of changing appliance usage (measured as cycles/year or volume/day), based on a user-specified usage function. The user also specifies characteristics of new appliances purchased in the first forecast year, allowing the modeling of purchase decisions for new homes and for replacement of appliances in existing homes. These characteristics include the marginal (new equipment) efficiency, the purchase price of appliances, an equation for appliance size in future years, and the market shares of technologies in new homes in the first forecast year.

Additional data on appliances depend on the choice between two modeling approaches, reduced-form and specific technology, as shown in Figure 2.2. The specification of generic technologies is the same for both approaches, as illustrated in Figure 2.2 and in Equation 2.1. Generic technologies are classes of appliances distinguished by fundamental features, such as gas vs. electric water heaters. For reduced-form specification, the user models efficiency changes as a function of exogenous variables (such as fuel prices) and demographic segmentation variables (such as housing type or income). Purchase price is modeled through a user-specified function based on size and efficiency. Consequently, there can be no feedback effect from purchase cost to efficiency because cost is determined after efficiency has already been calculated. The specific technology approach treats these changes differently by allowing the user to characterize technology options, with an associated purchase price, efficiency and availability. Availability includes specification of legal availability (appliance standards) and market availability, describing the relative penetration of the technology in the marketplace as constrained by maximum production capacity (among other possible causes) for a specific technology. The purchase decision models based on these characteristics are discussed in Section 3.

Figure 2.2: Specific Technology vs. Reduced-Form



Three general modeling steps are executed for each end-use: 1) base-year calibration, 2) decision-model calibration, and 3) forecast execution. In the base-year calibration, the Appliance Model is compared with the input housing stock and demographic characteristics to check for consistency. Base-year data on appliance saturations, sizes, efficiency levels and average UEC values are disaggregated by housing type and demographic segment. Usage is adjusted to be consistent with stock UEC values and vintage block information on vintage block shares, efficiencies and sizes. In the second step, decision-model calibration, the decision models are adjusted to fit the control (or "calibration") values specified in the first forecast year (1991 in this implementation of REEPS). These control values are referred to later as "control-year" data, and include the marginal appliance efficiencies and new home market shares. Finally, in the forecast execution step, decision models are used to predict new appliance ownership shares and efficiency choices. The algorithmic procedures in each of these three steps are detailed in the technical documentation for the Appliance Model (EPRI 1990).

2.3 Appliance End-use Structure and Assumptions

We used three housing types in configuring the appliance models: single-family, multifamily and manufactured homes. In the baseline analysis presented in this report, there is no additional economic or demographic segmentation beyond housing type, to avoid added complexity. We analyzed a total of nine end-uses and developed appliance models for use with REEPS for each of these end-uses. We model six of these end-uses with the specific technology characterization: refrigerators, freezers, water heaters, dishwashers, clothes washers, and dryers. The decision models we developed for these end-uses are discussed in Section 3 and the base-year and control data are discussed in Sections 8 and 9. We model three end-uses using the reduced form representation: lighting, cooking and miscellaneous. We discuss these end-uses and provide the base-year and control data in Sections 6 and 7. Due to the lack of data and the reduced form representation of the models, we have not estimated purchase decision models for these latter three end-uses.

The REEPS 2.1 modeling framework is data intensive, particularly since it requires data at the household level. The primary sources of base-year (1990 stock) and control-year (1991 new units) ownership data are the Residential Energy Consumption Surveys (RECS) conducted by the U.S. Energy Information Administration (EIA 1989b, EIA 1992, EIA 1993). To estimate the marginal shares of new homes built in 1991, we use RECS data for homes built in 1985 through 1990. For particular end-uses these data may differ somewhat from other published sources (such as the US Census Bureau American Housing Survey), but we have used RECS for all end-uses for the sake of consistency. For appliance stock data -- historic shipments, capacities and efficiencies -- we use data from the Association of Home Appliance Manufacturers (AHAM 1991). For cost-efficiency option data for new technologies, we use information developed for the U.S. Department of Energy (US DOE 1989, US DOE 1990, US DOE 1993a) in support of the National Appliance Energy Conservation Act of 1987 (NAECA) appliance efficiency standards. For the lighting end-use, we have relied on the results of monitored residential lighting usage in Washington state (Manclark 1991), lighting surveys from New York and New Jersey (Robinson 1992), and a recent residential lighting survey by Pacific Gas & Electric (Kelsey and Richardson 1992).

2.4 Policy Modeling

The flexibility of REEPS 2.1 allows the user to model a number of policies through the judicious modification of the appropriate parameters, equations, structure, and addition of new technologies. Government and utility policies have the potential to restrict the availability of certain appliance efficiency levels, energy prices, financial criteria for new equipment purchases, early retirement of appliances, and rates of technical innovation. The policy handles in REEPS 2.1 include: energy prices; functional forms and coefficients for choice equations; pre-failure replacement/conversion decision algorithm; restrictions on legal or market availability of specific technologies; and modification of specific technologies' purchase price or efficiencies. Table 2.1 lists policies by area of impact and the corresponding policy handles in REEPS 2.1.

Table 2.1: Policy Handles in EPRI-REEPS 2.1

Area of Impact	Policy Handle
EFFICIENCY LEVEL AVAILABILITY Minimum efficiency standards.	Restrict "legal availability" of specific technologies. Restrict "market availability" of specific technologies.
ENERGY PRICES Taxes energy taxes carbon tax	Electricity and fuel prices.
FINANCIAL CRITERIA FOR APPLIANCE INVESTMENT Equipment Subsidies by Utility (via Rate-of-Return Regulation) rebates low-interest loans installation at utility cost direct installation by utility Equipment Subsidies by Government performance based tax rebates investment tax credits direct government purchases Information Dissemination audit programs extension services advertising and labeling training	Reduce purchase price of specific technologies. Implicit Discount Rate, via parameters in consumer utility function for efficiency or fuel choice equations.
EARLY RETIREMENT OF APPLIANCES Equipment Subsidies by Utility (via Rate-of-Return Regulation) Equipment Subsidies by Government Residential Energy Conservation Ordinances	Add pre-failure replacement and conversion purchase decision state.
RATE OF TECHNICAL INNOVATION Research and Development Programs Demonstration Programs "Golden Carrot" Programs Patent Law	Add new technologies to list of specific technologies. Reduce purchase price of specific technology options ("cost multiplier"). Increase efficiency of specific technology options ("efficiency multiplier").

3. STRUCTURE OF APPLIANCE DECISION MODELS

For those appliances modeled with the specific technology approach, we have configured one generic technology for each commonly-used fuel type, as shown in Figure 3.1. The refrigerator, freezer, dishwasher, and clothes washer models are limited to only one fuel type -- electric. The water heater model has three fuel types -- electric, gas and oil. The dryer model has two fuel types -- electric or gas. Each generic technology has an associated ownership model, discussed in Section 3.1. For each generic technology, there is also a set of associated specific technologies, that can be considered appliance "models" differing in their efficiency levels and purchase price. We adopt this structure, as shown in Figure 3.2, for each generic technology shown in Figure 3.1. We developed an efficiency choice model for each of these generic technology types, and these models are described in Section 3.2. The combined effect of the ownership models and efficiency choice models determines the purchase decisions over the course of the forecast.

3.1. Ownership Models

Household ownership of appliances is determined through decision models which estimate the probability of ownership based on household characteristics and exogenous variables. For each year *t* during the course of the forecast, individual probabilities of ownership are calculated using a multinomial logit (MNL) equation:

$$\text{Probability of Ownership}^{t}_{h,s,n,g} = \frac{\exp(U_{h,s,n,g})}{\sum\limits_{g'} \exp(U_{h,s,n,g'})} \tag{3.1}$$

where *h* is the housing type, *s* is the demographic segment, *n* is the decision state, *g* is the generic technology of interest, *g'* is the set of all generic technologies, and *U* is the "utility function" or "desirability index."[2] The desirability index is specified by the user and may be dependent upon attributes of the appliance (purchase price, operating cost, warranty, etc.) as well as attributes of the decision-maker (income, household type, rural or urban, etc.). The individual probabilities of ownership are aggregated to estimate the overall marginal market saturations for decision state *n* and market segment *h, s*.

There are four user-specified decision states that can lead to the decision to acquire appliances: 1) new home construction, 2) decay and replacement, 3) non-owner acquisition, and 4) pre-failure replacement and conversion. Decisions to acquire appliances are modeled at the household level, based upon household characteristics and existing ownership status, and depending on which of the four decision states are active for a particular end-use. If a replacement model is not specified, then the model assumes 100% replacement with the same generic technology. We have activated the new home decision state for all models and the non-owner acquisition model for those end-uses where the appliance saturation is significantly less than 100%, namely dishwashers and freezers. We generally assume 100% replacement, except for freezers (and fuel-switching for water heaters), based on a comparison of historical shipments (AHAM 1991) and 1990 stock data (EIA 1992). The "pre-failure replacement and conversion" decision state is not active for the baseline forecasts. This decision state could be used in a scenario where utilities have appliance "buy-back" programs, or to model some other type of rebate program.

We have adopted the REEPS 2.1 default ownership models for all appliances covered in this report, except for water heaters. For water heaters, we developed a new model and estimated the parameters using data from the 1987 RECS. We discuss the new water heater ownership model in Section 5, and the REEPS 2.1 default ownership models are presented in the appropriate end-use sections.

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[2] The user also has the option in REEPS 2.1 of estimating market shares using a "nested logit" or GEV (generalized extreme value) model that allows simultaneous modeling of ownership and efficiency choice. Estimation of the GEV model requires a highly detailed and disaggregated data set, which is not available at the national level.

Figure 3.1: Appliance Model Structure

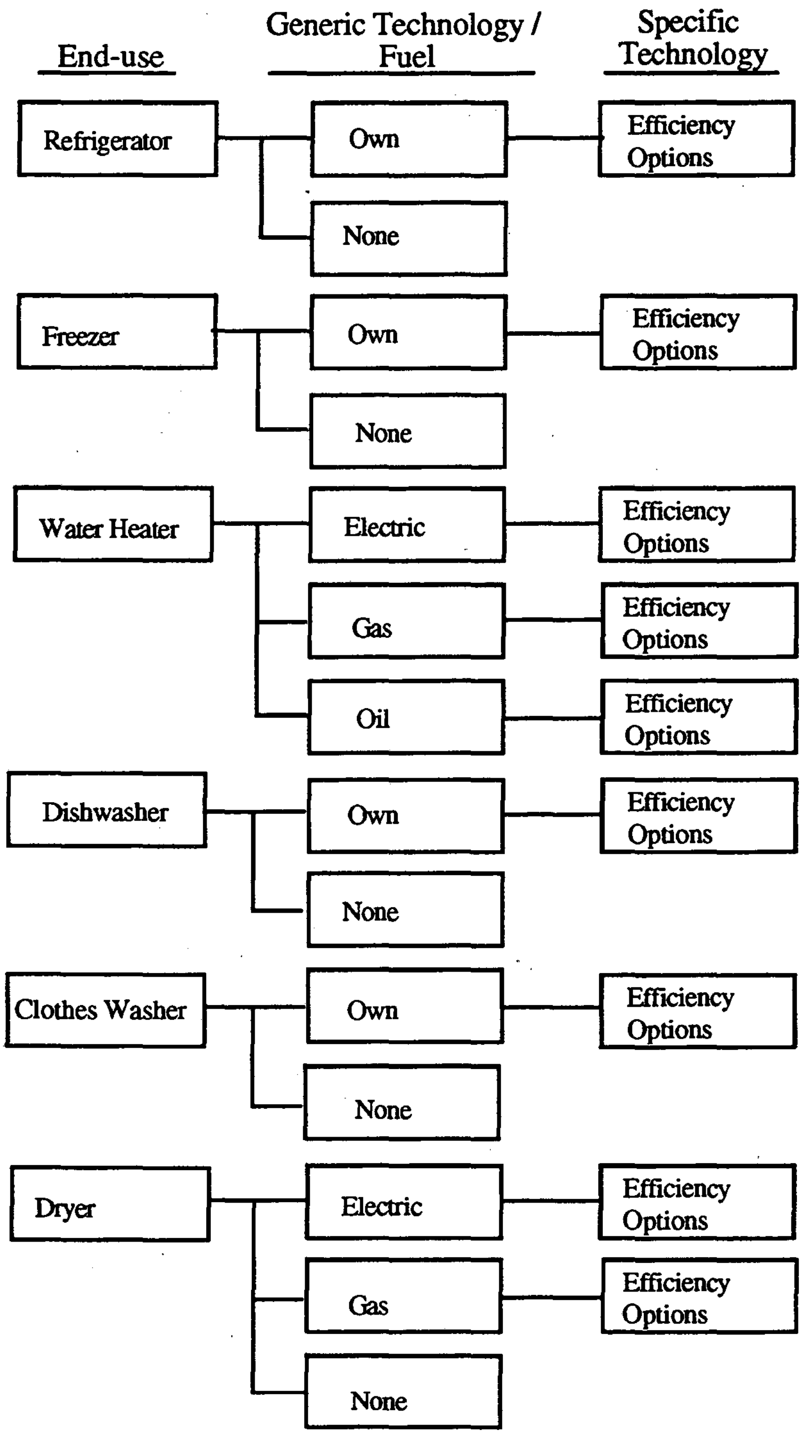
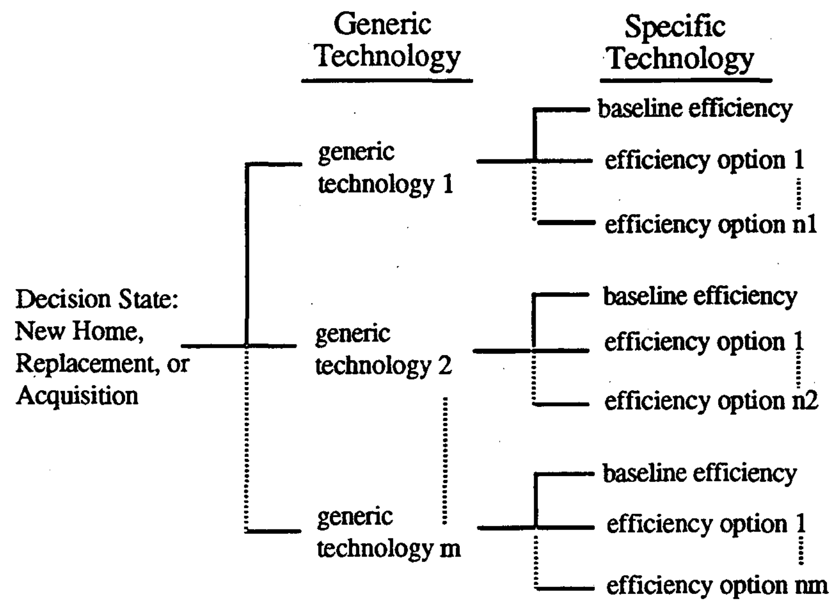


Figure 3.2: General Decision Model Structure



3.2. Efficiency Choice Models

We use the specific technology approach to model efficiency choice for refrigerators, freezers, dryers, water heaters, clothes washers and dishwashers. Other end-uses are modeled using a reduced-form efficiency-choice equation. The lighting end-use has no efficiency choice model, although the REEPS lighting model has been set-up with specific technologies to allow modeling of prescriptive policies. With the specific technology approach, the user inputs a list of specific technology options and the model calculates individual probabilities of purchase for each year *t* using a multinomial logit equation of the form:

$$\text{Probability of Ownership}^{t}_{h,s,n,ge} = \frac{\exp(U_{h,s,n,ge})}{\sum_{ge'} \exp(U_{h,s,n,ge'})} \tag{3.2}$$

where *h* is the housing type, *s* is the demographic segment, *n* is the decision state, *ge* is the specific efficiency option of interest, *ge'* is the set of all specific efficiency options, and *U* is the "utility function" or "desirability index." Our model specification for the utility function is discussed below. The probabilities are then aggregated to estimate the overall marginal market purchase shares for decision state *n* , housing type *h*, and demographic segment *s*.

We characterize overall market efficiency outcomes using a concept similar to that of a market discount rate. Ruderman et al. (1987) describe the concept of a market discount rate:

> ...the market discount rate characterizes the decisions of the market as a whole. Although different segments of the market do not necessarily make their decisions on the basis of minimum life-cycle cost, we can calculate the discount rate associated with a market that is treated in the aggregate as if it optimizes

efficiency decisions. In other words, we ask the question: if we treat the market conceptually as if the sum of all the appliance efficiency choices could be characterized by a type of life-cycle cost decision, what is the discount rate that would characterize the overall market? Decisions by manufacturers on which design options to produce, decisions by retailers and wholesalers on which models to advertise or discount, and the purchase decision affect the market discount rate.

Unlike Ruderman et al.'s model, we use a multinomial logit model that characterizes the market distribution of appliance efficiency choices, rather than just the overall market average. For the specification of the utility function used to choose among efficiency options, we use a standard model of consumer choice involving the implicit tradeoff between present purchase price and future operating cost (Train 1986). Confronted with j discrete appliance purchase options, a consumer selects the option that maximizes utility as a function of purchase price (PP) and operating cost (OC) as well as other factors (Z)[3]. If one assumes a linear utility function, then the utility, U, of a particular purchase option can be represented as:

$$U_j = b_1 PP_j + b_2 OC_j + b_3 Z_j \tag{3.3}$$

where $b1$, $b2$ and b_3 are unknown parameters to be estimated. The implicit market discount rate is given by:

$$\frac{b_1}{b_2} = \frac{r}{[1-(1+r)^{-T}]} \tag{3.4}$$

where r is the implicit discount rate, and T is the expected lifetime. If the lifetime is infinite, then the discount rate is simply the ratio of the cost coefficients, b_1 and b_2. We report the implicit discount rate for each decision model estimated in this analysis. These discount rates are provided solely as an intuitive interpretation of the logit parameters and cannot be reliably transferred to other consumer choice models, such as life-cycle cost minimization models.

Ideally, the parameters of multinomial logit models are estimated on household-level sample data. Unfortunately, such data do not exist at the national level for the application we are studying here. Thus, we have used aggregate, averaged national data to characterize overall market outcomes in terms of a "representative individual." To estimate the model parameters, we employed a least squares procedure developed by Berkson and described in Ben-Akiva and Lerman (Ben-Akiva and Lerman 1985). Berkson's procedure is based on the fact that a multinomial logit model with a linear-in-parameters utility function can be transformed into a form amenable to standard regression techniques. The MNL equation is transformed as follows:

$$\log\left(\frac{S_i}{S_j}\right) = b_1(PP_i - PP_j) + b_2(OC_i - OC_j) \tag{3.5}$$

where S_i is the share of option i and j is a generic technology option used as a constant reference.

Estimating the parameters in Equation 3.3 with aggregate and averaged data requires a data set of market share, purchase price and annual operating cost by efficiency level. We chose a single product class to represent each generic technology and chose a set of specific technology options from the supporting analysis for the federal energy conservation standards (US DOE 1989, US DOE 1990, US DOE 1993a). Purchase prices are estimated for each efficiency level by using a

[3] In the modeling framework adopted here, the "consumer" does not refer to specific purchasers or types of purchasers, but instead represents the behavior of the market for a particular appliance in aggregate, just as in Ruderman et al. (1987).

three-parameter curve that has been fit to the cost-efficiency data for the specific technology options (listed in Tables B.1, C.1, D.1, D.2, D.3, E.1, F.1, G.1 and G.2 in the appendices). We assume that the models offered at different efficiency levels do not have any additional attributes that affect the efficiency choice outcome (i.e., $Z_j = 0$ in Equation 3.3). Operating costs are estimated using the following equation:

$$\text{Annual Operating Cost} = \frac{\text{(annual usage)(avg size)}}{\text{(efficiency)}} \text{(Avg energy cost)} \tag{3.6}$$

Shares of appliance purchases by efficiency level were adopted from the LBL-REM input data sets with the exception of refrigerators and freezers. The share distributions are estimated so that the average efficiency matches published efficiency data, either shipment-weighted energy factors (SWEFs) or model-weighted energy factors (MWEFs) (AHAM 1991, GAMA 1991). In some cases, they are a combination of SWEFs and MWEFs. Estimations of the model parameters are discussed in Sections 4.3. and 5.3.

4. REFRIGERATOR, FREEZER AND DRYER MODELS

4.1. General Structure

Both the refrigerator/freezer model and the freezer model have one generic technology class. REEPS 2.1 normalizes all input saturations to unity, however, because refrigerator saturations are greater than one it is necessary to use two models, REF1 and REF2. For REF1, the new home and replacement shares are assumed to be 100% and no ownership model need be specified. For REF2, the base-year saturation for house type *h* is:

$$\text{Market Share}^{1990}_{h,\,\text{ref}2} = \text{Market Share}^{1990}_{h,\,\text{all ref}} - 1.0 \tag{4.1}$$

The ownership models for REF2 and freezers select between ownership or non-ownership. For dryers, there are three ownership choices: two generic technologies (electric and gas) and non-ownership.

4.2. Ownership Models

Data from RECS suggest the most important demographic factors affecting refrigerator and dryer ownership are income level and household size. For freezers, RECS suggests urban/rural status is also an important factor. We have adopted the REEPS 2.1 default market share equations, as shown in Table 4.1, which contain the appropriate factors.

