Modeling Household Energy Consumption and Adoption of Energy-efficient Technology Using Recent Micro-data

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Abstract

This paper presents a unified technology choice and energy consumption model (a "discrete/continuous model") that can be applied to study household energy use behavior. The model, stemming from consumer theory, ensures modeling of consumer short-run energy demand and long-run capital investment decisions in a mutually consistent manner. The model adopts a second-order translog flexible functional form that allows considerable structural flexibility in exploring consumer preferences and interplays among energy uses and between short-run and long-run choices. Using a unique California household dataset, the model is applied to examine the roles of household characteristics, energy prices, and energy and environmental policy in household energy use behavior. Estimation results demonstrate the modeling framework is robust and appropriate in studying household energy use behavior.

This study confirms two important market failures with respect to household energy technology choice behavior: the principal/agent problem and information imperfection. The empirical analysis finds strong evidence that information-based Energy Star program and energy efficiency standards influence the adoption of energy-efficient appliances. Surprisingly, financial incentives aimed to lower the initial costs of energy-efficient appliances, such as the popular rebate programs, are far less effective. Furthermore, at the household level the incentive for new technology adoption appears to be greater under direct regulation than under market-based instruments, such as a carbon cap-and-trade program or emission taxes.

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1. Introduction

Technological change and energy efficiency are recognized as important factors to address multiple energy and climate change challenges (Weyant 1993, Jaffe et al. 2003, and Pacala and Socolow, 2004).[2] According to the International Energy Agency, in order to stabilize carbon concentration in the atmosphere at 450 ppm by 2030 to avoid dangerous effects of climate change, over half of the global carbon dioxide (CO_2) emission reductions will come from greater energy efficiency in the world economy (Birol 2008). The diffusion and adoption of energy-efficient technology thus play a crucial role in energy and climate change policy.

In the United States, various policy programs have been devised to encourage the adoption of energy-efficient technology at the federal, state and local levels. These programs range from regulation, such as appliance energy efficiency standards, to incentive-based programs, such as federal tax incentives for fuel-efficient vehicles and utility rebates for energy-efficient appliances, to voluntary information and labeling programs, such as the Energy Star program. Many of these programs target the residential sector since residential households consume about one-fifth of the energy in the economy and the sector has some of the most cost-effective opportunities to reduce energy consumption.

In California, where the empirical analysis of this study focuses, households are found to be the most important determinants of the state's energy consumption (Roland-Holst 2008). In 2006, the state passed the California Global Warming Solutions Act ("Assembly Bill 32") to address global climate change. The Act mandates a cap on the state's greenhouse gas emissions at the 1990 levels by 2020 and a target to reduce the state's emissions by 80 percent from the 1990 levels by 2050. A suite of policy instruments are under consideration to fulfill the targets, including a cap-and-trade program, enhanced appliance efficiency standards, and energy efficiency measures such as green buildings in new construction and utility demand-side energy management programs.[3]

Given the important policy relevance of household behavior, better understanding is needed with respect to short-run energy consumption and long-run energy technology adoption, as well as with respect to responsiveness to price signals and incentive policy. However, empirical evidence to inform policymaking has been lacking in two important areas: (i) insights on consumer behavior with respect to adoption of energy-efficient technology, and (ii) effectiveness of alternative policy instruments (e.g., cap-and-trade programs, energy efficiency standards, and financial incentives) as a means of encouraging short-run and long-run household energy efficiency.

In this study, I develop a unified discrete technology choice and continuous energy consumption model (a "discrete/continuous model") from an underlying theoretical model of utility maximization. The approach, stemming from consumer theory, ensures modeling of consumer short-run demand and long-run capital investment decisions in a mutually congruent manner. The model adopts a second-order translog flexible form of the indirect utility function which allows considerable flexibility in the structure of consumer preferences and in the exploration of interplays among energy end uses both across different energy forms, and between energy demand and discrete appliance choices. This study extends the discrete/continuous model developed by Dubin and McFadden (1984) and is the first known application of the second-order translog flexible functional form in joint discrete/continuous modeling of consumer energy demand and appliance choice.

[2] This study adopts a service-minded definition and defines energy efficiency as the ratio of energy input for a given level of energy service output with the assumption that an energy service provides a consumable good (e.g., clean clothes and hot water), which provides utility to a consumer.

[3] Source: California's Climate Plan Fact Sheet, updated January 27, 2010 (accessed via www.climatechange.ca.gov).

Using a unique and rich micro-level household survey dataset in California, the model is applied to examine the roles of income, prices, household characteristics, and energy and environmental policy in short-run energy use and long-run technology choices. I estimate a system of short-run household demand equations for electricity and natural gas and long-run technology choices with respect to clothes washing, water heating, space heating, and clothes drying. The results, based on observations of recent energy consumption and appliance holdings among 2,408 households served by the Pacific Gas and Electric (PG&E) Company, demonstrate the modeling framework is appropriate and robust in studying household energy consumption and technology choice behavior.

Another unique contribution of this study is the insights on the effectiveness of alternative energy and environmental policy instruments (e.g., the market-based carbon cap-and-trade program, energy technology performance standards, financial incentives, and information programs) in encouraging the adoption of energy-efficient technology at the household level.

2. Relevant Literature

Analysis of consumer energy consumption and technology choices has long been used to assess the energy saving potential of energy efficiency programs and understand consumer investment decisions with respect to energy technology and conservation measures. In recent years, consumer energy consumption and technology choice behavior has received renewed interest in the context of climate change policy.

2.1 Energy-efficient technology adoption and policy

Rates of diffusion and adoption of apparently cost-effective energy efficiency investments are noted to have been slow. This phenomenon has come to be called the 'energy paradox.' This is now a subject studied extensively in the literature (e.g., Hassett and Metcalf 1993 & 1996, Jaffe and Stavins 1994, and DeCanio 1998). Using a simulation model, Jaffe and Stavins (1994) found that incomplete information, principal/agent problems, and artificially low energy prices inhibit the diffusion of energy-efficient technologies. Howarth and Sanstad (1995) argued that asymmetric information, bounded rationality, and transaction costs are major contributors to the energy paradox.

Early on, Hausman (1979) noted that individuals trade off capital costs and expected operating costs when making energy appliance purchase decisions. He found an implicit discount rate of about 20 percent in room air conditioner purchases. More recently, Hassett and Metcalf (1993) argued that the apparently high discount rates revealed in energy saving investment decisions were not irrational in the presence of substantial sunk costs and uncertainty about future savings. Train (1985) highlighted a wide range of estimates of implicit discount rates for different types of energy technology investments. He suggested that one possible explanation for the differences in discount rates is consumers' limited awareness of the true energy use and operating costs of some of the technologies. Train's argument is supported by recent consumer survey studies which found that limited knowledge of energy efficiency options inhibit adoption of energy saving measures (Hagler Bailly 1999 and Pacific Gas and Electric 2000).

The role of public policy in promoting energy efficiency and greenhouse gas emissions reductions has attracted great debate (e.g., Jaffe and Stavins 1994, Jaffe et al. 1999, Anderson and Newell 2002, Goulder et al. 1999, Levine et al. 1995, and Koomey et al. 1996). Based on a number of theoretical analyses, Jaffe et al. (2003) claim that the incentive for the adoption of new technologies is greater under market-based instruments than under direct regulation. A more recent analysis by Parry et al. (2010) evaluated the welfare impacts of energy efficiency standards for automobiles and electricity-consuming durables. The study supports the view that pricing mechanisms (e.g., energy taxes and emissions taxes) are preferred to regulatory approaches in correcting externalities associated with fossil fuel consumption.

In an analysis of market supply of air conditioners and water heaters, Newell et al. (1999) found evidence that both changes in energy prices and government regulations (energy efficiency labeling and energy efficiency standards) have affected energy efficiency in the menu of appliance models offered in the market. Hassett and Metcalf (1995) found evidence that government tax policies have significant impacts on the probability of residential energy conservation investments. Quigley (1984) evaluated the social costs of government policies designed to induce energy conservation by residential consumers (i.e., building codes and tax credits for energy efficiency improvements). His analysis provides support for government intervention on the basis that residential energy prices are less than marginal private or social costs.

Howarth et al. (2000) found strong evidence of energy efficiency improvements among private firms in the presence of the voluntary Green Lights and Energy Star programs. Anderson and Newell (2002) examined the effect of government energy-efficiency audit programs for industrial manufacturers' decisions on energy efficient technology adoption. They found that only half of the recommended energy efficiency projects were adopted by firms. They argue that information or institutional barriers does not fully explain firms' non-adoption behavior. The underlying economic reasons (e.g., longer than expected payback periods) ultimately affect firms' decisions on whether to adopt a recommended energy efficiency action.

2.2 Household energy demand and technology choice modeling

Conditional demand analysis (CDA) is a common approach for short-run household energy demand estimation that disaggregates total household energy consumption into appliance-specific estimates of demand functions based on explanatory variables such as energy price and household demographic characteristics given current appliance ownership. Parti and Parti (1980) developed one of the first conditional demand analysis models for residential electricity consumption using household data. A number of studies have estimated short-run household electricity consumption and demand elasticity using CDA models similar to Parti and Parti (e.g., Barnes, et al. 1981, Archibald, et al. 1982, and Aigner et al. 1984).

