ABSTRACT

Title of Document: MODELING HOUSEHOLD ENERGY CONSUMPTION AND ADOPTION OF ENERGY-EFFICIENT TECHNOLOGY USING RECENT MICRO-DATA

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This study develops 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 flexibility in the structure of consumer preferences and in the exploration of interplays among energy uses and between energy demand and 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.

Using a unique household-level dataset of 2,408 households served by the Pacific Gas and Electric Company in California, the model is applied to examine the roles of income, prices, household characteristics, and energy and environmental policy in household short-run energy use and long-run technology choices. The empirical analysis estimates 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 demonstrate the modeling framework is appropriate and robust in studying household energy use behavior.

Findings from the empirical analysis have important implications for policy design. This study confirms two important market failures with respect to household energy technology choice behavior: the principal/agent problem and information imperfection. In the case of clothes washer choices, the information-based Energy Star program emerges as the most significant factor influencing the adoption of energy-efficient front-loading clothes washers, followed by energy efficiency standards. Surprisingly, financial incentives, such as the popular rebate programs used to lower the initial capital cost of energy-efficient appliances, are found to be far less effective in influencing adoption of energy-efficient appliances.

Furthermore, the study finds at the household level that the incentive for new technology adoption is greater under direct regulation than under market-based instruments, such as a carbon cap-and-trade program or emission taxes.

MODELING HOUSEHOLD ENERGY CONSUMPTION AND ADOPTION OF ENERGY-EFFICIENT TECHNOLOGY USING RECENT MICRO-DATA

By

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Dedication

To my parents

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Chapter 1: Introduction

Energy supply and price have been public and political concerns over the last several decades. Increased awareness about global climate change in recent years has rejuvenated debate about policy options to reduce energy consumption and greenhouse gas emissions. 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).[1] 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 the federal appliance energy efficiency standards, to incentive-based programs, such as federal tax incentives for fuel-efficient vehicles and utility rebates for energy-efficient appliances (e.g., boilers, air conditioners and refrigerators), to voluntary information and labeling programs, such

[1] For the purpose of this study, I adopt a service-minded definition and define 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.

the Energy Star program. Many of these programs target the residential sector since residential households consume about one-fifth of the total energy in the economy and the sector has some of the most cost-effective opportunities to reduce energy consumption.[2]

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, vehicle fuel efficiency standards, enhanced appliance efficiency standards, significant increases in the share of clean, renewable energy in power supply and end use, and energy efficiency measures such as green buildings in new construction and utility demand-side energy management programs.[3] Many of these programs would have implications for residential energy use.

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

[2] The share of residential energy consumption is estimated based on historic average data between 1949 and 2008 reported in the Annual Energy Review 2008 published by the Energy Information Administration (Report No. DOE/EIA-0384).

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

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") derived 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.

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.

The remainder of this document is organized as follows. Chapter 2 reviews the relevant literature, discusses gaps in existing knowledge, and describes how my study contributes to the literature. Chapter 3 establishes the theoretical model for empirical investigation. Chapter 4 provides an overview of available data and describes data management procedures. Chapter 5 illustrates the estimation strategy. Chapter 6 presents the results of empirical estimation. Chapter 7 discusses the policy implications of the study findings. Finally, Chapter 8 concludes with thoughts on future research.

Chapter 2: Relevant Literature

This chapter reviews the literature related to energy efficiency policy and modeling of consumer energy demand and energy technology adoption behavior. Section 2.1 synthesizes the relevant policy discussions concerned with adoption of energy-efficient technology. Section 2.2 chronicles the evolution of energy demand modeling and the convergence to joint analysis of consumer energy demand and technology choice decisions. Section 2.3 discusses the gaps in existing literature and the unique contributions of this study.

2.1 Climate change and policy interest in energy-efficient technology adoption

Technological change and energy efficiency are recognized as important factors of environmental and climate change policies (Jaffe, et al., 2003; Weyant 1993). The process of technological change is often characterized in three stages: invention, innovation, and diffusion (Thirtle and Ruttan 1987). Diffusion refers to the process by which a new technology is adopted by firms or individuals.

Previous research on technology adoption has consistently shown that diffusion of new technology is a gradual process (e.g., Rogers 1957 and Mansfield 1989). Rates of adoption and diffusion of apparently cost-effective energy efficiency investments are also noted to have been slow. Hence, 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).

The energy paradox

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. Using firm level data on lighting upgrade investment decisions, DeCanio (1998) found that a large potential for profitable energy-saving investments has not been realized because of internal organizational and institutional impediments in the private and public sector.

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. In a stated preference study of untried, energy-saving durable goods, Houston (1983) found that many consumers appear to calculate rationally the net worth of a household investment, but a substantial minority appears to lack the skills or alertness to perceive investment opportunities or initiate analysis. 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 found estimates of 4-36% for space heating systems, 3-29% for air conditioners, 39-108% for refrigerators, and 4-67% for other appliances. 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).

In addition, energy market regulations and infrastructure constraints were noted as factors that affect consumer choices and lock in particular patterns of energy use (Azar and Dowlatabadi 1999).

Psychologists and market researchers have also been interested in consumers' attitudes towards energy conservation and perceptions of new, energy-efficient technology. Various studies have found little correlation between general energy efficiency attitudes and reported conservation actions (e.g., Olsen 1981, Hagler Bailly 1999, KEMA-XENERGY and Quantum Consulting 2003). In their examination of the experience during the ten years of oil crises between 1973 and 1982, Frieden and Baker (1983) found consumers' energy efficiency performance disappointing and concluded that the main driver of energy efficiency activity was energy price.

Labay and Kinnear (1981) explored the consumer decision process in the adoption of solar energy systems and found that product-related and economic factors are of the highest concerns to adopters and informed nonadopters. High perceived initial cost was found to remain the most pervasive barrier to the adoption of energy-efficient measures by Customer Opinion Research (1999). Although many of the market research studies do not put these various factors into structural models for empirical analysis, they point out that the costs and benefits of conservation seem to play significant roles in energy efficiency improvement investment decisions.

The potential of public policy

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). Some economists draw a distinction between 'market failures' (e.g., under-provision of information, principal/agent problems, subsidies, and environmental externalities) and 'market barriers' (i.e., private information costs, high discount rates, and hetereogeneity among potential adopters) that affect the adoption of energy-efficient technologies (e.g., Jaffe and Stavins 1994, Jaffe et al. 1999, and Anderson and Newell 2002). They argue for the necessity of understanding the sources that affect diffusion of energy-efficient technologies as a prerequisite for government intervention. In their view, market failures provide justification for government action whereas market barriers do not. However, others argue that if market imperfections impair producers' and consumers' ability to implement cost-effective energy savings, policy measures may be justified to improve market performance at prevailing prices (e.g., Howarth and Sanstad 1995; Howarth et al. 2000).

The effectiveness of alternative policy instruments in encouraging the adoption of energy-efficient technology has important implications for policy design. 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) used estimates of production and demand functions for housing services to evaluate the social costs of government policies designed to induce energy conservation by residential consumers (i.e., tax credits for energy efficiency improvements and building energy performance mandates). 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 sponsored by the U.S. Environmental Protection Agency. Anderson and Newell (2002) examined the effect of government energy-efficiency audit programs for industrial manufacturers' decisions on energy efficient technology adoption. 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

Analysis of household energy consumption and demand elasticities has long been used to (1) assess the energy saving potential of energy efficiency programs, (2) forecast energy demand and load profiles, and (3) plan future generation capacity needs. Following the energy crisis in the 1970s, interest emerged in understanding consumer investment decisions with respect to energy technology and conservation measures. Estimation of consumer energy technology choice largely began in the 1980s in response to this policy interest. In recent years, consumer energy consumption and technology choice behavior has received renewed interest in the context of climate change policy. This section reviews relevant methods and studies that model household energy demand and technology adoption, and highlights the latest developments in joint modeling of the two aspects of consumer decisions.

Energy demand analysis

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.[4]

Estimates of appliance energy consumption typically come from metering studies, engineering estimates, and statistical demand analyses (Wenzel et al. 1997). Metering data provide the most accurate estimates of energy use by appliance but are costly to collect and usually cover limited end uses in small samples. Engineering studies estimate appliance performance based on product specifications but do not address consumer behavior (e.g., price and income response). Statistical demand analyses are useful when appliance-specific energy consumption is not observed. Moreover, statistical models allow inference of changes in explanatory variables and are particularly useful for analyzing energy consumption impacts of policy and energy price changes.

Historically, most regression analyses of energy demand have relied on aggregate national or state data (e.g., Balestra and Nerlove 1966, Hartman and Werth 1981, Hartman 1983). Aggregate data are prone to aggregation bias and specification errors that pose challenges when evaluating consumer behavior. Detailed household information is desirable because of the ability to better predict consumer demand response to changes in energy price and income.

Parti and Parti (1980) developed one of the first conditional demand analysis models for residential electricity consumption using household data. Their model disaggregates a household's electricity consumption into appliance-specific

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[4] Conditional demand analysis is used in the economic literature of consumer energy consumption analysis. Most studies, however, do not give a precise definition of the term nor explain the theory from which CDA stems. Pollak (1969) discusses conditional demand functions in the context of consumer behavior analysis in the short run when "fixed commitments prevent instantaneous adjustment to the long-run equilibrium" or when some good(s) are pre-allocated (e.g., rationed).

consumption estimates assuming linear relationships between energy consumption and explanatory variables based on appliance ownership.

The basic CDA model in the spirit of Parti and Parti can be represented as

(1) $$X = \sum_{j=1}^{J} x_j = \sum_{j=1}^{J} \sum_{k=1}^{K} b_{jk} \theta_k d_j,$$

where X is the household's aggregate electricity consumption during a period of time (e.g., annual or monthly electricity consumption in kilowatt hours); $x_j = \sum_{k=1}^{K} b_{jk} \theta_k d_j$ is electricity consumption of the jth appliance for $j = 1,\ldots,J$; d_j is a dummy variable indicating ownership of the jth appliance; θ_k is the kth exogenous variable (e.g., energy price, income, climate, or house size) that influences electricity consumption for $k = 1,\ldots,K$; and b_{jk} is the coefficient of θ_k in the jth conditional demand function. Using microdata from over 5,000 households in San Diego County in 1975, they applied the model in equation (1) to estimate annual and monthly energy consumption of a set of 16 specified appliance categories and price and income elasticities of demand for each of the specified demand functions. Appliance-specific energy consumption during a time period is defined as "unit energy consumption" (UEC). UEC estimates are frequently used in demand forecasting.

A number of studies have estimated short-run household electricity consumption and demand elasticity using CDA models similar to Parti and Parti. Barnes, et al. (1981), used data from about 10,000 U.S. households in the 1972-73 Consumer Expenditure Survey and estimated demand functions for 11 end use categories including space heating, air conditioning and refrigeration.[5] In their model, UEC is a function of appliance ownership and utilization rate. The utilization rate is a linear function of the logarithms of the price and income variables and a vector of demographic variables (e.g., climate, region, and season dummy variables and household size).

Archibald, et al. (1982), estimated monthly and seasonal electricity demand equations for six classes of appliances using micro-data of 1,311 households in the national survey of Lifestyles and Household Energy Use of 1975. The UEC definition in Archibald, et al. (1982), is similar to Barnes, et al. (1981), but three types of utilization functions are considered depending on whether each energy use is affected by weather, housing characteristics or household demographic characteristics.[6] Using a seemingly unrelated regression system, Aigner, Soroothian and Kerwin (1984) estimated hourly load curves in a typical day for nine appliances. They used data for the months of August between 1978 and 1980 from a few hundred customers of the Los Angeles Department of Water and Power.[7]

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[5] Barnes et al. include "number of rooms" as an end-use category. It is a proxy for housing size and is not a proper energy end use category. Estimating the UEC of "number of rooms" using an OLS approach likely causes biased UEC estimates for end use categories correlated with housing size such as space heating and cooling.

[6] For instance, Archibald et al. assume that UEC for common appliances (e.g., television and, microwaves) is a linear function of energy price and income only; UEC for appliances whose utilization depends on a "thermostat" (e.g., water heaters and freezers) is a linear function of energy price, income, and weather; and UEC for heaters and air conditioners is a linear function of energy price, income, weather, and housing characteristics.

[7] Alternative forms of energy price representation have been used in estimation: marginal price, average price, and a declining-block rate schedule of prices. Taylor (1975) suggests that consumer demand for electricity under a multi-part rate schedule is more complex and demand equilibrium cannot be derived using conventional differential procedures. A number of CDA studies (e.g., Hartman and Werth 1981 and Barnes et al. 1981), include both a marginal price and a fixed price to reflect the block rate structure of electricity.

Technology Choice Modeling

Jaffe et al. (2003) reviewed two main models in the literature relevant to energy technology adoption: the *epidemic* model and the *rank* model. The epidemic model postulates that technology diffusion is a gradual process because a decision to adopt a new technology is a risky undertaking requiring considerable information both about the generic attributes of the new technology and about the details of its use. The epidemic model captures the information externality of technology adoption transmitted from early adopters to other potential adopters. The model yields an S-shape curve of technology adoption for the population over time.

In contrast, the rank model posits that potential adopters are heterogeneous and only those who face the value or return of a new technology above a threshold choose to adopt. The rank model is analogous to the *choice* model. The choice model assumes that, given a set of technology choices with different initial costs and returns over time, a consumer makes the technology choice that minimizes discounted total costs required to generate a level of desired energy services (Nyboer and Bataille 2000).

The epidemic model is more appropriate to describe the process of aggregate technology adoption in a population whereas the rank, or choice, model is more appropriate to explain technology adoption decisions faced by an individual consumer. Because the primary interest of this study is to better understand drivers of household choices of energy technology, the choice model is used for the purpose of this study.

Most choice models implicitly or explicitly assume some form of individual utility maximization. Empirically, logit and probit discrete choice models are used to explain the role of factors such as purchase cost, energy prices, technology attributes and consumer characteristics that influence consumer's technology choice decision (see a review of recent studies on green technology adoption in Jaffe et al. 2003).

Discrete/continuous modeling

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 correlated.[8] Balestra and Nerlove (1966) argued that demand for energy is a dynamic problem and that "the demand function should incorporate a stock effect and some assumptions about the adjustment of these stocks over time" (p. 585). As Hausman (1979) put it, "energy demand may be viewed usefully as part of a household production process in which the services of a consumer durable good are combined with energy inputs to produce household services" and warned that "[e]conometric models which do not differentiate the capital-stock decision from the utilization decision cannot capture the interplay of technological change and consumer choice in determining final energy demand" (p. 33-34). The conditional demand analyses cited above each report UEC by appliance and some discuss it interchangeably with UEC by end use. Such treatment reflects confusion between energy use and appliance choice.