Table 4.1: Appliance Ownership Models for Refrigerators, Freezers and Dryers		
Generic Technology	**Model Type**	**Utility Function**
Refrigerators	New Home Replacement	$U_{h,ref2} = 0.02*Inc_h + 0.5*HHSize_h - 1.0*PVOC/1000 + C_{h,ref2}$ 100% Replacement
Freezers	New Home or Replacement	$U_{h,n,frz} = -2.2 + 0.01*Inc_h + 0.9*HHSize_h + 0.85*Rural - 10*AvgE + C_{h,n,frz}$
Electric Dryers	New Home or Acquisition Replacement	$U_{h,n,de} = -5.0*LCC/1000 + 0.05*Inc_h + 0.14*HHSize_h + C_{h,n,de}$ 100% Replacement
Gas Dryers	New Home or Acquisition Replacement	$U_{h,n,dg} = -5.0*LCC/1000 + 0.05*Inc_h + 0.18*HHSize_h + C_{h,n,dg}$ 100% Replacement

Definitions: *h* is house type,
n is the decision state,
Inc is the average household income,
HHSize is the average number of household members,
PVOC is the present value of operating cost (averaged over all specific efficiency options) at a 40% discount rate[4],
Rural is the fraction of rural household in the total population,
AvgE is the average electricity price,
LCC is the life cycle cost (average) at 40% discount rate,
$C_{h,n,g}$ is the control-year calibration constant for generic technology *g*.

4.3. Efficiency Choice Model

4.3.1. Refrigerators and Freezers.

To estimate the multinomial logit efficiency choice model for refrigerators and freezers using aggregate data, we created disaggregate data sets of 1000 artificial observations using the following methodology. We chose 1989, the last year before the 1990 NAECA minimum efficiency standards, to characterize market decisions. Average efficiency choices for refrigerators and freezers are the 1989 AHAM shipment weighted efficiency for "Top mount freezer without ice" refrigerators and "Upright, Manual Defrost" freezers, respectively (AHAM 1991). Purchase price and operating costs are described by a three-parameter curve that we fit to the LBL cost-efficiency option list for "Top mount freezer without ice" refrigerators (Table B.1) and "Upright, Manual Defrost" freezers (Table C.1) (US DOE 1990). We assume that the models offered at different efficiency levels do not have any additional attributes which affect the efficiency choice outcome (i.e., $Z_j = 0$ in equation 3.3).

We assumed normal distributions of efficiencies with standard deviations based upon 1984 California shipments data for "Top mount freezer without ice refrigerators" and for all freezers (CEC 1987).[5] The distributions of efficiencies were then parsed into seven efficiency bins

[4] Note that this discount rate is for the appliance ownership model and is distinct from the "market discount rate" used to characterize the efficiency choices. In practice, the REEPS default ownership models are relatively insensitive to the discount rate, so the 40% discount rate has been selected to be generally representative of the market discount rates observed in the appliance end-uses.

[5] Despite the age and limited geographical extent of these data, we employ them because they are the only data that have been developed from true market surveys.

assuming a normal distribution, creating "market shares" for seven different efficiency levels. A data set of 1000 observations was created by assigning a market share of, say, 20% for option 2 to be equivalent to 200 observed selections of option 2. Finally, we estimated the models with a statistical package, SST, that uses maximum likelihood estimation techniques (Dubin and Rivers 1988). The results are presented in Table 4.2. Statistical measurements of goodness-of-fit, such as t-statistics, cannot be interpreted in a conventional manner from these results because the artificial observations do not contain variation within each efficiency bin with which to calculate such statistics, hence we do not report them here.

Table 4.2: Estimated Coefficients of Refrigerator and Freezer Efficiency Choice Models
Screen: AM- 6f

End-use	Variable	Parameter Estimate
Refrigerator		
	Purchase Price (b_1)	-0.0829
	Operating Cost (b_2)	-0.1207
	Implicit discount rate*	69%
Freezer		
	Purchase Price (b_1)	-0.0590
	Operating Cost (b_2)	-0.0651
	Implicit discount rate*	91%

* Assuming infinite lifetime.

4.3.2. Dryers

No data on shares by efficiency level are available for dryers. We selected the efficiency choice parameters so that average efficiencies calculated from the predicted shares would match 1990 SWEFs (AHAM 1991). Since there are an infinite number of combinations of parameters that will match the SWEFs, we normalized the operating cost parameter, b_2, to equal -0.1. Then we selected the parameter b_1 to be closest in absolute value to b_2 while yielding an average efficiency that matches the 1990 SWEF (using Equations 3.2 and 3.3 to estimate market shares of specific efficiency options). The results are presented in Table 4.3.

Table 4.3: Estimated Coefficients of Dryer Efficiency Choice Models
Screen: AM- 6f

Generic Technology	Variable	Parameter Estimate
Electric, Standard		
	Purchase Price (b_1)	-0.120
	Operating Cost (b_2)	-0.1
	Implicit discount rate*	120%
Gas, Standard		
	Purchase Price (b_1)	-0.062
	Operating Cost (b_2)	-0.1
	Implicit discount rate*	62%

* Assuming infinite lifetime.

5. WATER HEATER, DISHWASHER AND CLOTHES WASHER MODELS

5.1. Model Structure

5.1.1. Water Heating and Space Heating Fuel Dependence

There are three fuel choices for water heaters -- electric, gas or oil. A previous study, as well as analysis of RECS data, strongly suggest that water heater fuel choice is dependent upon space heating fuel choice (Dubin 1985, EIA 1989a) New homes with electric space heating rarely have piped gas service and therefore rarely have gas water heaters. New homes with gas space heating predominately have gas water heaters since, on average, gas-fired units have annual operating costs about half those of electric water heaters with comparable purchase prices. Figure 5.1 shows the dependency of the water heater fuel choice upon the space heating fuel choice in new homes.

To implement this choice structure in REEPS, we first run the HVAC model to obtain national average shares of gas space heating in new homes. The shares are used in the appliance model as an exogenous vector for the gas availability variable. The gas availability variable subdivides the new home water heater market into those with and those without gas space heating. Only the new homes with gas space heating are allowed to choose between all three fuel types. Those with electric and other space heating fuel types are allowed to choose between electricity and oil, with only a small fraction of these (about 5%) choosing oil.

As shown in Figure 5.2, the choice is similar for replacements. Those houses with gas space heating are highly likely to choose gas water heaters. The houses with electric space heating are highly likely to choose electric water heaters due to the lack of gas fuel hookup. Ideally, the replacement fuel decision would be conditional on the space heating fuel type. The existing REEPS algorithm, however, does not allow this structure to be implemented. Instead, the replacement fuel type is conditional upon the old water heater fuel type, which is closely correlated with the space heating fuel type.

Figure 5.1: Water Heater Model Structure for New Homes

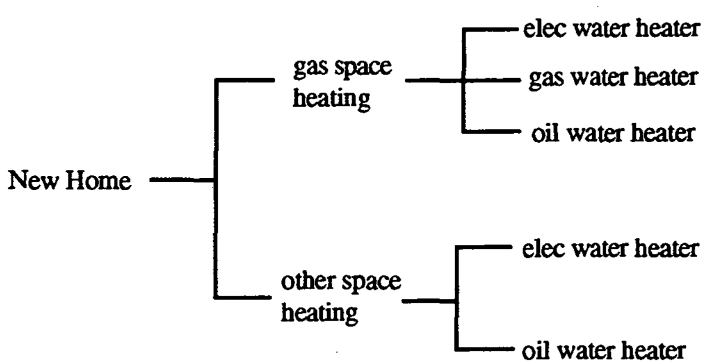
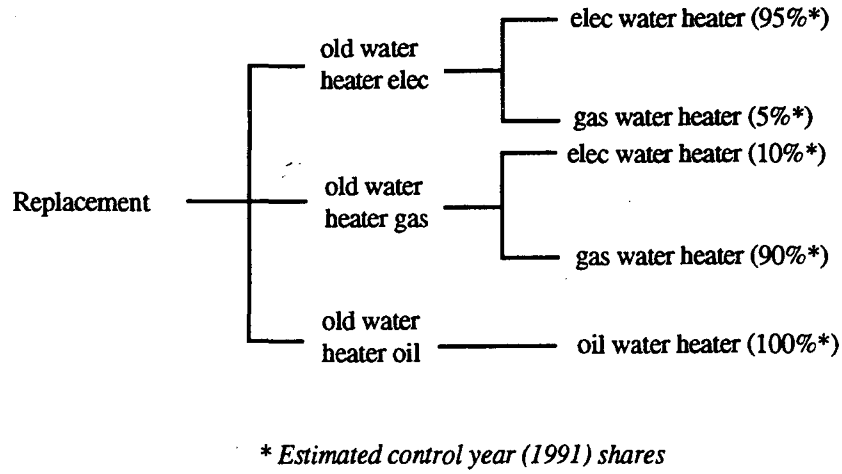


Figure 5.2: Water Heater Model Structure for Replacements



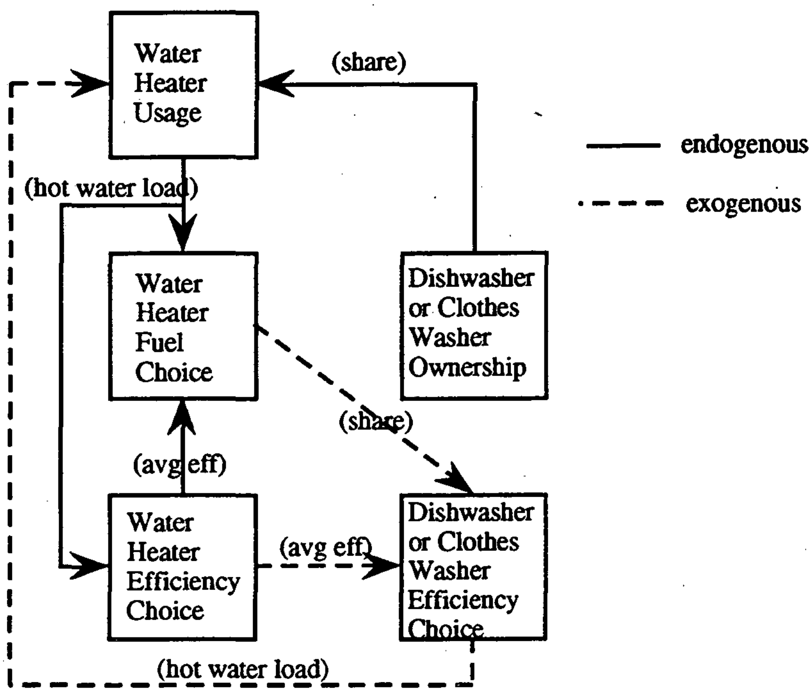
5.1.2. Water Heater, Dishwasher and Clothes Washer Interactions

Through hot water usage, the water heater, dishwasher and clothes washer models are interdependent. Figure 5.3 illustrates the influences these end-uses have on each other. Due to structural limitations in the REEPS algorithms, most of these influences cannot be modeled endogenously. Instead, they must be modeled iteratively through exogenous vectors. Water heater fuel and efficiency choices are influenced by saturations and efficiency choices of both dishwashers and clothes washers. Dishwasher and clothes washer efficiency choice, in turn, is affected by the water heater fuel and efficiency choices. As shown in Figure 5.3, only one type of these interactions can be modeled endogenously in REEPS: the interaction between the load on the water heater and the saturations of dishwashers and clothes washers (the solid line labeled "share" in Figure 5.3).

To implement this structure in REEPS, the model must be run iteratively. However, since the water heater fuel choice and efficiency choice models have relatively high discount rates (84% and 63 to 200%, respectively), their outcomes are relatively insensitive to the operating costs (and hence so are the hot water heat load outcomes from the dishwasher and clothes washers models).[6] Therefore, reasonable hot water loads can be inserted for the water heater hot water load and the results for the water heater shares and average efficiency choice can be used in the efficiency choice models for dishwashers and clothes washers (see Equation 5.4). The hot water load from dishwashers and clothes washers can then be fed back into the water heater model using exogenous variables in the REEPS water heater usage equation (the exogenous variables are shown in Tables E.7 and F.7 in the Appendices). If significantly lower discount rates are used in the water heater fuel and efficiency choice models, this method may no longer be appropriate.

[6] Hot water load is, however, important in the calculation of overall water heater energy consumption. Furthermore, if the discount rates are lowered, then the efficiency choice will become more sensitive to operating cost.

Figure 5.3 Water Heater, Dishwasher and Clothes Washer Model Interactions



Interaction Between Water Heater Load and Dishwashers and Clothes washers. Efficiency choice is partly a function of operating cost (Equation 3.3), which for water heaters is based on the following relationship[7]:

$$OC_{ge} = (P_j)\,(\overline{HWL_{wh}}/Eff_{ge}) \qquad (5.1)$$

where OC_{ge} = Annual water heating operating cost of specific option ge, \$/year

P_j = Energy price for fuel type j, \$/kWh or \$/MMBtu

$\overline{HWL_{wh}}$ = Average Hot Water Load, kWh.th/HH/year or Btu.th/HH-year[8]

Eff_{ge} = Efficiency of option ge, kWh.th/kWh.e or Btu.th/Btu.f

[7]Water heater efficiency is more accurately described by two terms: recovery efficiency and standby loss. REEPS 2.1 allows specific technology options to be described by only one efficiency term, thus the efficiency parameter described here is a combined efficiency measure, Energy Factor. A forthcoming version of REEPS will allow water heater efficiency to be specified using two terms.

[8] We adopt the following conventions:
1 kWh =3412 Btu
kWh.th or Btu.th = thermal heat content of the outlet hot water, in kWh or Btu,
kWh.e = energy content of input electricity, in kWh of electricity,
Btu.f = energy content of input fuel, in Btu of natural gas or oil.

The average hot water load, in turn, is calculated as a function of dishwasher and clothes washer average hot water loads and shares as shown in Equation 5.2.

$$\overline{HWL}_{wh} = \overline{B} + \overline{HWL}_{dw} + \overline{HWL}_{cw} \tag{5.2}$$

where $\overline{HWL}_{wh}$ = Average Hot Water Load, kWh.th/HH-year

$\overline{B}$ = Average Base Hot Water Load, kWh.th/HH-year

$\overline{HWL}_{dw}$ = Average Dishwasher Hot Water Load, kWh.th/HH-year
= (HWL_{dw}) $(Share_{dw})$

$\overline{HWL}_{cw}$ = Average Clothes Washer Hot Water Load, kWh.th/HH-year
= $(HWL_{cw}) \bullet (Share_{cw})$

Derivation of the Base Hot Water Load. The base hot water load is all hot water uses other than dishwashers and clothes washers. It is calculated as follows:

$$\overline{B} = 68.3\,(19.71+10.9 \bullet \text{HHsize})\,(X + Y\frac{\text{shflow}}{\text{bshflow}} + Z\frac{\text{ftflow}}{\text{bftlow}}) \tag{5.3}$$

where $\overline{B}$ = Average Base Hot Water Load, kWh.th/HH-yr,
68.3 converts gal/day to kWh.th/yr @ 77 F temperature rise (kWh.th-day/gal-yr),
(19.71+10.9•HHsize) is the average non-dishwasher/clothes washer household hot water usage (gal/day),
HHsize = Number of household occupants (exogenously forecast),
X = 0.36 (volume-dominated fraction of base load),
Y = 0.54 (shower (flow-dominated) fraction of base load),
Z = 0.10 (faucet (flow-dominated) fraction of base load),
shflow = stock average showerhead flowrate in future years,
bshflow = stock average showerhead flowrate in 1990,
ftflow = stock average faucet flowrate in future years, and
bftflow = stock average faucet flowrate in 1990.

The derivation of Equation 5.3. has two major components: developing a relationship between household hot water usage and HHsize (the first part of the equation), and disaggregating this base usage into end-use points to allow modeling of water conservation policies (the latter part of the equation). The fundamental relationship between base household usage and HHsize is derived from the Bonneville Power Administration's Regional End-use Metering Project (REMP) (Taylor et al. 1991). This report provides metered usage of electricity for water heating (kWh/yr) as a function of HHsize for 201 homes in the Pacific Northwest. These electricity usage data were used to estimate total hot water usage (gal/day-household) as a function of HHsize[9].

To determine the base hot water usage, dishwasher and clothes washer hot water usage was removed from the usage levels determined from the REMP data. This process is illustrated in Table 5.1. Using appliance saturations stratified by HHsize from the 1987 RECS (EIA 1989b) and assuming that appliance hot water usage varies as a function of HHsize, we subtracted the weighted-average appliance hot water usage from the total hot water usage by HHsize. This yielded the base hot water load for each integer value of HHsize, which we then scaled so that the average usage equaled the base, non-appliance hot water usage (47.9 gal/day-household) reported in Koomey et al. (1994b). This usage estimate is based on the most internally consistent data and we therefore feel that their average usage value is representative of actual usage levels. We then used the scaled hot water usage to derive the linear regression values in Equation 5.3.

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[9]Because the sample of homes had electric resistance water heating, we assume 100% recovery efficiency to convert from electricity consumption to hot water usage. Hot water usage is a quadratic function of HHsize because the REMP report notes the non-linear relationship between HHsize and kWh.

Table 5.1: Water Heater Base Usage Data Summary							
% of Houses in 1990 stock (1)	# of Household Occupants	Predicted UEC (2) (kWh/yr)	Total Hot Water Usage (3) (gal/day)	Saturation-Wtd. Hot Water Use (gal/day) (4)		Base Hot Water Use (5) (gal/day)	Scaled Base Use (6) (gal/day)
				CWash	DWash		
0%	0	1,154					
25%	1	2,790	24.0	3.7	1.0	19.2	29.0
33%	2	3,784	38.5	8.3	2.6	27.6	41.6
17%	3	4,672	51.5	11.7	3.5	36.3	54.8
15%	4	5,505	63.7	16.4	4.9	42.4	64.0
7%	5	6,303	75.4	20.5	6.3	48.6	73.3
4%	6	7,077	86.7	25.0	5.7	56.0	84.4
Wgtd. Avg.	2.6	4,248	45.3	10.4	3.1	31.8	47.9

Notes:
(1) From 1990 RECS (EIA 1992).
(2) Based on REMP data, assuming that hot water usage is a quadratic function of HHsize, of the form: STANDBYLOSS + a(HHsize) + b(HHsize^0.5), where STANDBYLOSS=1154 kWh/yr, a=539, and b=1098.
(3) Assumes 77F temperature rise, and 100% electric resistance water heater recovery efficiency.
(4) Water use is weighted by the saturation of clothes washers and dishwashers within each HHsize bin. Assumes that 3-member households use the average amount of hot water (14.19 gal/day for clothes washers and 7.39 gal/day for dishwashers, based on 1990 stock average UEC (AHAM 1991)). 6-member households use 2x average, 1-member households use 0.5x average. Other household sizes are linearly interpolated between these values.
(5) Hot water used by faucets and showers, net of clothes washer and dishwasher use.
(6) Base hot water use within each HHsize bin has been scaled so that weighted average matches 47.9 gal/day base usage estimated in Koomey et al. (1994b).

Household hot water usage is further disaggregated into household end-use points to allow modeling of the impacts of the showerhead and faucet efficiency standards in the Energy Policy Act of 1992 (EPAct 1992). We subdivided the base hot water load into flow-dominated endpoints (showerheads and some faucet use) and volume-dominated endpoints (filling of sinks and bathtubs). The flow-dominated endpoints will be impacted by future changes in fixture flowrates, whereas volume-dominated endpoints are not affected since usage in these cases is determined by volume. The household end-use point disaggregation is from Koomey et al. (1994b), who estimate the portion of base hot water usage that is volume-dominated (36%), flow-dominated for showers (54%), and flow-dominated for faucets (10%).

Shflow and *Ftflow*, the estimates of average flowrates of the showerhead and faucet ("plumbing fitting") stock in future years, are calculated outside of the model, and account for changes in the stock from new purchases and replacements. The average flowrates of the stock in 1990 are input as the denominators in the equation. We estimate that typical "high" flowrate fittings use 3.5 gallons/minute (gpm), and that 10% of households already have low-flow fittings (2.5 gpm). Thus, the base average flowrates for each are 3.4 gpm (Koomey et al. 1994b). EPAct standards (EPAct 1992) mandate 2.5 gpm or less flowrates beginning in 1994. We calculate average stock flowrate in future years assuming a 20-year lifetime for the fittings and a constant replacement rate (implying that 5% of the fixture stock is replaced each year). Table 5.2 shows the resulting time series of average flowrate used as an exogenous input for the variables *Shflow* and *Ftflow* in Equation 5.3. 85% of the fitting stock existing in 1993 has been replaced by the year 2010, leading to a 21% reduction in total, non-appliance base hot water load from the 1990 level.