Although the short-run decision focuses on the intensity of technology utilization, neglecting capital stock holdings and household decisions regarding technology choice biases estimation of the demand function because technology choice and usage decisions are interlinked (Balestra and Nerlove 1966 and Taylor 1975). Hanemann (1984) showed that the discrete technology choice and continuous consumption decisions derived from an underlying theoretical model of utility maximization are consistent with the economic theory of consumer behavior and should be modeled in a mutually consistent manner. Dubin and McFadden (1984) demonstrated empirically that modeling energy demand without consideration of endogenous technology choice yields biased and inconsistent estimates. They proposed an approach that jointly estimates the discrete decisions on appliance choice and continuous decisions on usage (the "discrete/continuous model"). In a recent study, Davis (2008) used the discrete/continuous model to estimate household demand for energy and water from a field trial of energy-efficient clothes washers among 98 households in Bern, Kansas. He found that when simultaneity of appliance choice is ignored, estimates of price elasticities are biased away from zero.

The application of discrete/continuous modeling for energy use was sparse in the U.S. until the recent years. With increased policy interests in climate change and energy efficiency, the discrete/continuous modeling approach has regained popularity. Newell and Pizer (2008) use this approach to estimate fuel choices and energy demand in the U.S. commercial sector in an effort to estimate a carbon mitigation cost curve for the sector. Mansure et al. (2008) apply the method to evaluate changes in fuel choices and energy demand among U.S. households and firms in response to long-term weather change due to climate change. Both studies largely followed the two-step estimation method of the Dubin & McFadden model whereby a multinomial logit model of fuel choices is estimated first, followed by fuel-specific conditional demand analysis that incorporates selection error terms from the first stage.

In sum, joint modeling of household long-run energy technology choice decisions and short-run energy use is recognized as a holistic approach to evaluate household energy use behavior. However, its application is still very limited. Most existing empirical studies are based on outdated data or data of limited scope for the purpose of robust inference. Moreover, empirical evaluation of the effectiveness of alternative energy and environmental policy instruments for encouraging consumer adoption of energy-efficient technology in this consistent analytical framework is even more sparse.

3. A Model of Household Energy Demand and Technology Choices

This section presents the conceptual framework for joint modeling of household consumption and energy durable choice decisions. The details of model setup can be found in Li (2011).

3.1 Model setup

The household is assumed to maximize utility from consuming two groups of goods, a composite of market goods (E_0) and energy uses $E = \{E_1,...,E_J\}$ (e.g., space heating and clothes washing), in each time period. Utility maximization is represented as

(1) $$\max_{E_0, E_1,..E_J} u(E_0, E_1,..,E_J;\theta),$$

where θ is a vector of household characteristics (e.g., household size and square footage) that influence household demand.

Demand for each energy service E_j is met through utilization of a household energy production technology i (an appliance) with energy efficiency φ_{ij} using fuel l as an input. The energy service production function is represented by [4]

(2) $$E_j = \varphi_{ij} x_{l(i),j}, \qquad j = 1,...,J,$$

where $x_{l(i),j}$ is input of fuel $l(i)$ associated with technology i for end use j.[5]

In the short-run, the household capital stock (e.g., appliances and housing) is fixed and production of the desired level of an energy service is determined by the intensity with which the chosen technology is utilized. Therefore, the short-run household optimization problem generates a derived demand for fuel. In the long run, however, the household will consider both the capital costs and the future flow of operating costs associated with each of the alternative technologies in the technology decision-making process.

3.2 Short-run fuel demand

The short-run optimization problem can be formalized as utility maximization as in equation (1) subject to the production function in equation (2), and the budget constraint

[4] I assume output nonjointness, i.e., no appliance produces more than one energy service, and input nonjointness, i.e., fuel allocated to one appliance does not affect production of others.
[5] The use of such functions in this model avoids estimating certain phenomena in broad reduced form relationships for which physical relationships are known comparatively precisely.

(3) $$E_0 + \sum_{l=1}^{L} p_l x_l = E_0 + \sum_{j=1}^{J} p_{l(j),j} x_{l(j),j} \le y^* \equiv y - \sum_{j=1}^{J} \rho_{i(j),j} k_{i(j),j},$$

where $p_l \equiv p_{l(j),j}$ is the price of fuel *l* regardless of the energy use, $x_l \equiv \sum_{j=1}^{J} x_{l(j),j}$ is the total household use of fuel *l*, *i(j)* is the technology currently in place for energy use *j*, *y** is the amount of income (*y*) not already committed to fixed payments including appliance payments (represented as annualized costs), $k_{i(j),j}$ is the capital cost of technology *i* for end use *j*, and $\rho_{i(j),j}$ is annualized fixed cost rate of technology *i* for end use *j* that accounts for appliance lifetime and financing costs. The budget constraint in (3) implies that the implicit price of energy service *j*, i.e., the effective cost per unit of energy output for the *j*th energy use, is

(4) $$r_j \equiv (p_{l(j),j} x_{l(j),j}) / (\varphi_{i(j),j} x_{l(j),j}) = p_{l(j),j} / \varphi_{i(j),j}, \qquad j = 1,..J.$$

Solving the utility maximization problem given the current appliance stock yields the conditional indirect utility function

(5) $$V = V(r, y^*, \theta),$$

where *r* is a vector including r_0, the price of the composite good, and the r_j's across all energy end uses for *j* = 1,…,*J*. I adopt a version of the second-order translog flexible functional form of the conditional indirect utility function following Berndt et al (1977). Demographic variables are incorporated by interacting them with price terms using "demographic translating" discussed in Pollak and Wales (1992). In addition, a vector of household characteristics that may influence energy technology choices and disturbances associated with individual technology choices for energy service production are included. This functional form yields

(6) $$\begin{aligned} V(r, y^*, \theta, \varepsilon) = \exp\{\overline{\alpha} + \sum_{j=0}^{J} \alpha_j \ln(r_j / y^*) + \sum_{j=0}^{J}\sum_{j'=0}^{J} \beta_{jj'} \ln(r_j / y^*) \ln(r_{j'} / y^*) \\ + \sum_{j=0}^{J} \ln(r_j / y^*) \Gamma_j \theta + \sum_{j=1}^{J} \mathrm{H}_{i(j),j} \theta + \sum_{j=1}^{J} \varepsilon_{i(j),j}\}, \end{aligned}$$

where '0' denotes the composite good, $\overline{\alpha}$, α_j, *j* = 0,…,*J*, and $\beta_{jj'}$, *j,j'* = 0,…,*J*, are scalar parameters, and Γ_j, *j* = 0,…,*J* and $\mathrm{H}_{i(j),j}$, *j* = 1,…,*J* are row-vector parameters of the indirect utility function, and $\varepsilon_{i(j),j}$ is a disturbance. Both the parameter vector $\mathrm{H}_{i(j),j}$ and the disturbance $\varepsilon_{i(j),j}$ are associated with the specific technology *i* chosen for energy use *j*. I assume separability in demand between the composite good and the choice of energy technology alternatives.

Using the Roy's identity, imposing normalization constraints for the translog system, re-arranging terms, and aggregating household fuel use, the following budget share equations for fuel demand are obtained

$$
\begin{aligned}
\omega_l &= \frac{x_l p_l}{y*} \\
&= \sum_{j=1}^{J} \Psi(x_{l(j),j} > 0) \frac{x_{l(j),j} p_{l(j),j}}{y*} \\
&= \frac{\sum_{j=1}^{J} \Psi(x_{l(j),j} > 0) \left[\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) - 2\ln y* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta \right]}{1 + 2\sum_{j''=0}^{J} \sum_{j'=1}^{J} \beta_{j''j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) + \sum_{j''=0}^{J} \Gamma_{j''} \theta} + \mu_l, \\
& \qquad l = 1,\ldots,L,
\end{aligned} \tag{7}
$$

where $\Psi(x_{l(j),j} > 0)$ is an indicator variable that equals to one if energy use j uses fuel l and is zero otherwise, and μ_l is an error term to represent errors in fuel use decisions. Similarly, the budget shares for the composite goods E_0 is expressed as

$$
\begin{aligned}
\omega_0 &= \frac{y* - \sum_{j=1}^{J} p_{l(j),j} x_{l(j),j}}{y*} \\
&= \frac{\alpha_0 + 2\sum_{j'=1}^{J} \beta_{0j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) - 2\ln y* \sum_{j'=0}^{J} \beta_{0j'} + \Gamma_0 \theta}{1 + 2\sum_{j''=0}^{J} \sum_{j'=1}^{J} \beta_{j''j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) + \sum_{j''=0}^{J} \Gamma_{j''} \theta} + \mu_0,
\end{aligned} \tag{8}
$$

where μ_0 is a disturbance.