[8] For example, a household with high demand for air conditioning is likely to purchase an energy-efficient air conditioner with higher capital cost but lower operating cost.

In his survey article of electricity demand analyses, Taylor (1975) explored econometric specifications that capture both short-run and long-run aspects of demand for electricity and suggested that demand for capital stock should be modeled explicitly to evaluate the long-run demand for energy. Hausman (1979) evaluated individual decisions on purchase and utilization of energy-using durables. He emphasized the tradeoff between capital costs for more energy efficient appliances and operating costs for appliances. Using a two-stage optimization approach, he modeled household utilization and choice of room air conditioners. In the first stage, utility maximization determines optimal utilization of air conditioners. The information on utilization function is then used to model consumer air conditioner choices.

Dubin and McFadden (1984) demonstrated that modeling energy demand without consideration of endogenous technology choice as in Parti and Parti (1980) 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”). The essence of the Dubin and McFadden model is described below.

Assuming the consumer chooses an appliance portfolio i from m choices to maximize utility, the consumer has a conditional indirect utility function

(2) $$u = V(i, y - r_i, p, \eta_i, \varepsilon_i),$$

where r_i is the annualized cost of appliance i, y is income, p is the price of fuel, η_i represents the observed attributes of appliance i, and ε_i represents unobserved attributes of appliance i.[9] By Roy's identity, the energy (fuel) consumption, given appliance choice i, is

(3) $$x = \frac{-\partial V(i, y - r_i, p, \eta_i, \varepsilon_i) / \partial p}{\partial V(i, y - r_i, p, \eta_i, \varepsilon_i) / \partial y} + \mu$$

where μ is a random disturbance in fuel demand typically added for econometric purposes, $E(\mu) = 0.$.

The probability that appliance i is chosen is

(4) $$P_i = \Pr\{(\varepsilon_1, .., \varepsilon_m) : V(i, y - r_i, p, \eta_i, \varepsilon_i) > V(i', y - r_{i'}, p, \eta_{i'}, \varepsilon_{i'}) \forall i' \neq i\}.$$

Joint estimation of equations (3) and (4) is required for efficient and congruent estimation because the two equations have common parameters. In principle, any function $V(\cdot)$ with the necessary and sufficient properties of an indirect utility function can be used to construct econometric forms for estimation.

Dubin and McFadden (1984) illustrated the discrete/continuous model by jointly estimating technology choice and energy demand for space heating and water heating. For simplicity, they limited the choice set to two alternatives of space heating and water heating equipment that use the same fuel (i.e., either both use electricity or both use natural gas). Their study used a subsample of 313 households from a 1975 survey.

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

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[9] Dubin and McFadden (1984) include two fuel prices in the model: price of own fuel (e.g., electricity) and price of alternative fuel (e.g., natural gas).

should be modeled in a mutually consistent manner. 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 discrete/continuous modeling approach has been applied to analyze short-run and long-run energy use in Europe. For instance, Dagsvik et al. (1987) used a dynamic discrete/continuous choice model to analyze gas demand in the residential sector of Western Europe. Vaage (2000) and Nesbakken (2001) applied discrete/continuous models to evaluate household heating technology choice and fuel demand in Norway. Vaage (2000) used a version of the discrete/continuous model in Hanemann (1984) and adopted a two-step estimation approach; Nesbakken (2001) applied the Dubin and McFadden model and used the full information maximum likelihood estimation method. Using a two-step discrete/continuous approach, Halvorsen and Larsen (2001) effectively estimated the short- and long-run price elasticities of residential electricity demand in Norway.

The application of discrete/continuous modeling for energy use was sparse in the U.S. until the recent years. With increased interests in climate change, fuel efficiency, and clean energy, 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.

2.3 Conclusions

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.

This study contributes to the literature by developing a discrete/continuous model based on a second-order translog flexible function form of the indirect utility function, and applying the model to empirically estimate household demand for both electricity and natural gas and technology choices for clothes washers, water heaters, space heating systems and clothes dryers. This is the first known study to evaluate multiple household energy uses under this comprehensive analytical framework. In addition, the study contributes to the ongoing policy debate about the effectiveness of alternative policy instruments for encouraging household energy efficiency and greenhouse gas emission reductions through robust empirical analysis.

Chapter 3: Modeling Household Energy Demand and Technology Choice

This chapter develops a conceptual framework for joint modeling of household consumption and energy durable choice decisions. Section 3.1 establishes the underlying household model. Section 3.2 derives the household short-run demand model. Section 3.3 develops the long-run technology choice model. Section 3.4 concludes with discussions on model applications.

3.1 Model setup

I assume the household maximizes utility from consumption of two groups of goods, market goods and energy uses, in each time period. Market goods are represented as a composite good E_0 and energy uses by a vector $E = \{E_1, ..., E_J\}$. Utility maximization is represented as

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

where

E_0 = a composite market good, represented as a scalar numeraire,

E_j = energy use *j*, *j* = 1,…,*J* (e.g., space heating, water heating, clothes washing, clothes drying, etc.); E_j is measured in the physical units of energy output, e.g., BTUs of heat from a space heater, and

θ = a K-dimensional column vector of household and housing characteristics that influence household demand, e.g., household size, house square-footage, and climate.

The utility function is assumed to be increasing and quasi-concave in E_0 and E. Both E_0 and E are assumed to be essential goods. Utility maximization is constrained by household production technologies and the budget constraint.

Demand for each energy service E_j is met through utilization of a household energy production technology (i.e., an appliance) using fuel as an input. I assume that household energy service production does not require household labor.[10] I further assume independence of energy production technologies, i.e., no appliance produces more than one energy service (output nonjointness) so that each energy service has a unique production function.[11] In addition, I assume input nonjointness, i.e., fuel must be allocated among appliances that produce energy services so that fuel allocated to one appliance (energy service) does not affect production of others. If a single technology is used to produce a given end use j, then the energy service production function is represented by

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

where

[10] This assumption is reasonable as a majority of energy services do not involve labor. A few energy uses have time implications, such as cooking and clothes washing. However, for energy service production that requires time, the time requirement is relatively inelastic with respect to the energy price. One can argue that demand for time has an income effect. This question is worth pursuing but is beyond the scope of this study.

[11] In a few cases, multiple energy services are produced using the same appliance (e.g., a heat pump is used for both space heating and cooling).

i = technology choice index, $i \in I_j$, where I_j is the technology choice set for end use *j*,

$x_{l(i),j}$ = input of fuel *l*(*i*) associated with technology *i* for end use *j* where *l* is the energy source (e.g., electricity and natural gas), and

φ_{ij} = the average energy-efficiency coefficient (i.e., energy output per unit of energy input) associated with technology *i* for energy use *j*.

Energy service production functions of the form in (6) are widely used in energy engineering models to calculate the energy output for a given level of energy input or, conversely, the energy input requirement given a level of energy service load (e.g., Wenzel et al. 1997).[12] 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. In this setup, I assume the technology choice determines the fuel choice as represented by *l*(*i*). That is, once technology i is chosen from the technology set I_j to meet energy service demand E_j, the fuel choice *l(i)* is determined.

Some energy uses can be met with more than one fuel technology (e.g., electricity or natural gas appliances can be used for water heating, space heating, and clothes drying); other energy use categories (e.g., lighting, refrigerators, and freezers) have only one practical fuel possibility (electricity). Although the model I develop here assumes that each energy service is met through a single technology, multiple

[12] The exact definition of the energy-efficiency coefficient (φ_{ij}) varies by energy use. For example, the energy-efficiency level of heating equipment is typically measured by the annual fuel utilization efficiency (AFUE), whereas the energy-efficiency level of an air conditioner is measured by its energy efficiency rating (EER) or seasonal energy efficiency rating (SEER).

technologies are used to produce some energy services (e.g., both a central air furnace and a portable space heater may be used simultaneously for space heating). To capture this case, equation (6) can be represented more generally as $E_j = \sum_{i \in I_j} \varphi_{ij} x_{I(i),j}$. The model generalization for the multiple technology case is presented in Appendix 3.1 at the end of this Chapter.

In the short-run, the household capital stock (e.g., appliances and housing stock) is likely 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 that treats the technology choice as given and does not depend on factors that affect technology choice. In the long run, however, the household will "weigh the alternatives of each appliance against expectations of future use, future energy prices, and current financing decisions" (Dubin and McFadden 1984). In other words, the household will consider both the capital costs and the future flow of operating costs associated with each of the alternative technologies in the decision-making process.

The two sections below discuss household decisions on short-run fuel use and the long-run technology choice, respectively. I demonstrate that theoretically both decisions flow from the same underlying utility maximization problem so that a unified framework applies to analysis of both household energy consumption and technology choice behavior.

3.2 *Short-run fuel demand*

Ignoring the case of using multiple technologies for individual energy uses for conceptual simplicity of presentation, the short-run optimization problem discussed above can be formalized as utility maximization as in equation (5) subject to the production function in equation (6), and the budget constraint

$$(7) \qquad E_0 + \sum_{l=1}^{L} p_l x_l = E_0 + \sum_{j=1}^{J} p_{l(j),j} x_{l(j),j} \le y^* \equiv y - \sum_{j=1}^{J} \rho_{i(j),j} k_{i(j),j},$$

where

$p_l \equiv p_{l(j),j}$ = the price of fuel l regardless of the energy use, i.e., for all $j = 1,\ldots,J$,

$x_l \equiv \sum_{j=1}^{J} x_{l(j),j}$ = total household use of fuel l,

$i(j)$ = the technology currently in place for meeting energy service j,

$l(j) \equiv l(i(j))$ = the fuel choice associated with end use j, which is implicitly determined by technology choice i,

y^* = the amount of income not already committed to fixed payments including appliance payments (represented as annualized costs),

y = household income,

$k_{i(j),j}$ = capital cost of technology i for end use j, and

$\rho_{i(j),j}$ = annualized fixed cost rate of technology i for end use j that accounts for appliance lifetime and financing costs.

I assume that $E_j \ge 0 \ \forall \ j$, and require that $E_0 > 0$ following LaFrance and Hamemann (1989) to avoid a technical continuity issue.

The budget constraint in (7) implies that the cost of producing the quantity E_j of energy service j is

(8) $c_j = p_{l(j),j} x_{l(j),j}, \qquad j = 1,...J.$

The implicit price of energy service *j*, i.e., the effective cost per unit of energy output for the *j*th energy use, is

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

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

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

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, and $V(\cdot)$ is assumed to be continuous and quasiconvex in r and y^*, monotonically decreasing in r, and monotonically increasing in y^*.

I adopt a version of the second-order translog flexible functional form of the conditional indirect utility function following Berndt et al (1977). The indirect utility function also incorporates demographic variables by interacting them with price terms using the "demographic translating" technique discussed in Pollak and Wales (1992).[13] In addition, I include a vector of household characteristics that may influence energy technology choices and disturbances associated with individual technology choices for energy service production. This functional form yields

[13] The inclusion of household and housing characteristics in the demand functions is based on the common sense and significance of statistical test results.

$$V(r, y^*, \theta, \varepsilon) = \exp\{\overline{\alpha} + \sum_{j=0}^{J} \alpha_j \ln(r_j / y^*) + \sum_{j=0}^{J}\sum_{j'=0}^{J} \beta_{jj'} \ln(r_j / y^*) \ln(r_{j'} / y^*) + \sum_{j=0}^{J} \ln(r_j / y^*) \Gamma_j \theta + \sum_{j=1}^{J} \mathrm{H}_{i(j),j} \theta + \sum_{j=1}^{J} \varepsilon_{i(j),j}\}, \tag{11}$$

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.

Flexible functional forms have desirable properties as they do not constrain price and income elasticities at a base point *a priori* (Berndt et al. 1977). Popular functional forms include the almost ideal demand system (AIDS) (e.g., Deaton and Muellbauer 1980), the transcendental logarithmic (Translog) system (e.g., Christensen, Jorgenson, and Lau 1975), the generalized Leontief (e.g., Diewert 1971), and the generalized Cobb-Douglas (e.g., Diewert 1973). Using Bayesian procedures, Berndt et al. (1977) compared the translog, generalized Leontief, and generalized Cobb-Douglas using Canadian data, and concluded that the translog functional form is preferable on theoretical and econometric grounds. Lewbel (1989) showed that the AIDS and translog models are about equal in terms of both explanatory power and estimated elasticities. Cameron (1985) used a translog indirect utility function to estimate household energy conservation retrofit decisions and found that estimated coefficients were robust across different specifications such as the generalized Leontief and the quadratic form.