Table 5.2: Showerhead and Faucet Flowrates Resulting from EPAct Standard		
Year	Showerhead & Faucet Stock Average Flowrate (gpm)	% Decline in Base Hot Water Usage as a Result of EPAct Standard
1990	3.40	0
1991	3.40	0
1992	3.40	0
1993	3.40	0
1994	3.34	2
1995	3.27	3
1996	3.21	5
1997	3.16	6
1998	3.10	7
1999	3.05	9
2000	2.99	10
2001	2.94	11
2002	2.89	13
2003	2.84	14
2004	2.80	15
2005	2.75	16
2006	2.71	17
2007	2.66	18
2008	2.62	19
2009	2.58	20
2010	2.54	21

Source: Hot water load disaggregated into end-use points based on data in Koomey et al. (1994b).
(1) Stock turnover assumes 20 year fitting lifetime and constant replacement rate of 5% per year. EPAct plumbing standard does not take effect until 1994.
(2) Base hot water usage is total, non-appliance hot water usage, including sink- and bathtub-filling uses which are not affected by EPAct standard.

Interaction Between Dishwasher and Clothes Washer Efficiency Choice and Water Heaters. As indicated in Equation 3.3, the desirability index for the efficiency choice model is a linear function of purchase price (PP) and operating cost (OC) of the specific efficiency option. Operating cost for dishwashers and clothes washers can be expressed as:

$$\overline{OC}_{ge} = \overline{OCnhw}_{ge} + \overline{OChw}_{ge} \qquad (5.4)$$

where $\overline{OC}_{ge}$ = Average Operating Cost for efficiency option e of generic technology g, \$/unit/year

$\overline{OCnhw}_{ge}$ = Average Operating Cost for non-hot water load, \$/unit/year

$\overline{OChw}_{ge}$ = Average Operating Cost for hot water load, \$/unit/year

The average operating cost of the non-hot water load is the motor operating cost for clothes washers, and the motor, heater and dryer operating costs for dishwashers. It is calculated from the efficiency data specified in the input data sets for the specific technologies (Tables E.1 and F.1 in the Appendices). We do not include the cost of water or detergent in these operating costs because the units with which these parameters are specified (gallons/cycle or \$/cycle) are incompatible with the electrical energy operating costs specified above (cycles/kWh). The only significant impact of this simplification is on horizontal axis clothes washers, which consume 50-75% less water and detergent than the other specific efficiency options.

The average operating cost for the hot water load is estimated as a linear combination of the electric water heating and gas water heating costs as follows:

$$\overline{OChw}_{ge} = (hwl_{ge}) \cdot (usage) \cdot \left\{ \frac{Share_{whe} \cdot P_e}{Eff_{whe}} + \frac{Share_{whg} \cdot P_g}{Eff_{whg}} \right\} \tag{5.5}$$

where $\overline{OChw}_{ge}$ = Average Operating Cost for efficiency option *e* of generic technology *g*, \$/unit/year,
hwl_{ge} = Hot water load for efficiency option *e* of generic technology *g*, kWh.th/year/unit,
usage = Usage index normalized to 229 cycles/year for dishwashers and 380 for clothes washers,
$Eff_{whe,g}$ = Efficiency (Energy Factor) of electric or gas water heater,
$Share_{whe,g}$ = Average saturation of electric or gas water heater,
$P_{e,g}$ = Price of electricity or gas.

The shares and efficiencies are exogenously specified variables, shown in Table D.13, that vary over time and are determined as discussed in the water heater ownership and efficiency choice sections. The shares are based upon the average market shares of the water heater fuel types. The water heater efficiencies are average efficiencies for the electric or gas water heating stock. The fuel prices, P_e and P_g, are exogenously specified.

Energy Sales Accounting. All hot water usage is accounted for under the water heater end-use. The energy consumption reported for dishwashers and clothes washers is for all other energy not associated with hot water heated by the hot water heater. For dishwashers, it is energy consumption for the motor, heater and dryer. For clothes washers, it is energy consumption for the motor only.

5.2. Ownership Models

5.2.1. Water Heaters

We estimated an ownership model for water heaters with a desirability index of the same form as our efficiency choice model:

$$U_g = b_1 PP_g + b_2 OC_g \tag{5.6}$$

PPg is now the average purchase price of generic technology *g* and *OCg* is the average operating cost of generic technology *g*. The costs are averages across the specific efficiency options using shares predicted by the efficiency choice model.

Our ownership model for water heaters has three generic technologies based on fuel choice: electric, gas and oil. Since these generic technologies are differentiated by fuel, and we assume that all households have a water heater, the ownership decision model reduces to a fuel choice model. Estimation of the model parameters requires data describing recent purchases of water heaters, including information on the households as well as information on the annual operating cost and purchase price of the water heaters in each household. Household-level price data are generally not available, so we chose a data set of households in the 1987 RECS who had purchased water heaters within the previous two years (i.e., 1986 or 1987). This data set included water heaters purchased for new homes and for replacement of existing water heaters.

There were a total of 575 households in this RECS sub-sample, which after weighting each sample by its statistical weight in the RECS, produces a weighted representation of 8.77 million households.

For each household in this sample, we extracted relevant information from RECS. This included the water heater fuel choice, space heating fuel, number of bathrooms, number of bedrooms, number of occupants, ownership of a clothes washer, and ownership of a dishwasher. We used this information to estimate the hot water usage and the capacity of the water heater for each household. The hot water usage is based on the DOE test procedure (64.3 gal/day-household)[10], which has been disaggregated by household size according to the relationship described in Section 5.1.2. The annual operating cost is then based on this usage profile and 1986-87 fuel prices. Since the RECS does not have data on purchase prices, we estimated the purchase price as a function of the fuel type, capacity, and average efficiency for each water heater in the RECS sub-sample. We assigned a capacity to the water heater for each household based on the number of bedrooms, number of bathrooms and the number of occupants (ASHRAE 1991), assuming only three choices for water heater capacity: 30, 40, and 52 gallons. The relationship between cost and capacity (for each water heater fuel type) was derived from cost estimates published by R.S. MEANS (1991). The relationship between cost and efficiency was based on information used in analyzing federal energy conservation standards (US DOE 1993a). The operating cost and purchase price estimates were used in Equation 5.6 to estimate the ownership model parameters shown in Table 5.3.

Table 5.3: Estimated Coefficients of Water Heater Fuel Choice Model

Variable	Parameter Estimate
Purchase Price (b_1)	-0.0107
Operating Cost (b_2)	-0.0127
Implicit discount rate*	84.2%

* Assuming infinite lifetime.

To estimate the model parameters, we employed Berkson's procedure as described in Section 3.2. The generic technology market shares (S_i in Equation 3.5) are from the 1987 RECS purchase sample described above.

5.2.2. Dishwashers and Clothes Washers.

We adopt the REEPS 2.1 default ownership models for dishwashers and clothes washers, shown in Table 5.4.

[10]The DOE hot water usage level was initially used to estimate the water heater ownership model, but is not entirely consistent with the revised usage estimate (61.4 gal/day-household) described in Section 5.1.2. We did not re-estimate the water heater ownership model using the updated hot water usage because the effect on the ownership model parameters is minimal.

Table 5.4: Appliance Ownership Models for Dishwashers and Clothes Washers		
Generic Technology	**Model Type**	**Utility Function**
Dishwasher	New Home	$U_{h,dw} = 0.045{*}Inc_h + 0.04{*}HHSize_h - 0.2{*}Rural - 3.0{*}AvgE + C_{h,dw}$
	Replacement	100% Replacement
	Acquisition	$U_{h,dw} = -3.5 + 0.045{*}Inc_h + 0.04HHSize_h - 0.2{*}Rural - 3.0{*}AvgE + C_{h,dw}$
Clothes Washer	New Home or Replacement	$U_{h,n,cw} = 0.04Inc_h + 0.262HHSize_h + 0.041(Year-1987) + C_{h,n,cw}$
Definitions: *h* is house type, *n* is the decision state (new construction, replacement, or non-owner acquisition), *Inc* is the average household income, *HHSize* is the average number of household members, *Rural* is the fraction of rural households in the total population, *AvgE* is the average electricity price, $C_{h,n,g}$ is the control-year calibration constant for generic technology *g*.		

5.3. Efficiency Choice Model

Efficiency choice model parameters were derived using data sets described in Section 3.2. For electric and gas water heaters, the efficiency data are shown in Table 5.5. No data on market share by efficiency level is available for oil water heaters. Thus, for oil water heaters we selected the efficiency choice parameters so that average efficiency calculated using the estimated market shares and the efficiency options in Appendix Table D.3 will match the shipment weighted energy factor (0.55) in the LBL-REM input set (US DOE 1993a). This is similar to the technique used for dryers described in Section 4.3.2. For dishwashers and clothes washers, the efficiency distribution data used to estimate the efficiency choice model are shown in Table 5.6. We employed Berkson's procedure, as described in Section 3.2, to estimate the efficiency choice parameters. The results are shown in Tables 5.7 and 5.8.

Table 5.5: Water Heater Efficiency Distribution Data			
Electric		**Gas**	
Energy Factor	**Market Share**	**Energy Factor**	**Market Share**
0.74	0.2%	0.46	1.9%
0.76	0.2%	0.47	1.5%
0.78	1.9%	0.49	1.9%
0.80	0.4%	0.53	0.2%
0.87	3.9%	0.54	12.5%
0.88	20.8%	0.55	26.4%
0.89	12.0%	0.56	25.4%
0.90	19.3%	0.57	5.1%
0.91	3.0%	0.58	9.0%
0.92	8.6%	0.59	2.7%
0.93	5.4%	0.60	4.3%
0.94	11.6%	0.61	1.9%
0.95	3.9%	0.62	5.5%
0.96	7.1%	0.63	1.0%
0.97	1.9%	0.72	0.5%
		0.74	0.3%
0.91	100%	0.56	100%
Source: US DOE (1993a).			

Table 5.6: Dishwasher and Clothes Washer Efficiency Distribution Data			
Dishwasher		**Clothes Washer**	
UEC (1)	**Market Share**	**UEC (2)**	**Market Share**
709.9	0.5%	1672	0.3%
687.0	1.0%	1558	0.6%
664.2	22.1%	1482	0.6%
641.2	9.3%	1406	8.1%
618.3	10.3%	1330	0.6%
595.4	14.7%	1254	4.9%
572.5	8.8%	1178	19.5%
549.6	17.6%	1102	9.9%
526.7	9.3%	1026	9.0%
503.8	6.4%	950	11.9%
		874	16.6%
		798	15.4%
		722	2.6%
596	100%	1037	100%

Source: US DOE (1990)
(1) UEC includes motor, booster heater, dryer and hot water energy, assuming 229 cycles/yr and electric water heater with no standby losses (EF=1).
(2) UEC includes motor and hot water energy, assuming 380 cycles/yr, 2.6 ft3 capacity, and electric water heater with no standby losses (EF=1).

Table 5.7: Estimated Coefficients of Water Heater Efficiency Choice Models

Generic Technology	Variable	Parameter Estimate
Electricity		
	Purchase Price (b_1)	-0.0216
	Operating Cost (b_2)	-0.0195
	Implicit discount rate*	111%
Gas		
	Purchase Price (b_1)	-0.0719
	Operating Cost (b_2)	-0.1136
	Implicit discount rate*	63%
Oil		
	Purchase Price (b_1)	-0.10
	Operating Cost (b_2)	-0.05
	Implicit discount rate*	200%

* Assuming infinite lifetime.

Table 5.8: Estimated Coefficients of Dishwasher and Clothes Washer Efficiency Choice Models		
End-use	**Variable**	**Parameter Estimate**
Dishwasher		
	Purchase Price (b_1)	-0.2738
	Operating Cost (b_2)	-0.2463
	Implicit discount rate*	111%
Clothes washer		
	Purchase Price (b_1)	-0.3811
	Operating Cost (b_2)	-0.0974
	Implicit discount rate*	391%
* Assuming infinite lifetime.		

6. LIGHTING MODEL

This section documents the baseline energy consumption for residential lighting. There has only recently been an effort by energy analysts to characterize the lighting end-use in the residential sector. Typically lighting has been treated as one of the miscellaneous energy uses in residences, but recent surveys[11] suggest that lighting may represent a more significant use than originally thought. We estimate that lighting accounts for approximately 10% of residential electricity consumption, and is thus a major end-use. For this reason, we treat lighting separately from the miscellaneous end-use category. Our understanding of the lighting end-use, however, only encompasses current equipment saturations and usage patterns. Thus, for implementation in REEPS we did not have sufficient data to estimate ownership and efficiency choice models, so we omit these models from the discussion. Nevertheless, the lighting baseline is quite useful because it allows modeling of prescriptive policies and provides a better understanding of potential market niches for lighting technologies.

Residential lighting exhibits a great deal of diversity in usage (hours) and equipment size (lamp wattage). This situation is further complicated by the fact that the usage level affects the service life of the device. For instance, an incandescent bulb used one hour per day will last approximately three years, while the same bulb operated three hours per day will last less than one year. The lifetime, in turn, largely determines the cost-effectiveness of energy-efficient lighting technologies. For these reasons, we account for the heterogeneity in lighting usage by modeling several discrete usage levels as separate end-uses in REEPS. This allows for more accurate comparisons between lighting applications of differing usage intensity.

The fundamental unit of analysis used in this analysis is the individual incandescent light socket. However, for modeling in REEPS the baseline UEC is over all light sockets in the house. The saturation of each end-use (discrete usage level) is based on the fraction of light bulbs having the designated usage level in the average house. Baseline consumption is further disaggregated into three housing types: single-family, multifamily and manufactured homes.

[11] Such as the PG&E residential lighting survey documented by Kelsey and Richardson (1992) and another survey by Grays Harbor PUD (1992).

6.1. Baseline Lighting Usage

We divide the current stock of light *sockets* into five usage bins: less than 1 hour, 1 to 2, 2 to 3, 3 to 4, and greater than 4 hours per day. This distribution includes both interior and exterior lighting. The fraction of sockets assigned to each bin (Table 6.1) is based on monitored residential lighting usage in Washington state (Manclark 1991). Although these data come from a limited sample of houses, the usage distribution is similar to another monitoring study in Washington state (Grays Harbor PUD 1992) in which the weighted average usage is 2.5 hours/day. Moreover, the mean usage used here is lower than generally cited in some other studies (see Appendix H).

Table 6.1: Monitored Lighting Usage Characteristics

Daily Usage (hours/day)	Average Usage in Bin (hours/day)	Fraction of Bulbs (%)	Weighted-Average Usage (hours/day)
0-1	0.5	40%	0.20
1-2	1.5	20%	0.30
2-3	2.5	10%	0.25
3-4	3.5	10%	0.35
>4	5	20%	1.00
Total		100%	2.10

Source: Manclark (1991). Measured data from Yakima, WA. Adapted from a study of 52 homes.

We believe that the usage distribution in this study (Table 6.1) is representative of residential lighting usage in the US, and any bias it may contain would tend to *understate* lighting usage. There are two significant reasons why earlier studies have overestimated lighting usage. First, most studies only concentrate on high-use sockets because these are generally the locations where more efficient lighting technologies are most cost-effective. Second, most studies estimate hours of usage by surveying the building occupants, but it is difficult for lighting users to accurately gauge the average annual usage of each lighting socket. Moreover, the surveys are usually conducted in the course of utility programs to identify high-usage sockets and retrofit them with compact fluorescent lamps. This gives the building occupants an incentive to overestimate usage in order to maximize the number of utility-provided retrofit lamps. In one study by the New England Electric Service (NEES), users who kept diaries of lighting usage *reported* 37% lower hours of usage than they originally had *estimated* for the same sockets (Granda 1992).

6.2. Baseline Installed Wattage

In this study, we principally consider the consumption of incandescent lamps because they comprise the vast majority of lighting in the residential sector. For instance, a comprehensive lighting survey in Northern California found that 88% of the existing lamps in residences were general service or reflector incandescents (Kelsey and Richardson 1992). Because California's residential building code requires fluorescent lighting in kitchens and bathrooms of new houses, the fraction of incandescents in California is probably lower than other parts of the US. We take this as a lower bound on the fraction of incandescents in houses nationwide. The largest saturation of non-incandescent lamps, however, are linear fluorescent tube lamps (four or eight feet long). For this reason, we include full-size fluorescent lamps as a separate REEPS end-use, but do not differentiate between housing types. In addition, compact fluorescent lamps (CFLs) have a small, but growing, saturation. The PG&E lighting survey found CFLs in approximately 2% of the light sockets surveyed (one CFL in half the homes) (Kelsey and Richardson 1992). Due to this small saturation, we do not treat CFLs separately from the incandescent lighting stock in the REEPS lighting model, but rather as a generic technology within the incandescent lighting end-uses. In the baseline REEPS model, CFL saturation is assumed to be fixed at the current level because we have no data with which to estimate an ownership decision model. The user can model prescriptive policies by exogenously increasing CFL saturation.

To disaggregate the stock incandescent lamp wattages we have assumed that all lamps are one of the most common wattages – 40, 60, 75, 100, or 150 Watts. We used a survey of homes in New York and New Jersey (Robinson 1992) as the basis for the relative frequency of each lamp size. The wattage distribution has been modified somewhat by aggregating the smallest and largest wattages (e.g., bulbs smaller than 40 watts are added to the 40W bin) as shown in Table 6.2. The aggregated distribution retains sufficient detail for forecasting purposes, yet simplifies the analysis.

Table 6.2: Installed Incandescent Wattage Distribution

		Estimated Installed Wattage Distribution (1)		Aggregated Installed Wattage Distribution Used for this analysis		
Incandescent Bulb Size (Watts)	**Average Size for Category (Watts)**	**Share of Incandescent Bulbs**	**Weighted-Average Watts**	**Average Size for Category (Watts)**	**Share of Incandescent Bulbs**	**Weighted-Average Watts**
<40	25	9%	2.3			
40	40	16%	6.4	35	25%	8.8
60	60	37%	22.2	60	37%	22.2
75	75	20%	15.0	75	20%	15.0
100	100	12%	12.0	100	12%	12.0
150	150	5%	7.5	150	6%	9.0
>150	175	1%	1.8			
Total / Weighted-Average:		100%	67.1		100%	67.0

(1) Source: Robinson (1992)

6.3. Baseline Energy Consumption

The baseline lighting UEC is calculated at the level of the individual light socket, and then aggregated to estimate a whole-house lighting UEC. Two types of data are needed to calculate the baseline lighting consumption: The annual consumption for each socket, and the average number of sockets per house. Table 6.3 shows the calculation of socket UECs, based on the usage and wattage distributions presented above. Each combination of lamp wattage and daily usage leads to a unique annual socket UEC (25 levels, ranging from 6 to 274 kWh per year). In Table 6.4, these individual UECs are then weighted according to their frequency of occurrence in the housing stock (the bulb and wattage fractions in Table 6.4), in order to calculate an average socket UEC. Table 6.4 also disaggregates this average socket UEC to indicate which wattage/usage combinations are the largest contributors to a house's lighting consumption.

Table 6.3: Annual Incandescent Socket UEC (cross-tabulation of usage and wattage: annual kilowatt-hours)						
		Wattage (Mean Wattage in bin)				
		≤40 35	**60** 60	**75** 75	**100** 100	**≥150** 150
Daily Usage (hours)	**Mean Usage in Bin**	**Unit Energy Consumption (UEC) per socket**				
0-1	0.5	6	11	14	18	27
1-2	1.5	19	33	41	55	82
2-3	2.5	32	55	68	91	137
3-4	3.5	45	77	96	128	192
>4	5	64	110	137	183	274
Source: Wattage - Robinson (1992); Usage - Manclark (1991)						

Table 6.4: Fraction of Incandescent Lighting UEC (cross-tabulation of usage, wattage, and saturation)								
			Wattage (% of Installed Wattage)					Total
			≤40 25%	**60** 37%	**75** 20%	**100** 12%	**≥150** 6%	100%
Daily Usage (hours)	**Mean Usage in Bin**	**Bulb Fraction**	**Fraction of Average Socket UEC**					
0-1	0.5	40%	1%	3%	2%	2%	1%	10%
1-2	1.5	20%	2%	5%	3%	3%	2%	14%
2-3	2.5	10%	2%	4%	3%	2%	2%	12%
3-4	3.5	10%	2%	6%	4%	3%	2%	17%
>4	5	20%	6%	16%	11%	9%	6%	48%
	Total:	100%	13%	33%	22%	18%	13%	100%
Average UEC per socket (kWh/yr): 51.4								

Thus far, the data presented have described the usage and wattage of individual lamps; multiplying these data by the number of sockets per house yields the whole-house UEC. Starting with the average socket UEC calculated in Table 6.4, we use the number of incandescent sockets per house as a variable in order to calibrate the incandescent lighting power density (installed watts per square foot) to the value found in the PG&E survey (Kelsey and Richardson 1992). The calibration accounts for the fact that the floor areas used in this study are different than the average floor area in the PG&E survey, and our assumed usage is slightly higher. Table 6.5 illustrates the calibration process. The resulting number of sockets per house is well within the range of several surveys recently conducted, some showing well in excess of thirty sockets per (single-family) house (see for example Manclark (1991) and Robinson (1992)).

In residential lighting analyses, the whole-house lighting UEC is typically used for comparison to determine if a survey or calculation is yielding approximately the correct results. We use the whole-house lighting UEC in a similar way to assure the accuracy of the aggregate lighting consumption. The annual lighting UEC is thought to vary between 750 and 1500 kWh per year, depending on the location and type of house. We estimate that the whole-house lighting UEC is

1469 kWh/yr (1313 kWh/yr for incandescent and 156 kWh/yr for fluorescent) averaged over all housing types. This is approximately 20% higher consumption than PG&E's lighting survey, which yielded a whole-house UEC of 1274 kWh per year (Kelsey and Richardson 1992). The principal reasons for the higher UEC in this study are larger floor areas and slightly higher hours of usage.