3.3 Long-run technology choice

The household long-term optimization problem involves capital stock decisions. Assuming household's future price and income expectations at each point in time are given by current prices and income, the long term problem can be represented as

$$
\max_{i(j) \in I_j, j=1,\ldots,J} u(E_0^*, E_1^*, \ldots, E_J^*; \theta), \tag{9}
$$

subject to

$$
E_0 + \sum_{j=1}^{J} p_{l(i(j)),j} x^*_{l(i(j)),j} + \sum_{j=1}^{J} \rho_{i(j),j} k_{i(j),j} = y.
$$

After the short-term optimization and imposing $r_0 = 1$ using the normalization constraints, the indirect utility function (6) becomes

$$V(r,y^*,\theta,\varepsilon)=\exp\{\overline{\alpha}_0-\ln y^*+\sum_{j=1}^{J}\alpha_j\ln r_j-2\,lny^*\sum_{j=0}^{J}\sum_{j'=1}^{J}\beta_{jj'}\ln r_{j'}$$

(10)
$$+\sum_{j=1}^{J}\sum_{j'=1}^{J}\beta_{jj'}\ln r_j\ln r_{j'}+\sum_{j=1}^{J}\ln r_j\Gamma_j\theta-\ln y^*\sum_{j=0}^{J}\Gamma_j\theta+\sum_{j=1}^{J}\mathrm{H}_{i(j),j}\theta$$

$$+\sum_{j=1}^{J}\varepsilon_{i(j),j}\},$$

where $\overline{\alpha}_0=\overline{\alpha}+\alpha_0$.

I assume household energy technology choice for each energy use is independent of choices for all other energy uses. This is a reasonable assumption as appliance purchase and replacement decisions are typically motivated by an old appliance wearing out, which occurs at random times.[6] Under this assumption, this model reduces to independent minimization of the implicit cost of individual energy uses. For this purpose, I define

(11) $y_j=y-\sum_{\substack{j'=1\\ j'\neq j}}^{J}\rho_{ij'}k_{ij'}$, and

(12) $y_{ij}=y-\sum_{\substack{j'=1\\ j'\neq j}}^{J}\rho_{ij'}k_{ij'}-\rho_{ij}k_{ij}$.

where y_j represents income available given commitments to fixed payments associated with all energy services other than j, and y_{ij} represents income available after choosing technology alternative i for energy service j. Analogous to r_j as defined in equation (4), I also define $r_{ij}\equiv p_{l(i(j)),j}/\varphi_{i(j),j}$ as the effective cost per unit of energy service j where $i(j)$ is the chosen technology.

The indirect utility function in (6) can be denoted as

(13) $V_j(i,\rho_{ij},k_{ij},y_j,\theta,\varepsilon_{ij})=\{V(r,y_{ij},\theta,\varepsilon)\,|\,i(j)=i,i(j)\ for\ j'=1,...,J;j'\neq j\}$,

where V is the same indirect utility function with the same parameters as defined in (6). The indirect utility function V_j can be decomposed into two components: the terms that vary with the technology choice for energy use j and the terms that are constant regardless of this technology choice. For convenience, I introduce the following notation for the right-hand side expression in (13) $V_j(r,y_{ij},\theta,\varepsilon_{ij})=\exp(W_{ij}B_j+W_j^0+\varepsilon_{ij})$. The probability that the household chooses technology i from the set I_j of alternatives for energy service j can then be represented as

[6] There are realistic cases where this assumption may be challenged (e.g., new home construction or retrofitting when appliance choices are made at the same time). The technology choice independence assumption can be tested empirically by comparing the independent choice case with a joint technology choice case. Statistical tests will reveal the appropriateness of the assumption.

$$
\begin{aligned}
P_{ij} &= \Pr\{V_j(i, y_{ij}, \theta, \varepsilon_{ij}) > V_j(i', y_{i'j}, \theta, \varepsilon_{i'j}) \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{\exp(W_{ij} B_j + W_j^0 + \varepsilon_{ij}) > \exp(W_{i'j} B_j + W_j^0 + \varepsilon_{i'j}), \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{W_{ij} B_j + W_j^0 + \varepsilon_{ij} > W_{i'j} B_j + W_j^0 + \varepsilon_{i'j}, \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{\varepsilon_{i'j} - \varepsilon_{ij} < W_{ij} B_j - W_{i'j} B_j, \forall i' \neq i; i, i' \in I_j\}
\end{aligned} \tag{14}
$$

where

$$
\begin{aligned}
W_{ij} &\equiv \{-\ln y_{ij}, \ln r_{ij}, -2\ln y_{ij} \ln r_1, ..., -2\ln y_{ij} \ln r_J, 2\ln r_{ij} \ln r_1, ..., 2(\ln r_{ij})^2, ..., 2\ln r_{ij} \ln r_J, \\
&\quad \ln r_{ij}\theta, -\ln y_{ij}\theta, \theta\} \\
B_j &\equiv \{1, \alpha_j, \sum_{j=0}^{J} \beta_{j1}, ..., \sum_{j=0}^{J} \beta_{jJ}, \beta_{j1}, .. \beta_{jJ}, \Gamma_j', \sum_{j=0}^{J} \Gamma_j', \mathrm{H}_{i(j),j}'\}'.
\end{aligned}
$$

As shown in (14), the W_j^0 terms conveniently cancel out of this expression. Thus, only choice-related variables and technology choice disturbances are relevant. Assuming $\varepsilon_{ij} \forall\, i \in I_j$, are identically and independently distributed with zero means and follow extreme value (EV) type I distributions, the difference between two disturbances follows the logistic distribution function. Following the well-known results developed and popularized by McFadden (1974), the EV error term distribution leads to a logit model of the discrete choice probability where the probability that technology *i* yields the highest indirect utility among all possible technologies is given by

$$
\begin{aligned}
P_{ij} &= \frac{\exp(W_{ij} B_j)}{\sum_{i' \in I_j} \exp(W_{i'j} B_j)} \\
&= \frac{\exp\left\{ \begin{array}{l} -\ln y_{ij}\left[1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j''} + \sum_{j=0}^{J} \Gamma_j \theta\right] \\ \qquad + \ln r_{ij}\left[\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} + \Gamma_j \theta\right] + \mathrm{H}_{ij}\theta \end{array} \right\}}{\sum_{i' \in I_j} \exp\left\{ \begin{array}{l} -\ln y_{i'j}\left[1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j''} + \sum_{j=0}^{J} \Gamma_j \theta\right] \\ \qquad + \ln r_{i'j}\left[\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} + \Gamma_j \theta\right] + \mathrm{H}_{i'j}\theta \end{array} \right\}} \\
&= \frac{\exp(-\ln y_{ij} A_0 + \ln r_{ij} A_j + \mathrm{H}_{ij}\theta)}{\sum_{i' \in I_j} \exp(-\ln y_{i'j} A_0 + \ln r_{i'j} A_j + \mathrm{H}_{i'j}\theta)},
\end{aligned} \tag{15}
$$

where

$$
A_0 \equiv 1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j''} + \sum_{j=0}^{J} \Gamma_j \theta, \text{ and}
$$

$$A_j \equiv \alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} + \Gamma_j \theta.$$

Thus, A_0 and A_j are, in effect, scalars that do not vary with the chosen technology for a given energy service (and household). Equation (15) shows that when the long-run technology choice decisions and the short-run energy demands are both derived from the same underlying indirect utility function, coefficients for the income variable ($\ln y_{ij}$) and price variables ($\ln r_{ij}$) in the long-run technology choice model are the same as those that appear in the short-run fuel demand model in equation (7). In addition, equation (15) shows how the household variables in θ can influence the propensity that the household chooses technology i for energy use j in a mixed logit framework.

4. Data Description

The empirical study uses micro-data collected for the 2003 Statewide Residential Appliance Saturation Study (RASS) in California. The study was conducted by the California Energy Commission (CEC) with sponsorship from the major investor-owned utilities in the state. This analysis uses a subsample of 2,408 households served by PG&E for both natural gas and electricity in the RASS. The subsample only includes households with both electricity and natural gas consumption in order to empirically estimate the system of equations that represents tradeoffs of fuel use both in the short run and the long run as well as between short-run and long-run decisions.

The RASS dataset contains variables including household socio-economic characteristics (e.g., income, household size and education level), housing characteristics (e.g., housing type, square-footage, vintage and ownership), appliance holdings by energy use (e.g., technology, age and fuel type), and annual consumption of electricity and natural gas. The dataset also assigns individual households with climate zone and heating degree days (HDDs) and cooling degree days (CDDs) data, which can help determine households' heating and cooling loads. Historic heating and cooling degree days between 1950 and 2003 were merged with the RASS based on climate zone.

The PG&E sample presents sufficient variations in household characteristics, fuel consumption and appliance choices for meaningful analysis. Table 1 provides the summary statistics of selected key variables of the PG&E sample.

Table 1. Summary statistics of selected variables used in analysis

Variable	Mean	Standard Deviation	Minimum	Maximum
Annual electricity use (kWh)	7023.14	3844.53	299.95	33739.49
Annual natural gas (therms)	564.24	278.62	9.02	3058.37
Average income (2000$)	87326.29	47866.74	15000	214454.7
Household size (persons)	2.79	1.46	1	13
Own dwelling dummy	0.92	0.27	0	1
House age (years)	13.73	11.97	1	37
Square footage (sqft)	1890.78	761.82	375	6000
Heating degree days	2630.76	394.53	2207	5267
Cooling degree days	751.07	627.19	0	2060

Source: Author's estimates based on the 2,408 households in the subsample used for estimation.