LaFrance and Hanemann (1989) show that when utility maximization subject to a linear budget constraint satisfies the standard regularity properties and income is greater than total expenditure on a subset of goods, the associated incomplete demand system (i.e., without estimation of demand for the numeraire E_0) can be treated virtually the same as a complete demand system. This permits recovery of the implied preference structure for the subset of goods.[14] Thus, the optimal level of the jth energy service can be derived using Roy's identity

$$(12)\qquad E_j = \frac{y^*}{r_j}\frac{\alpha_j + 2\sum_{j'=0}^{J}\beta_{jj'}\ln(r_{j'}/y^*) + \Gamma_j\theta}{\sum_{j''=0}^{J}\alpha_{j''} + 2\sum_{j''=0}^{J}\sum_{j'=0}^{J}\beta_{j''j'}\ln(r_{j'}/y^*) + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \qquad j = 0,\ldots,J.$$

Substituting $\ln(r_j/y^*) = \ln r_j - \ln y^*$ and imposing the adding-up and symmetry normalization constraints $\sum_{j=0}^{J}\alpha_j = 1$, $\beta_{jj'} = \beta_{j'j}$, and $\sum_{j=0}^{J}\sum_{j'=0}^{J}\beta_{jj'} = 0$ for the translog system, equation (12) can be simplified as

$$(13)\qquad E_j = \frac{y^*}{r_j}\frac{\alpha_j + 2\sum_{j'=0}^{J}\beta_{jj'}\ln r_{j'} - 2\ln y^*\sum_{j'=0}^{J}\beta_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=0}^{J}\beta_{j''j'}\ln r_{j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \qquad j = 0,\ldots,J.$$

Since $r_0 = 1$ and thus $\ln r_0 = 0$, the demand system equation (13) can be re-written as

[14] The standard regularity properties are: (i) the demands are positive valued; (ii) the demands are zero degree homogenous in all prices and income, and (iii) the $J \times J$ matrix of compensated substitution effects for E is symmetric, negative semidefinite.

$$(14)\qquad E_0 = y^* \frac{\alpha_0 + 2\sum_{j'=1}^{J}\beta_{0j'}\ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J}\beta_{0j'} + \Gamma_0\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\ln r_{j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta},$$

and

$$(15)\qquad E_j = \frac{y^*}{r_j}\frac{\alpha_j + 2\sum_{j'=1}^{J}\beta_{jj'}\ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J}\beta_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\ln r_{j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \qquad j = 1,\dots,J.$$

Given that E_j is an unobserved household quantity, equation (15) can be converted to an estimable equation by substituting (6),

$$(16)\qquad E_j = \varphi_{i(j),j}x_{l(j),j} = \frac{y^*}{r_j}\frac{\alpha_j + 2\sum_{j'=1}^{J}\beta_{jj'}\ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J}\beta_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\ln r_{j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \qquad j = 1,\dots,J,$$

and rearranging to get

$$(17)\qquad x_{l(j),j} = \frac{y^*}{\varphi_{i(j),j}r_j}\frac{\alpha_j + 2\sum_{j'=1}^{J}\beta_{jj'}\ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J}\beta_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\ln r_{j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \qquad j = 1,\dots,J.$$

Further substituting (9) obtains

$$(18)\qquad x_{l(j),j} = \frac{y^*}{p_{l(j),j}}\frac{\alpha_j + 2\sum_{j'=1}^{J}\beta_{jj'}\ln(p_{l(j'),j'}/\varphi_{i(j'),j'}) - 2\ln y^* \sum_{j'=0}^{J}\beta_{jj'} + \Gamma_j\theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\ln(p_{l(j'),j'}/\varphi_{i(j'),j'}) + \sum_{j''=0}^{J}\Gamma_{j''}\theta}, \quad j = 1,\dots,J.$$

The associated budget share equations by energy end use are thus

$$(19) \qquad \frac{x_{l(j),j}\, p_{l(j),j}}{y^*} = \frac{\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) - 2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) + \sum_{j''=0}^{J} \Gamma_{j''}\theta}, \quad j = 1,\ldots,J.$$

The budget constraint in (7) suggests that the amount of y^* allocated to the composite good (the numeraire) is $E_0 = y^* - \sum_{j=1}^{J} p_{l(j),j} x_{l(j),j}$. Thus, the budget share for the numeraire ω_0 can be expressed as

$$(20) \qquad \begin{aligned} \omega_0 &= \frac{y^* - \sum_{j=1}^{J} p_{l(j),j} x_{l(j),j}}{y^*} \\ &= \frac{\alpha_0 + 2\sum_{j'=1}^{J} \beta_{0j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) - 2\ln y^* \sum_{j'=0}^{J} \beta_{0j'} + \Gamma_0 \theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) + \sum_{j''=0}^{J} \Gamma_{j''}\theta} + \mu_0, \end{aligned}$$

where μ_0 is a disturbance.

If only aggregate household use of each fuel is observed, equation (19) can be aggregated over end uses by fuel type to get budget shares by fuel type, ω_l . Here I also introduce an error term for econometric purposes to represent errors in fuel use decisions

$$\omega_l = \frac{x_l p_l}{y^*}$$

$$= \sum_{j=1}^{J} \Psi(x_{l(j),j} > 0) \frac{x_{l(j),j} p_{l(j),j}}{y^*}$$

(21)
$$= \frac{\sum_{j=1}^{J} \Psi(x_{l(j),j} > 0) \left[\begin{array}{r} \alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) \\ -2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta \end{array} \right]}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln(p_{l(j'),j'} / \varphi_{i(j'),j'}) + \sum_{j''=0}^{J} \Gamma_{j''}\theta} + \mu_l,$$

$$l = 1, \ldots, L,$$

where define indicator variable, and μ_l is a disturbance of fuel use decisions with respect to fuel type *l*. Demand for numeraire and fuels are nonrandom to households but unobservable to researchers. I assume the disturbances μ associated with consumption are correlated with household taste (e.g., for energy efficiency) which also affects choices of energy technology. For the empirical analysis of household energy demand among California households, equation (21) consists of two estimable budget share equations, i.e., L = {electricity, natural gas}.[15] The model setup presented above only addresses situation that an energy service is met through a single technology. The model expressions and estimation equations for multiple technology case are presented in Appendix 3.1 at the end of this Chapter.

Estimation of the demand system in equations (20) and (21) retrieves parameters of the demand equations and the indirect utility function. If the appliance

[15] According to the 2005 Residential Energy Consumption Survey conducted by the EIA, electricity and natural gas consumption accounts for over 93 percent of an average California household's fuel expenditure. (Source: Table US10 "Average Expenditures by Fuels Used, 2005" in the 2005 Residential Energy Consumption Survey--Detailed Tables, published by the EIA, 2008. Accessed via http://www.eia.doe.gov/emeu/recs/recs2005/c&e/detailed_tables2005c&e.html on March 2, 2008)

engineering energy-efficiency coefficients $\varphi_{i(j),j}$ are unobserved, equation (21) can incorporate suitable estimable expressions for them. For example, suppose $\ln\varphi_{ij} = \gamma_{ij} w_{ij}$, where w_{ij} is a column vector of relevant explanatory variables possibly including appliance age and the appliance energy-efficiency standard, and γ_{ij} is a corresponding row vector of related coefficients. Substituting this specification, replacing $\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'} \equiv \sum_{j''=0}^{J}\sum_{j'=0}^{J}\beta_{j''j'} - \sum_{j''=0}^{J}\beta_{j''0} \equiv -\sum_{j''=0}^{J}\beta_{j''0}$, and imposing $p_l \equiv p_{l(j),j}$, equation (21) becomes

$$\omega_l = \frac{\sum_{j=1}^{J}\Psi(x_{l(j),j} > 0)\left[\begin{array}{l}\alpha_j + 2\ln(p_l / y^*)\sum_{j'=1}^{J}\beta_{jj'} - 2\ln y^*\beta_{j0} \\ \qquad\qquad - 2\sum_{j'=1}^{J}\beta_{jj'}\gamma_{i(j'),j'}w_{i(j'),j'} + \Gamma_j\theta\end{array}\right]}{1 - 2\ln p_l\sum_{j''=0}^{J}\beta_{j''0} - 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\gamma_{i(j'),j'}w_{i(j'),j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta} + \mu_l, \tag{22}$$

$$l = 1,\ldots,L.$$

and the budget share for the numeraire ω_0 in equation (20) can be expressed as

$$\omega_0 = \frac{\alpha_0 + 2\ln(p_l / y^*)\sum_{j'=1}^{J}\beta_{0j'} - 2\ln y^*\beta_{00} - 2\sum_{j'=1}^{J}\beta_{0j'}\gamma_{i(j'),j'}w_{i(j'),j'} + \Gamma_0\theta}{1 - 2\ln p_l\sum_{j''=0}^{J}\beta_{j''0} - 2\sum_{j''=0}^{J}\sum_{j'=1}^{J}\beta_{j''j'}\gamma_{i(j'),j'}w_{i(j'),j'} + \sum_{j''=0}^{J}\Gamma_{j''}\theta} + \mu_0. \tag{23}$$

Equations (22) and (23) are jointly estimated in this case.

3.3 Long-run technology choice

Turning to the long-term capital stock decision, the household optimization problem can be represented as

$$(24) \qquad \max_{i(j)\in I_j, j=1,\ldots,J} \sum_{t=1}^{T} \lambda^t u(E_{0t}^*, E_{1t}^*, \ldots, E_{Jt}^*; \theta),$$

subject to

$$E_{0t} + \sum_{j=1}^{J} p_{l(i(j)),jt} x_{l(i(j)),jt}^* + \sum_{j=1}^{J} \rho_{i(j),jt} k_{i(j),jt} = y_t, \quad t = 1,\ldots,T,$$

where λ is a discount factor, t subscripts denote time, T is the planning horizon, and '*' denotes optimal choice functions conditioned on technology choices according to successive applications of the short-term decision model of the previous section. Again, I assume only one technology is chosen to meet each energy use for conceptual simplicity of presentation, although generalizations are easily added. I assume that appliances have appropriate resale value consistent with remaining lifetime when sold as part of selling a house and that T is sufficiently large to avoid dependence of ownership costs on the planning horizon.

The modeling of household energy technology choices requires some simplifying assumptions because the treatment of appliance usage depends on future price expectations. Hausman (1979) modeled consumer decisions with respect to purchase and utilization of room air conditioners. He recognized the challenge of modeling future price expectations and used marginal electricity price in the year of study to estimate the expected operating costs. Dubin and McFadden (1984) modeled household technology choice as contemporaneous with utilization decisions. They acknowledge that their assumption is realistic only if "there are perfect competitive rental markets for consumer durables." They used electricity price in the year of study to calculate operating cost over the appliance lifetime, and relied on exogenous estimates of ‘typical’ unit energy consumption (UEC) of appliances to derive future usage estimates.

In a review article, Rust (1986) noted that what is needed to be accurate is “a formal dynamic programming model of the appliance investment decision, which models consumer expectations of future prices by specification of a parametric stochastic process governing their law of motion.” However, no study has been able to achieve this ideal. For example, in a much more recent study of energy consumption and technology choice for space heating in Norway, Nesbakken (2001) used real energy price in the year of appliance purchase as the expected energy price.

For my analysis, I assume future price and income expectations at each point in time are given by current prices and income. Thus, the long term problem in (24) reduces to the single time period problem,

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

subject to

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

A comparison of the budget constraints in the long- and the short-term problems implies compatibility such that

(26) $$y^* = y - \sum_{j=1}^{J} \rho_{i(j),j} k_{i(j),j} \ ,$$

where y^* is the available income for short-term decisions once the technology choices in the long-term decision problem are made. To further attain compatibility of the short- and long-term decision problems requires use of the same indirect utility function (11), where y^* now depends on the $i(j)$ technology choices through the $\rho_{i(j),j}$'s and $k_{i(j),j}$'s that determine y^* in (26), and the r_j's depend on the $i(j)$'s through equation (9) above.

After the short-term optimization and imposing $r_0 = 1$ using the normalization constraints, the indirect utility function (11) becomes

$$
\begin{aligned}
V(r, y^*, \theta, \varepsilon) = \exp\{ & \overline{\alpha}_0 - \ln y^* + \sum_{j=1}^{J} \alpha_j \ln r_j - 2 \ln y^* \sum_{j=0}^{J} \sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} \\
& + \sum_{j=1}^{J} \sum_{j'=1}^{J} \beta_{jj'} \ln r_j \ln r_{j'} + \sum_{j=1}^{J} \ln r_j \Gamma_j \theta - \ln y^* \sum_{j=0}^{J} \Gamma_j \theta + \sum_{j=1}^{J} \mathrm{H}_{i(j),j} \theta \\
& + \sum_{j=1}^{J} \varepsilon_{i(j),j} \},
\end{aligned} \tag{27}
$$

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

In order to study household energy technology choice behavior, I treat appliance choice for each energy use in isolation of others assuming that appliances for all other energy service production remain unchanged. This is a reasonable assumption as the household's decision to replace a clothes washer is unlikely to be affected by the decision to buy a specific type of water heater. Moreover, appliance replacement decisions are typically motivated by an old appliance wearing out, which occurs at random times. Such decisions are made one at a time as they arise.

Therefore, the unobservables that affect appliance choices are likely from different time periods and thus likely to be independent of one another.[16]

Under the technology-choice-independence assumption, this model reduces to independent minimization of the implicit cost of individual energy uses. That is, individual appliance choice decisions can be represented by defining *V* as a function of *i*(*j*) for a given energy use *j* assuming no other appliance choice problem arises simultaneously, i.e., other appliances are held fixed. For this purpose, I define

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

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

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 (9), 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 (11) can be denoted as

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

[16] However, 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.

where V is the same indirect utility function with the same parameters as defined in (11). 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 (30):

$$V_j(r, y_{ij}, \theta, \varepsilon_{ij}) = \exp(W_{ij}B_j + W_j^0 + \varepsilon_{ij}), \tag{31}$$

where

$$\begin{aligned}
W_{ij} &\equiv \{-\ln y_{ij}, \ln r_{ij}, -2\ln y_{ij} \ln r_1, ..., -2\ln y_{ij} \ln r_J, 2\ln r_{ij} \ln r_1, ..., 2(\ln r_{ij})^2, ..., 2\ln r_{ij} \ln r_J, \\
&\qquad \ln r_{ij}\theta, -\ln y_{ij}\theta, \theta\} \\
B_j &\equiv \{1, \alpha_j, \sum_{j=0}^{J}\beta_{j1}, ..., \sum_{j=0}^{J}\beta_{jJ}, \beta_{j1}, ..\beta_{jJ}, \Gamma_j{}', \sum_{j=0}^{J}\Gamma_j{}', \mathrm{H}'_{i(j),j}\}' \\
W_j^0 &= \overline{\alpha}_0 + \sum_{\substack{j'=1 \\ j\neq j^*}}^{J}\alpha_{j'} \ln r_{j'} + \sum_{\substack{j'=1 \\ j'\neq j}}^{J}\sum_{\substack{j''=1 \\ j''\neq j}}^{J}\beta_{j'j''} \ln r_{j'} \ln r_{j''} + \sum_{\substack{j'=1 \\ j'\neq j}}^{J}\Gamma_{j'}\theta \ln r_{j'} + \sum_{\substack{j'=1 \\ j'\neq j}}^{J}\mathrm{H}_{i(j'),j'}\theta + \sum_{\substack{j'=1 \\ j'\neq j}}^{J}\varepsilon_{i(j'),j'}.
\end{aligned}$$

The probability that the household chooses technology i from the set I_j of alternatives for energy service j can then be represented as

$$\begin{aligned}
P_{ij} &= \Pr\{V_j(i, y_{ij}, \theta, \varepsilon_{ij}) > V_j(i', y_{i'j}, \theta, \varepsilon_{i'j}) \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{\exp(W_{ij}B_j + W_j^0 + \varepsilon_{ij}) > \exp(W_{i'j}B_j + W_j^0 + \varepsilon_{i'j}), \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{W_{ij}B_j + W_j^0 + \varepsilon_{ij} > W_{i'j}B_j + W_j^0 + \varepsilon_{i'j}, \forall i' \neq i; i, i' \in I_j\} \\
&= \Pr\{\varepsilon_{i'j} - \varepsilon_{ij} < W_{ij}B_j - W_{i'j}B_j, \forall i' \neq i; i, i' \in I_j\}
\end{aligned} \tag{32}$$

As shown in (32), 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,

(33) $$F(\varepsilon_{i'i}^{j}) = \exp(-e^{-\varepsilon_{i'i}^{j}}),$$

where $\varepsilon_{i'i}^{j} = \varepsilon_{i'j} - \varepsilon_{ij}$. Following the well-known results developed and popularized by McFadden (1974), the EV error term distribution leads to a logistic model of the discrete choice probability where the probability that technology *i* yields the highest indirect utility among all possible technologies is given by

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

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). If the energy-efficiency coefficients used to define r_{ij} are not observed, suitable expressions, e.g., $\ln\varphi_{ij} = \gamma_{ij} w_{ij}$, can be inserted in their definition. Then equation (34) can be re-written as

$$
(35)\qquad
\begin{aligned}
P_{ij} &= \frac{\exp(-\ln y_{ij} A_0 + \ln(p_{l(i),j} / \varphi_{ij}) A_j + \mathrm{H}_{ij}\theta)}{\sum_{i' \in I_j} \exp(-\ln y_{i'j} A_0 + \ln(p_{l(i'),j} / \varphi_{i'j}) A_j + \mathrm{H}_{i'j}\theta)} \\
&= \frac{\exp(-\ln y_{ij} A_0 + \ln p_{l(i),j} A_j - w_{ij}\gamma_{ij} A_j + \mathrm{H}_{ij}\theta)}{\sum_{i' \in I_j} \exp(-\ln y_{i'j} A_0 + \ln p_{l(i'),j} A_j - w_{i'j}\gamma_{i'j} A_j + \mathrm{H}_{i'j}\theta)}.
\end{aligned}
$$

Equation (34) 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 (21). In addition, equation (34) 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.