Table 6.5: Calibration of Lighting Intensity (W/sf) to PG&E survey value

		Housing Type			
Parameter	PG&E (2)	Single-Family	Multifamily	Mobile Homes	Total
% of 1990 households:		*69%*	*26%*	*6%*	*100%*
Lighting UEC (kWh/yr)	1,274	-	-	-	-
Fluorescent UEC (kWh/yr)	156	-	-	-	-
Incandescent UEC (kWh/yr)	1,118	-	-	-	-
Floor area (sq ft)	1,400	1,865	928	921	1,569
Installed incandescent watts	1,552	2,052	964	1,013	1,712
Avg. incandescent usage (hr/day)	1.94	2.10	2.10	2.10	2.10
Annual incandescent UEC (kWh/yr)	1,098	1,574	739	777	1,313
Inc. UEC per socket (kWh/socket/yr)	44.7	51.4	51.4	51.4	51.4
Sockets/house	25	31	14	15	26

(1) Source for 1990 housing stock: RECS (EIA 1993)

(2) Results of PG&E Lighting Survey are documented in Kelsey & Richardson (1992).

(3) Lighting UEC in first row includes incandescent and fluorescents together. Incandescent UEC is net of tube fluorescent lamps. Fluorescent UEC calculated based on Kelsey & Richardson (1992), 3.2 lamps per house @ 41.1 Watts/lamp used 3.8 hrs. per day and 5 out of every 6 days during the year.

(4) PG&E floor area from survey. Floor area by house type from 1990 RECS (EIA 1992).

(5) Installed wattage based on PG&E survey; 1.25 W/sf for single-family and mobile home, 1.18 W/sf for multifamily, reduced by 12% to account for the fact that incandescent lamps are 88% of installed wattage.

(6)PG&E average usage value based on customer-reported usage; US value from Table 6.1.

(7) PG&E value for UEC per socket based on survey data; US value from Table 6.4.

(8) Annual UEC (kWh/yr) equals average usage * installed watts * 365/1000.

(9) PG&E value for sockets/house based on survey data; US values = annual UEC + UEC per socket.

The final step in estimating the lighting baseline is to convert the data presented above into a form usable by REEPS. As mentioned previously, we model lighting as several REEPS end-uses to reflect the different usage socket levels. In this model formulation, all incandescent sockets operated between one and two hours per day are accounted for in their own end-use and have a unique saturation in the housing stock. In this case, the end-use saturation is not the fraction of houses owning light bulbs, but rather the fraction of bulbs that are operated at a particular usage level in the average house. To calculate the annual whole-house UEC, we multiply the annual hours of operation for a particular end-use by the average bulb wattage and the number of light sockets in each house type. The results of these calculations are shown in Table 6.6. The end-use UECs appear to be quite different from the PG&E survey data presented earlier. However, the values in Table 6.6 are calculated as if *all* sockets in the house were operated at the usage level indicated by the end-use. In fact, each end-use actually represents only a portion of the total number of bulbs in a house, and the true whole-house UEC is a weighted average of all the REEPS end-uses in Table 6.6.

We have also modeled full-size fluorescent lamps as a separate end-use, but we do not have sufficient data to disaggregate fluorescents according to usage or house type. The PG&E survey indicates that full-size fluorescents comprise approximately 9% of the installed wattage, or 135 Watts of fluorescent lamps. Thus the fluorescent stock (and UEC) is small in comparison with the incandescent end-uses (due to fluorescents' higher efficacy, however, the lumens provided by fluoroescents are a significant fraction of the total delivered lumens).

Table 6.6 also includes the weighted average UEC for each housing type and usage bin. These data are for informational purposes only, since they are not used as input to REEPS. Finally, the rightmost column in Table 6.6 (total incandescent lumens) is not an end-use but rather is an input to REEPS indicating the level of lighting service demanded by each house type. This information will be useful in implementing size and efficiency choice models at a future date.

Table 6.6: Lighting Model Input Data for REEPS

House Type	Lighting End-uses for REEPS							Total	Total
	0-1 Hours UEC (kWh)	1-2 Hours UEC (kWh)	2-3 Hours UEC (kWh)	3-4 Hours UEC (kWh)	>4 Hours UEC (kWh)	Wtd. Avg. Incand. UEC (kWh)	Fluor-escent UEC (kWh)	Lighting UEC (kWh)	Incand-escent Lumens
Saturation:	*40%*	*20%*	*10%*	*10%*	*20%*				
Single-Family	379	1137	1895	2653	3790	1668	156	1824	32,369
Multifamily	171	514	856	1198	1712	753	156	909	14,618
Manufactured Homes	183	550	917	1284	1834	807	156	963	15,662
Wgtd.-Avg.	314	943	1571	2200	3142	1383	156	1539	26,836

(1) UECs calculated assuming all incandescent bulbs in the house are operated at the indicated usage level.
(2) Weighted-averages calculated using housing type distribution from Table 6.5.
(3) Weighted-average incandescent UEC (1383 kWh/yr) differs slightly from value in Table 6.5 (1313 kWh/yr) because the number of incandescent sockets per house has been constrained to an integer value.

The REEPS lighting data presented here are based on an analysis methodology similar to that used in LBL's Lighting Policy Analysis (LPA) (Atkinson et al. 1992). The current analysis, however, uses updated data on lighting usage and installed wattage from surveys and monitoring studies. The general effect of these updates is to increase the number of light sockets and decrease the average hours of use per socket, leading to a small increase in annual household UEC (1469 kWh/household-year vs. 1294 estimated in the LPA). In essence, the lighting characterization presented here includes many low-use sockets that have been left out of previous studies. These low-use sockets are not significant for their energy consumption (accounting for only about 10% of the household lighting UEC), but rather because they are an important part of the lighting stock and lamp market.

7. COOKING AND MISCELLANEOUS MODELS

The cooking end-use includes several types of appliances, such as ranges or cooktops, gas or electric ovens and microwave ovens. A full technology characterization and cost analysis appears in the recent appliance standards analysis (US DOE 1993b) for ranges, ovens and microwave ovens. Due to the recent publication of this source, we have not been able to incorporate its findings and instead have used the default data for cooking equipment provided by Regional Economic Research (McMenamin et al. 1992). This approach aggregates cooking equipment into a reduced-form model for each generic technology, which in this case is simply by fuel: electric, gas and other. The "other" category for cooking includes miscellaneous minor cooking fuels such as oil, LPG and wood. Table 7.1 shows the Unit Energy Consumption for the three classes, along with the base year stock and new home market shares.

Table 7.1: Cooking Model Input Data
Screens: AM-3a, AM-3f, AM-4e

Housing Type	Stock Shares (percent)	New Home Shares (percent)	UEC
Electric Cooking			kWh/yr
Single-Family	62	75	617
Multifamily	45	76	486
Manufactured Homes	41	60	567
Gas Cooking			kBtu/yr
Single-Family	32	23	5153
Multifamily	55	24	4256
Manufactured Homes	29	18	4514
Other Fuels-Cooking			kBtu/yr
Single-Family	6	2	5000
Multifamily	0	0	N/A
Manufactured Homes	30	22	4700

Source: REEPS default input set (McMenamin et al. 1992)

The miscellaneous end-use encompasses those appliances not covered in the end-uses we have outlined thus far. We consider only electric appliances in this category, although it is possible that a rather small amount of energy consumption may remain unaccounted for among fuels due to outdoor equipment and other fuel-using appliances with low saturations in the current housing stock. The miscellaneous category of electricity end-uses actually includes many different minor appliances and appears to represent a growing share of electricity consumption, in some cases accounting for as much as 20% of total household electricity consumption (Meier et al. 1992, Rainer et al. 1990). A few appliances in the miscellaneous category, such as televisions and pool heaters, were also covered in the recent appliance standards analysis (US DOE 1993b). Again due to the recent release of this document, we rely on the default characterization provided for the miscellaneous end-use (McMenamin et al. 1992). Since the REEPS default miscellaneous category includes lighting, we subtract the lighting UECs as given in Table 6.6 for each housing type. The lighting-adjusted miscellaneous UECs are given in Table 7.2. The saturations (market shares) are 100% because the end-use describes an aggregation of appliances present in the typical home, rather than a particular appliance.

Table 7.2: Miscellaneous End-Use Input Data
Screens: AM-4a, AM-4b, AM-4e

Housing Type	Stock Shares (percent)	New Home Shares (percent)	REEPS Default Misc. UEC (kWh/yr)	Lighting UEC (1) (kWh/yr)	Adjusted Misc. UEC (2) (kWh/yr)
Miscellaneous Electric					
Single-Family	100	100	3085	1824	1261
Multifamily	100	100	1525	909	616
Manufactured Homes	100	100	2307	963	1344

Source: REEPS default input set (McMenamin et al. 1992)
(1) Lighting UEC from Table 6.6.
(2) Adjusted Miscellaneous UEC = REEPS default UEC - Lighting UEC.

8. SPECIFIC TECHNOLOGY OPTIONS DATA

Table 8.1 lists the product classes defined in NAECA. The historic data used in this report (i.e., vintage block data) are averages over all product classes. However for new appliances, we choose one product class to represent each fuel type in a given end-use. Typically, one or two classes dominate sales, making the choice of product class straightforward. For refrigerators, "Top mounted auto defrost" was selected to represent the end-use because it accounts for over two-thirds of all refrigerator shipments and, as shown in Figure 8.1, its shipment-weighted efficiency closely tracks the average efficiency for all refrigerators (AHAM 1991). For freezers, "Upright, Manual Defrost" was selected because, as shown in Figure 8.2, its historic average efficiency closely tracks that of the average efficiency for all freezers (AHAM 1991). For dishwashers, appliance efficiency standards taking effect in 1995 will require that "Standard Dishwashers" include water heaters, effectively making them "Water-Heating Dishwashers, Standard." Hence, we elected to use water-heating dishwashers rather than the soon-to-be eliminated class of standard dishwashers. For clothes washers and dryers, a single product class dominates sales in each generic technology.

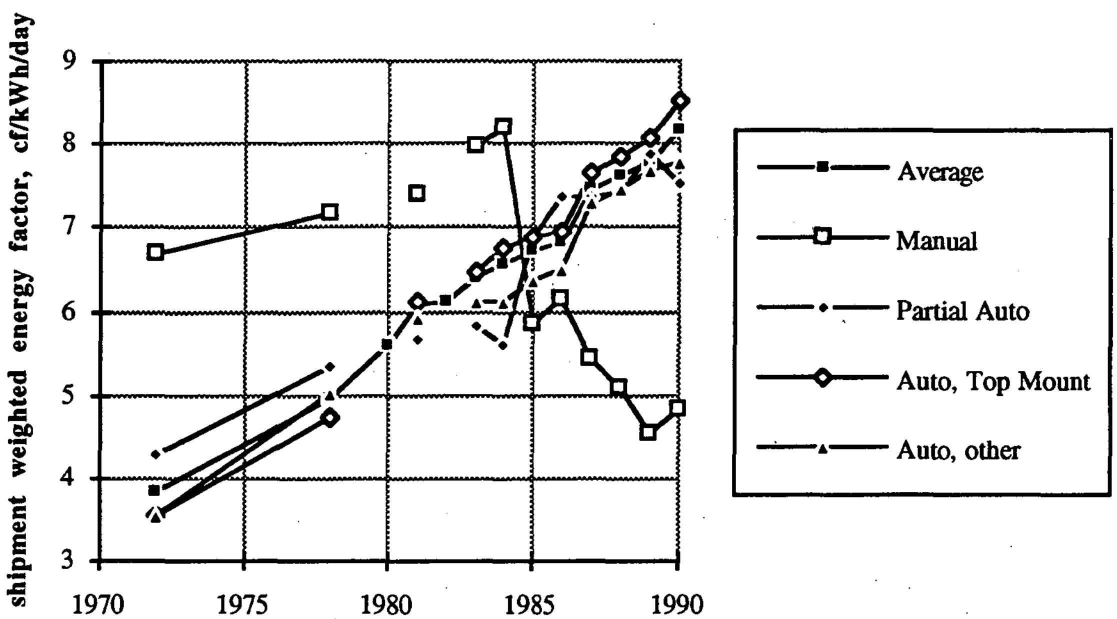
8.1 Specific Technology Efficiency and Cost

Specific technology design options for each end-use are listed in Appendix Tables B.1 (refrigerators), C.1 (freezers), D.1, D.2, D.3 (water heaters), E.1 (dishwashers), F.1 (clothes washers), G.1 and G.2 (dryers). Each successive option represents a design change that impacts the efficiency and/or purchase price of the appliance. For a complete description of the design options, see the appropriate DOE Technical Support Document. The option lists begin with option "0," which is the base marginal unit in 1987 (US DOE 1989, US DOE 1990) or 1990 (US DOE 1993a). All costs in the TSDs are quoted in base year 1987 (US DOE 1989, US DOE 1990) or 1990 (US DOE 1993a) dollars. Some designs already exist in models currently on the market, and others are still being developed. Arthur D. Little developed the original lists in the early 1980s (ADM 1987), and Lawrence Berkeley Laboratory updated and expanded the lists in the late 1980s (US DOE 1989). The most efficient options on the lists are currently commercially available for some end-uses and exist only as prototypes in other end-uses. In some policy forecast cases, restricting our options to these lists may under-predict the potential for conservation since it does not account for the innovation of new, more efficient appliance options in future years.

We inflated the 1987 base-year purchase prices to 1990 dollars using either the Consumer Price Index-urban (CPI-urban) for Refrigerators and Freezers, the CPI-urban for Laundry Equipment, the CPI-urban for Stoves, Ovens, Dishwashers and Air conditioners, or in the case of water heaters, the Producer Price Index (PPI) for Household Equipment, Other. Appendix Tables A.1 and A.2 give the CPIs and PPIs for recent years. Another influence on the price of refrigerators and freezers is the 1996 CFC ban. Tables B.2 and C.2 show the price effect of the CFC ban (in the column labeled "Cost multiplier without CFCs").

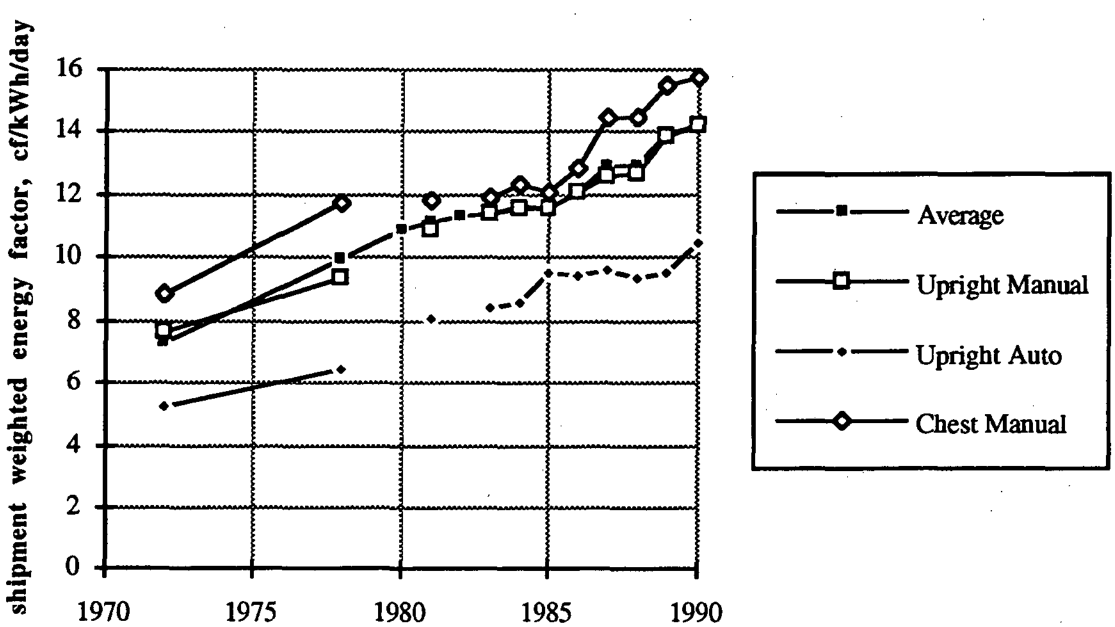
Table 8.1 NAECA Product Classes
Refrigerators and RefrigeratorsFreezers
1) Refrigerators and Refrigerator-Freezers with manual defrost
2) Refrigerator-Freezers-partial automatic defrost
3) Refrigerator-Freezers-automatic defrost with:
a) Top mounted freezer without ice (1)
b) Side mounted freezer without ice
c) Bottom mounted freezer without ice
d) Top mounted freezer with through the door ice service
e) Side mounted freezer with through the door ice service
Freezers
1) Chest, Manual Defrost
2) Upright, Manual Defrost (1)
3) Upright, Automatic Defrost
Water Heaters
1) Gas-fired Storage (1)
2) Electric-fired Storage (1)
3) Oil-fired Storage
4) Gas-fired Instantaneous (2)
Dishwashers
1) Compact Dishwasher
2) Standard Dishwasher
3) Water-Heating Dishwasher, Compact (115V)
4) Water-Heating Dishwasher, Standard (115V) (1)
5) Water-Heating Dishwasher, Compact (220V)
6) Water-Heating Dishwasher, Standard (220V)
Clothes Washers
1) Top-Loading, Compact
2) Top-Loading, Standard (1)
3) Top-Loading, Large
4) Top-Loading, Semi-Automatic
5) Front Loading
6) Suds Savers (2)
Dryers
1) Electric, Standard (1)
2) Electric, Compact 120V
3) Electric, Compact 240V
4) Gas, Standard (1)
5) Gas, Compact
Notes: (1) Product classes in bold type were chosen to represent the fuel-specific end-use in the LBL version of REEPS 2.1. (2) Not analyzed.

Figure 8.1: Shipment Weighted Energy Factors--Refrigerators



Source: AHAM Shipment data (AHAM 1991).
(1) Gaps in data series (after 1975) represented by unconnected points.

Figure 8.2: Shipment Weighted Energy Factors--Freezers



Source: AHAM Shipment data (AHAM 1991).
(1) Gaps in data series (after 1975) represented by unconnected points.

8.2 Specific Technology Market Shares and Availability

As described in Section 3.2, REEPS is unique in that it can model specific equipment technologies and forecast the market share of these options using multinomial logit models. While this technique can be quite powerful, it requires comprehensive market data in order to specify the logit models. As described in Sections 4 and 5, we did not have access to detailed purchase data at the national level and therefore estimated the specific technology efficiency choice models using aggregate and average data. These data were sufficient to specify the efficiency choice models, but we did not have a second, independent data source for control-year market shares to calibrate the efficiency choice models. For this reason, the control-year market share data in the Appendices are simply outputs from the efficiency choice models, for use as place holders in REEPS. The specific technology market shares shown in Tables B.2, C.2, D.4, D.5, D.6, E.2, F.2, G.3, and G.4 are based on operating costs using 1991 fuel prices and the specific technology options available in 1991. REEPS uses these market share values to calibrate the efficiency choice equations during forecast execution, but the calibration constants are assigned near-zero values because the control-year market shares are outputs of the model being calibrated. This is admittedly not an effective means of calibrating the efficiency choice models, but we are forced to use this method due to the requirements of the REEPS model and a lack of sufficiently detailed appliance purchase data.

In describing specific technology options, REEPS allows the user to restrict the choice of options in particular years if it is believed that certain options will not be available for purchase by consumers. There are two types of availability parameters: market and legal availability. Market availability refers to the maximum market share that can be met by manufacturers. Options that are not fully available on the market represent technologies that are produced in limited quantity due to manufacturing constraints or because manufacturers target them at niche markets. In years when future options are not available on the market (temporary market availability of zero), those options are simply ignored in REEPS 2.1 when the efficiency shares are calculated. Legal availability refers to technology options that are no longer offered because they do not meet minimum efficiency standards. In REEPS 2.1, options that are not legally available after some year (due to minimum efficiency standards) are then assigned a "legal availability" value of zero.[12] Once standards take effect, REEPS 2.1 models the impacts of standards by allocating the predicted shares of options not legally available to the next available option on the list.

Legal and Market Availability, Refrigerators. The base 1987 unit (option 0) is more efficient than the 1990 NAECA minimum efficiency standards, and is therefore still legally available in 1990, along with options 2 and 3. We assume that the remaining options require further development not completed until 1992. The five least efficient options -- 0, 2, 3, 4 and 5 -- are not available starting in 1993 due to federal efficiency standards taking effect that year. For the remaining years, we assume all other options are available on the market. The input data for refrigerator legal and market availability are shown in Table B.2.