The analysis of short-run fuel demand and long-run technology choices explicitly models four categories of energy services: clothes washing, water heating, space heating, and clothes drying. Together, these four energy use categories represent 65 percent of the average household energy consumption.[7] These energy uses are chosen for analysis mainly because of the availability and quality of technology data for technology choice analysis. In the short-run demand analysis, all other energy uses are grouped in an "other" category.

Despite its rich information, the RASS dataset lacks a few key variables required for the analysis, including fuel prices (p_l), appliance capital costs (k_{ij}), energy efficiency characteristics (φ_{ij}), and household fixed payments to derive the expenditure variable (y^*). Historic electricity and natural gas tariffs were collected from PG&E and assigned to households based on definitions of service categories. Annual fuel expenditures are estimated using household annual fuel consumption and assigned energy prices. Energy efficiency measures of various appliances are derived from a number of household and market survey studies that estimated average energy efficiency levels of existing appliance stock in California (e.g., RLW Analytics 2001 and 2005, Hanford et al. 1994, and Wenzel et al. 1997). Appliance costs and energy efficiency characteristics are compiled through the databases developed by the CEC and CPUC and the Lawrence Berkeley Lab. Household fixed payments are estimated based on a regression analysis of the relationship between household income and fixed payments using the Consumer Expenditure Survey.

5. Estimation Strategy

The discrete/continuous model developed in Section 3 consists of a system of simultaneous equations with continuous demand and discrete choice endogenous variables and a set of exogenous explanatory variables consisting of prices, income and household characteristics. This system notably has a recursive structure between the discrete and continuous components whereby energy consumption depends on observed appliance choice but not vice versa. I adopt a two-step limited information maximum likelihood (LIML) approach to estimate the model. Because the vast majority of observations on appliance choice pertain to decisions made in a different time period, the assumption of uncorrelated disturbances is well motivated. This yields a block recursive system of equations in which blocks of equations can normally be estimated separately with asymptotic efficiency.

The estimation procedure is implemented as follows. The first step estimates the system of short-run demand equations (7) and (8) using the iterated feasible generalized nonlinear least squares (FGNLS) method to produce asymptotically consistent estimators. With normally distributed disturbances, estimates using iterated FGNLS are theoretically equivalent to ML estimates (Greene 2008). The adding-up condition implies that covariance matrix is singular and nondiagonal. Therefore, one equation is dropped from the system to obtain identification.[8]

Then, the technology choice equations are evaluated separately using the method of ML without imposing any structural constraints. Because choices of different appliances are made at different points in time, correlation among the disturbances is likely minor if present at all, in which case separate estimation does not sacrifice efficiency aside from ignoring parameter constraints among equations. Four separate energy technology choice equations are then estimated, representing clothes washing (*cw*), water heating (*wh*), space heating (*sph*) and clothes drying (*cd*). Technology choice sets consist of two choice alternatives for

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[7] An initial analysis was carried out which consider joint choices of water heater and space heater given the possible correlation of fuel choices for these two energy services. However, a statistical test of the nested model of fuel choices cannot reject the null hypothesis that fuel choices for water heating and space heating are independent.

[8] Specification tests show that among different combinations using two of the three budget share equation specifications, the system of budget share equations for the numeraire and natural gas yields the highest log likelihood value, although all choices should yield the same asymptotic results.

clothes washing and clothes drying. Thus a binary logit choice model is appropriate. For water heating and space heating, three choice alternatives are involved in each case so a multinomial logit choice model is appropriate.

In the second step, equation (15) is re-estimated by imposing parametric constraints on parameters A_0 and A_j implied by parameter estimates from the short-run demand model estimated using the maximum likelihood obtained in step one. The vector of the remaining parameters is estimated, producing the ML estimator of the parameters and the associated ML estimator of the covariance matrix of the parameters. Then, the covariance matrix is corrected that accounts for the covariance matrix estimator of the short-run parameters to obtain the asymptotic covariance matrix. The correction follows the procedure developed by Murphy and Topel (2002).

6. Estimation Results

The results of the short-run demand analysis and the technology choice analysis are summarized in Section 6.1 and 6.2, respectively.

6.1 Short-Run Energy Demand

Table 1 below presents the estimation results of four specifications using the FGNLS procedure. Model 1a includes only price variables $\ln r_j$, the income variable $\ln y^*$, and demand interaction terms. Model 1b builds on Model 1a and adds household-demand interaction terms. Inclusion of household and demand interaction terms is guided by the features of energy service demands and significance of statistical tests. A log likelihood ratio test between Model 1a and Model 1b rejects the null hypothesis that the household-demand interaction terms in the model are jointly zero with a p-value less than 0.001, suggesting household variables—household size, dwelling square footage, heating degree days and the age of dwelling in this specification—influence household energy demand significantly.

Model 1c builds on Model 1b and instead of using average energy efficiency indicators to derive the price variable for clothes washing, $\ln r_{cw}$, it treats energy efficiency of clothes washers as an estimable linear function of the energy efficiency standards ("Standard") and the EnergyStar information program ("*EnergyStar*") aside from an error term, i.e., $\ln r_{cw} = \ln(p_{l(cw)} / \varphi_{i(cw)}) = \ln p_{l(cw)} - \ln \varphi_{i(cw)}$, where $\ln \varphi_{i(cw)} = \gamma_1 Standard_i + \gamma_2 EnergyStar + e_{i(cw)}, E(e_{i(cw)}) = 0$. Average energy efficiency indicators are used to derive the price variables for water heating, space heating, and clothes drying. Compared with Model 1b, the model fit of Model 1c improves significantly with much higher log likelihood and pseudo-R^2 values with a p-value less than 0.001. The results indicate potential measurement errors by using the average energy efficiency of the clothes washer stock in the demand analysis. This is likely due to a substantial improvement in energy efficiency performance of clothes washers over the past two decades as a result of technology improvement and energy efficiency policy.

Changes in the energy efficiency performance of water heaters, space heaters and clothes dryers were modest during the study period. Nonetheless, a specification test is performed to see whether use of average energy efficiency indicators for water heaters is statistically equivalent to modeling energy efficiency of water heaters as an estimable function of appliance age (Model 1d). In Model 1d, the energy efficiency of water heaters is modeled as a linear function of the age of water heater ("*age_wh*") and an error term, i.e., $\ln \varphi_{i(wh)} = \lambda_1 age\_wh_i + e_{i(wh)}, E(e_{i(wh)}) = 0$. The log likelihood ratio test between Model 1d

Table 1. Coefficient estimates of the short-run demand equations

Coefficient	Definition	**Model 1a** Without household variables	**Model 1b** With household variables	**Model 1c** With energy efficiency of clothes washers	**Model 1d** With energy efficiencies of clothes washers and water heaters
a_0	intercept – *numeraire*	1.07892***	0.92969***	0.81503***	0.80212***
		(149.241)	(166.703)	(84.181)	(65.717)
a_1	intercept-*cw*	-0.03500*	-0.03577***	0.06756***	0.10859***
		(-2.385)	(-4.121)	(5.456)	(6.854)
a_2	intercept-*wh*	0.06316	0.02998	-0.02994	-0.01002
		(1.279)	(0.893)	(-0.857)	(-0.226)
a_3	intercept-*cd*	-0.03620**	0.03689***	0.03209***	-0.00099
		(-3.101)	(4.138)	(3.774)	(-0.118)
a_4	intercept-*sph*	-0.03062	0.02915	-0.02322	-0.01592
		(-0.882)	(1.214)	(-0.925)	(-0.619)
β_{01}	cross demand *numeraire-cw*	-0.01047***	0.01596***	0.01142***	0.01094***
		(-8.144)	(14.497)	(7.430)	(6.680)
β_{02}	cross demand *numeraire-wh*	0.00265*	0.00341*	-0.00265	-0.00222
		(2.447)	(2.498)	(-1.401)	(-1.226)
β_{03}	cross demand *numeraire-cd*	0.00158*	0.00194***	0.00116	-0.00180**
		(2.425)	(3.736)	(1.764)	(-3.114)

(Continued on next page)

β_{04}	cross demand	-0.00072	0.00643***	0.00271	0.00318*
	numeraire-sph	(-0.667)	(4.798)	(1.731)	(2.022)
β_{05}	cross demand	0.04241***	0.02293***	0.03754***	0.03999***
	numeraire-oth	(32.445)	(12.234)	(14.173)	(14.105)
β_{11}	own demand	0.02324***	0.02383***	0.04820***	0.05129***
	cw	(7.540)	(30.328)	(15.794)	(15.795)
β_{12}	cross demand	-0.00609***	0.00056***	-0.00208	-0.0023
	cw-wh	(-6.231)	(3.471)	(-1.127)	(-1.156)
β_{13}	cross demand	0.00042	0.00046**	-0.00252**	-0.00085
	cw-cd	(1.395)	(2.749)	(-2.769)	(-0.719)
β_{22}	own demand	0.09579	0.01308	-0.01877	0.00505
	wh	(1.630)	(0.352)	(-0.437)	(0.147)
β_{25}	cross demand	-0.09331	-0.01231	0.01938	-0.00501
	wh-oth	(-1.582)	(-0.331)	(0.450)	(-0.147)
β_{33}	own demand	-0.00422**	0.00260***	0.00403***	-0.00057
	cd	(-3.250)	(3.454)	(3.912)	(-0.344)
β_{44}	own demand	-0.11814	-0.02305	-0.0569	-0.06193
	sph	(-1.877)	(-0.579)	(-1.445)	(-1.559)
β_{45}	cross demand	0.12151	0.02735	0.05789	0.0642
	sph-oth	(1.921)	(0.685)	(1.468)	(1.615)