To illustrate the model in the case of binary choice (e.g., two technology choices for energy use j), equation (34) reduces to

$$
(36)\qquad
\begin{aligned}
P_{ij} &= \frac{\exp(-\ln y_{ij} A_0 + \ln r_{ij} A_j + \mathrm{H}_{ij}\theta)}{\exp(-\ln y_{ij} A_0 + \ln r_{ij} A_j + \mathrm{H}_{ij}\theta) + \exp(-\ln y_{i'j} A_0 + \ln r_{i'j} A_j + \mathrm{H}_{i'j}\theta)} \\
&= \frac{1}{1 + \exp[-(\ln y_{i'j} - \ln y_{ij}) A_0 + (\ln r_{i'j} - \ln r_{ij}) A_j + \mathrm{H}^j_{i'i}\theta]},
\end{aligned}
$$

where $\mathrm{H}^j_{i'i} \equiv \mathrm{H}_{i'j} - \mathrm{H}_{ij}$. The log-odds ratio of the probability that technology alternative i is chosen is

$$\log \frac{P_{ij}}{P_{i'j}} = \log \frac{P_{ij}}{1-P_{ij}}$$

(37)
$$= \log \frac{\dfrac{1}{1+\exp[-(\ln y_{i'j} - \ln y_{ij})A_0 + (\ln r_{i'j} - \ln r_{ij})A_{j*} + \mathrm{H}_{i'i}^{j}\theta]}}{\dfrac{\exp[-(\ln y_{i'j} - \ln y_{ij})A_0 + (\ln r_{i'j} - \ln r_{ij})A_j + \mathrm{H}_{i'i}^{j}\theta]}{1+\exp[-(\ln y_{i'j} - \ln y_{ij})A_0 + (\ln r_{i'j} - \ln r_{ij})A_j + \mathrm{H}_{i'i}^{j}\theta]}}$$

$$= (\ln y_{i'j} - \ln y_{ij})A_0 - (\ln r_{i'j} - \ln r_{ij})A_j - \mathrm{H}_{i'i}^{j}\theta.$$

If more than two technology choice alternatives are involved, the model in (34) is a multinomial logit model. To identify the parameters, one alternative i^* is designated as the reference choice alternative, i.e., the probability that technology i^* is chosen is

(38)
$$P_{i^*j} = \frac{1}{1+\sum_{\substack{i'\in I_j \\ i'\neq i^*}} \exp(W_{i'j}B_j)},$$

and the probability that technology i ($i \neq i'$) is chosen becomes

(39)
$$P_{ij} = \frac{\exp(W_{ij}B_j)}{1+\sum_{\substack{i'\in I_j \\ i'\neq i^*}} \exp(W_{i'j}B_j)}.$$

One remaining consideration in applying this appliance choice model has to do with future price and income expectations. While the same preference parameters from the underlying utility maximization model appear in both short-run use equations and long-run appliance choice equations (assuming stable preferences), consumers may have different expectations for prices and income that will prevail over the appliance life. If consumers naively expect current prices and income to continue, then no modification in the model is needed. However, if consumers expect different prices and income to prevail during the appliance lifetime, then those expectations may modify the prices and income used in the appliance choice model.

3.4 Conclusions

This chapter develops a consistent theoretical framework that can be used to analyze household behavior with respect to short-run energy demand and long-run technology choices. The model, derived from underlying utility maximization using a second-order translog indirect utility function, provides a transparent structure with great flexibility to empirically investigate consumer preferences and the role of prices, income and household characteristics in energy consumption and technology adoption decisions. This model addresses several unique features of consumer energy use and allows analysis of demand interactions, demand aggregation, and fuel substitution.

The empirical application of the model presented in the subsequent chapters shows that the model predicts household energy demand and technology choice decisions quite well given the extent of structure, validating the usefulness and appropriateness of the model in studying household energy use behavior.

The modeling framework allows analysis of the likelihood that a technology is chosen based on variations in its attributes (e.g., capital and operating costs, and energy efficiency characteristics) and household characteristics (e.g., income, education, and climate) given future expectations. Similarly, the impacts of prices, income and household characteristics on short-run energy consumption can be evaluated given technology choices. Analysis of these questions in this consistent framework assures that the short- and long-run answers to these questions are mutually congruent and sensible.

The effects of policy instruments designed to encourage household energy efficiency can also be analyzed in this framework. For instance, incentive-based policy, such as utility rebates or government tax incentives on technology purchases, lower the capital cost of targeted technologies; energy efficiency performance standards affect the energy efficiency performance (φ_{ij}) of targeted technologies; and public or utility information and outreach programs that promote energy-efficient technology potentially change the household's perception on the attributes of the technology.

On the other hand, climate change policies, such as a carbon cap-and-trade program or emissions taxes, can potentially change the resource costs of fossil-based energy supplies (natural gas, oil, and electricity) and thus related fuel prices. The effects of these policy-induced changes on households' technology choices and utilization can be analyzed efficiently using this modeling framework.

Appendix 3.1. Model setup for demand analysis with multiple technology ownerships for a given energy service

If multiple technologies are used to meet the demand of energy service j, equation (6) can be represented as

$$(40) \qquad E_j = \sum_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j}, \qquad j = 1,\ldots,J,$$

then, with a slight generalization in notation, the budget constraint (7) can be written as

$$(41) \qquad \begin{aligned} & E_0 + \sum_{l=1}^{L} p_l x_l = E_0 + \sum_{j=1}^{J} \sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j} \le y^* \\ & y^* \equiv y - \sum_{j=1}^{J} \sum_{i \in I_j} \rho_{i(j),j} k_{i(j),j} \Psi(x_{l(i(j)),j} > 0), \end{aligned}$$

where

$$p_l \equiv p_{l(i(j)),j} \text{ for } i \in I_j,\ j = 1,\ldots,J,\ l = 1,\ldots,L,$$
$$x_l \equiv \sum_{j=1}^{J} \sum_{i \in I_j} x_{l(i(j)),j},\ l = 1,\ldots,L,$$
$\Psi(\cdot) = 1$ when the expression in the parentheses is true and 0 otherwise.

In this case, the cost of producing the quantity E_j of energy service j becomes

$$(42) \qquad c_j = \sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j}, \qquad j = 1,\ldots,J.$$

The implicit price of energy service j is then

$$(43) \qquad r_j \equiv \sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j} \Big/ \sum_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j}, \quad j = 1,\ldots J,$$

which is the average cost to produce a unit of energy output for energy service *j* using multiple technologies. If the multiple technologies use the same fuel *l*, equation (43) is reduced to

$$(44) \qquad r_j \equiv p_{l(j),j} x_{l(j),j} / \sum\nolimits_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j} = p_{l(j),j} / \sum\nolimits_{i \in I_j} \varphi_{i(j),j} \varpi_{l(i(j)),j}, \qquad j = 1,...J,$$

where $x_{l(j),j} \equiv \sum\nolimits_{i \in I_j} x_{l(i(j)),j}$, and $\varpi_{l(i(j)),j}$ is the share of fuel input *l* of technology *i*, $i \in I_j$, for energy use *j*. If the multiple technologies use different fuels, equation (43) can be re-written as

$$(45) \qquad r_j \equiv \sum\nolimits_{i \in I_j} p_{l(j),j} \varpi_{l(i(j)),j} / \sum\nolimits_{i \in I_j} \varphi_{i(j),j} \varpi_{l(i(j)),j}, \quad j = 1,...J.$$

In both cases, r_j is the weighted average cost to produce a unit of energy output for energy use *j* with consideration of the energy efficiency and relative intensity of utilization (thus fuel input) of each technology.

The subsequent model expressions for short-term fuel demand in equations (12)–(18) are modified similarly for the multi-technology case. Specifically, equation (12) becomes

$$E_j = \sum\nolimits_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j} = \frac{y^*}{r_j} \frac{\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j'} + \sum_{j''=0}^{J} \Gamma_{j''} \theta}$$

$$(46) \qquad = \frac{y^* \sum\nolimits_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j}}{\sum\nolimits_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j}} \frac{\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j'} + \sum_{j''=0}^{J} \Gamma_{j''} \theta},$$

$$j = 1,..., J.$$

Cancelling $\sum_{i \in I_j} \varphi_{i(j),j} x_{l(i(j)),j}$ and rearranging terms obtain

$$\text{(47)} \qquad \frac{\sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j}}{y^*} = \frac{\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j'} + \sum_{j''=0}^{J} \Gamma_{j''} \theta}, \qquad j = 1, \ldots, J,$$

where $\sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j} / y^*$ is the budget share of fuel consumption for the *j*th energy use.

The estimation equation of aggregate budget share for each fuel type in equation (21) then becomes

$$\omega_l = \frac{p_l x_l}{y^*} = \frac{\sum_{j=1}^{J} \sum_{i \in I_j} p_{l(i(j)),j} x_{l(i(j)),j} \Psi(x_{l(i(j)),j} > 0)}{y^*}$$

$$\text{(48)} \qquad = \frac{\sum_{j=1}^{J} \Psi(x_{l(j),j} > 0)[\alpha_j + 2\sum_{j'=1}^{J} \beta_{jj'} \ln r_{j'} - 2\ln y^* \sum_{j'=0}^{J} \beta_{jj'} + \Gamma_j \theta]}{1 + 2\sum_{j''=0}^{J}\sum_{j'=1}^{J} \beta_{j''j'} \ln r_{j'} + \sum_{j''=0}^{J} \Gamma_{j''} \theta} + \mu_l,$$

$$l = 1, \ldots, L,$$

where $\Psi(x_{l(j),j} > 0)$ equals to one if energy service *j* uses fuel *l* and equals to zero otherwise. The budget share equation in (48) of the multiple technology case only differs from that of the single technology case shown in equation (21) in two terms: r_j now reflects the weighted average cost per unit of energy output for energy use *j*, and *y**, the amount of income available after paying for fixed costs of appliances, includes fixed payment for multiple appliances for energy service *j*. The estimation procedure for the multiple technology case is essentially the same as for the single technology case except for modifications on variables r_j and y^*.

Chapter 4: California Household Data

This chapter describes the available data used to empirically apply the discrete/continuous model developed in Chapter 3. Section 4.1 reviews a micro-level survey dataset of energy use and appliance holdings among California households, and explains additional data collection and data management procedures. Section 4.2 summarizes California households' energy technology choices for clothes washing, water heating, space heating, and clothes drying, the four energy uses that are empirically analyzed later, and presents technology costs, energy performance, and relevant policy considerations. Section 4.3 discusses the relevance of the data for empirical estimation.

4.1 Data Overview

RASS household survey data

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 (IOUs) in the state (KEMA-XENERGY et al. 2004). The utilities that participated in the survey include Pacific Gas & Electric Company (PG&E), Southern California Edison (SCE), San Diego Gas & Electric Company (SDG&E), Southern California Gas Company (SCG), Los Angeles Department of Water & Power (LADWP), and a few other municipal utilities. Sample frames are the electric customer population of the utilities. Based on a stratified random sampling of the population frames, the study collected data from 21,920 households across different utility service areas and climate zones in California.[17]

This analysis uses a subsample of 2,408 households served by PG&E for both natural gas and electricity in the RASS.[18,19] The subsample only includes households with both electricity and natural gas consumption in order to empirically estimate the system of equations shown in equation (52) 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 PG&E subsample is used for analysis mainly driven by the availability and quality of historic energy price data. PG&E provides natural gas and electric services to approximately 15 million people, or 44 percent of the California population, throughout northern and central California.

In 2002, a typical California household consumed 5,914 kWh of electricity and 536 therms (15,705 kWh equivalent) of natural gas.[20] In comparison, in 2005 the nationwide average electricity consumption per household was 11,480 kWh and the average natural gas consumption was 689 therms.[21] Lower energy consumption by

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[17] The total population was stratified based on electric utility, house age, presence of electric heat, house type (e.g., single- or multi-family), and climate zone.

[18] The RASS has 7,295 households served by PG&E for electricity and gas. Data were cleaned by excluding households not in the clothes washer, water heater, space heater and clothes dryer choice sets (31.3 percent), households with missing values for variables (i.e., income, fuel consumption, and household variables) used in the analysis (32.4 percent), and a few outliers of households with less than one member or 20 or more members (0.08 percent) or with a budget share for fuel consumption greater than 30 percent (0.07 percent).