Legal and Market Availability, Freezers. Due to the 1990 minimum efficiency standards, the base 1987 unit (option 0) is not available in 1990. We assume that only options 1 and 3 are available on the market in 1991. Examination of the 1991 AHAM appliance directory suggests

[12]Legal availability is a binary function, in other words partial availability is not possible. In reality, appliance models that do not meet the standard may still be available (for a year or two) as dealers' inventories clear. While this can be an important effect in particular regions or markets, we ignore this effect on the national level and assume that models not meeting the standard are unavailable in the year the standard becomes effective.

that this is a reasonable assumption (AHAM 1992). In 1992, we assume options 4 and 5 become available, and thereafter all other options are assumed to be available on the market, except options 1 and 3, which are not available starting in 1993 due to minimum efficiency standards taking effect that year. The legal and market availability of freezer technology options are shown in Table C.2.

Legal and Market Availability, Water Heaters. Tables D.4, D.5, and D.6 show the availability of water heater technology options. Some of the more advanced water heater technology options were not available on the market during the period 1990-92 because they required further development. For electric water heaters, we assume only options 0, 1, and 2 were available during this period. Similarly, we assume option 14 for gas water heaters, and option 4 for oil water heaters were *not* available during the 1990-92 period.

Legal and Market Availability, Dishwashers, Clothes Washers and Dryers. Minimum efficiency standards take effect in 1994 for dishwashers, clothes washers and dryers. For standard water heating dishwashers, the standards will eliminate options 0, 1, and 2, as shown in Table E.2. For standard clothes washers, the 1994 standards eliminate options 0 and 1, as shown in Table F.2. For dryers, the 1994 standards eliminate the first two efficiency options (options 0 and 1) for both electric and gas dryers. Generally, the technology for dishwashers, clothes washers and dryers is not developing at a rapid rate, thus most specific technology options are available on the market at the beginning of the forecast (1990). The only exception is for the clothes washer end-use, in which all technology options more efficient than option 2 are assumed not available in significant quantities until 1992.

9. APPLIANCE STOCK DATA

Stock Characteristics. To maintain accounts of appliance stocks, REEPS 2.1 requires data on efficiency, capacity, and base-year shares, disaggregated by vintage blocks (the year of appliance purchase). These appliance stock vintage data are presented in Tables B.3, C.3, D.7, D.8, D.9, E.3, F.3, G.5, and G.6. In addition, the user specifies stock decay function parameters, described below. The average efficiency and capacity data shown in the tables are calculated from AHAM shipments data (AHAM 1991).

9.1 Base-Year Vintage Shares

Base-year shares by vintage for refrigerators, freezers, water heaters, dishwashers, clothes washers and dryers are based on the number of the appliances in each vintage block that survive from the year of purchase to the base year 1990, using the decay function described below.

Decay Function. REEPS 2.1 computes survival and decay rates for appliance vintage blocks using a stepwise linear decay function in which 100% of the vintage block survives until a minimum lifetime and thereafter decays linearly so that no appliances survive beyond the maximum lifetime. To accurately estimate the minimum and maximum lifetimes, we varied these lifetime parameters to find the best fit to the following formula:

$$\mathrm{Stock}_{1990} = \sum_{vy} (\mathrm{Shipments}_{vy} \cdot \mathrm{SurvivalRate}_{vy,\, min,\, max}) \tag{9.1}$$

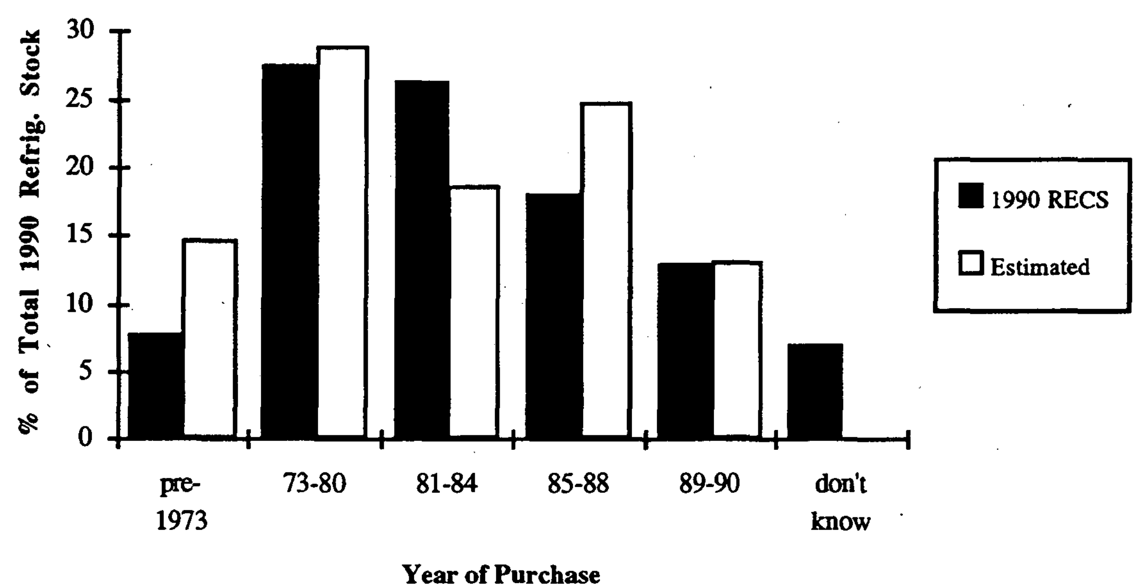
where *vy* is the vintage year, $Stock_{1990}$ is the 1990 RECS appliance stock, $Shipments_{vy}$ are the AHAM shipments for vintage year *vy*, and *Survival Rate* is the fraction of appliances of vintage year *vy* surviving in 1990, computed from the decay function using lifetime parameters *min* and *max*. The resulting best-fit lifetime parameters are shown in Tables B.4, C.4, D.10, E.4, F.4, and G.7.

We rely on AHAM shipment data to disaggregate the stock of refrigerators, freezers, water heaters, dishwashers, clothes washers and dryers into vintage blocks (AHAM 1991). For vintage blocks earlier than the first year in the AHAM data, we assumed the first year of shipment data holds true for the entire period prior to the first year of shipment data. For example, since AHAM shipments data start in 1972, we assumed 1972 shipment levels for the period prior to 1972. In cases where data were missing for intervening years, we linearly interpolated the shipments data. We used refrigerators and freezers as sample end-uses for a cross-check of this method, as shown in Figures 9.1 and 9.2. Comparing our results to the 1990 RECS (EIA 1993) cross-sectional vintage data on refrigerators and freezers shows that our method approximately re-creates the RECS vintage distribution.

9.2. Base-Year Ownership Shares and UEC

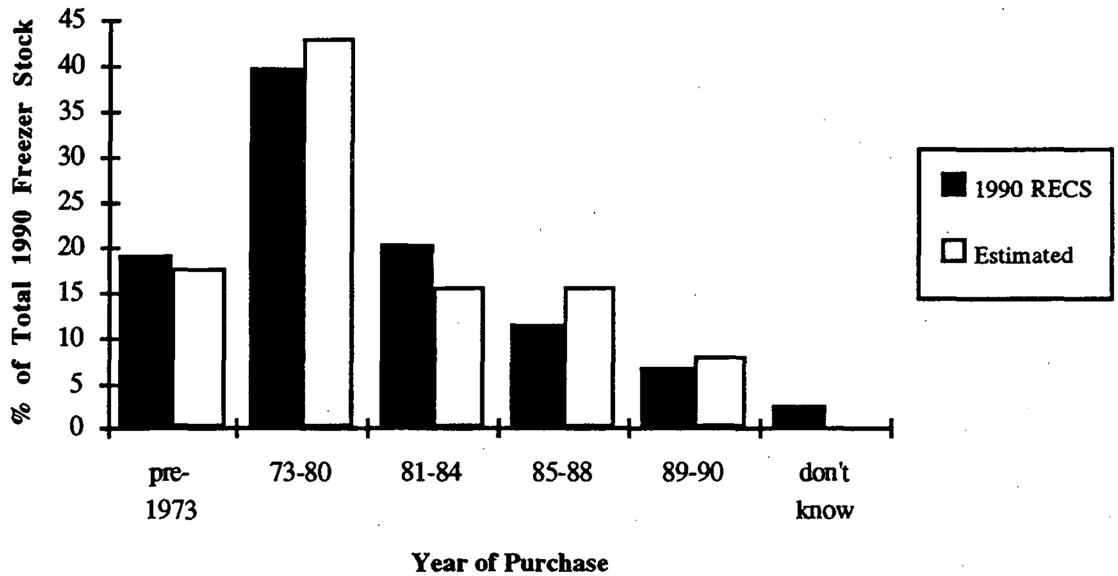
1990 ownership shares (total saturation for each generic technology) by housing type are from the 1990 RECS (EIA 1993). In the case of common water heaters in multi-family buildings, we count each housing unit served by a common water heater as a single individual unit for saturation purposes. We assume the average UEC (unit energy consumption) is the same for all housing types (except for water heaters, due to the strong interaction of housing type and usage in water heating). The average UEC is a weighted average of the vintage-block UECs, using the 1990 vintage-block shares as weights (from Appendix Tables B.3, C.3, D.7, D.8, D.9, E.3, F.3, G.5, and G.6). The resulting average UEC values, along with the 1990 ownership shares by housing type, are shown in Appendix Tables B.5, C.5, D.11, E.5, F.5, and G.8.

Figure 9.1: Shares of 1990 Stock by Vintage -- Household Refrigerators



Source: 1990 RECS (EIA 1992) and CEC (1987).

Figure 9.2: Shares of 1990 Stock by Vintage -- Household Freezers



Source: 1990 RECS (EIA 1992) and CEC (1987).

9.3. Control-Year Data

During forecast execution, REEPS 2.1 adjusts the decision model parameters to fit the values specified for the first forecast year, 1991. In order to allow this calibration process, the user must provide control-year values for: new home shares (i.e., the saturation of generic technologies in new homes), appliance replacement rates (e.g., the fraction of homes choosing to replace a decayed appliance), and the marginal size of new equipment. These data are presented in Appendix Tables B.6, C.6, D.12, E.6, F.6, and G.9.

The new home shares for all end-uses are derived from the 1990 RECS data tapes, and represent the shares for homes built during the period 1985 to 1990 (EIA 1993).

We generally assume that 100% of existing appliances are replaced when retired, except in the case of freezers. We estimated freezer replacement rates, RR, by calculating the best fit to the following equation:

$$\Delta \mathrm{Stock}_{1981\text{-}1990} = \begin{array}{l} \sum_{81}^{87} [(\mathrm{NHShares}_h^{80\text{-}87} \bullet \mathrm{HStarts}_h^t) - (\mathrm{ADecay}_h^t \bullet (\mathrm{RR}-1))] \\ + \sum_{88}^{90} [(\mathrm{NHShares}_h^{88\text{-}90} \bullet \mathrm{HStarts}_h^t) - (\mathrm{ADecay}_h^t \bullet (\mathrm{RR}-1))] \end{array} \qquad (9.2)$$

The change in stock from 1981 to 1990, $\Delta Stock_{1981\text{-}1990}$, is calculated from RECS data (EIA 1983, EIA 1992)). The new home shares for the period 1980 to 1987, $NHShares_h^{80,87}$, were derived from the 1987 RECS data tapes, and represent the shares for new homes built during the period 1981 to 1987 (EIA 1989a). The housing starts, $HStarts_h^t$, are from the Census Bureau Current Construction Reports (U.S. Bureau of the Census, various years). Appliance decay totals, $ADecay_h^t$, are estimated as the difference between the AHAM shipment data (AHAM 1991) and the RECS appliance stock data (EIA 1983, EIA 1992). Replacement rates, *RR*, are assumed to be constant over time and for all housing types. The results of these estimates are shown in Appendix Table C.6. For water heaters, we assume that the overall replacement rate is 100%, but that some substitution between fuel types may occur at the time of replacement. The water heater replacement rates shown in Appendix Table D.12 account for these fuel-switching replacements. These replacement rates are calculated so as to reconcile new home shares with historical shipments data.

The marginal size of new equipment is from AHAM shipment data (AHAM 1991). If these data are not available for a particular end-use the marginal size is assumed to be constant (constant equipment sizes are normalized to a value of 1).

10. FUTURE WORK

The following are ways the REEPS appliance model can be enhanced, given sufficient data and/or code changes to the REEPS software.

Estimate ownership (market share) models. In the current version of the model, we have relied upon the REEPS default ownership models for refrigerators, freezers, dishwashers, clothes washers and dryers. Although ownership shares forecast with these models are generally consistent with historical trends, it would be preferable to re-estimate these models with more recent and more detailed data on technologies and market shares. Cross-sectional as well as longitudinal data are necessary for proper estimation. The source of the data would most likely be RECS from various years. This is an econometric task, requiring the testing of various model specifications in order to determine the most statistically valid model.

Make relationships endogenous in Water Heater Model. As discussed in Section 5.1.2 and shown in Figure 5.3, REEPS is unable to endogenously model four important interactions between the water heater model and the dishwasher or clothes washer models. This limitation forces the user to undertake a time-consuming, iterative approach to run a forecast. Making these relationships endogenous requires changes to the REEPS computer code.

Make replacement water heater fuel type conditional on heating fuel type. Currently, we model the replacement fuel type as conditional on the old water heater fuel type. Heating fuel type is a better indicator of the availability of gas hookup. This task also requires modification of the REEPS computer code.

Vary decay function by product class. This is relevant for those products with multiple fuel types or product classes (i.e., water heaters, dryers, lighting). For instance, it is thought that electric water heaters have a longer lifetime than gas water heaters, due to, in part, less corrosion. The current REEPS code has a single decay function for each product; upgrading to multiple decay functions would require software changes to the REEPS code.

Replace cooking model. The model currently in-place is the REEPS default. A more detailed model could be added with specific technology options based on the recently published appliance standards analysis (US DOE 1993b).

Lighting model As better monitored usage data and lighting inventories become available, we will incorporate these into the REEPS lighting model. The lighting usage equation should also be a function of floor area, to incorporate the effect of changing floor area on the number of sockets. We also could define specific efficiency options for the lighting end-uses and estimate an efficiency choice model in order to forecast naturally-occurring improvements to the lighting stock.

Additional models. Other end-uses which might be given a more detailed treatment are microwaves and televisions. This will hopefully improve modeling of the miscellaneous category of end-uses because televisions and microwaves are currently included in that end-use.

11. CONCLUSIONS

Using the REEPS modeling system, we have created an appliance forecasting model with nine end uses: refrigerators, freezers, water heaters, dishwashers, clothes washers, dryers, lighting, cooking, and miscellaneous. For the first six of these end-uses, we have configured cost and efficiency data on specific technologies and estimated models to predict the efficiency choice for these technologies. The decision models are based upon the tradeoff between purchase price and operating cost. For water heaters, we have also estimated a decision model to predict market shares based on fuel type. The other end-uses (except lighting) have ownership models based on the REEPS default models.

This report has described the theoretical basis, methodology and input data used to develop a new configuration of the REEPS 2.1 forecasting model. Future reports in this series will describe results from the model and use these results to investigate alternative policy scenarios.

REFERENCES

ADM. 1987. *Costing Analysis of Design Options for Residential Appliances and Space Conditioning Equipment.* Arthur D. Little Associates, Inc., Sacramento, CA. December.

AHAM. 1991. *Energy Efficiency and Consumption Trends, various appliances.* Association of Home Appliance Manufacturers, Chicago.

AHAM. 1992. *AHAM Appliance Directory.* Association of Home Appliance Manufacturers.

ASHRAE. 1991. "Service Water Heating." In *ASHRAE Handbook of HVAC Applications,*. Atlanta, GA: American Society of Heating, Refrigerating, and Air-Conditioning Engineers.

Atkinson, Barbara, James E. McMahon, Evan Mills, Peter Chan, Terry Chan, Joseph H. Eto, Judith D. Jennings, Jonathan G. Koomey, Kenny W. Lo, Matthew Lecar, Lynn Price, Francis Rubinstein, Osman Sezgen and Tom Wenzel. 1992. *Analysis of Federal Policy Options for Improving U.S. Lighting Energy Efficiency: Commercial and Residential Buildings*. Lawrence Berkeley Laboratory. LBL-31469. December.

Ben-Akiva, Moshe and Steven R. Lerman. 1985. MIT Series in Transportation Studies. *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge, MA: MIT Press.

CEC. 1987. *California Market Trends for More Efficient Appliances: An Analysis of California and National Shipment Data in the Early 1980's.* California Energy Commission, principal author Michael Messenger. P400-87-005. July.

Cowing, Thomas G. 1992. "Residential End-Use Energy Demand Modeling and Models". Presented at Eighth Electric Utility Forecasting Symposium in Baltimore, Maryland. Published by Electric Power Research Institute.

Cowing, Thomas G. and Daniel L. McFadden. 1984. *Microeconomic Modeling and Policy Analysis: Studies in Residential Energy Demand.* Academic Press.

Dubin, Jeffrey A. 1985. *Consumer Durable Choice and the Demand for Electricity.* Amsterdam, Holland: North-Holland.

Dubin, Jeffrey A. and Douglas R. Rivers. 1988. *SST Users Guide*. Pasadena, CA: Dubin, Rivers Associates.

EIA. 1983. *Housing Characteristics 1982, Residential Energy Consumption Survey (RECS).* Energy Information Administration. DOE/EIA-0314(82). August.

EIA. 1989a. *1987 Residential Energy Consumption Survey (RECS): Data Tapes*. Energy Information Administration.

EIA. 1989b. *Housing Characteristics 1987, Residential Energy Consumption Survey (RECS).* Energy Information Administration, U.S. Dept. of Energy, Washington, DC. DOE/EIA-0314(87). May.

EIA. 1990. *Energy Consumption and Conservation Potential: Supporting Analysis for the National Energy Strategy*. Energy Information Administration. SR/NES/90-02.

EIA. 1992. *Housing Characteristics 1990, Residential Energy Consumption Survey (RECS).* Energy Information Administration. DOE/EIA-0314(90). May.

EIA. 1993. *1990 Residential Energy Consumption Survey (RECS): Data Tapes.* Energy Information Administration. April.

EPAct. 1992. *Energy Policy Act of 1992.* US House of Representatives. Conference Report 102-1018 to accompany H.R. 776. October 5th.

EPRI. 1982. *Residential End-Use Energy Planning System (REEPS).* prepared by Cambridge Systematics, Inc. for Electric Power Research Institute. EA-2512. July.

EPRI. 1990. *REEPS 2.0 Appliance Model Logic.* prepared by Regional Economic Research, Inc. for Electric Power Research Institute. May 29.

GAMA. 1991. *Statistical Highlights.* annual memo from Gas Appliance Manufacturer's Association, Arlington, VA.

Goett, Andrew, Kent Van Liere and Dan Quigley. 1992. "Customer Acceptance and Use of Compact Fluorescents: Results from a Comprehensive Evaluation of PG&E's Program." In *ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Economy.

Gordon, Lois M. 1992. "Capturing the Resource in New Residential Construction: Program Strategies." In *ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Econom.

Granda, Christopher. 1992. "A Statistically Based Impact Evaluation of a Direct Install Compact Fluorescent Distribution Program." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Economy.

Grays Harbor PUD. 1992. *The Grays Harbor PUD Compact Fluorescent Maximization Study.* Grays Harbor, Washington.

Hausman, J.A. 1979. "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *Bell Journal of Economics and Management.* vol. 10, no. 3, Spring. p. 33.

Hewitt, David C., Jeffrey R. Pratt, Paul I. Berkowitz, Patricia C. McCarthy and Kathleen A. Kelly. 1992. "Shooting in the Dark: Making Residential Lighting Programs Work." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Economy.

Hirst, E. and J. Carney. 1978. *The ORNL Engineering-Economic Model of Residential Energy Use.* Oak Ridge National Laboratory. ORNL/CON-24. July.

Horowitz, Marvin and Mary Lynn Spada. 1992. "Energy Savings for Residential Lighting Programs: There's More to it Than Just Counting Lamps." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Economy.

Hummel, P. and J. S. McMenamin. 1992. "Residential Technology Scenario Analysis: Defining the Role of Efficiency Standards, DSM, and Market Forces." In *Proceedings of the ACEEE*

1992 Summer Study on Energy Efficiency in Buildings. Washington DC: American Council for an Energy-Efficient Economy.

Johnson, Francis X., James W. Hanford, Richard E. Brown, Alan H. Sanstad and Jonathan G. Koomey. 1994. *Residential HVAC Data, Assumptions and Methodology for End-Use Forecasting with EPRI-REEPS 2.1.* Lawrence Berkeley Laboratory. LBL-34045. June.

Johnson, Francis X., Jonathan Koomey and James E. McMahon. 1992. "Incorporating Technology Choices Into Residential End-Use Forecasting: Evaluation and Comparison of Three Models with Respect to Space Heating." In *Proceedings of the 1992 ACEEE Summer Study on Energy Efficiency in Buildings.* Washington, DC: American Council for an Energy Efficient Economy.

Kelsey, Jim and Valarie Richardson. 1992. "1991 Residential Appliance Saturation Survey -- A Profile of the Residential Lighting Load in Northern California." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington DC: American Council for an Energy-Efficient Economy.

Koomey, Jonathan G., Richard E. Brown, Francis X. Johnson, Roland J. Hwang, James W. Hanford and Alan H. Sanstad. 1994a. *Residential Sector End-use Forecasting with EPRI-REEPS 2.1: Summary Input Assumptions and Results.* Lawrence Berkeley Laboratory. LBL-34044. June.