β_{55}	own demand	-0.06206	-0.0249	-0.07699	-0.05884
	oth	(-0.783)	(-0.496)	(-1.455)	(-1.200)
d_1	*hh_size-wh*		-0.00038***	-0.00037***	-0.00038***
	interaction		(-7.049)	(-6.649)	(-6.620)
d_2	*sqft–sph*		0.00053***	0.00069***	0.00072***
	interaction		(4.781)	(6.031)	(6.080)
d_3	*age–oth*		-0.00069***	-0.00074***	-0.00075***
	interaction		(-10.822)	(-11.098)	(-10.888)
d_4	*hhd–sph*		0.00213***	0.00220***	0.00226***
	interaction		(10.792)	(10.869)	(10.776)
γ_1	Standard-*cw*			-0.00515	-0.00521
				(-0.428)	(-0.430)
γ_2	EnergyStar-*cw*			-0.00647	-0.00714
				(-0.640)	(-0.694)
λ_1	technology				0.04578
	change-*wh*				(0.146)
Observations		2408	2408	2408	2408
Log likelihood		14827	15414	15516	15519
R^2 numeraire		0.385	0.579	0.604	0.604
R^2 gas		0.414	0.777	0.788	0.788

Notes: (1) Asterisks in the table denote significance in terms of p-values as follows: ‘*’ for $p < 0.05$, ‘**’ for $p < 0.01$, and ‘***’ for $p < 0.001$. (2) Values in parentheses are t-statistics.

and Model 1c suggests that modeling energy efficiency of water heaters as a function of technology change is preferred to using average energy efficiency indicators with a p-value of 0.021.[9] Model 1d is thus used as the main specification for subsequent discussions and the parametric estimates imposed in the second stage estimation of technology choices.

The coefficients derived from the estimation are difficult to interpret on their own. Demand elasticities are more revealing. The estimated income and own price elasticities are presented in Table 2 and 3 below, respectively. Cross price elasticities between electricity and natural gas are unlikely to be important as substitution between the fuels is limited in the short run.

Table 2. Estimated short-run income elasticities of demand for fuels

Model	Mean	Standard Deviation	Minimum	Maximum
<u>Electricity</u>				
Model 1a	0.0816	0.0843	-0.2623	2.1148
Model 1b	0.3436	0.0804	0.2560	0.8703
Model 1c	0.5032	0.0658	0.4267	1.0038
Model 1d	0.4182	0.1786	0.3189	1.6974
<u>Natural Gas</u>				
Model 1a	-0.0698	0.0358	-0.0933	0.1417
Model 1b	-0.7127	0.2457	-0.9537	0.8085
Model 1c	-0.3096	0.1201	-0.4029	0.4024
Model 1d	-0.4201	0.1639	-0.5963	0.5113

Table 3. Estimated short-run price elasticities of demand for fuels

Model	Mean	Standard Deviation	Minimum	Maximum
<u>Electricity</u>				
Model 1a	0.2533	0.1480	0.1538	2.8310
Model 1b	-0.1313	0.0609	-0.5339	-0.0474
Model 1c	-0.0641	0.0831	-0.7499	-0.0359
Model 1d	-0.1343	0.1410	-1.0913	-0.0677

[9] An additional specification test shows that using average energy efficiency indicators for space heating systems is not statistically different from explicitly modeling the energy efficiency of space heating systems with a p-value of 0.072. Thus, using average space heating energy efficiency indicators does not introduce significant measurement errors.

Natural Gas				
Model 1a	-0.2060	0.4769	-0.3311	2.8901
Model 1b	-0.1473	0.1992	-0.2611	1.0758
Model 1c	-0.1262	0.1107	-0.3432	0.6230
Model 1d	-0.1188	0.1439	-0.1775	0.8373

The mean estimates of income elasticity for electricity are positive in all four specifications and less than unity (Table 2). Model 1d, the preferred specification, has a mean estimated income elasticity of 0.418 for electricity and a range between 0.319 and 1.697. The maximum estimates of income elasticity for electricity are greater than unity in three out of the four cases. As expected, the results show that electricity is a superior good. The estimated mean income elasticity for natural gas is consistently negative in all four cases. However, in all four cases, income elasticities range widely over both negative and positive values. For Model 1d, the mean estimate of income elasticity for natural gas is -0.420 with a minimum value of -0.596 and a maximum value of 0.511. These results suggest that natural gas is an inferior good for many households, which is not surprising.

The mean estimates of own price elasticity for electricity are all negative except for Model 1a (Table 3), the least preferred model. For Model 1d, the estimated own price elasticity for electricity has a mean of -0.134 and a range between -1.091 and -0.068, which appears quite plausible. The mean estimates of price elasticity for natural gas are consistently negative. Similar to estimates of income elasticity for natural gas, however, the ranges of estimates among individual households include both negative and positive values. In Model 1d, the estimate of own price elasticity for natural gas has a mean of -0.119 and a range between -0.177 and 0.837, although very few households (3.3 percent) fall in the positive range.

6.2 Energy Technology Choices

Clothes Washer Choices

Table 4 reports the estimation results of the binary logit model of clothes washer choices with four specifications. Model cw1a and Model cw1b investigate two specifications using average energy efficiency indicators to derive the expected operating costs; Model cw2a and Model cw2b have the same sets of specifications except that the perceived energy efficiency of the choice alternatives is modeled as a function of the energy efficiency standards and the Energy Star program as in the short-run demand analysis. Model 1a and Model 2a evaluate the roles of the initial capital cost and the expected operating cost of technology alternatives in clothes washer choices. Variable *ln_incCW* is the negative of the logarithm of household income not already committed to fixed payments minus the annualized capital costs between the choice alternatives. In Model cw1a, the expected operating cost is represented by the logarithm of the operating cost derived from average energy efficiency indicators (*ln_oCostCW*). In Model cw2a, the expected operating cost consists of three components: the logarithm of fuel price (*ln_fuel*), a dummy variable representing the presence of clothes washer energy efficiency standards (*Standard*), and a dummy variable representing the presence of clothes washer Energy Star criteria (*EnergyStar*).

Model cw1b and Model cw2b add household variables to examine whether household characteristics may have influenced clothes washer choices. Specifically, three household variables are included: (1) the home ownership dummy (*own*), (2) the household size (*household size*), and (3) a college education dummy (*college*). The college education dummy is an instrument to represent consumers' ability to understand and interpret energy consumption and performance information pertaining to home appliances.

A second step of constrained estimator is performed with the specification of Model cw2b by imposing parametric constraints on the common variables (*ln_incCW* and *ln_fuel*) based on coefficient estimates from the short-run demand model (Model 1d). Column 5 in Table 4 presents the results of the constrained estimation as Model cw2b*.

Table 4. Estimated coefficients of the clothes washer choice model

Regressor	Model				
	cw1a	**cw1b**	**cw2a**	**cw2b**	**cw2b***
ln_incCW	-100.190***	-65.476***	-184.026***	-145.925***	
	(-5.47)	(-3.95)	(-4.50)	(-3.62)	
ln_oCostCW	1.516***	2.738***			
	(20.96)	(8.60)			
ln_fuel			0.635	0.695	
			(0.73)	(0.78)	
Standard			1.127**	1.092**	0.889*
			(2.70)	(2.61)	(2.12)
EnergyStar			2.144***	2.136***	1.925***
			(7.68)	(7.66)	(8.37)
Own		0.620		0.635	0.847*
		(1.94)		(1.92)	(2.59)
Household size		0.102*		0.049	0.062
		(2.56)		(0.99)	(1.39)
College		0.586***		0.447*	0.798***
		(3.71)		(2.73)	(5.00)
Constant			-2.683	-3.689*	-5.910***
			(-1.60)	(-2.09)	(-11.15)
Observations	2408	2408	2408	2408	2408
Log likelihood	-841	-828	-718	-712	-734

Notes: (1) Asterisks in the table denote significance in terms of p-values as follows: '*' for $p < 0.05$, '**' for $p < 0.01$, and '***' for $p < 0.001$. (2) Values in parentheses are t-statistics. (3) A top-loading clothes washer is the base case in this analysis.

As shown in Table 4, the coefficient of the household expenditure variable that incorporates the initial cost of clothes washer alternatives (*ln_incCW*) is significant across all specifications. The negative coefficient of *ln_incCW* suggests that a reduction in the initial capital cost will increase the probability of front-loading clothes washer adoption. The expected operating cost, derived using average energy efficiency indicators (Model cw1a and Model cw1b), also significantly influences clothes washer choices.