[19] The subsample of PG&E households with both electricity and natural gas service excludes 1,500 households served with only electricity (15.5 percent of PG&E households), which have no natural gas service in their neighborhoods.

[20] This average household electricity consumption comes from a conditional demand analysis based on the household energy consumption survey results of the Residential Appliance Saturation Study by KEMA-XENERGY et al. (2004); the average household natural gas consumption is based on "California Residential Natural Gas Consumption," Energy Almanac, California Energy Commission, accessed via http://energyalmanac.ca.gov/naturalgas/residential_natural_gas_consumption.html, on November 30, 2009.

[21] These estimates based on the 2005 Residential Energy Consumption Survey of the Energy Information Administration.

California households is due in large part to structural factors such as less floor area per household, greater reliance on natural gas, and the significantly milder heating season compared to the national average (Schipper and McMahon 1995). Policy programs such as appliance energy efficiency standards, building codes, and utility demand-side management (DSM) programs help to reduce residential energy use in California (Schipper and McMahon 1995).

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.[22] 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.[23] Historic heating and cooling degree days between 1950 and 2003 were provided by the CEC and merged with the RASS based on climate zone. In addition, county code was provided by the CEC and merged with the dataset based on zip code data in the RASS.

Technology choices (i.e. appliance type and associated fuel type) are available for major categories of household energy services including clothes washing, water heating, space heating, and clothes drying. Appliance efficiency and capacity are not

[22] The reported household annual consumption of electricity and natural gas in the RASS is estimated based on household billing data and is calendarized and normalized by climate.

[23] Both heating degree days and cooling degree days are quantitative indices designed to reflect energy needed to heat or cool a structure. Heating degree days represents the number of degrees that the daily mean temperature is below the base of 65°F; cooling degree days represents the number of degrees that the daily mean temperature is above the base of 65°F. Annual heating and cooling degree days are aggregate degree days over a year.

reported. However, appliance ages are provided in most cases and used to construct energy-efficiency indicators.

The PG&E subsample 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 subsample. Overall, the characteristics of the PG&E households in the subsample are fairly similar to the characteristics of the households in the RASS sample except for several measures: higher mean income ($87,326 vs. $63,981), higher mean natural gas consumption (564 vs. 472 therms), higher mean heating degree days (2,631 vs. 2,090) and lower mean cooling degree days (751 vs. 894), all with smaller standard deviations than the whole sample. The higher mean income is mainly due to data cleaning and higher natural gas consumption is due to higher demand for heating with cooler climate in northern and central California.

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.[24,25] These energy uses are chosen for analysis mainly because of the availability and quality of technology data for technology choice analysis. Details of these energy uses are discussed in Section 4.2. 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 ($y*$). Electricity and natural gas tariffs are 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; appliance costs and energy efficiency characteristics are compiled through a number of sources; household fixed payments are estimated based on a regression analysis of the relationship between household income and fixed payments using the Consumer Expenditure Survey. The data are cleaned and merged with the RASS dataset. The subsections below describe the data collection and management procedures.

[24] This estimate is based on estimated household average energy consumption by end use in California by KEMA-XENERGY et al. (2004).
[25] 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.

Energy prices

Since households' billing data and actual charges are unobserved, the rate schedules are used to assign energy prices to individual households. Tariff schedules are collected from the PG&E website and through personal contacts with the utility.[26] On the PG&E website, historic tariffs date back to 1998 for electricity and 1986 for natural gas. The residential electric tariff books provide various rate schedules (i.e., tiered energy charges, time-of-use, and seasonal) as well as estimated average electricity prices for each residential service category (e.g., regular or discount program) in dollars per kilo-watt hour ($/kWh). For natural gas, rate schedules are provided in dollars per therm ($/therm) on a monthly basis, including the tiered energy charge for baseline and excess quantities. In addition to regular charges, the utility also implements a low-income CARE (California Alternate Rates for Energy) program, which provides a monthly discount on energy bills for income-qualified households and housing facilities (e.g., multi-family and mobile homes).

Historic average residential energy prices are used to model long-run technology choice analysis as consumers are more likely to be concerned about the trend of energy price changes, with or without some form of price expectations to make trade-offs between upfront capital cost and operating cost. The appropriate representation of energy prices in energy demand analysis is much debated in the literature (see discussions in Taylor 1975). Alternative forms of energy price representation have been used, i.e., marginal price (e.g., Hartman and Werth 1981, and Hartman 1983), average price (e.g., Parti and Parti 1980), and increasing-block

[26] Access via http://www.pge.com/tariffs/.

rate schedules (e.g., Barnes et al. 1980 and Archibald et al. 1982). Recently, empirical studies and surveys suggest that individuals may not respond to nonlinear pricing in a way that the standard economic model predicts (see a review in Ito 2010). For instance, using a panel data set of monthly billing records among households in southern California, Ito (2010) found strong empirical evidence that consumers respond to average price rather than marginal price when faced with nonlinear electricity price schedules.

Between 2002 and 2003, a majority (95 percent) of the PG&E residential customers was covered under a two-tier, increasing-block rate structure, a small fraction (5.7 percent) of which was under the residential CARE discount rate. Less than five percent of all residential customers were under *time-of-use* (TOU) and *seasonal* rate structures.[27] The TOU and seasonal rate structures reflect a move to marginal pricing. However, they were not implemented more broadly until after 2004. Thus, this analysis focuses on the two-tier, increasing-block rate structure. The first tier, also referred to as the "baseline" level, sets a level of price for baseline consumption. According to the CPUC, the baseline quantities are set at about 50-60 percent of average electricity and natural gas consumption to allow a 'reasonable price of energy' (CPUC code 739.4/5). The second tier, also referred to as the "excess" level, sets a higher level of tariff for consumption above the baseline quantity.

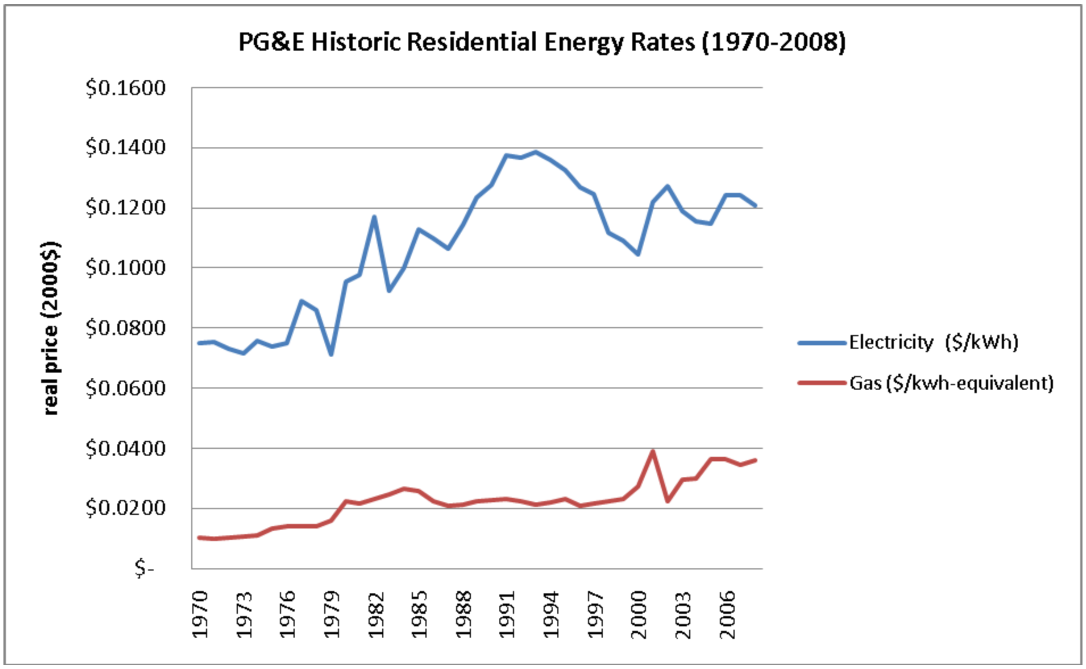
Between July 2001 and March 2003, the electricity charge was \$0.1117/kWh (2000\$) for the baseline quantity and \$0.1284/kWh (2000\$) for excess quantity. In

[27] The percentages are estimated based on utility service data in the Statewide Residential Lighting and Appliance Saturation Study (RLW Analytics 2000).

2003, the natural gas tariff was \$0.8496/therm (2000\$) for baseline consumption and \$1.0563/therm (2000\$) for excess quantity. In the absence of actual household billing data to carry out specification tests, average energy prices between 2002 and 2003 are used in the short-run energy demand analysis, corresponding to the energy consumption data in the subsample.

Figure 1 shows the historic trend of *real* average PG&E residential electricity and natural gas prices (in 2000\$/kWh equivalent) between 1970 and 2008. Between 1970 and 2003, the real natural gas prices increased by 7 percent per year and real electricity prices increased by 2 percent per year. Between 1980 and 2003, the estimation period, changes in real energy prices were more moderate: the real electricity and natural gas prices had increased by 1 percent per year. Figure 1 puts the widely-cited California energy crisis that occurred in 2001 and 2002 in historical context. Real natural gas price shows to have spiked in 2001, about 70 percent higher than in the pre-crisis year of 1999. Electricity price in 2001 also increased sharply from the 1999-2000 level, but was much below the peak around the early- to mid-1990s. The energy crisis, with interrupted energy supply and higher energy prices, likely triggered demand-side conservation response and increased adoption of energy-efficient technologies. The short-term price response is captured in the energy price elasticities in the short-run analysis; the long-run response to energy price changes is captured in the technology choice analysis.

Figure 1. PG&E's historic average residential energy rates



Source: Author's estimates based on data provided by PG&E.

In the short-run energy demand analysis, natural gas prices are expressed in dollar per therm (2000$/therm) to match the consumption data; in the long-run technology choice analysis, natural gas prices are converted to 2000$/kWh-equivalent in order to compare operating costs of alternative technologies using the two different fuels. As shown in Figure 1, the real natural gas prices, measured in $/kWh-equivalent, are about one-fifth of the real electricity prices.

Appliance capital costs

Collecting consistent historic appliance capital cost data has proven to be challenging. As observed by XENERGY, an energy consulting firm involved in the various data collection efforts in California, "[D]espite decades of experience and multi-million dollar budgets, obtaining accurate estimates of changes in [energy-efficiency measure] prices over time remains a daunting challenge." (XENERGY

2001) For this analysis, historic capital cost curves are constructed for various appliances based on a number of energy-efficient measure cost databases.[28]

The California Public Utility Commission (CPUC) and the California Energy Commission maintain an online Database for Energy Efficient Resources (DEER) with estimates on the capital, labor and installation costs of several hundreds of residential and nonresidential energy technologies and conservation measures.[29] Two waves of data from DEER are used in this analysis, DEER 2001 and DEER 2005. The DEER cost estimates come from sources including manufacturers, wholesale distributors, contractors, retail stores, websites, and utility program records (XENERGY 2001, Itron 2005). The CPUC provided two earlier versions of the database, Measure Cost Study 1992 and 1994 (XENERGY 1992 and XENERGY 1994). These earlier measure cost studies were conducted for similar purposes using similar methodology. Costs are constructed for 1991, 1993, 2000 and 2003 and linear extrapolations are used for other years.[30,31]

Due to the availability of technology cost data, the technology choice analysis only includes choice decisions between 1990 and 2003 with the exception of space heating equipment. The technology cost and efficiency estimates for space heating and ventilation systems, obtained from two versions of the *Energy Data Sourcebook for the U.S. Residential Sector* produced by the Lawrence Berkeley Laboratory

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[28] The analysis, which uses estimated appliance costs from the various sources, does not take into consideration potential rebates or discounts offered by retailers due to lack of data availability.

[29] The latest data (2005 DEER and 2008 DEER) can be accessed via http://www.energy.ca.gov/deer/

[30] Considering the time lag between data collection and report publication, I assume a one-year lag in reported cost data.

[31] Appliance ages are reported in intervals in the RASS (i.e., less than one year, one to three years, four to eight years, nine to thirteen years, fourteen to thirty years, and over 30 years), the middle year of an appliance age category is used to represent the value of technology cost. Specifically, data in years 2002, 2000, 1996, 1993, and 1991 are used.

(Hanford et al. 1994 and Wenzel et al. 1997), date back to 1980. The mean values of cost estimates are used to represent the average cost of a category of appliances (e.g., a top-load washer and a gas tank water heater). Such a procedure matches the level of detail of appliance holdings in the sample as only the broad category of appliance ownership (e.g., front-load vs. top-load clothes washer, gas vs. electric tank water heater) is reported. For water heating and space heating equipment, technology costs are missing in some years. For these years, the appliance costs are extrapolated using the rate of change in manufacturing costs in the Producer Price Index.

Annual appliance capital cost payments of an appliance are estimated based on the average appliance lifetime and the interest rate at the time of purchase. Specifically, I use the average of annual prime interest rates for time intervals by which appliances purchases are recorded in the data. Table 2 below reports the assumed appliance lifetimes used in the analysis.

Table 2. Assumed appliance lifetimes used in the analysis

Technology	Appliance Type	Average Lifetime (years)
Clothes washer		13
Clothes dryer		14
Water heater	Tank	13
Water heater	Tankless	20
Space heater	Furnace	20
Space heater	Other	18

Note: These estimates are derived from DEER 2005 and Wenzel et al. 1997.

Energy efficiency measures

The model developed in Chapter 3 assumes that the energy efficiency levels of alternative technologies affect technology choice decisions and thus actual energy use. Since only broad categories of appliance choices are observed, average energy efficiency performance estimates for a given category of appliance stock provides the best approximation for the specific appliance a household owns. A number of household and market survey studies have estimated average energy efficiency levels of existing appliance stock in California. For example, the California Statewide Residential Lighting and Appliance Efficiency Saturation Study 2000 and 2005 (RLW Analytics 2001, RLW Analytics 2005) provide survey results of household energy appliance ownerships, appliance capacity distributions and energy efficiency estimates based on on-site home audits.

In addition, the Lawrence Berkeley Laboratory reports (Hanford et al. 1994 and Wenzel et al. 1997) developed energy efficiency estimates for major energy technologies between 1972 and 1990. These studies are used to construct average energy efficiency indicators for the various categories of appliances in the sample. Fortunately, these studies, sponsored by the same utilities as the RASS, have similar categories of appliances and the energy efficiency indicators are matched closely with those in the subsample.