Koomey, Jonathan G., Camilla Dunham and James D. Lutz. 1994b. "The Effect of Efficiency Standards on Water Use and Water Heating Energy Use in the U.S.: A Detailed End-use Treatment". Presented at ACEEE 1994 Summer Study on Energy Efficiency in Buildings in Asilomar, CA. Published by American Council for an Energy Efficiency Economy (also LBL-35475).

Manclark, Bruce. 1991. "Of Sockets, Housecalls, and Hardware". *Home Energy.* November/December. p. 22.

McFadden, D., A. Goett, P. Ruud and K. Train. 1992. *Workshop on Qualitative Choice Analysis.* Econometrics Laboratory, Department of Economics, University of California at Berkeley.

McMahon, James E. 1987. "The LBL Residential Energy Model: An Improved Policy Analysis Tool." *Energy Systems and Policy.* vol. 10, no. 1.

McMenamin, Stuart, Ingrid Rohmund, John Pritchard and Dave Fabiszak. 1992. *REEPS 2.1: Residential End-Use Energy Planning System User's Guide.* Prepared by Regional Economic Research, Inc. for the Electric Power Research Institute. EPRI Research Project 2863-01.

Meier, Alan K., Steve Greenberg and Leo Rainer. 1992. "Emerging Miscellaneous Uses of Electricity in Homes." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings.* Washington, DC: American Council for an Energy Efficient Economy.

NAECA. 1987. *National Appliance Energy Conservation Act of 1987.*

R.S. MEANS Co. 1991. *MEANS Residential Cost Data.* 1992 Edition Kingston, MA:

Rainer, Leo, Steve Greenberg and Alan Meier. 1990. "The Miscellaneous Electrical Energy Use in Homes." In *Proceedings of the 1990 ACEEE Summer Study on Energy Efficiency in Buildings.* Washington, DC: American Council for an Energy Efficient Economy.

Robinson, Donna M. 1992. "Comprehensive Residential Lighting Retrofits: A Case Study." In *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings*. Washington, DC: American Council for an Energy-Efficient Economy.

Ruderman, Henry, Mark D. Levine and James E. McMahon. 1987. "The Behavior of the Market for Energy Efficiency in Residential Appliances Including Heating and Cooling Equipment." *The Energy Journal.* vol. 8, no. 1. p. 101.

Taylor, M. E., K.G. Ritland and R. G. Pratt. 1991. *Hot Water Electric Energy Use in Single-Family Residences in the Pacific Northwest: Regional End-Use Metering Project.* Office of Energy Resources, Bonneville Power Administration. DOE/BP-13795-27. September.

Train, K. 1986. *Qualitative Choice Analysis*. Cambridge, MA: MIT Press.

US Bureau of Labor Statistics. various years. *Consumer Price Index, Detailed Report.* US Department of Commerce, Washington DC.

US DOE. 1979. *Consumer Product Manufacturer Survey by Trade Associations.* US Department of Energy. DOE/CS-0179.

US DOE, U.S. Department of Energy. 1989. *Technical Support Document: Energy Conservation Standards for Consumer Products: Refrigerators and Furnaces.* U.S. Department of Energy, Assistant Secretary, Conservation and Renewable Energy, Building Equipment Division. DOE/CE-0277. November.

US DOE, U.S. Department of Energy. 1990. *Technical Support Document: Energy Conservation Standards for Consumer Products: Dishwashers, Clothes Washers, and Clothes Dryers.* U.S. Department of Energy, Assistant Secretary, Conservation and Renewable Energy, Building Equipment Division. DOE/CE-0299P. December.

US DOE, U.S. Department of Energy. 1993a. *Technical Support Document: Energy Conservation Standards for Consumer Products: Room Air Conditioners, Water Heaters, Direct Heating Equipment, Mobile Home Furnaces, Kitchen Ranges and Ovens, Pool Heaters, Fluorescent Lamp Ballasts, and Television Sets.* U.S. Department of Energy, Assistant Secretary, Energy Efficiency and Renewable Energy, Building Equipment Division. Volume 3: Water Heaters, Pool Heaters, Direct Heating Equipment, Mobile Home Furnaces; DOE/EE-0009. November.

US DOE, U.S. Department of Energy. 1993b. *Technical Support Document: Energy Conservation Standards for Consumer Products: Room Air Conditioners, Water Heaters, Direct Heating Equipment, Mobile Home Furnaces, Kitchen Ranges and Ovens, Pool Heaters, Fluorescent Lamp Ballasts, and Television Sets.* U.S. Department of Energy, Assistant Secretary, Energy Efficiency and Renewable Energy, Building Equipment Division. Volume 2: Fluorescent Lamp Ballasts, Television Sets Room Air Conditioners, and Kitchen Ranges and Ovens; DOE/EE-0009. November.

GLOSSARY

Building Type	A class of buildings with similar characteristics, such as the number of households living within one building, relationship to neighboring buildings, floor area, and construction practices. Typical building types include single-family detached, multifamily, manufactured homes, etc.
Control Data	Observed data from the first forecast year (1991 for the LBL REEPS implementation) describing actual characteristics of the appliance stock (market shares, sizes, etc.). These data are used to calibrate the REEPS model before forecast execution.
Decay	The process by which an appliance reaches the end of its useful life and is removed from the appliance stock.
Decision Model	A mathematical representation of the purchase decisions made in the appliance market. Four classes of decision models are available in REEPS: a) ownership in new construction, b) decay and replacement decisions, c) non-owner acquisition, and d) pre-failure replacement and conversion.
DOE	US Department of Energy
EPAct	Energy Policy Act of 1992
EPRI	Electric Power Research Institute
Generic Technology	A group of appliances distinguished by their product class, fuel type, physical configuration, mechanical methods, or general level of efficiency. For example, electric and gas water heaters are separate generic technologies.
HVAC	Heating, Ventilation, and Air Conditioning
Logit Model	A form of qualitative choice model that estimates the probability of a decision-maker selecting a specific option among several discrete choices. See Appendix I for a more detailed discussion.
Market Share	For a given year, the fraction of units shipped that belong to a Specific Technology group.
MWEF	Model-Weighted Efficiency Factor = the average efficiency of all models offered for sale in a given year.
NAECA	National Appliance Energy Conservation Act of 1987
RECS	Residential Energy Consumption Survey, conducted by DOE's Energy Information Administration (EIA).
REEPS	Residential End-Use Energy Planning System

RER	Regional Economic Research, Inc. Developers of the REEPS end-use forecasting model under contract to EPRI. 12520 High Bluff Dr., Suite 220 San Diego, CA 92130-2062 (619) 481-0081
Saturation	The fraction of households owning a particular appliance.
Specific Technology	A narrowly defined equipment category (represented by one efficiency level) within a generic technology group. Also called a specific efficiency option.
State-Based Decision Model	Models consumer decisions based on the "state" of the decision-maker, i.e., the characteristics of the household and their existing appliance ownership status.
SWEF	Shipment-Weighted Efficiency Factor = the average efficiency for all units shipped in a given year, weighted by the relative number of units shipped within each efficiency level.
UEC	Unit Energy Consumption. Annual energy consumption for an individual appliance unit.
Vintage Block	A group of appliances shipped (or houses built) during a specific time period.

APPENDICES

The following appendices provide a complete listing of the REEPS input data generated by this analysis. There is one appendix for each residential end-use. Many of the tables of REEPS inputs have the caption "Screens:" beneath the table heading, followed by codes such as "AM-4f." These refer to the specific REEPS appliance model screen(s) in which the data in that table would be entered.

Appendix A documents macroeconomic data (such as consumer price indices) used in this analysis, as well as exogenous variables used for appliance forecasting. Appendices B-G present REEPS inputs for individual end-uses. The specific efficiency options described in these appendices (such as Table B.1) are listed by option number from the appropriate DOE Technical Support Document. The option numbers are not necessarily consecutive, but are drawn directly from the TSD appliance design lists. Appendix H contains a summary of residential lighting usage surveys. Appendix I describes the qualitative choice models used in REEPS, and the theory underlying our implementation of the models.

APPENDIX A: MACROECONOMIC DATA AND EXOGENOUS VARIABLES

Table A.1: Consumer Price Indices (1982-84 = 100)

Year	*House Furnishings*	*Appliances, inc. electronic equipment*	*Major Household Appliances*	*Refrigerators and home freezers*	*Laundry Equipment*	*Stoves, ovens, dishwasher, and air conditioners*
1986	102.2	92.8		100.0	104.8	
1987	103.6	91.4	100.5	100.2	104.1	100.6
1988	105.1	90.2	101.0	101.0	105.1	100.6
1989	105.5	89.1	101.5	103.0	105.9	99.7
1990	106.7	87.8	101.2	102.6	107.2	98.5
1991	107.5	86.0	100.1	101.5	106.2	97.1

Source: (US Bureau of Labor Statistics various years)

Table A.2: Producer Price Indices (1982 = 100)

Year	*Finished Consumer Goods*	*Major Household Appliances*	*Household Cooking*	*Household - Other*
1986	108.9	100	108.7	109.3
1987	111.5	99.7	109.3	106.5
1988	113.8	100.4	107.8	108.6
1989	117.6	102.9	109.2	111.6
1990	120.4	105.2	110.7	116.9
1991		106	110.7	119.1

Source: (US Bureau of Labor Statistics various years)

Table A.3: REEPS Piped Natural Gas Exogenous Variables				
Year	Piped Gas Availability		Piped Gas Space Heating Saturation	
	New Construction	Existing Homes	New Construction	Existing Homes
1990	52%	67%	37%	55%
1991	54%	67%	37%	55%
1992	55%	66%	36%	54%
1993	55%	66%	36%	54%
1994	55%	66%	36%	54%
1995	55%	66%	36%	53%
1996	55%	65%	36%	53%
1997	55%	65%	35%	53%
1998	55%	65%	35%	53%
1999	55%	65%	35%	52%
2000	55%	64%	35%	51%
2001	55%	64%	35%	51%
2002	55%	64%	35%	51%
2003	55%	64%	35%	51%
2004	55%	63%	35%	51%
2005	55%	63%	34%	51%
2006	55%	63%	34%	50%
2007	55%	62%	34%	50%
2008	55%	62%	34%	50%
2009	55%	62%	34%	50%
2010	55%	62%	34%	50%

Source: LBL-REM

(1) These data are forecast by LBL-REM and are used as an exogenous input to the REEPS water heater fuel choice module.

APPENDIX B: REFRIGERATOR DATA

Table B.1: Specific Efficiency Data,
Top Mount Auto Defrost without Through the Door Features with CFCs (1)
(Adjusted Volume = 20.8 cf)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption(3) (kWh/yr)	Purchaser's Cost 1987 $	Purchaser's Cost 1990 $(2)	Efficiency (cf/kWh/day)
0	Baseline, 1987	947	512.38	524.68	8.02
2	0 + 4.50 Compressor	841	519.54	532.01	9.03
3	1 + 5.00 Compressor	787	522.32	534.86	9.65
4	3 + k=0.11 Foam Insulation	745	528.74	541.43	10.19
5	4 + 5.30 Compressor	714	540.32	553.29	10.63
6	5 + 2" Door	683	559.21	572.63	11.12
9	7 + k=0.10 Foam Insulation	615	618.86	633.71	12.34
10	8 + 2.5" Thick Sides	595	638.33	653.65	12.76
11	10 + 2.5" Door	582	657.93	673.72	13.04
12	8 + Evacuated Panels	515	719.54	736.81	14.74

Notes: (1) (US DOE 1989).
(2) Inflated using CPI for Refrigerators and Freezers, CPI(1990)/CPI(1987) = 1.028.
(3) UEC based on DOE test procedure.

Table B.2 Specific Efficiency Options, Shares and Availability,
Top Mount Auto Defrost without Through the Door Features, with CFCs
Screens: AM-4f, AM-5e

Option Number	Control -Year (1991) Shares(1) (percent)	Legal Availability	Market Availability	Cost Multiplier without CFCs (5)
0	33.4	not available after 1992 (2)	constant	1.04
2	28.0	not available after 1992 (2)	constant	1.03
3	38.6	not available after 1992 (2)	constant	1.02
4	0	not available after 1992 (2)	available after 1990 (3)	1.02
5	0	not available after 1992 (2)	available after 1990 (3)	1.03
6	0	constant	available post-1992 (4)	1.04
9	0	constant	available post-1992 (4)	1.10
10	0	constant	available post-1992 (4)	1.13
11	0	constant	available post-1992 (4)	1.16
12	0	constant	available post-1992 (4)	1.41

Notes: (1) Predicted by logit efficiency choice equation.
(2) Below 1993 Federal Standard. Predicted shares are added to share for next available option (6).
(3) Market availability is "zero" in 1990 so that control year calibration does not set the "desirability index" of these options to -100, which would effectively give them zero market share for the entire forecast.
(4) These high-efficiency options are assumed to be unavailable until 1993.
(5) Calculated from data in US DOE (1989). Cost multiplier reflects higher design and production costs of models using non-CFC refrigerants.

Table B.3: Refrigerator Stock Data Screens: AM-2d, AM-3c				
Year of Purchase	Unit Energy Consumption (kWh/yr)	Average Efficiency (1) (cf/kWh/day)	Average Adjusted Volume(1) (cf)	Share of 1990 Stock(2) (percent)
pre-1973	1726	3.84	18.16	14.7
1973, 1974	1655	4.09	18.55	6.7
1975, 1976	1561	4.46	19.08	5.7
1977, 1978	1473	4.86	19.61	8.0
1979, 1980	1320	5.43	19.63	8.4
1981, 1982	1191	6.10	19.91	8.0
1983, 1984	1150	6.48	20.41	10.6
1985, 1986	1065	6.78	19.79	11.6
1987, 1988	969	7.53	19.99	13.1
1989, 1990	925	7.96	20.18	13.1

Source: (1) AHAM shipment data, 1972-1990, averaged over two-year intervals (AHAM 1991). Pre-1972 vintages assumed same as 1972.
(2) Calculated from AHAM shipments data , minimum lifetime of 7 years and maximum lifetime of 29 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table B.4: Refrigerator Minimum and Maximum Lifetimes (years) Screen: AM-2b	
Minimum Lifetime	7
Maximum Lifetime	29

Notes: (1) Minimum and maximum lifetimes calculated to match historical shipment data with 1990 RECS stock of 99.8 million units (AHAM 1991, EIA 1992).
(2) REEPS assumes a linear decay between the minimum and maximum lifetimes.

Table B.5: Refrigerator Base-Year 1990 Stock Average Screens: AM-3a, AM-3f				
Housing Type	Share of 1990 Stock[1] (percent)			Unit Energy Consumption[2] (kWh/yr)
	Total	REF1	REF2	
Single Family	121.6	100	21.6	1273
Multi-Family	102.5	100	2.5	1273
Manufactured Homes	103.5	100	3.5	1273

Source: (1) 1990 RECS (EIA 1993).
(2) Calculated from AHAM shipments data (AHAM 1991) and vintage shares (Table B.3).

Table B.6: Refrigerator Control -Year 1991 Marginal Shares Screens: AM-4a, AM-4b, AM-4e					
Housing Type	New Home Shares(1) (percent)			Replacement Rates(2) (percent)	Marginal Size(3) (cf)
	Total	REF1	REF2		
Single Family	123.5	100	23.5	100	20.45
Multi-Family	101.6	100	1.6	100	20.45
Manufactured Homes	102.8	100	2.8	100	20.45

Source: (1) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993).
(2) Replacement shares are assumed to be 100% for REF1. Replacement share for REF2 is described in Table 4.1.
(3) From 1990 AHAM shipments data (AHAM 1991). cf = cubic feet.

APPENDIX C FREEZER DATA

Table C.1 Specific Efficiency Data, Upright Manual Defrost Freezers with CFCs (1)
(Adjusted Volume = 26.95 cf)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (2) kWh/yr	Purchaser's Cost 1987 $	Purchaser's Cost 1990 $ (3)	Efficiency cf/kWh/day
0	Baseline, 1987	777	361.00	369.66	12.66
1	0 + 4.50 Compressor	704	366.21	375.00	13.97
3	1 + 5.00 Compressor	606	374.42	383.41	16.23
4	3 + k=0.11 Foam Insulation	544	381.16	390.31	18.08
5	4 + 5.30 Compressor	511	392.70	402.12	19.25
7	5 + 2" Door	489	400.04	409.64	20.12
8	7 + k=0.10 Foam Insulation	453	417.54	427.56	21.71
10	8 + 2.5" Thick Sides	431	440.55	451.12	22.82
11	10 + 2.5" Door	416	448.01	458.76	23.65
12	8 + Evacuated Panels	343	505.05	517.17	28.68

Source: (1) US DOE (1989)
(2) UEC based on DOE test procedure.
(3) Inflated using CPI for Refrigerators and Freezers, CPI(1990)/CPI(1987) = 1.028.

Table C.2: Specific Efficiency Options, Shares and Availability, Upright Manual Defrost Freezers with CFCs
Screens: AM-4f, AM-5e

Option Number	Control -Year Shares (1) (percent)	Legal Availability	Market Availability	Cost Multiplier without CFCs (6)
0	0.0 (30.66)	not available (2)	constant	1.021
1	64.39 (33.73)	not available after 1992 (3)	constant	1.021
3	35.6	not available after 1992 (3)	constant	1.021
4	0	constant	available by 1992 (4)	1.021
5	0	constant	available by 1992 (4)	1.021
7	0	constant	available by 1993 (5)	1.021
8	0	constant	available by 1993 (5)	1.021
10	0	constant	available by 1993 (5)	1.021
11	0	constant	available by 1993 (5)	1.021
12	0	constant	available by 1993 (5)	1.021

Notes: (1) Shares adjusted for legal availability of option 0. Numbers in parentheses are actual inputs. Because option 0 has a legal availability of "0" in 1991, REEPS calibrates the "actual inputs" (in parentheses) to the desired values (values not in parentheses).
(2) Below 1990 NAECA Standard. Predicted shares after 1990 are added to the share of the next available option (Option 1).
(3) Below 1993 NAECA Standard. Predicted shares after 1992 are added to the share of the next available option (Option 4).
(4) Market availability is "zero" in 1990 so that control year calibration does not set the "desirability index" of these options to -100, effectively giving them zero market share for the entire forecast.
(5) These high-efficiency options are assumed to be unavailable until 1993.
(6) Calculated from data in US DOE (US DOE 1989) Cost multiplier reflects higher design and production costs of models using non-CFC refrigerants.

Table C.3: Freezer Stock Data
Screens: AM-2d, AM-3c

Year of Purchase	Unit Energy Consumption (kWh/yr)	Average Efficiency (1) (cf/kWh/day)	Average Adjusted Volume(1) (cf)	Share of 1990 Stock(2) (percent)
pre-1973	1461	7.290	29.18	17.7
1973, 1974	1318	7.911	28.56	12.7
1975, 1976	1171	8.680	27.85	10.1
1977, 1978	1011	9.761	27.03	8.9
1979, 1980	909	10.603	26.41	11.4
1981, 1982	824	11.212	25.30	7.6
1983, 1984	807	11.477	25.36	8.1
1985, 1986	770	11.809	24.92	7.6
1987, 1988	681	12.920	24.09	8.1
1989, 1990	597	14.240	23.28	7.8

Source: (1) AHAM shipment data, 1972-1990 (AHAM 1991). Pre-1972 vintages assumed same as 1972 vintage.
(2) Calculated from AHAM shipment data, minimum lifetime of 11 years and maximum lifetime of 31 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table C.4: Freezer Minimum and Maximum Lifetimes (years)
Screen: AM-2b

Minimum Lifetime	11
Maximum Lifetime	31

Notes: (1) Minimum and maximum lifetimes calculated to match AHAM historical shipment data with 1990 RECS stock total of 32.4 million units (AHAM 1991, EIA 1992).
(2) REEPS assumes a linear decay between the minimum and maximum lifetimes.
(3) REEPS constrains lifetimes to integer values.

Table C.5 : Freezer Base-Year 1990 Stock Average
Screens: AM-3a, AM-3f

Housing Type	Share of 1990 Stock(1) (percent)	UEC (2) (kWh/yr)
Single Family	44.4	1027
Multi-Family	9.6	1027
Manufactured Homes	28.9	1027

Source: (1) 1990 RECS (EIA 1993)
(2) Calculated from AHAM shipments data (AHAM 1991) and vintage shares (Table C.3).

Table C.6 : Freezer Control-Year 1991 Marginal Shares
Screens: AM-4a, AM-4b, AM-4e

Housing Type	New Home Shares(1) (percent)	Replacement Rates(2) (percent)	Marginal Size(3) (cf)
Single Family	32.4	69	23.31
Multi-Family	9.8	69	23.31
Manufactured Homes	26.7	69	23.31

Source: (1) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993).
(2) Replacement shares are calculated to be historically consistent with new home shares. Assumed to be constant over period 1982-1990 and over all housing types.
(3) From 1990 AHAM shipments data (AHAM 1991). cf = cubic feet.