The positive coefficient of *ln_oCostCW* implies that an increase in expected operating cost encourages adoption of front-loading clothes washers. When the perceived energy efficiency of choice alternatives is modeled as a function of policy interventions (Model cw2a and Model cw2b), the positive coefficient of *ln_fuel* also implies that a higher energy price increases the propensity of front-loading clothes washer choice. However, the effect of energy price appears not to be statistically significant. This could suggest an exceptionally high discount rate or great uncertainty regarding future energy prices on the part of consumers when they make their choices.

When the household perception of energy efficiency of alternative clothes washer choices is modeled as a function of the energy efficiency standard and the Energy Star program (Model cw2 in columns 3 and 4), the model fit improves significantly compared to using average energy efficiency indicators, suggesting that households' formation of energy efficiency perceptions for clothes washers is more likely influenced by information conveyed through energy efficiency standards and Energy Star labels. The positive and significant coefficients for both the energy efficiency standards and Energy Star program suggest that these policy interventions have strong influences over the propensity of front-loading clothes washer adoption.

A log ratio test of the restricted model (Model cw2b*) and the unrestricted model (Model cw2b) rejects the null hypothesis that the common parameters between the short-run demand model and the long-run clothes washer choice model are equivalence with a p-value less than 0.001. This is a very different outcome from the results for the other three end uses analyzed below. The rejection of parametric equivalence between the short-run demand model and the clothes washer choice model raises concern that the household clothes washer choice behavior may be mis-specified in the preference function. In California where water supply is constrained, the water saving benefits of front-loading washers may be a further significant factor that drives clothes washer choice decisions. Unfortunately, water price data were not available to further test this hypothesis at the time this study was completed.

Estimated coefficients are fairly consistent across specifications except for the common parameters. Household characteristics are found to play a role in the choice decisions. Specifically, having a college education positively and significantly influences the choice of front-loading clothes washers. Home ownership also positively influences the choice of front-loading washers. However, the significance of this effect varies by specification. In addition, having a larger household size appears to favor adoption of top-loading clothes washers, possibly due to preference for the larger capacity of top-loading washers over the more compact front-loading washers. But the effect of household size is not significant except for specification Model cw2b.

Water Heater Choices

Table 5 reports three specifications of the multinomial logit model of water heater choices. Model wh1a evaluates the effect of a household expenditure term that incorporates the initial capital cost of water heaters and the effect of expected operating cost of alternative water heaters. Two variables are included in Model wh1a: the negative of the logarithm of household income not already committed to fixed payments minus annualized capital costs of water heater choice alternatives (*ln_incWH*), and the logarithm of the expected operating costs of technology alternatives using average energy efficiency indicators (*ln_oCostWH*). Since the energy efficiency of water heaters has only changed moderately during the study period, using average energy efficiency indicators of the alternative water heater stock is likely a reasonable proxy for consumers' perceptions of water heater alternatives.

Model wh1b adds household variables to test the significance of household characteristics in determining water heating technology choices. Three household variables are included: the home ownership dummy (*own*), the household size (*household size*), and the college education dummy (*college*).

A second step constrained estimation (Model wh1b*) is carried out by imposing parametric constraints from the short-run demand analysis on Model wh1b. A log likelihood ratio test between the constrained model (Model wh1b*) and the unconstrained model (Model wh1b) cannot reject the null hypothesis of parametric equivalence between the short-run demand model and the long-run water heater choice model with a p-value of 0.297. The parametric equivalence between the short-run demand model and water heater choice model suggests that the theoretical model is robust as common parameters explain both consumer water heater choice behavior and short-run use behavior.

Table 5. Estimated coefficients of the water heater choice model

Regressor	**Model**		
	wh1a	**wh1b**	**wh1b***
ln_incWH	-10.059	-21. 845	
	(-0.57)	(-0.99)	
ln_oCostWH	1.499	1.425	
	(1.86)	(1.87)	
Water heater choice = natural gas tankless system			
Own		-0.814	-0.695
		(-1.66)	(-1.34)
Household size		0.151	0.163
		(1.74)	(1.96)
College		-0.820*	-0.682
		(-1.99)	(-1.81)
Constant	-3.569***	-2.769***	-3.824***
	(-8.38)	(-4.33)	(-7.83)
Water heater choice = electric tank system			

Own		-1.260***	-1.269***
		(-4.25)	(-4.28)
Household size		-0.052	-0.071
		(-0.49)	(-0.66)
College		0.370	0.428
		(1.44)	(1.63)
Constant	-5.495***	-4. 424***	-2.388***
	(-4.85)	(-3.99)	(-6.20)
Observation	2408	2408	2408
Log_likelihood	-496	-483	-485

Notes: (1) Asterisks in the table denote significance in terms of p-values as follows: '*' for $p < 0.05$, '**' for $p < 0.01$, and '***' for $p < 0.001$. (2) Values in parentheses are t-statistics. (3) A natural gas tank system is the base case in the analysis.

In contrast to the clothes washer choice analysis, the household expenditure variable (*ln_incWH*) is not a statistically significant determinant of water heater choices. The expected operating cost (*ln_oCostWH*) is also a statistically insignificant predictor of water heater choices.

Home ownership is a significant predictor of water heater choices. A home owner is estimated to be more likely to choose a gas tank system over an electric tank system compared to a renter. This can be explained by the fact that a home owner is more likely to pay for the operating cost of water heater usage than a renter. Along this line of thinking, one would expect that a home owner is more likely to choose a tankless system than a tank system, which has much lower operating cost. The regression results show that a home owner is less likely to choose a tankless gas system over a tank system, but the estimated coefficient is statistically insignificant. The logistics as well as high cost of retrofitting an existing home with a tankless system may be an important deterrent.

The college education dummy is also a significant explanatory variable for water heater choices. A household with at least a college education is also more likely to choose a natural gas tank water heater over a tankless system but more likely to choose an electric tank system over a natural gas tank system, although only the former relationship is statistically significant. Larger household sizes tend to choose a tankless system over a natural gas tank system and a natural gas tank system over an electric tank system, but neither estimated effect is statistically significant.

Space Heating System Choices

Table 6 reports the results of three specifications of the multinomial logit model of space heating system choices. Similar to water heater choice model, Model sph1a evaluates the logarithm of household expenditure, which incorporates the capital costs of choice alternatives (*ln_incSPH*) and the logarithm of the expected operating costs of technology alternatives using average energy efficiency indicators (*ln_oCostSPH*). Using average energy efficiency estimates is reasonable in this case as the energy efficiency of space heating systems did not change dramatically during the study period. Model sph1b includes household variables to detect whether housing and household characteristics influence space heating technology choices. Four household variables are included: (1) the home ownership dummy (*own*), (2) age of the house (*house age*), (3) historic mean heating degree days between 1985 and the year of system installation (*hdd_mean*), and (4) the college education dummy (*college*).

A second step constrained estimation (Model sph1b*) is also carried out by imposing parametric constraints from the short-run demand analysis on Model sph1b.

Table 6. Estimated coefficients of the space heating system choice model

Regressor	**Model**		
	sph1a	**sph1b**	**sph1b***
ln_incSPH	-3.083	-4.576	
	(-0.78)	(-1.62)	
ln_oCostSPH	0.430	0.310	
	(0.91)	(0.65)	
Space heater choice = natural gas radiator			
Own		-1.038	-0.964
		(-1.36)	(-1.21)
House age		-0.258	-0.259
		(-0.68)	(-0.78)
Hdd_mean		2.881**	2.861*
		(2.60)	(2.39)
College		-0.198	-0.106
		(-0.31)	(-0.16)
Constant	-5.244***	-11.413***	-11.726***
	(-13.97)	(-3.35)	(-3.43)
Space heater choice = electric central forced-air system			
Own		-0.050	-0.054
		(-0.12)	(-0.13)

House age		0.285**	0.291**
		(3.08)	(3.16)
Hdd_mean		-0.322	-0.368
		(-0.78)	(-0.84)
College		-0.528*	-0.517*
		(-2.28)	(-2.24)
Constant	-3.955***	-3.105*	-2.566*
	(-6.14)	(-2.38)	(-2.19)
Observation	2408	2408	2408
log_likelihood	-412	-400	-399

Notes: (1) Asterisks in the table denote significance in terms of p-values as follows: '*' for $p < 0.05$, '**' for $p < 0.01$, and '***' for $p < 0.001$. (2) Values in parentheses are t-statistics. (3) A natural gas central forced-air system is the base case in this analysis.

A log likelihood ratio test between the constrained model (Model sph1b*) and the unconstrained model (Model sh1b) cannot reject the null hypothesis of parametric equivalence between the short-run demand model and the long-run space heater choice model with a p-value of 0.634. Again, the parametric equivalence between the short-run demand model and space heater choice model suggests that the theoretical model outlined in Section 3 is robust in as an explanation of both consumer space heater choice behavior and short-run energy demand.

Similar to the water heater choice analysis, the household expenditure variable, which incorporates annualized capital cost of the technology alternatives (*ln_incSPH*) and the expected operating cost (*ln_oCostSPH*) are found not to be significant determinants of space heating technology choices.