Average energy efficiency indicators are assigned to various space heaters (gas or electric forced-air furnaces, floor or wall heaters, hot water radiators, electric resistance systems, and heat pumps), water heaters (gas tank or tankless systems, and electric tank or tankless systems), clothes washers (top-load and front-load washers) and clothes dryers (gas and electric dryers). The energy efficiency indicators do not distinguish potential differences in energy efficiency performance by appliance vintage because such data were not available.

Given the potential measurement errors by using average energy efficiency estimates, alternative treatments of appliance energy efficiency are tested in both the short-run demand analysis and the long-run technology choice analysis. In the short-run demand analysis, the model fit improves significantly when the energy efficiency of clothes washers is modeled as a function of technology change and policy interventions (i.e., energy efficiency standards and Energy Star Program). This is mainly because the energy efficiency of clothes washers improved substantially over the last two decades. To a lesser extent, statistical analysis shows that modeling the energy efficiency levels of water heaters as a function of technology change is preferred to using average energy efficiency estimates. In the short-run modeling, the energy efficiency levels of clothes washers and water heaters are modeled explicitly as a function of appliance age and policy interventions. Average energy efficiency estimates are used for other energy appliances based on specification tests.

Similarly, the two alternative treatments of appliance energy efficiency are tested in the long-run technology choice analysis, each representing different perceptions of the energy efficiency performance of alternative technology choices at the time of appliance purchase. Again, the model fits improve significantly when the consumers' energy efficiency perception is modeled as a function of some form of technological change and policy variables such as energy efficiency standards and information programs rather than using average energy efficiency estimates. Arguably, consumers likely rely more on obvious signals about the energy performance of appliance alternatives from energy labels such as through the Energy Star program than estimates of the average energy efficiency of an appliance stock such as provided by an energy analyst. The implications of the alternative modeling of appliance energy efficiency are examined in Chapter 6.

In addition to the four specific energy services examined, the model also includes a category of other energy use to represent all other energy services. Average energy efficiency indicators are developed for these other electricity-consuming and natural gas-consuming appliances. Natural gas, water heating, space heating and clothes drying account for 93 percent of average natural gas consumption. The other main gas-consuming energy service is cooking. I assign an energy factor of 0.5 for the gas-using "other" services based on the average energy factor for gas stovetops in Hanford et al. (1994). The main electricity-using services in the "other" category are for lighting, refrigerators/freezers, office equipment, TVs, computers, air conditioners, and spas. For electricity-using "other" services, I estimate a weighted average energy efficiency factor of 0.44 based on shares of various energy uses and estimates of energy factors in Hanford et al. (1994) and RLW Analytics (2005). I then separately calculate the unit cost of energy output for "other" electricity-consuming energy services ($r_{e,other}$) and "other" natural gas-consuming energy services ($r_{g,other}$). The unit cost of energy output for the "other" energy services category (r_{other}) is the weighted average of $r_{e,other}$ and $r_{g,other}$ based on average household electricity and natural gas consumption for these other energy uses.

Consumer expenditures

To derive relationships between household income and fixed payments, regression analysis is undertaken using the Consumer Expenditure Survey (CES) of the Bureau of Labor Statistics.[32] A dataset of pre-tax income and expenditures is constructed by pooling consumer units in different income groups between 1990 and 2002 reported in the CES tables.[33] Income before taxes is used as the income variable to match the income data in the sample. Annual fixed payments, including for housing, vehicle purchase, and health care, are estimated. Fixed housing expenditures distinguish between home owners and renters. Fixed payments for owned dwelling include mortgage interest and charges, property taxes, maintenance, repairs, insurance and other expenses; fixed payment for rented dwellings is the rent reported. Fixed payments for vehicle purchase include net outlay of vehicle purchases, finance charges, insurance, vehicle rental, leases, licenses, and other charges. Health care costs include health insurance, medical services, drugs and medical supplies.

All income and expenditure data are converted to 2000 dollar value using the Consumer Price Index. Figure 2 shows scatter plot of the pooled real income, total expenditure, fixed payment variables, and expenditure of major appliances based on the CES.

As shown in Figure 2, expenditures and fixed payments appear to grow relatively linearly with income for real income above $7,500 (2000$). For real income lower than $7,500 (2000$), expenditures and income appear to have inverse relationships.

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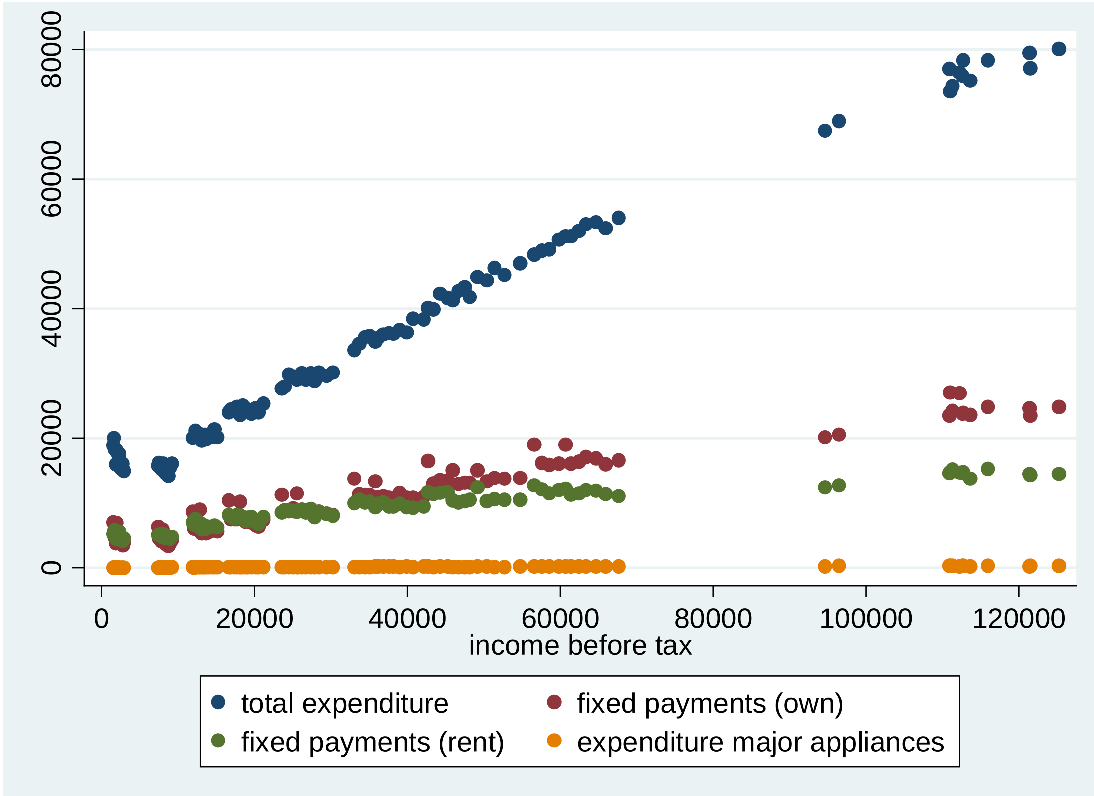
[32] Accessed via http://www.bls.gov/cex/csxstnd.htm. The average values for consumer units in each income group are treated as characteristics of *a* typical consumer unit (i.e., household).

[33] The income groups include: less than $5,000, $5,000-$9,999, $10,000-$14,999, $15,000-$19,999, $20,000-$24,999, $25,000-$29,999, $30,000-$39,999, $40,000-$49,999, $50,000-$69,999, and $70,000 and more.

Figure 2. Scatter plot of income and expenditure using CES data (2000 dollars)



The following quadratic linear regression model is thus hypothesized

(49) $$fixed\_payment_{n*} = f_0 + f_1 income_{n*} + f_2 income_{n*}^2 + e_{n*}$$

where $fixed\_payment_{n*}$ is the real fixed payment variables (i.e., for house owners or renters, respectively) for consumer unit n^*, $income_{n*}$ is the real income before taxes for consumer unit n^*. The random variable e_{n*} is assumed to have mean zero and variance σ_e^2. Ordinary least square (OLS) of equation (49) are carried out using the pooled data. OLS estimates of the coefficients would be unbiased and consistent if assumption of the random variable holds.[34] Estimated coefficients and standard errors

[34] Equation (49) is also estimated using panel data methods (pooled OLS and pooled feasible generalized least square, with and without error correlation and autocorrelation). Results of estimated models are fairly consistent.

of the model using robust standard error are reported in equation (50) below. Regressions are carried out for owners and renters respectively. The estimated coefficients are used to derive annual fixed payments for the PG&E households in the subsample according to the following regression results (with standard errors in parentheses):

$$\begin{aligned}
&fixed_payment_own_{n*} = \underset{(310.504)}{2086.558} + \underset{(0.00756)}{0.234} income_{n*} - \underset{(0.0000000575)}{0.000000513} income_{n*}^2 \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \mathrm{R}^2 = 0.991
\end{aligned} \tag{50}$$

$$\begin{aligned}
&fixed_payment_rent_{n*} = \underset{(199.702)}{3552.863} + \underset{(0.00574)}{0.169} income_{n*} - \underset{(0.0000000446)}{0.000000719} income_{n*}^2 \\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \mathrm{R}^2 = 0.970
\end{aligned}$$

In addition, the CES also reports expenditure on “major appliances,” which includes the majority of energy-using appliances except for water heaters and space heaters. The relationship between income and expenditure on “major appliances” is estimated to obtain estimates on the average household spending on these energy appliances. According to the CES definition, major appliances include refrigerators and freezers, dishwashers and garbage disposals, stoves and ovens, vacuum cleaners, microwaves, air-conditioners, sewing machines, washing machines and dryers, and floor cleaning equipment.[35] As shown in Figure 2, spending on home appliances is a small fraction of household income and is relatively inelastic with respect to changes in income. Nonetheless, OLS regression analysis using robust standard error is carried out to derive estimated fixed payments for energy appliances in the analysis. The estimated regression equation (with standard errors in parentheses) is

[35] Source: http://www.bls.gov/cex/csxgloss.htm#housing

$$appliance\_payment = 46.479 + 0.00340 income - 0.0000000102 income^2$$

(51) $$(9.613) \quad (0.000235) \qquad (0.00000000196)$$

$$R^2 = 0.915$$

Policy and Incentive Programs

Policy and incentive programs are evaluated in the model framework to the extent possible. Historic federal, state and utility policy programs, such as building and appliance energy efficiency standards, and tax incentives that have affected California residential consumers were collected and reflected in the model. Historic and current federal energy efficiency standards and associated implementation schedules were collected from the Department of Energy website.[36] California state energy efficiency standards for residential buildings were collected from the California Energy Commission website.[37] Historic and current utility energy efficiency programs were collected from the utility websites and from a searchable data portal, CALMAC, established by the CPUC and CEC.[38]

4.2 Household Technology Choices and Technology Characteristics

Clothes Washer Choices

In the PG&E subsample, 88.6 percent of the households have top-loading washers and 11.4 percent have front-loading washers. The front-loading washers are predominantly newer. About 88 percent of them were purchased within three years

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[36] These are accessible via http://www.eere.energy.gov/consumer/your_home/appliances/index.cfm/mytopic=10050 (last accessed on July 10, 2008).

[37] Historic standards can be accessed via http://www.energy.ca.gov/title24/standards_archive/.

[38] CALMAC publications can be accessed via http://www.calmac.org/search.asp.

after 2000, compared to only 43 percent of top-loading washers purchased within the same period.[39]

Front-loading washers are distinctively more energy efficient, consuming about 40 percent less water per load and more than 60 percent less energy than top-loading clothes washers (Natural Resources Canada 2005). According to a household appliance energy efficiency survey conducted in California, in 2000 the average energy efficiency level of existing front-loading washer stock was 3.95 measured by energy factor (EF) whereas the average energy efficiency of existing top-loading washer stock was 1.26 EF (RLW Analytics 2000). By 2005 the average energy efficiency level of existing front-loading washer stock in California rose to 4.13 EF and the average energy efficiency of existing top-loading washer stock declined to 1.22 EF (RLW Analytics 2005).

With higher efficiency performance, front-loading washers come with higher upfront costs due to more electronics, more complicated motors, control and suspension systems, and weight (DOE 2004).[40] Figure 3 below presents average capital costs of the two alternatives used in the analysis. Cost difference between a top-load washer and a front-load washer is in the range of $322 and $374 in real price (2000$) between 1996 and 2004, consistent with industry sources that cite around $350 of price difference.

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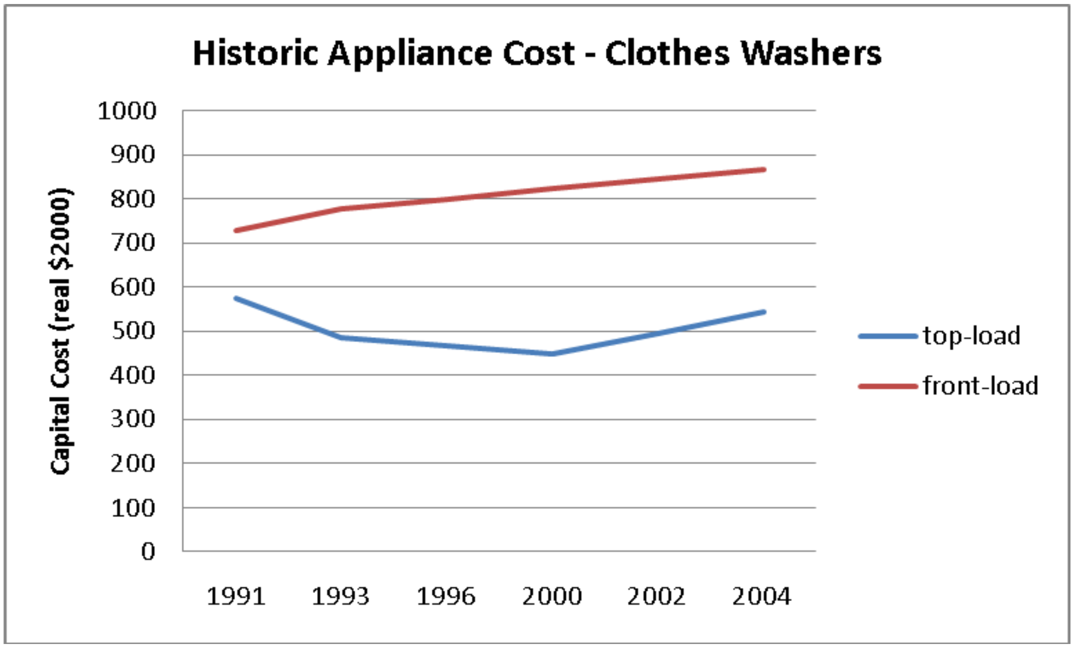
[39] Before 1997, the energy-efficient front-loading clothes washers available were mostly European models that were considered small and expensive by American standards. Maytag and Frigidaire both introduced energy-efficient washers in 1997, which changed the market substantially. By 2001, there were 18 different manufacturers and 62 different models available on the market (Pacific Energy Associates, 2001).