APPENDIX D: WATER HEATER DATA

Table D.1: Specific Efficiency Data, Electric Storage Water Heater(1)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (kWh/yr)	Purchaser's Cost 1990 $	Efficiency (kWh.th/kWh.e)
0	Baseline	5096	265.31	0.862
1	0 + Reduce Heat Leaks	5024	268.00	0.874
2	1 + Heat Traps	4900	272.16	0.896
9	2 + R-25 Insulation	4737	307.35	0.927
3	2 + Add On Heat Pump	2479	626.67	1.772
7	3 + R-25 Insulation	2317	659.69	1.896
5	2 + Integral Heat Pump	1731	1099.62	2.538

Source: (1) Source: US DOE (1993a)
(2) kWh.th/kWh.e is the thermal efficiency of the design.

Table D.2: Specific Efficiency Data, Gas-fired Storage Water Heater(1)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (2) (MMBtu/yr)	Purchaser's Cost (1990 $)	Efficiency (Btu.th/Btu.f)
0	Baseline	27.55	281.60	0.544
1	0 + Heat Traps	27.22	286.72	0.551
2	1 + Reduce Heat Leaks	27.07	288.95	0.554
3	2 + R-16 Insulation	26.31	305.65	0.570
14	3 + R-25 Insulation	26.02	341.20	0.576
12	3 + IID w/ Flue Damper	23.37	390.15	0.641
24	0 + Condense Flue Gases	17.01	1183.4	0.881

Source: (1) Source: US DOE (1993a)
(2) Some gas water heater designs also use electricity for the intermittent ignition device (IID), but REEPS only considers one fuel for each generic technology..

Table D.3: Specific Efficiency Data, Oil-fired Storage Water Heater(1)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (2) (MMBtu/yr)	Purchasers Cost (1990 $)	Efficiency (Btu.th/Btu.f)
0	Baseline	28.32	724.66	0.529
1	0 + 1 in Foam	25.71	738.55	0.583
4	3 + Reduce Heat Leaks	25.12	745.49	0.597
?		24.87	758.25	0.603
5	4 + 2 in Foam	23.78	785.99	0.630
6	5 + Flue Damper	22.11	857.21	0.678
7	6 + Multiple Flues	21.39	991.68	0.701
8	0 + Condensing	19.01	2241.08	0.788

Source: (1) Source: US DOE (1993a)
(2) All oil water heater designs also use electricity for the burner ignition , but REEPS only considers one fuel for each generic technology..

Table D.4 : Specific Efficiency Options, Shares and Availability, Electric Storage Water Heaters Screens: AM-4f, AM-5e			
Option Number	**Control -Year (1991) Shares (1) (percent)**	**Legal Availability**	**Market Availability**
0	31.80	constant	constant
1	32.80	constant	constant
2	35.81	constant	constant
9	0	constant	available by 1993 (2)
3	0	constant	available by 1993 (2)
7	0	constant	available by 1993 (2)
5	0	constant	available by 1993 (2)
Source: (1) 1990 RECS (EIA 1993). (2) These high-efficiency options are assumed to be unavailable in significant numbers until 1993.			

Table D.5: Specific Efficiency Options, Shares and Availability, Gas-fired Storage Water Heaters Screens: AM-4f, AM-5e			
Option Number	**Control -Year (1991) Shares (1) (percent)**	**Legal Availability**	**Market Availability**
0	32.82	constant	constant
1	28.04	constant	constant
2	26.28	constant	constant
3	12.86	constant	constant
14	0	constant	available by 1993 (2)
12	0	constant	available by 1993 (2)
24	0	constant	available by 1993 (2)
Source: (1) 1990 RECS (EIA 1993). (2) These high-efficiency options are assumed to be unavailable in significant numbers until 1993.			

Table D.6: Specific Efficiency Options, Shares and Availability, Oil-fired Storage Water Heaters Screens: AM-4f, AM-5e			
Option Number	**Control -Year (1991) Shares (1) (percent)**	**Legal Availability**	**Market Availability**
0	60	constant	constant
1	40	constant	constant
4	0	constant	available by 1993 (2)
?	0	constant	available by 1993 (2)
5	0	constant	available by 1993 (2)
6	0	constant	available by 1993 (2)
7	0	constant	available by 1993 (2)
8	0	constant	available by 1993 (2)
Source: (1) 1990 RECS (EIA 1993). (2) These high-efficiency options are assumed to be unavailable in significant numbers until 1993.			

Table D.7: Electric Storage Water Heater Stock Data Screens: AM-2d, AM-3c				
Year of Purchase	Unit Energy Consumption (1) (kWh/yr)	Average Efficiency (2) (kWh.th/kWh.e)	Average Volume (2) (normalized)	Share of 1990 Stock (3) (percent)
pre-1973	5508	0.798	1.0	10.5
1973, 1974	5492	0.800	1.0	5.5
1975, 1976	5471	0.803	1.0	5.9
1977, 1978	5451	0.806	1.0	7.5
1979, 1980	5416	0.811	1.0	7.9
1981, 1982	5348	0.822	1.0	8.9
1983, 1984	5274	0.833	1.0	12.4
1985, 1986	5189	0.847	1.0	13.9
1987; 1988	5101	0.862	1.0	13.9
1989, 1990	5016	0.876	1.0	13.6

Source: (1) UEC assumes DOE test procedure hot water usage (64.3 gal/day).
(2) GAMA shipment data (GAMA 1991). Efficiencies from US DOE (US DOE 1979) and estimated from GAMA directories. 1990 efficiency value from NAECA standard (NAECA 1987).
(3) Calculated from GAMA shipment data, minimum lifetime of 5 years and maximum lifetime of 30 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table D.8: Gas-fired Storage Water Heater Stock Data Screens: AM-2d, AM-3c				
Year of Purchase	Unit Energy Consumption (1) (MMBtu/yr)	Average Efficiency (2) (Btu.th/Btu.f)	Average Volume (2) (normalized)	Share of 1990 Stock (3) (percent)
pre-1973	31.6	0.474	1.0	14.7
1973, 1974	31.5	0.476	1.0	5.1
1975, 1976	31.3	0.479	1.0	6.0
1977, 1978	31.2	0.481	1.0	7.1
1979, 1980	30.9	0.485	1.0	7.5
1981, 1982	30.7	0.489	1.0	8.5
1983, 1984	30.4	0.493	1.0	10.6
1985, 1986	29.5	0.508	1.0	12.5
1987, 1988	28.5	0.527	1.0	13.9
1989, 1990	27.5	0.545	1.0	14.1

Source: (1) UEC assumes DOE test procedure hot water usage (64.3 gal/day).
(2) GAMA shipment data (GAMA 1991).. Efficiencies from US DOE (US DOE 1979) and estimated from GAMA directories. 1990 efficiency value from NAECA standard (NAECA 1987).
(3) Calculated from GAMA shipment data, minimum lifetime of 5 years and maximum lifetime of 30 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table D.9: Oil-fired Storage Water Heater Stock Data
Screens: AM-2d, AM-3c

Year of Purchase	Unit Energy Consumption (1) (MMBtu/yr)	Average Efficiency (2) (Btu.th/Btu.f)	Average Volume (2) (normalized)	Share of 1990 Stock (3) (percent)
pre-1973	30.7	0.488	1.0	13.5
1973, 1974	30.7	0.488	1.0	5.4
1975, 1976	30.7	0.488	1.0	5.4
1977, 1978	30.7	0.488	1.0	5.4
1979, 1980	30.7	0.488	1.0	5.4
1981, 1982	30.7	0.489	1.0	11.2
1983, 1984	30.5	0.491	1.0	11.2
1985, 1986	30.4	0.493	1.0	12.9
1987, 1988	30.3	0.495	1.0	14.6
1989, 1990	30.1	0.498	1.0	15.0

Source: (1) UEC assumes DOE test procedure hot water usage (64.3 gal/day).
(2) GAMA shipment data (GAMA 1991).. Efficiencies from US DOE (US DOE 1979) and estimated from GAMA directories. 1990 efficiency value from NAECA standard (NAECA 1987).
(3) Calculated from GAMA shipment data, minimum lifetime of 5 years and maximum lifetime of 30 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table D.10: All Water Heaters, Minimum and Maximum Lifetimes (years)
Screen: AM-2b

Minimum Lifetime	5
Maximum Lifetime	30

Notes: (1) Minimum and maximum lifetimes calculated to match GAMA historical shipment data with 1990 RECS stock total of 90.1 million units (EIA 1992, GAMA 1991).
(2) REEPS assumes a linear decay between the minimum and maximum lifetimes.
(3) REEPS constrains lifetimes to integer values.

Table D.11 Water Heater Base-Year 1990 Stock Average
Screens: AM-3a, AM-3f

Housing Type	Shares of 1990 Stock (1) (percent)	UEC (2) (units)
Standard Electric Storage Water Heater		kWh/yr
Single Family	36.4	4508
Multi-Family	33.9	3718
Manufactured Homes	64.6	4193
Standard Gas-fired Storage Water Heater		MMBtu/yr
Single Family	58.3	25.66
Multi-Family	57.1	21.16
Manufactured Homes	35.2	23.86
Standard Oil-fired Storage Water Heater		MMBtu/yr
Single Family	4.6	26.07
Multi-Family	8.8	21.51
Manufactured Homes	0.2	24.25

Source: (1) 1990 RECS (EIA 1993). Common units in multi-family housing modeled as individual storage water heaters.
(2) Calculated from AHAM shipment data (AHAM 1991) and vintage shares (Tables D.7-9).

Table D.12: Water Heater Control-Year 1991 Marginal Shares
Screens: AM-4a, AM-4b, AM-4e

New Home Shares(1)		Replacement Rates(2)	
Housing Type	(percent)	Replacement Type	(percent)
Electric Storage Water Heater			
Single Family	52.3	Electric	95
Multi-Family	82.0	Gas-fired	5
Manufactured Homes	73.4	Oil-fired	0
Gas-fired Storage Water Heater			
Single Family	45.1	Electric	10
Multi-Family	18.0	Gas-fired	90
Manufactured Homes	26.6	Oil-fired	0
Oil-fired Storage Water Heater			
Single Family	2.1	Electric	0
Multi-Family	0	Gas-fired	0
Manufactured Homes	0	Oil-fired	100

Source: (1) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993).
(2) Replacement shares are calculated to be historically consistent with new home shares. Assumed to be constant over period 1982-1990 and all housing types.

Table D.13: Water Heater Exogenous Variables (Used in Dishwasher and Clothes Washer Efficiency Choice Models)			
	Stock Average		
Year	**Electric Water Heater Saturation**	**Water Heater Energy Factor**	
		Electric	**Gas**
1990	38%	0.83	0.50
1991	38%	0.84	0.50
1992	39%	0.84	0.52
1993	39%	0.84	0.51
1994	40%	0.85	0.51
1995	41%	0.85	0.52
1996	41%	0.86	0.52
1997	42%	0.86	0.52
1998	43%	0.86	0.53
1999	44%	0.87	0.53
2000	45%	0.87	0.53
2001	46%	0.87	0.53
2002	47%	0.87	0.54
2003	48%	0.88	0.54
2004	49%	0.88	0.54
2005	50%	0.88	0.54
2006	51%	0.88	0.54
2007	53%	0.88	0.55
2008	54%	0.88	0.55
2009	55%	0.88	0.55
2010	56%	0.88	0.55
Source: Preliminary run of REEPS water heater model described in this report.			

APPENDIX E: DISHWASHER DATA

Table E.1: Specific Efficiency Data,
Standard Water Heating Dishwasher (1)
Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Energy Consumption [Motor+Dryer+ Heater Only] (2) (kWh/yr)	Purchaser's Cost (1987 $)	Purchaser's Cost (1990 $) (3)	Efficiency [Motor+Dryer+ Heater Only] (cycle/kWh)	Hot Water UEC (4) (kWh.e/yr)
0	Baseline	178	320.03	313.35	1.28	539
1	Reduce Water Use	168	330.81	323.90	1.36	431
2	1 + Reduce Booster Use	147	333.71	326.74	1.56	431
3	2 + Improved Motor	134	339.90	332.80	1.71	431
4	3 + Fill Control	134	352.43	345.07	1.71	418

Source: (1) US DOE (1990).
(2) Assuming 229 cycles/year.
(3) Inflated using CPI for stoves, ovens, dishwashers and air conditioners, CPI(1990)/CPI(1987) = 0.98.
(4) Hot water UEC assumes electric water heater with EF=0.85 and 229 cycles/year. Used in operating cost calculations.

Table E.2: Specific Efficiency Options, Shares and Availability,
Standard Water Heating Dishwasher
Screens: AM-4f, AM-5e

Option Number	Control Year (1991) Shares (1) (percent)	Legal Availability	Market Availability
0	64.9	not available after 1994(2)	constant
1	18.8	not available after 1994(2)	constant
2	13.1	not available after 1994(2)	constant
3	3.1	constant	constant
4	0.1	constant	constant

Source: (1) Shares predicted by logit equation.
(2) Below 1994 NAECA Standard. Predicted shares after 1994 are added to the share of the next available option (option 3).

Table E.3: Dishwasher Stock Data Screens: AM-2d, AM-3c				
Year of Purchase	Energy Consumption [Motor+Dryer+ Heater Only] (1) (kWh/yr)	Average Efficiency [Motor+Dryer+ Heater Only] (2) (cycle/kWh)	Average Adjusted Volume (normalized)	Share of 1990 Stock (3) (percent)
pre-1973	178	1.285	1.0	6.2
1973, 1974	178	1.285	1.0	5.5
1975, 1976	178	1.285	1.0	5.7
1977, 1978	178	1.285	1.0	8.3
1979, 1980	178	1.285	1.0	8.4
1981, 1982	178	1.285	1.0	7.1
1983, 1984	178	1.285	1.0	11.4
1985, 1986	178	1.285	1.0	14.3
1987, 1988	178	1.285	1.0	16.6
1989, 1990	178	1.285	1.0	16.6

Source: (1) Assuming 229 cycle/yr.
(2) 1987 Baseline [Motor+Dryer+Heater] efficiency (US DOE 1990).
(3) Calculated from AHAM shipment data (AHAM 1991, US DOE 1990), minimum lifetime of 0 years and maximum lifetime of 25 years.

Table E.4: Dishwasher Minimum and Maximum Lifetimes (years) Screen: AM-2b	
Minimum Lifetime	0
Maximum Lifetime	25

Notes: (1) Minimum and maximum lifetimes calculated to match AHAM historical shipment data with 1990 RECS stock total of 42.7 million units(AHAM 1991, EIA 1992).
(2) REEPS assumes a linear decay between the minimum and maximum lifetimes.
(3) REEPS constrains lifetimes to integer values.

Table E.5: Dishwasher Base-Year 1990 Stock Average Screens: AM-3a, AM-3f		
Housing Type	Shares of 1990 Stock (1) (percent)	UEC (2) (kWh/yr)
Single Family	50.6	178
Multi-Family	37.2	178
Manufactured Homes	20.1	178

Source: (1) 1990 RECS (EIA 1993)
(2) Calculated from AHAM shipment data (AHAM 1991) and vintage shares (Table E.3).

Table E.6: Dishwasher Control-Year 1991 Marginal Shares(1) Screens: AM-4a, AM-4b, AM-4e			
Housing Type	**New Home Shares(2)** (percent)	**Acquisition Rates(3)** (percent)	**Marginal Size(4)** (normalized)
Single Family	84.8	1.2	1.0
Multi-Family	83.7	0.3	1.0
Manufactured Homes	31.8	1.5	1.0

Source: (1) Replacement rates assumed to be 100%.
(2) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993)
(3) REEPS default data set values.
(4) From 1990 AHAM shipments data (AHAM 1991).

Table E.7: Dishwasher Hot Water Load Exogenous Variable; Used in Water Heater Usage Equation	
Year	**Stock Average Hot Water Load** (kBtu/yr)
1990	505
1991	495
1992	487
1993	479
1994	473
1995	467
1996	454
1997	442
1998	432
1999	423
2000	416
2001	409
2002	403
2003	399
2004	394
2005	391
2006	388
2007	385
2008	382
2009	379
2010	377

Source: Forecast by REEPS baseline dishwasher model described in this report.

APPENDIX F: CLOTHES WASHER DATA

Table F.1: Specific Efficiency Data, Standard Clothes Washer (1) (Capacity = 2.6 cf) Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Energy Consumption of Motor (2) (kWh/yr)	Purchaser's Cost (1987 $)	Purchaser's Cost (1990 $) (3)	Efficiency of Motor Only (cycle/kWh)	Hot Water UEC (4) (kWh.e/yr)
0	Baseline 5 Settings	102	400.04	409.20	3.72	848
1	Eliminate Warm/Warm Setting	102	400.04	409.20	3.72	644
2	Eliminate Warm Rinse	102	400.04	409.20	3.72	571
6	2 + Improved Motor	89	411.53	420.95	4.29	571
7	6 + Plastic Tub	88	421.07	430.71	4.31	569
8	7 +Thermal Mix. Valve	89	441.79	451.91	4.29	565
3	2 + Horizontal Axis	57	570.86	583.93	6.66	205
4	3 + Plastic Tub	57	580.41	593.70	6.69	204
5	4 +Thermal Mix. Valve	57	601.14	614.91	6.66	202

Source: (1) US DOE (1990).
(2) Assuming 380 cycles/yr.
(3) Inflated using CPI for Laundry equipment, CPI(1990)/CPI(1987) = 1.023.
(4) Hot water UEC assumes electric water heater with EF=0.85 and 380 cycles/year. Used in operating cost calculations.

Table F.2: Specific Efficiency Options, Shares and Availability, Standard Clothes Washer Screens: AM-4f, AM-5e

Option Number	Control Year (1991) Shares (1) (percent)	Legal Availability	Market Availability
0	95.0	not available after 1994 (2)	constant
1	2.5	not available after 1994 (2)	constant
2	2.5	constant	constant
6	0	constant	available by 1992 (3)
7	0	constant	available by 1992 (3)
8	0	constant	available by 1992 (3)
3	0	constant	available by 1992 (3)
4	0	constant	available by 1992 (3)
5	0	constant	available by 1992 (3)

Source: (1) Shares predicted by logit efficiency choice equation using 1991 fuel prices.
(2) Below 1994 NAECA Standard. Predicted shares after 1994 are added to the share of the next available option (option 2).
(3) These high-efficiency options are assumed to be unavailable in significant quantities until 1992.

Table F.3: Clothes Washer Stock Data Screens: AM-2d, AM-3c				
Year of Purchase	**Energy Consumption [Motor Only] (1)** (kWh/yr)	**Average Efficiency [Motor Only] (2)** (cycle/kWh)	**Average Adjusted Volume (2)** (normalized)	**Share of 1990 Stock (3)** (percent)
pre-1973	102	3.717	1.0	7.42
1973, 1974	102	3.717	1.0	5.35
1975, 1976	102	3.717	1.0	5.41
1977, 1978	102	3.717	1.0	7.24
1979, 1980	102	3.717	1.0	8.06
1981, 1982	102	3.717	1.0	8.20
1983, 1984	102	3.717	1.0	10.74
1985, 1986	102	3.717	1.0	13.70
1987, 1988	102	3.717	1.0	16.58
1989, 1990	102	3.717	1.0	17.30

Source: (1) Assuming 380 cycles/yr.
(2) AHAM shipment data, 1972-1990 (AHAM 1991).
(3) Calculated from AHAM shipment data (AHAM 1991, US DOE 1990), minimum lifetime of 2 years and maximum lifetime of 25 years. Shares are generally consistent with 1990 RECS vintage data (EIA 1992).

Table F.4: Clothes Washer Minimum and Maximum Lifetimes (years) Screen: AM-2b	
Minimum Lifetime	2
Maximum Lifetime	25

Notes: (1) Minimum and maximum lifetimes calculated to match AHAM historical shipment data with 1990 RECS stock total of 71.7 million units (AHAM 1991, EIA 1992).
(2) REEPS constrains lifetimes to integer values.

Table F.5: Clothes Washer Base-Year 1990 Stock Average Screens: AM-3a, AM-3f		
Housing Type	**Shares of 1990 Stock (1)** (percent)	**Energy Consumption [Motor Only] (2)** (kWh/yr)
Single Family	92.7	102
Multi-Family	31.9	102
Manufactured Homes	81.5	102

Source: (1) 1990 RECS (EIA 1993)
(2) Calculated from AHAM shipment data (AHAM 1991), vintage shares (Table F.3) and assuming 380 cycles/yr.

Table F.6: Clothes Washer Control-Year 1991 Marginal Shares Screens: AM-4a, AM-4b, AM-4e			
Housing Type	**New Home Shares (1)** (percent)	**Non-Owner Acquisition Rates (2)** (percent)	**Marginal Size** (normalized)
Single Family	96.7	0.50	1.0
Multi-Family	73.2	0.25	1.0
Manufactured Homes	91.8	0.40	1.0
Source: (1) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993). (2) Data are REEPS default values. (3) Replacement rate assumed to be 100%.			

Table F.7: Clothes Washer Hot Water Load Exogenous Variable; Used in Water Heater Usage Equation	
Year	**Stock Average Hot Water Load (kBtu/yr)**
1990	969
1991	952
1992	936
1993	922
1994	909
1995	898
1996	865
1997	834
1998	806
1999	781
2000	758
2001	737
2002	718
2003	700
2004	684
2005	670
2006	656
2007	643
2008	631
2009	620
2010	610
Source: Forecast by REEPS baseline clothes washer model described in this report.	