On the other hand, the age of dwelling and average heating degree days significantly influence space heating system choices. Older houses are more likely to have an electric central forced-air heating system than a natural gas central forced-air system, and are less likely to have a natural gas-based radiator system, although only the former relationship is statistically significant. This former effect seems plausible given the fact that natural gas had gained popularity over time with its cost-effectiveness as a residential fuel source. This effect represents the impact of increasing energy consciousness with rising energy prices. In areas where the heating load is higher (as reflected in higher heating degree days), a hydronic gas-based radiator system is preferred over a central forced-air system, probably because of the higher energy efficiency performance of radiator systems, and thus the lower operating cost. Electric central force-air systems are less preferred in colder areas, as one would expect, but the estimated effect is not statistically significant. In addition, a college education is estimated to be a significant predictor of space heating system choices whereby a natural gas forced-air system is preferred over an electric forced-air system.

The household education level is estimated to be a significant predictor of space heating system choices while home ownership is not. This is likely due to the fact that the decision regarding the type of space heating system in a home is an integral part of building design and construction. Thus, a home owner would have a weaker role in the decision making unless involved in the original construction. In contrast, the two types of housing that dominate the PG&E area of California are the older homes that are beyond their first owner and the more recent large-scale developments of builders. Thus, energy technology durables such as space heating and water heating equipment are likely heavily determined by developers if not the more aged housing stock.

While one might argue that a developer would tailor these choices to potential buyers' preferences, a home buyer likely will weigh other attributes of a house (such as location and size) more heavily than the type of space heating system. The significance of college education in choosing a natural gas space heating system over an electricity-based space heating system, on the other hand, suggests that a household with better ability to interpret energy performance information of different energy systems is more likely to make a rational choice of the system that has lower operating cost.

Clothes Dryer Choices

Table 7 reports the estimation results. Model cd1a evaluates the negative of the logarithm of household expenditure which incorporates the capital costs of choice alternatives (*ln_incCD*) and the logarithm of the expected operating costs of technology alternatives assuming average energy efficiency indicators (*ln_oCostCD*). Again, average energy efficiency estimates of the clothes dryer choice alternatives are seen as reasonable to represent consumers' perception of energy efficiency as the energy performance of clothes dryers had not changed significantly during the study period. Model cd1b includes household variables. Three household variables are included: (1) the home ownership dummy (*own*), (2) household size (*household size*), and (3) the college education dummy (*college*).

A second step constrained estimation (Model cd1b*) is carried out by imposing parametric constraints from the short-run demand analysis on Model cd1b. In this case, the log likelihood ratio test of parametric equivalence between the short-run demand model and the long-run clothes dryer choice model can be mildly rejected at the 10 percent level but cannot be rejected at more conservative levels of 1, 2, or 5 percent. The p-value is 0.051.[10]

Table 7. Estimated coefficients of the clothes dryer choice model

Regressor	Model		
	cd1a	**cd1b**	**cd1b***
ln_incCD	-333. 829*	-165.752	
	(-2.51)	(-1.21)	
ln_oCostCD	0.604	-0.087	
	(0.87)	(-0.12)	

[10] One possible mis-specification of the clothes dryer choice model has to do with the electricity voltage in the laundry area of a dwelling. Most electric dryers operate on 240-volt current, twice the strength of ordinary household current. If the laundry area is not equipped with a 240-volt outlet, one either has to choose a natural gas clothes dryer or install a 240-volt outlet in order to run an electric clothes dryer. If natural gas service is already available, a household might choose a gas clothes dryer over reconfiguration of the electricity outlet, especially if the home is not equipped with a 240-volt service panel as is the case with many older homes. Unfortunately, the electricity voltage data are not available to be included in the model for further tests.

Own		-0.430**	-0.471**
		(-2.65)	(-2.92)
Household size		-0.106***	-0.111***
		(-3.51)	(-3.98)
College		-0.029	-0.080
		(-0.32)	(-0.92)
Constant	-0.636	1.138	1.155
	(-0.61)	(1.01)	(6.34)
Observations	2408	2408	2408
Log likelihood	-1624	-1615	-1618

Notes: (1) Asterisks in the table denote significance in terms of p-values as follows: '*' for $p < 0.05$, '**' for $p < 0.01$, and '***' for $p < 0.001$. (2) Values in parentheses are t-statistics. (3) A gas-fired clothes dryer is the base case in this analysis.

Comparing results of Model cd1b with Model cd1a shows that household characteristics are significant predictors of clothes dryer choices. Home owners are more likely to choose a gas-fired clothes dryer than an electric clothes dryer. A household with more members is more likely to choose a gas clothes dryer than an electric clothes dryer. Even though the operating cost variable turns out to be statistically insignificant in the analysis, one may still reach the conclusion that the significant coefficients of ownership and household size suggest that the operating cost of clothes dryer usage is taken into consideration when making clothes dryer choices.

The negative coefficient on the expected operating cost (*ln_oCostCD*) suggests that when the expected operating cost increases a household is more likely to choose a gas-fired clothes dryer over an electric-based dryer. This result is sensible. However, similar to the analyses of water heater choices and space heating technology choices, the household expenditure variable which incorporates annualized capital cost of technology alternatives (*ln_incCD*) and the expected operating cost (*ln_oCostCD*) are not significant determinants of clothes dryer choices.

6.3 Conclusions

The empirical analysis shows that the discrete/continuous model based on the second-order translog indirect utility function is fairly robust across energy forms and appliance choices in explaining household energy consumption and technology choice behavior. With the exception of parametric estimates in the clothes washer choice model, the parameters obtained from the short-run demand analysis are statistically equivalent to the parameters obtained in the long-run technology choice model, although weakly so for clothes drying. The non-equivalence of parametric estimates in the clothes washer choice model is likely due to the omission of water price and water efficiency in the clothes washer choice model. These are potentially important factors influencing clothes washer choices in the water scarcity conditions of California. For clothes dryer choices, a potentially important unobserved factor influencing choices between a natural gas clothes dryer and an electric-based clothes dryer is the presence of 240-volt service.

The mean short-run income and price elasticities of energy consumption derived from the short-run demand model are all in reasonable ranges. A few of the price elasticities of natural gas demand of individual households are implausible ranges but no more than typically obtained with the flexibility of the translog model.

7. Policy Implications for Household Energy Efficiency

Residential consumer energy consumption is a critical aspect of energy and climate change policy. Findings from the empirical analysis using the unified modeling framework have important implications for policy design aimed to reduce greenhouse gas emissions and improve energy efficiency in the residential sector.

7.1 Energy-efficient Technology Adoption

This study confirms two important market failures with respect to household energy technology choice behavior: the principal/agent problem and information imperfection. Home ownership appears to significantly influence household choices of some energy durables, suggesting that policy programs targeting residential energy efficiency should carefully distinguish the principal decision makers and appropriately differentiate market segments.

In the case of clothes washer choices, the voluntary, information-based Energy Star program emerges as the most significant factor influencing adoption of energy-efficient front-loading clothes washers, followed by energy efficiency standards. The establishment of Energy Star criteria for clothes washers produces an average increase in the propensity of energy-efficient front-loading clothes washers by 17 percent. The presence of energy efficiency standards is predicted on average to increase the propensity of front-loading washers adoption by 8 percent. The results suggest that policy programs aimed at providing energy technology performance information are highly effective in promoting the adoption of energy-efficient technology at the household level as these programs likely reduce consumers' search cost. In fact, they may override cost considerations that are highly uncertain at the point of decision making in the store.

Surprisingly, the financial incentives for energy-efficient appliances, such as through popular federal income tax credits or federal and state rebate programs, are found to be far less effective in influencing the adoption of energy-efficient appliances. For instance, a $100 reduction in the purchase cost of energy-efficient front-loading washers increases the propensity of front-loading clothes washer adoption by only 0.5 percent. Perhaps consumers who take advantage of such programs have *a priori* preferences for energy efficiency, so that financial incentives only provide a windfall to such consumers. In the case of water heater and space heating system choices, the capital cost of technology alternatives appear to be an insignificant determinant of technology choices, suggesting that changes in the relative cost of energy-efficient technologies would have limited impacts on their adoption.[11] Given their popularity, these financial incentive programs and their cost-effectiveness should be carefully examined.

Furthermore, contrary to the claim that incentives for the adoption of new technologies is greater under market-based instruments than under direct regulation (e.g., by Jaffe et al. 2003), this empirical study finds that market-based policy instruments, such as a carbon cap-and-trade program or carbon taxes which induce energy price changes, have limited impacts on energy-efficient technology adoption decisions at the household level. For instance, a 20 percent increase in energy (electricity) price increases the propensity of front-loading washer adoption by only 2.5 percent.

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[11] However, it should be pointed out that the technology choice analyses for water heating and space heating examine the choices among broad categories of technology systems (e.g., a tank water heater versus a tankless system), rather than choices among different brands and models of a technology that have varying energy efficiency performance. Further, the absence of statistical significance of cost variables in these cases may be largely due to the minor differences in costs among technologies even though consumers may respond to more substantial cost variation. Inference about incentive policy based on these results should be made carefully.