[40] Source: memo, "U.S. Department of Energy ENERGY STAR® Criteria for Clothes Washer Meeting," August 31, 2004.

Figure 3. Historic clothes washer capital costs used in the analysis



Source: Appliance cost estimates are based on several appliance and energy efficiency measure cost studies in California (XENERGY 1992, XENERGY 1994, DEER 2001, and DEER 2005).

Clothes washers are regulated under federal energy efficiency standards. The Energy Policy and Conservation Act of 1975 directed the Department of Energy to establish minimum energy efficiency standards for various home appliances, including clothes washers. The first federal clothes washer standard and test procedure were adopted in 1994, which requires a minimum energy factor of 1.18, in terms of cubic feet per kilowatt-hour per cycle (cf^3/kWh/cycle), for standard top-loading clothes washers of 1.6 cubic feet or greater capacity.[41] The 1994 standard did not specify a minimum energy efficiency level for front-loading washers except that it required them to have an unheated rinse option.

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[41] Clothes washer efficiency ratings are based on estimated annual energy use (kWh) under "typical conditions" and an average of 392 loads, or cycles, per year (source: Federal Registry, Vol. 66, No. 9, January 12, 2001, pp 3315).

The standard was updated on January 1, 2004 and the required minimum energy efficiency level was revised to 1.04 modified energy factor (MEF) or higher. The revised standard applies to both front-loading washers and top-loading washers of 1.6 cubic feet or greater capacity. The standard was changed from "energy factor" to "modified energy factor" to account for the amount of dryer energy used to remove the remaining moisture content in washed items.[42] On January 1, 2007, the standards were revised to 1.26 MEF. The State of California has implemented the state standards for clothes washers following the federal schedule and stringency levels.

Minimum energy efficiency standards change the menu of products offered in the market (Newell et al. 1994). Voluntary, information-based labeling programs, such as Energy Star, convey energy performance information of a product to consumers. The Energy Policy Act of 1992 directs the U.S. Environmental Protection Agency and the U.S. Department of Energy to establish voluntary Energy Star programs that promote products more efficient than minimum federal or state codes.[43] In principle, the top 25 percent energy efficient products in the market are deemed eligible for the label. The first Energy Star criteria for residential clothes washers were established in 1997 which require a minimum energy factor of 2.5 compared to the federal minimum standard of 1.18 EF. By 2001, the Energy Star criteria changed to 1.26 MEF. Energy Star is moving toward more stringent criteria of a minimum MEF of 2.0 and a maximum water factor of 6.0. If implemented, it would disqualify every Energy Star-qualified top-loading model currently on the market and

[42] Numerical measures of energy efficiency expressed in "energy factor" and "modified energy factor" cannot be directly compared.

[43] Source: "ENERGY STAR Criteria for Clothes Washers: Overview of ENERGY STAR Criteria Setting Process and History of Clothes Washer Criteria." A power point presentation by Richard H. Karney of the U.S. Department of Energy, August 31, 2004.

effectively force any consumer who desires an Energy Star qualified washer to purchase a front-loading unit.[44]

Utilities in California have implemented incentive programs to encourage adoption of energy-efficient clothes washers. The most popular incentive programs are rebates. Rebates are only available for front-loading high efficiency washers (Itron 2009). PG&E offers a $35 rebate for selected clothes washers with a minimum MEF of 2.0 and a maximum WF of 6.0 and a $75 rebate for clothes washers with a minimum MEF of 2.2 and maximum WF of 4.5. The San Diego County Water Authority provides financial incentives to customers who purchase a high efficiency washer with a maximum WF of 5.0. The program is co-funded by SDG&E and offers a rebate of up to $185.

Water Heater Choices

Among households served by PG&E in the RASS dataset, 90.5 percent reported to have a primary water heater. Among those households with primary water heaters, 92.6 percent have natural gas tank (storage) systems, 4.6 percent have electric tank (storage) systems, 1.8 percent have whole-house gas tankless systems, and 0.4 percent have solar systems with or without backup of a gas or electric tank. Other water heater choices include propane tank systems (0.2%) and electric heat pump (0.2%).[45]

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[44] Source: "Market Impact Analysis of Potential Changes to the ENERGY STAR® Criteria for Clothes Washers", January 9, 2008.

[45] In addition, 3.6 percent of the households reported to have a second water heater system of known type. The most frequently reported secondary water heaters are electric-based systems (e.g, electric tanks, heat pumps, point-of-use tankless systems, and whole house tankless systems) and the next group is solar-based systems. Since households choosing an additional water heater are a small fraction of the sample, the analysis focuses on the choices of primary water heaters.

The water heater technology choice analysis only considers three natural gas- and electric-fueled technology alternatives due to the availability of historic capital cost data: natural gas tank system, natural gas tankless system, and electric tank system.[46] The choice frequencies of these three alternatives are 95.6 percent, 1.3 percent, and 3.1 percent, respectively. These three alternatives represent over 99% of household choices of the primary water heating system.[47]

According to household appliance energy efficiency surveys conducted in 2000 and 2005, majority of water heaters in California were 40 gallon tank systems (RLW Analytics 2000 and 2005). The average energy efficiency, measured by energy factor (EF), was 0.57-058 for gas tank systems and 0.89-0.90 for electric tank systems. Gas tankless water heaters have significantly higher energy efficiency than gas tank systems, with average energy factors in the range of 0.80-0.82 during the study years. Studies show that energy efficiency for tank water heating systems had changed modestly in the last few decades. In 1990, the shipment-weighted energy factor was 0.55 for gas tank water heaters and 0.88 for electric tank water heaters (Hanford et al. 1994 and Wenzel et al. 1997). Therefore, using average energy efficiency levels from the recent surveys will unlikely introduce significant measurement errors in the choice analysis.

With higher energy efficiency, the average purchase price of gas tankless systems is significantly higher than that of the gas tank systems, by about $500-800

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[46] Analysis of household choices of solar heating systems is of interest given the energy and environmental benefits of solar energy. However, conversations with industry experts suggest that despite generous federal tax credits and various state and utility incentive programs, a mature solar hot water heater market does not yet exist in California or elsewhere in the U.S.

[47] A formal test cannot reject the null hypothesis of independence of irrelevant alternatives (IIA) of the smaller set of alternatives included in the analysis, suggesting that omitting choice alternatives will unlikely alter the results significantly.

even though the price gap has reduced over time.[48] The average installation cost of gas tank water heaters is about \$150 higher than the price for electric tank water heaters. The average annual operating cost of tankless systems is about \$100 lower than that of gas tank systems and about \$200 lower than that of electric tank systems.[49] The rates of changes in real water heating equipment manufacturing costs in the Producer Price Index are used to calculate the equipment costs of water heater alternatives. According to the Producer Price Index, the real value of electric water heater manufacturing had decreased by 1 percent per year between 1990 and 2003. The real value of natural gas water heater manufacturing had increased by 1 percent per year between 1990 and 2003.

The first federal water heater energy efficiency standards were implemented in 1990 based on the size of water heater systems. The 1990 minimum standard was 0.54 EF for 40-gallon gas tank water heaters and 0.90 EF for 40-gallon electric water heaters. The standards did not change till 2004 when the equivalent standards tightened to 0.59 EF for gas tank water heaters and 0.92 EF for electric tank water heaters. Energy Star criteria did not include water heaters until 2008.[50] The water heater choice analysis covers the period from 1990 to 2003. Therefore, the effects of water heater energy efficiency standards and Energy Star criteria cannot be identified.

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48 The higher cost of tankless products is partially offset by the federal Energy Incentives Act of 2005, which provides tax credits of up to \$300 per unit for gas water heaters with EF$\geq$0.80.

49 Source: American Council for Energy-Efficient Economy (http://www.aceee.org/consumer/water-heating).

50 Press release "U.S. Department of Energy Implements Criteria for ENERGY STAR® Water Heaters", U.S. Department of Energy, released on April 1, 2008.

The federal Energy Incentives Act of 2005 provides tax credits of up to $300 per unit for gas water heaters with energy factor greater than 0.80, which partially offset the higher cost of tankless products.

Space Heating System Choices

Of the 7,295 PG&E households in the subsample, 7,053 households report a primary space heating device. The primary space heating systems are predominantly (90 percent) natural gas-based systems. Electricity-based systems account for about 8 percent of primary space heaters. A small percentage of primary space heaters (2 percent) are fueled by bottled gas, solar and wood. The PG&E subsample used in the empirical estimation contains three electric- and natural gas-consuming space heating technology choices: natural gas central forced-air systems (96.3 percent), natural-gas-based radiator systems (0.4 percent), and electric central forced-air systems (3.3 percent).[51] These three alternatives represent 74 percent of space heating system choices among PG&E households.[52]

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[51] Nine electricity- or natural gas-based space heating technology choice alternatives are reported in the RASS data and are included in the short-run fuel demand analysis in the subsample. However, only five choice alternatives are included in the long-run technology choice analysis, of which three are natural gas-based systems (gas central forced-air furnaces, gas floor/wall heaters and natural gas radiator systems) and two are electricity-based systems (electric resistance systems and electric central forced-air furnaces). These five alternatives represent 95 percent of choices by PG&E households. The other four, of which three are electricity-based systems (central heat pumps, through-the-wall heat pumps and portable heaters) and one is a natural gas-based system (other natural gas system type), are excluded in the analysis due to the lack of reliable capital cost data. These four alternatives represent 3.3 percent of choices by PG&E households. When the observations with missing values for income, fuel consumption and household variables are removed (as explained in footnote 18), only the three choice situations described above remain. Because the excluded observations are removed for reasons unlikely to be related to space heating system choice, their exclusion likely does not cause any serious bias in the estimation results.

[52] About 35 percent of the PG&E households with a primary space heating system also reported to have a secondary space heating device. The secondary heaters are predominantly wood-fired stoves or

The energy efficiency of space heating equipment is expressed as annual fuel utilization efficiency (AFUE), a percentage of energy output per energy input. Electric heating equipment is usually assumed to be 100 percent efficient (RLW Analytics 2005). Based on appliance energy efficiency surveys conducted in California, the average energy efficiency of gas-based central forced-air heating equipment is 0.78 and the average energy efficiency of gas radiator systems is 0.80 (RLW Analytics 2000). In addition to the heating units, the three system choice alternatives also involve heating distribution systems. According to Hanford et al. (1994) and Wenzel et al. (1997), the average distribution efficiency of central forced-air systems is estimated to be 0.7, and the hydronic radiator system is estimated to have an average distribution efficiency of 0.9.

The average installation cost of a gas central forced-air heater is about $150-200 (2000$) higher than an electric central forced-air heater. The average installation cost of a radiator system is significantly higher, about $1500 (2000$) higher than a gas central forced-air heater. In addition, the distribution system of a hydronic radiator system costs about $1.22 more, on a per square foot basis, than the distribution system of a central forced-air system. The rates of change in real space heating equipment manufacturing costs in the Producer Price Index are used to calculate the equipment costs of space heating alternatives over time. The Consumer Price Index is used to calculate changes in installation costs.

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fireplaces (45 percent) for which no data on wood consumption was available, followed by electric-based heaters (38 percent) and natural gas-based systems (12 percent). The remaining 5 percent of secondary heaters are bottled gas and solar-based systems.

Effective in 1990, the U.S. Department of Energy established minimum energy performance standards for space heating furnaces and boilers. The standards require that fossil-fueled warm-air furnaces must meet a minimum energy efficiency of 0.78 AFUE and fossil-fueled boilers must meet a minimum energy efficiency of 0.80 AFUE.[53]

Energy-efficient heating furnaces and boilers are subject to financial incentives. For example, currently, the federal government offers a tax credit of $150for high-efficiency gas or oil-fired furnace with energy efficiency equal to or above 0.95. The California state government offers rebates of up to $4,000 for system upgrades including furnaces. PG&E offers $150-300 for energy-efficient central natural gas heating units.[54]

Clothes Dryer Choices

In the PG&E subsample, 40.9 percent of households have gas-fired clothes dryers and 59.1 percent have electric-fired dryers. The energy performance of the two types of clothes dryers is fairly similar. According to RLW Analytics (RLW Analytics 2000), in California the average energy efficiency of gas-fired clothes dryers is 2.67 measured by the energy factor (EF) and the average energy efficiency of electric-fired clothes dryers is 3.01. As a result, clothes dryers are not included in the U.S. Department of Energy's minimum energy efficiency standards for home appliances. The technology costs of the two clothes dryer alternatives are also fairly similar. According to California technology cost data sources, on average, gas-fired clothes dryers cost about $30 more than electric-fired clothes dryers.

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[53] Source: http://www.energysavers.gov/your_home/space_heating_cooling/index.cfm/mytopic=12530

[54] Source: http://www.dsireusa.org

4.3 Conclusions

This chapter describes the available data and California household energy use and technology choice characteristics. Notwithstanding a few weaknesses, this unique dataset provides rich details for meaningful empirical investigation of household energy use decisions pertaining to short-run energy demand and long-run technology choices formulated in Chapter 3.

Chapter 5: Estimation Strategy

The discrete/continuous model developed in Chapter 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. The maximum likelihood (ML) method is suitable to obtain consistent and asymptotically efficient estimators for the set of parameters. Estimation by ML can be implemented using two different approaches: limited information maximum likelihood (LIML) and full information maximum likelihood (FIML).

In principle, all the unknown parameters in the system of equations can be estimated simultaneously using FIML. With LIML, equations are estimated individually or in groups. One possible approach in this case is to use a two-step procedure that first maximizes the likelihood function of the continuous demand equations, and then maximizes the conditional log-likelihood functions of the discrete choice equations using parametric estimates from the continuous demand model.