APPENDIX G: DRYER DATA

Table G.1: Specific Efficiency Data, Standard Electric Dryer (1) (Capacity = 5.9 cf) Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (2) (kWh/yr)	Purchaser's Cost (1988 $)	Purchaser's Cost (1990 $) (3)	Efficiency (lb/kWh)
0	Baseline	1023.1	300.03	308.96	2.60
1	Automatic Termination	901.7	313.01	322.33	2.95
2	1 +Insulation	883.7	323.72	333.36	3.01
3	2 +Recycle Exhaust	828.7	372.34	383.43	3.21
4	2 +Microwave	653.6	467.45	481.37	4.07
5	2 +Heat Pump	308.9	695.31	716.02	8.61

Source: (1) US DOE (1990).
(2) Assuming 2660 lbs/yr (=380 cycles/yr x 7 lb/cycle).
(3) Inflated using CPI for Laundry equipment, CPI(1990)/CPI(1988)=1.03.

Table G.2: Specific Efficiency Data, Standard Gas Dryer (1) (Capacity = 5.9 cf) Screens: AM-4f, AM-5d

Option Number	Specific Technology Design	Unit Energy Consumption (2) (MMBtu/yr)	Purchaser's Cost (1988 $)	Purchaser's Cost (1990) $ (3)	Efficiency (lb/kBtu)
0	Baseline	3.95	340.03	350.16	0.674
1	Automatic Termination	3.48	353.02	363.53	0.765
2	1 +Insulation	3.40	363.72	374.55	0.783
3	2 +Recycle Exhaust	3.20	412.34	424.62	0.832

Source: (1) US DOE (1990).
(2) Assuming 2660 lbs/yr (=380 cycles/yr x 7 lb/cycle).
(3) Inflated using CPI for Laundry equipment, CPI(1990)/CPI(1988)=1.03.

Table G.3: Specific Efficiency Options, Shares and Availability, Standard Electric Dryer Screens: AM-4f, AM-5e

Option Number	Control -Year (1991) Shares (1) (percent)	Legal Availability	Market Availability
0	55.6	not available after 1994 (2)	constant
1	33.2	not available after 1994 (2)	constant
2	11.2	constant	constant
3	0.1	constant	constant
4	0	constant	constant
5	0	constant	constant

Source: (1) Shares predicted by logit efficiency choice equation using 1991 fuel prices.
(2) Below 1994 NAECA Standard. Predicted shares after 1994 are added to the share of the next available option (option 2).

Table G.4: Specific Efficiency Options, Shares and Availability, Standard Gas Dryer
Screens: AM-4f, AM-5e

Option Number	Control Year (1991) Shares (1) (percent)	Legal Availability	Market Availability
0	52.2	not available after 1994 (1)	constant
1	30.6	not available after 1994 (1)	constant
2	16.3	constant	constant
3	0.9	constant	constant

Source: (1) Shares predicted by logit efficiency choice equation using 1991 fuel prices.
(2) Below 1994 NAECA Standard. Predicted shares after 1994 are added to the share of the next available option (option 2).

Table G.5: Standard Electric Dryer Stock Data
Screens: AM-2d, AM-3c

Year of Purchase	Average Efficiency (1) (lb/kWh)	Average Adjusted Volume (2) (normalized)	Share of 1990 Stock (3) (percent)
pre-1973	2.480	1.0	12.7
1973, 1974	2.492	1.0	6.6
1975, 1976	2.510	1.0	5.8
1977, 1978	2.527	1.0	7.9
1979, 1980	2.544	1.0	8.2
1981, 1982	2.561	1.0	7.7
1983, 1984	2.578	1.0	10.4
1985, 1986	2.595	1.0	12.7
1987, 1988	2.612	1.0	14.3
1989, 1990	2.617	1.0	13.6

Source: (1) AHAM shipment data, 1972-1990 (AHAM 1991). Assumes 2660 lbs/yr usage (Proctor and Gamble usage data).
(2) No data available.
(3) Calculated from AHAM shipment data (AHAM 1991, US DOE 1990), minimum lifetime of 9 years and maximum lifetime of 30 years. Shares are generally consistent with 1990 RECS stock data (EIA 1992).

Table G.6: Standard Gas Dryer Stock Data Screens: AM-2d, AM-3c			
Year of Purchase	**Average Efficiency (1)** (lb/kBtu)	**Average Adjusted Volume (2)** (normalized)	**Share of 1990 Stock (3)** (percent)
pre-1973	0.616	1.0	17.2
1973, 1974	0.638	1.0	6.1
1975, 1976	0.669	1.0	5.8
1977, 1978	0.699	1.0	7.1
1979, 1980	0.728	1.0	7.6
1981, 1982	0.738	1.0	7.1
1983, 1984	0.742	1.0	9.1
1985, 1986	0.746	1.0	12.0
1987, 1988	0.750	1.0	14.1
1989, 1990	0.750	1.0	13.9

Source: (1) AHAM shipment data, 1972-1990 (AHAM 1991). Assumes 2660 lbs/yr usage (Proctor and Gamble usage data).
(2) No data available.
(3) Calculated from AHAM shipment data (AHAM 1991, US DOE 1990), minimum lifetime of 9 years and maximum lifetime of 30 years. Shares are generally consistent with 1990 RECS stock data (EIA 1992).

Table G.7 Dryer Minimum and Maximum Lifetimes (years) Screen: AM-2b	
Minimum Lifetime	9
Maximum Lifetime	30

Notes: (1) Minimum and maximum lifetimes calculated to match AHAM historical shipment data with 1990 RECS stock total of 64.9 million units (AHAM 1991, EIA 1992).
(2) REEPS constrains lifetimes to integer values.

Table G.8 Dryer Base-Year 1990 Stock Average Screens: AM-3a, AM-3f		
Housing Type	**Shares of 1990 Stock (1)** (percent)	**UEC (2)**
Standard Electric Dryer		kWh/yr
Single-Family	64.1	920
Multifamily	19.3	920
Manufactured Homes	63.5	920
Standard Gas Dryer		kBtu/yr
Single-Family	21.0	3384
Multifamily	5.9	3384
Manufactured Homes	8.3	3384

Source: (1) 1990 RECS (EIA 1993)
(2) Calculated from AHAM shipment data (AHAM 1991) and vintage shares (Tables G.5 & G.6), assuming 2660 lbs/year usage.

Table G.9: Dryer Control-Year 1991 Marginal Shares Screens: AM-4a, AM-4b, AM-4e			
Housing Type	**New Home Shares (1)** (percent)	**Non-Owner Acquisition Shares (2)** (percent)	**Marginal Size** (normalized)
Standard Electric Dryer			
Single-Family	85.9	1.5	1.0
Multifamily	40.9	1.0	1.0
Manufactured Homes	68.6	1.5	1.0
Standard Gas Dryer			
Single-Family	14.2	0.5	1.0
Multifamily	1.9	0.3	1.0
Manufactured Homes	8.5	0.5	1.0

Source: (1) New home shares are from 1990 RECS for houses built during the period 1985-1990 (EIA 1993).
(2) REEPS default data set.
(3) Replacement rates assumed to be 100%.

APPENDIX H: LIGHTING DATA

Table H.1: Residential Lighting Usage Studies

Daily Usage (hours)	Source	Type (1)	Notes
3.1	Goett, et al. (1992)	M	Metered during March (equal to user-reported value for same period)
3.6	Goett, et al. (1992)	U	Annual average for 18 watt CFL (user-installed)
3.9	Goett, et al. (1992)	U	Annual average for 27 watt CFL (user-installed)
2.75	Gordon (1992)	U	Range = 0.5 to 6.7 hrs./day (calibrated w/ Yakima & Grays Harbor metered data)
2.5	Grays Harbor PUD (1992)	M	10-17 fixtures metered in 6 houses in Grays Harbor, WA; December-June metering period
4.5	Hewitt, et al. (1992)	U	Northeast Utilities post-retrofit survey (user installation)
5.6	Hewitt, et al. (1992)	U	Northeast Utilities phone survey of CFL usage (utility installation based on minimum usage)(2)
3.2	Horowitz & Spada (1992)	U	Telephone survey of CFL purchasers
2.1	Manclark (1991)	M	2 post-retrofit bulbs metered in 53 houses in Yakima, WA; spring/summer metering period
2.7	Robinson (1992)	U	User-reported for post-retrofit CFLs. NJ program not limited to high-use sockets
5.3	Robinson (1992)	U	User-reported for post-retrofit CFLs. NY program -- limited to high-use sockets
Average Usage Reported by Lighting Users = 3.85 hours/day.			
Average Usage from Metering Studies = 2.57 hours/day.			

Notes: (1) Study types: U = User-reported; M = Metered. The studies collecting user-reported data were nearly all for the purpose of identifying high-use sockets for CFL retrofit, and are therefore not representative of all residential lighting sockets.

(2) CFL = Compact Fluorescent Lamp

APPENDIX I: QUALITATIVE CHOICE ANALYSIS

Qualitative Choice Analysis (QCA) provides the theoretical framework for the appliance decision models we adopted in this analysis. In this appendix, we provide a brief overview of several key ideas of QCA. The material herein is taken primarily from Train (Train 1986) and from notes from a workshop sponsored by the Econometrics Laboratory on the U.C. Berkeley campus (McFadden et al. 1992).

Two of the hallmarks of neo-classical economic analysis are a focus on aggregate-that is, market-level-phenomena and the assumption of continuity (and usually differentiability) of the variables under study. The latter assumption is reflected both in the basic theory of consumer choice, including the assumption of smooth indifference curves, and in the econometric estimation of market demand functions; at the market level, where individual differences are too fine to be captured, the modeling assumption of continuity is generally thought to be a good approximation to reality.

It is arguable, however, that 1) phenomena such as aggregate demand, being just the sum of many individual decisions, should ideally be studied with methods that explicitly capture individual-level behavior, and 2) at the level of the individual, many if not most real-life choices have a discrete rather than continuous quality to them. Thus, for example, a consumer buying a refrigerator will ultimately choose between, for example, manual defrost and auto defrost, rather than some combination of the two. In buying a car, a consumer must ultimately purchase a Toyota or a Honda or a Ford or a Chevrolet--not some combination of the four. Qualitative choice analysis was devised for the economic analysis of such situations. Train describes QCA as "[one of a variety of] methods for examining the behavior of individuals when continuous methods are inappropriate." "Methods" here refers to both a theoretical or conceptual approach to the choice problem and to the econometric techniques that have been developed for this type of analysis.

Before providing a more technical description of these methods, an informal discussion may be helpful. To begin, the individual ("consumer") is seen, as suggested above, as choosing one from among a number of discrete alternatives. The individual is conceived of as a decision-making "black box:" she evaluates the options in terms of their various features as well as her own preferences, and chooses what she considers the best alternative (in economic terms, the one that maximizes her utility). So for example, she may be choosing between a manual and an auto-defrost refrigerator; she will (in some manner that is left unspecified) evaluate, for example, the purchase prices, operating costs, convenience features, colors, styles, and possibly other features, and then choose one in a way that may also depend on such factors as her income or beliefs. Several things about this picture deserve emphasis. First, exactly "how" the decision is made--for example, the psychological process involved--is essentially ignored by saying that the decision is a matter of "maximizing utility." (This approach is, of course, characteristic of economic modeling.) Furthermore, in this way in thinking, the decision-maker is a *deterministic* black box; that is, the output (the decision) is a non-probabilistic function of the inputs (the features of the alternatives and her own characteristics).

As the reader may know, however, QCA models themselves are probabilistic in nature. The idea is that the observer cannot possibly see everything that went into the decision, such as "beliefs." So the observer can, in principle, predict only imperfectly what decision will be made even knowing such things as certain characteristics of the alternatives and the decision-maker. The probabilistic elements of QCA arise from this state of partial ignorance of the observer. In particular, the aim of QCA models is not to elicit or to study (directly, at least) the form of the function transforming inputs into decisions. Rather, *it is to derive numerical estimates of the probabilities that the decision-maker will make various choices, given certain assumptions about (among other things) the form of the decision-maker's utility function, and given observations of the decision-maker's actual choices and information about the decision-maker herself.* There are several interpretations of what concept of "probability" is at work here. One can think, for example, of a decision-maker repeatedly facing the same choice; then the probability that a particular alternative will be chosen can be interpreted as the limiting proportion of the number of times that alternative is in fact chosen as the number of repeats becomes "large." Or, one can think of a number of decision-makers with the same observable characteristics being observed, sequentially, facing the same choice situation; then the probability can again be interpreted as a limiting proportion. The point is, again, that the probabilistic nature of the models is interpreted in terms of the relationship between the observer and the decision-maker; QCA models are *not* models of "decision-making under uncertainty" as these are typically defined in economics or operations research.

To begin a more precise description, the technical specification of the decision-maker's situation is that the possible alternatives form a *finite partition* of her universe of choice, that is, the alternatives are a) finite in number, b) mutually exclusive, and c) exhaustive (that is, she must choose one and only one alternative). It is often possible to adjust the model so that these conditions are satisfied in situations in which they are not readily apparent.

Now suppose one wishes to analyze some such situation, for example, a choice among appliances or cars. Following is a description of the generic qualitative choice model (Train's notation will be used for the duration). A particular decision-maker will be indicated by the index n. Denote the set of alternatives she faces by J_n, the observed (by the researcher) characteristics of alternative i as faced by decision-maker n as the vector z_{in}, and the observed characteristics of the decision-maker as the vector s_n. Then the probability that decision-maker n chooses alternative i is a parametric function of the form

$$P_{in} = f(z_{in}, z_{jn} \forall j \in J_n, j \neq i, s_n, \beta),$$

where the expression "$\forall j \in J_n$" means "for all j in J_n," and β is a vector of parameters. This equation describes, conceptually, the overall framework of QCA analysis. The details and the applications have to do primarily with first specifying the function f and then estimating the vector of parameters.

The first step in implementing this abstract framework is to examine more carefully the relation between what the decision-maker is doing and what the observer is seeing, and to introduce notation that reflects this distinction between "observable" and "unobservable." We write the utility that decision-maker n derives from selecting alternative i as a function of x_{in}, the relevant characteristics of the alternative, and r_n, the relevant characteristics of the decision-maker; thus,

$$U_{in} = U(x_{in}, r_n)$$

for all i in J_n. Here, U is a function whose form we have yet to describe. We partition x_{in} into those characteristics of the alternative that are observed by the researcher, labeled z_{in} as before, and those that are not (and are left unlabeled), and we partition r_n into characteristics of the decision-maker that are observed by the researcher, labeled s_n as before, and those that are not (and again are left unlabeled). Finally, we break up $U(x_{in}, r_n)$ into an observed component that is known up to a vector β of parameters to be estimated and that we label $V(z_{in}, s_n, \beta)$, and an unknown component which we label e_{in}. Then we can write the utility derived by the decision-maker from alternative i as

$$U_{in} = V(z_{in}, s_n, \beta) + e_{in}.$$

At this point, a more concrete specification can be provided. To apply the general scheme, one needs to first view e_{in} as a random variable, and specify a particular form for it, and second to specify a particular form for the observable (or "representative") utility $V(z_{in}, s_n, \beta)$. Different qualitative choice models, such as logit or probit, arise from particular specifications of the random variable. For our purposes, the model of interest is the logit. *The logit model is obtained by assuming that the error terms* e_{in}*, where the index i ranges over all alternatives in* J_n*, are independently and identically distributed according to the extreme value (also called "Weibull") distribution.* (The adjective "multinomial" in this context simply means that more than two alternatives are available.) In addition, in our applications (and in many others) it is assumed that the observable utility function is linear, that is, we assume that this function is of the form

$$V_{in} = \beta w(z_{in}, s_n),$$

where w is a vector function of the observable data and β is, as before, a vector of parameters. (Note that the expression $\beta w(z_{in}, s_n)$ is a vector or inner product.) If we suppress the functional dependence of the function w on the data and simply write is as w_{in}, then it can be shown that the probabilities take the form

$$P_{in} = \frac{e^{\beta w_{in}}}{\sum_{j \in J_n} e^{\beta w_{jn}}}.$$

(Note that two steps have been combined into one here; the logit probabilities always take this form of "exponential divided by sum of exponentials;" the exponents themselves are the representative utilities, which in the case just written--but not in general-- are linear.)

There are several things to note about this last expression. First, the probabilities defined in this way sum to one (as they should). Second, if one graphs P_{in} as a function of w_{in}, the familiar "S-shaped" or logit curve is obtained. (This is also true more generally, that is, it doesn't depend on the linearity of representative utility.) Third (actually a corollary of the latter observation), probability is a (highly) non-linear function of the data; this is the source of the oft-mentioned caution against constructing a model of this form and then plugging averaged data into it.

Another point is worth noting here: the primary reason for the particular stochastic specification that gives rise to the logit (that is, independent and identically distributed Weibull) is "analytical tractability." The probit model is based on the more natural assumption that the error terms have a joint multivariate normal distribution with a general variance-covariance matrix. This model, however, gives rise to some very difficult integrals in the expressions for the choice probabilities, with attendant estimation problems. (Hausman used a probit model in his famous 1979 air conditioner choice paper, which is a good example of that type of approach (Hausman 1979))

We will now write down how the above formalism looks in an example. Suppose that a decision-maker--a household--is to choose between a gas and an electric oven, and that we decide that the decision will be made on the basis of (or, "utility depends upon") the purchase price and operating cost, which we can observe, and upon the household's view of other characteristics of the ovens, such as appearance, quality, and so forth, which we can't observe. If we also assume that observed utility is a linear function of these factors, then we can write the utility of the two choices, respectively, as

$$U_g = \beta_1 PP_g + \beta_2 OC_g + e_g \quad \text{and} \quad U_r = \beta_1 PP_r + \beta_2 OC_r + e_r,$$

where the subscripts indicate gas and electric, respectively, PP is purchase price and OC operating cost, and the beta's are scalar parameters. If the error terms are distributed Weibull, then the probability that the household chooses the gas oven is

$$P_g = \frac{e^{\beta_1 PP_g + \beta_2 OC_g}}{e^{\beta_1 PP_g + \beta_2 OC_g} + e^{\beta_1 PP_r + \beta_2 OC_r}},$$

and the probability it chooses electric is analogous.

The parameters in the logit models are estimated by maximum likelihood methods (given certain assumptions on the character of the sampled data). Briefly, these are statistical optimization methods in which the maximization of what is called a "(log) likelihood function" yields the values of the parameters that give the highest probability that the decision-makers made the choices that are actually observed. The log likelihood is also used to construct what is called the "likelihood ratio index," which is a measure of goodness-of-fit, and can be used in hypothesis testing. In addition, standard hypothesis tests can be performed on individual parameters using the t-test.

One important elaboration of the basic logit model that we should mention briefly is the adding of constant terms--so-called "alternative-specific constants"--to the linear observable utility functions. This has several important functions. First, it corrects the (probably false) assumption that the errors have zero mean (which is a feature of the standard Weibull distribution). (In this sense, it is like adding intercept terms in a linear regression.) Second, when the parameters are estimated, it results in observed proportions in the sample being reproduced exactly in the model. Third, it allows up to a certain point for the correction of a central potential flaw in the underlying model, which we now discuss.

One mathematical consequence of the logit model is a property called "the independence of irrelevant alternatives (IIA)," which means that according to the model the ratio of the probabilities associated with any two choices is independent of any other alternative. Conceptually, this property enables one to correctly estimate a model on only a subset of observed alternatives, and also, given an estimated model, to predict demand for new alternatives.

There are some situations in which IIA may hold for some pairs of alternatives but not for others, or, put another way, there are "nests" of alternatives for which IIA holds. Another qualitative choice model, the "GEV" (for "generalized extreme value") or "nested logit" is appropriate in these situations. The GEV model is derived from the assumption that the error terms as described above--the e_{in}--are distributed in accordance with a generalized extreme value (or GEV) distribution. Under this assumption, one can derive expressions for the choice probabilities that are analogous to those in the logit (and reduce to them in the case where the error terms are uncorrelated) but are more elaborate; we won't write down the general form here. GEV models can also be estimated globally by maximum likelihood techniques. More common, however, is to perform a "bottom-up" sequential estimation (imagine here the usual upside-down "tree" diagram with two levels) starting at the lower or "nest" level; this exploits the fact that GEV choice probabilities can be decomposed into conditional and marginal probabilities that are logit.

There are several ways of obtaining aggregate (i.e., population) estimates from QCA models. The most straightforward is sample enumeration. Each individual in the sample is given a weight w_n (where the subscript n corresponds to the individual) depending on the characteristics of the sample, assuming "exogenous" samples, i.e., random or stratified random samples in which the strata (if any) are exogenous to the choice being studied. If the sample is random and consists of N observations, the weight is $1/N$ for each individual; if the sample is stratified, the weight varies over strata but is the same for all individuals within strata. In any case, the average probability for alternative i is estimated as

$$\overline{P_i} = \sum_n w_n P_{in},$$

and the number of individuals in the population predicted to choose alternative i is estimated as

$$N_i = N\overline{P_i}.$$

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