7.2 Short-run Household Energy Efficiency

The study finds that in the short-run, energy price-induced household energy efficiency is moderate. According to the analysis, the average price elasticity is -0.13 for electricity and -0.12 for natural gas. Therefore, a 20 percent increase in the electricity price on average would reduce its consumption by 2.6 percent; a 20 percent increase in the natural gas price on average would reduce its consumption by 2.4 percent. These results are reasonable given estimates and conventional wisdom that implies household energy demand is highly inelastic in the short run.

The short-run demand analysis also highlights the importance of using accurate estimates of appliance energy efficiency in energy demand modeling. The energy efficiency level of household energy durables affects the amount of energy consumed by a household to meet energy service demands. Very often, the energy efficiency of home appliances is unknown. At best, modelers and researchers rely on market surveys with estimates of the average energy efficiency of the appliance stock. In this study, two alternative representations of appliance energy efficiency are tested for clothes washers and water heaters. The first approach uses average energy efficiency indicators of energy technology based on market surveys. The second approach assumes household appliance energy efficiency is unobserved and explicitly models energy efficiency as a function of technological change and possible policy interventions such as energy efficiency standards. Compared to the survey data on average energy efficiency, embedding this causal model of energy efficiency improves model fit for clothes washers and water heaters significantly, producing higher log likelihood values, and suggesting potential measurement errors by using average energy efficiency data on the appliance stock.

References

Aigner, D.J., C. Sorooshian, and P. Kerwin. 1984. "Conditional demand analysis for estimating residential end-use load profiles." *Energy Journal* 5(3), 81-97.

Anderson, S.T., and R.G. Newell. 2002. *Information Programs for Technology Adoption: The Case of Energy-Efficiency Audits*, Resources for the Future RFF Discussion Paper 02-58. Washington DC.

Archibald, R.B., D.H. Finifter and C.E. Moody Jr. 1982. "Seasonal variation in residential electricity demand: evidence from survey data." *Applied Economics* 14, 167-181.

Baker, P., R. Blundell, J. Michlewright. 1989. "Modelling Household Energy Expenditures Using Micro-Data," *The Economic Journal* 99(397): 720-738

Balestra, P., and M. Nerlove. 1966. "Pooling gross section and time series data in the estimation of a dynamic model: the demand for natural gas." *Econometrica* 34(3), 585-612.

Barnes, R., R.G. Gillingham, and R. Hagemann. 1981. "The short-run residential demand for electricity." *The Review of Economics and Statistics* 63(4), 541-552.

Berndt, E.R., M.N. Darrough, and W.E. Diewert. 1977. "Flexible functional form and expenditure distributions: an application to Canadian consumer demand functions." *International Economic Review* 18(3), 651-75.

Birol, F., editor. 2008. *World Energy Outlook*. The International Energy Agency. Paris, France.

Davis, L.W. 2008. "Durable goods and residential demand for energy and water: evidence from a field trial." *RAND Journal of Economics* 39(2), 530-546.

Deaton, A. and J. Muellbauer. 1980. *Economics and consumer behavior*. Cambridge: Cambridge University Press.

DeCanio, S.J. 1998. "The efficiency paradox: bureaucratic and organizational barriers to profitable energy-saving investments." *Energy Policy* 26(5): 441-454.

Dubin, J.A., and D.L. McFadden. 1984. "An econometric analysis of residential electric appliance holding and consumption." *Econometrica* 52(2): 345-362.

Frieden, B.J., and K. Baker. 1983. "The Market Needs Help: The Disappointing Record of Home Energy Conservation." *Journal of Policy Analysis and Management* 2(3): 432-448.

Goulder, L.H., I.W Parry, R.C. Williams III, and D. Burtraw. 1999. "The Cost-Effectiveness of Alternative Instruments For Environmental Protection in a Second-Best Setting." *Journal of Public Economics* 72(3): 329–360.

Greene, W. H. 2008. *Econometric Analysis* (6th Edition). Pearson Prentice Hall. NJ.

Hanford, J.W., J.G. Koomey, L.E. Stewart, et al. 1994. *Baseline Data for the Residential Sector and Development of a Residential Forecasting Database*. A report of the Lawrence Berkeley Laboratory, University of California. Berkeley, CA. 179 pp.

Hanemann W.M. 1984. “Discrete/continuous models of consumer demand.” *Econometrica* 52(3), 541-561.

Hassett, K.A. and G.E. Metcalf. 1993. “Energy conservation investment: Do consumers discount the future correctly?” *Energy Policy* 21(6): 710-16.

Hassett, K.A. and G.E. Metcalf. 1995. “Energy tax credits and residential conservation investment: Evidence from panel data.” *Journal of Public Economics 57*: 201-17.

Howarth, R.B. and A.H. Sanstad. 1995. “Discount rates and energy efficiency.” *Contemporary Economic Policy* 13(3): 101-109.

Howarth, R.B., B.M. Haddad, and B. Paton. 2000. “The Economics of Energy Efficiency: Insights from Voluntary Participation Programs.” *Energy Policy* 28: 477–86.

Jaffe, A. B., and R. N. Stavins. 1994. “The Energy Paradox and the Diffusion of Conservation Technology.” *Resource and Energy Economics* 16(2): 91–122.

Jaffe, A.B., R.G. Newell, and R.N. Stavins. 2003. “Technological Change and the Environment.” Chapter 11 in the *Handbook of Environmental Economics*, Volume 1, Edited by K.-G. Maler and J.R. Vincent. Elsevier Science B.V. 461-516.

Koomey, J.G. 1996. *Trends in Carbon Emissions from U.S. Residential and Commercial Buildings: Implications for Policy Priorities*. LBNL-39421. Lawrence Berkeley National Laboratory, Berkeley, CA. 20pp.

Levine, M.D., A.H. Sanstad, E. Hirst, J.E. McMahon, and J.G. Koomey. 1995. "Energy Efficiency Policy and Market Failures." In *Annual Review of Energy and the Environment 1995*. Edited by J. M. Hollander. Palo Alto, CA: Annual Reviews, Inc.

Mansure, E.T., R. Mendelsohn, and W. Morrison. 2008. “Climate change adaptation: A study of fuel choice and consumption in the US energy sector.” *Journal of Environmental Economics and Management* 55(2): 175-193.

McFadden, D.L. 1974. “Conditional logit analysis of qualitative choice behavior.” In *Frontiers in Econometrics*. New York: Academic Press.

Murphy and Topel, 2002. “Estimation and Inference in Two-Step Econometric Models.” *Journal of Business & Economic Statistics* 3(4), 370-379. Reprinted, 20, 2002, 88-97.

Newell, R.G., A.B. Jaffe, and R.N. Stavins. 1999. “The Induced Innovation Hypothesis and Energy-Saving Technological Change.” *Quarterly Journal of Economics* 114 (3): 941-975.

Newell, R.G., and W.A. Pizer. 2008. “Carbon mitigation costs for the commercial sector: discrete-continuous choice analysis of multifuel energy demand.” *Resource and Energy Economics* 30(4): 527-539.

Parry, I., D. Evans, and W.E. Oates. 2010. *Are Energy Efficiency Standards Justified*? Resources for the Future Discussion Paper 10-59. Washington DC.

Parti, M., and C. Parti. 1980. “The total and appliance-specific conditional demand for electricity in the household sector.” *The Bell Journal of Economics* 11, 309-321.

Pacala S. and R. Socolow, 2004. **“**Stabilization Wedges: Solving the Climate Problem for the Next 50 Years with Current Technologies.” *Science* 305 (5686): 968 – 972.

Pollak, R.A., and T.J. Wales. 1992. *Demand System Specification and Estimation*. Oxford: Oxford University Press.

Quigley, J.M. 1984. “The production of housing services and the derived demand for residential energy.” *Rand Journal of Economics* 15(4): 555-567.

RLW Analystics. 2005. 2005 *California Statewide Residential Lighting and Appliance Efficiency Saturation Study*. A report prepared for California’s Investor Owned Utilities. Sonoma, CA. 124 pp.

Roland-Holst, D. 2008. *Energy Efficiency, Innovation, and Job Creation in California*. Center for Energy, Resources, and Economic Sustainability. Department of Agricultural and Resource Economics, University of California, Berkeley. 82 pp.

Sanstad, A., and R.B. Howarth. 1994. *Consumer Rationality and Energy Efficiency*, paper presented to the ACEEE Summer Study on Energy Efficiency in Buildings, Carmel, California.

Taylor, L. D. 1975. “The demand for electricity: a survey.” *Bell Journal of Economics* 6, 74-110.

Train, K. 1985. “Discount rates in consumers’ energy-related decisions: a review of the literature.” *Energy* 10(12), 1243-1253.

Wenzel, W.P., J.G. Koomey, G.J. Rosenquist, M. Sanchez, and J.W. Hanford. 1997. *Energy Data Sourcebook for the U.S. Residential Sector*, Lawrence Berkeley National Lab LBNL-40297, Berkeley, CA.

Weyant, J.P. 1993. “Costs of reducing global carbon emissions”, *Journal of Economic Perspectives* 7:27–46.