If the specification of all equations is correct, then LIML and FIML both yield the same results asymptotically because both methods produce consistent estimators, although FIML estimation is asymptotically efficient. If some part of the model is incorrectly specified, however, then specification errors propagate through the system with FIML estimation, possibly affecting all equations, and possibly making LIML the more reliable of the two approaches, i.e., the adverse implications of a specification error are confined to the particular equation in which specification error is present.

Beyond the preference for estimation properties of LIML when some specification error may exist in any particular equation, FIML is more complicated to implement in practice in the case of discrete/continuous modeling. Greene (2008) notes that it can be very complicated to derive the joint distribution since the continuous and discrete variables come from different kinds of populations.[55] In some cases, it is unclear theoretically what the joint distribution might be (Murphy and Topel 2002).

Maximizing the joint log-likelihood can also be computationally costly or infeasible particularly when a large number of coefficients are involved (Blanchard 1983). In addition, the normal equations may have multiple roots so that convergence to the global maximum is not always guaranteed (Hanemann 1984). This is perhaps why the two-step approach is more widely applied to evaluate discrete/continuous models (e.g., Hausman 1979, Dubin and McFadden 1984, Vaage 2000, Newell and Pizer 2005, and Mansure et al. 2005).[56]

The empirical estimation of the discrete/continuous model in this study also adopts a two-step LIML approach. 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. In this case, when

[55] This is due to the fact that not all households make appliance choice decisions in every period as energy consumption.

[56] Kline (1988) developed a model of household energy demand and technology choice for energy service (space heating) that jointly considers energy service production and consumption. Space heating production cost, expenditure share and demand equations are derived and estimated simultaneously using a 3SLS procedure.

disturbances are uncorrelated between the continuous and discrete components, the LIML approach becomes asymptotically efficient aside from imposing common parameter constraints. Furthermore, 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 conditioned on the current appliance stock 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 technology choice equations are evaluated separately using the method of ML to provide a benchmark 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.

Based on these results, estimates of the short-run demand system and the long-run technology choices are compared to test applicability of structural parameter constraints implied by the underlying utility maximization model. Thus, a second step is implemented by imposing parametric constraints on technology choices implied by parameters estimated in the short-run demand analysis in step one. The remaining vector of parameters is estimated using the ML method.

The rationale for imposing the first-step estimates in the second step is as follows. The parameters estimated in the first step (appliance use) appear only in highly aggregated form in the second-step (appliance choice) model as is evident in equation (34). Thus, the second-step estimation provides no information regarding the individual parameters estimated in the first-step given aside from these aggregates. Thus, even if a fully efficient estimation method incorporating parameter constraints were feasible in practice, the impact of second-step information on the estimates of parameters of the first-step model would likely be minor. Thus, I proceed by testing applicability of the first-step estimates to the second-step model as a means of model validation. The asymptotic covariance matrix derived in step two is corrected based on the method developed by Murphy and Topel (2002). The following section details the empirical procedure of the LIML estimation.

5.1 Step one: Estimating the Short-run Demand System

The system of short-run demand functions consist of three nonlinear budget share equations for the numeraire, electricity, and natural gas. For household *n*, equations (20) and (21) are rewritten as follows:

$$\omega_{n,0} = h_0(\mathrm{X}_n, \beta_d) + \mu_{n0} = \frac{\alpha_0 + 2\sum_{j'=1}^{5}\beta_{0j'}\ln r_{ij'} - 2\ln y^* \sum_{j'=0}^{5}\beta_{0j'} + \Gamma_0\theta_n}{1 + 2\sum_{j''=0}^{5}\sum_{j'=1}^{5}\beta_{j''j'}\ln r_{ij'} + \sum_{j''=0}^{5}\Gamma_{j''}\theta_n} + \mu_{n0},$$

$$
\begin{aligned}
\omega_{n,e} &= h_e(\mathrm{X}_n, \beta_d) + \mu_{ne} \\
&= \frac{\sum_{j=1}^{5} \Psi(x_{n,e(j),j} > 0)[\alpha_j + 2\sum_{j'=1}^{5} \beta_{jj'} \ln r_{ij'} - 2\ln y_n^* \sum_{j'=0}^{5} \beta_{jj'} + \Gamma_j \theta_n]}{1 + 2\sum_{j''=0}^{5}\sum_{j'=1}^{5} \beta_{j''j'} \ln r_{ij'} + \sum_{j''=0}^{5} \Gamma_{j''}\theta_n} + \mu_{ne},
\end{aligned} \tag{52}
$$

$$
\begin{aligned}
\omega_{n,g} &= h_g(\mathrm{X}_n, \beta_d) + \mu_{ng} \\
&= \frac{\sum_{j=1}^{5} \Psi(x_{n,g(j),j} > 0)[\alpha_j + 2\sum_{j'=1}^{5} \beta_{jj'} \ln r_{ij'} - 2\ln y_n^* \sum_{j'=0}^{5} \beta_{jj'} + \Gamma_j \theta_n]}{1 + 2\sum_{j''=0}^{5}\sum_{j'=1}^{5} \beta_{j''j'} \ln r_{ij'} + \sum_{j''=0}^{5} \Gamma_{j''}\theta_n} + \mu_{ng},
\end{aligned}
$$

where $\omega_{n,0}$ is household *n*'s budget share for the numeraire good, $\omega_{n,e}$ is budget share of electricity consumption, $\omega_{n,g}$ is budget share of natural gas consumption, $h.(\mathrm{X}_n, \beta_d)$ denotes the nonstochastic, nonlinear portion of the demand functions, X_n is the vector of exogenous variables, β_d is the vector of coefficients of interest, α_j is constant associated with the *j*th energy service demand, θ_j is household variable that influences demand for the *j*th energy service,[57] j = 0,..,5, where

j = 0 is the numeraire good,

j = 1 is clothes washing (*cw*),

j = 2 is water heating (*wh*),

j = 3 is clothes drying (*cd*),

j = 4 is space heating (*sph*), and

j = 5 is an index of all other energy services (*oth*).

All other notation is the same as defined in Chapter 3.

[57] Inclusion of household variables is guided by the significance of specification tests.

The column vector of the system of short-run budget share equations for the sample is

(53) $$\omega = \begin{bmatrix} \omega_{1.} \\ . \\ . \\ . \\ \omega_{N.} \end{bmatrix} = \begin{bmatrix} h.(X_1, \beta_d) + \mu_{1.} \\ . \\ . \\ . \\ h.(X_N, \beta_d) + \mu_{N.} \end{bmatrix}.$$

And the column vector of disturbances of the system is defined as

(54) $$\mu = \begin{bmatrix} \mu_{1.} \\ . \\ . \\ . \\ \mu_{N.} \end{bmatrix},$$

where μ has a multivariate normal distribution with mean vector zero and covariance matrix Σ. The adding-up condition implies that Σ is singular and nondiagonal. Therefore, one of the demand equations is dropped from the system to obtain identification. In this case, the share equation for electricity, ω_e, is dropped and the remaining two share equations for the numeraire (ω_0) and natural gas (ω_g) consumption are estimated. This specification fully utilizes constraints for the translog system and estimates all parameters of the system directly, which provides important identifying structure to the estimation.[58]

Seemingly unrelated regression (SUR) is appropriate for estimation of linear systems when each equation includes only one endogenous variable. The underlying

[58] 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.

theory for nonlinear estimation of systems of equations is similar to that for linear systems (Greene 2008). Specifically, the generalized nonlinear least-squares system estimator is defined as[59]

$$(55)\qquad \hat{\beta}_d \equiv \arg\min_{\beta_d} \sum_{n=1}^{N} \{\omega_{n.} - h.(\mathrm{X}_n, \beta_d)\}\Sigma^{-1}\{\omega_{n.} - h.(\mathrm{X}_n, \beta_d)\}'.$$

An estimate of Σ is required to make the estimator feasible. The iterated procedure first sets $\hat{\Sigma} = I$, which results in an inefficient but consistent estimator $\hat{\beta}_{d,nls}$ of β_d. Thus, residuals are

$$(56)\qquad \hat{u}_{n.} = \omega_{n.} - h.(X_n, \hat{\beta}_{d,nls}),$$

and the covariance matrix is estimated by

$$(57)\qquad \hat{\hat{\Sigma}} = \frac{1}{N}\sum_{n=1}^{N} \hat{u}_{n.}^{'}\hat{u}_{n.}.$$

A new estimate $\hat{\beta}_d$ is then obtained and the procedure is iterated until the relative change in $\hat{\beta}_d$ and $\hat{\Sigma}$ is less than specified tolerance values. The variance-covariance matrix of $\hat{\beta}_d$ is

$$(58)\qquad \hat{\mathrm{V}}_d = \sum_{n=1}^{N} (\mathrm{X}_n^{'}\hat{\hat{\Sigma}}^{-1}\mathrm{X}_n)^{-1},$$

and the robust covariance matrix estimator, $\hat{V}_{d,r}$, is

$$(59)\qquad \hat{\mathrm{V}}_{d,r} = \left(\sum_{n=1}^{N} \mathrm{X}_n^{'}\hat{\hat{\Sigma}}^{-1}\mathrm{X}_n\right)^{-1} \sum_{n=1}^{N} \mathrm{X}_n^{'}\hat{\hat{\Sigma}}^{-1}\hat{u}_{n.}^{'}\hat{u}_{n.}\hat{\hat{\Sigma}}^{-1}\mathrm{X}_n \left(\sum_{n=1}^{N} \mathrm{X}_n^{'}\hat{\hat{\Sigma}}^{-1}\mathrm{X}_n\right)^{-1}.$$

[59] The iterated feasible generalized nonlinear least square procedure outlined here is based on –nlsur-procedure for estimation of nonlinear systems of equations developed by Stata Corp.

The concentrated log-likelihood function for the two equations of N households is

$$\text{(60)} \qquad \ln L(\beta_d) = \sum_{n=1}^{N} \ln f_{n,d} = -\frac{N}{2}\{2(1+\ln 2\pi) + \ln|\hat{\Sigma}|\}.$$

Iterated FGNLS yields a consistent maximum likelihood estimator $\hat{\beta}_d$ of β_d, and the associated robust covariance matrix $\hat{V}_{d,r}$.

5.2 Step Two: Estimating Energy Technology Choice Equations

Four separate energy technology choice equations are then estimated, representing clothes washing, water heating, space heating and clothes drying. Technology choice sets consist of two choice alternatives for clothes washing (*cw*) and clothes drying (*cd*). Thus a binary logit choice model is appropriate. For water heating (*wh*) and space heating (*sph*), three choice alternatives are involved in each case so a multinomial logit choice model is appropriate. The binary choice model is a special case of the multinomial logit choice model. The general procedure is thus illustrated for the multinomial logit choice model.

The multinomial choice probability that alternative i is chosen by household n from choice set I_j for energy use j is represented as

$$\text{(61)} \qquad P_{ij,n} = \frac{\exp(-\ln y_{ij} A_0 + \ln r_{ij} A_j + \mathrm{H}_{ij}\theta_{j,n})}{\sum_{i' \in I_j} \exp(-\ln y_{i'j} A_0 + \ln r_{i'j} A_j + \mathrm{H}_{i'j}\theta_{j,n})},$$

where j ={1,2,3, and 4} as defined in equation (52), and $\theta_{j,n}$ is the vector of household variables included in the choice equation for energy use j. The model is estimated using the method of maximum likelihood (ML) that maximizes the likelihood function,

(62) $$L(\beta_{c,j}) = \prod_{n=1}^{N} \ln f_{n,j} = \prod_{n=1}^{N} \prod_{i \in I_j} (P_{ij,n})^{d_{ij,n}},$$

where $\beta_{c,j}$ is the vector of multinomial choice parameters for energy use *j*, and $d_{ij,n}$ is an indicator variable equal to one if technology alternative *i* is chosen for energy use *j* by household *n* and equal to zero otherwise. Equation (62) is transformed into a log-likelihood function for ML estimation,

(63) $$LL(\beta_{c,j}) = \sum_{n=1}^{N} \ln f_{n,j} = \sum_{n=1}^{N} \sum_{i \in I_j} d_{ij,n} \ln P_{ij,n}.$$

The ML estimators of A_0 and A_j from equation (63) are compared with the implied parametric estimates derived from the short-run demand analysis in step one. With the exception of the clothes washer choice equation, parametric estimates of A_0 and A_j are statistically equivalent between the short-run demand model and the three equations of the long-run technology choice model for water heating, space heating and clothes drying. This provides considerable validation of the underlying translog indirect utility specification.

A second step of constrained estimation is then implemented by re-estimating equation (61) by imposing parametric constraints on parameters A_0 and A_j implied by parameter estimates from the short-run demand model estimated in step one,

(64) $$P_{ij,n} = \frac{\exp(-\ln y_{ij} \hat{A}_{0,n} + \ln r_{ij} \hat{A}_{j,n} + \mathrm{H}_{ij} \theta_{j,n})}{\sum_{i' \in I_j} \exp(-\ln y_{i'j} \hat{A}_{0,n} + \ln r_{i'j} \hat{A}_{j.n} + \mathrm{H}_{i'j} \theta_{j,n})},$$

where $\hat{A}_{0,n} \equiv 1 + 2 \sum_{j''=0}^{5} \sum_{j'=1}^{5} \hat{\beta}_{j''j'} \ln r_{j''} + \sum_{j''=0}^{5} \hat{\Gamma}_{j''} \theta_n$ and $\hat{A}_{j,n} \equiv \hat{\alpha}_j + 2 \sum_{j'=1}^{5} \hat{\beta}_{jj'} \ln r_{j'} + \hat{\Gamma}_j \theta_n$ are the maximum likelihood estimators of common parameters A_0 and A_j obtained from step one. The vector of the remaining parameters, $\beta_{c,j}$, is estimated, producing the ML estimator of the parameters $\hat{\beta}_{c,j}$ and the associated ML estimator of the covariance matrix of the parameters, $\hat{V}_{c,j}$.

However, $\hat{V}_{c,j}$ is not the appropriate estimator of the asymptotic covariance matrix of $\hat{\beta}_{c,j}$ without a correction that accounts for the covariance matrix estimator $\hat{V}_{d,r}$ of $\hat{\beta}_d$. Following Murphy and Topel (2002), the following formula is used to obtain the asymptotic covariance matrix of $\hat{\beta}_{c,j}$ [60]

(65) $$\hat{V}^*_{c,j} = \frac{1}{N}\left\{\hat{V}_{c,j} + \hat{V}_{c,j}\left[\hat{C}_j\hat{V}_{d,r}\hat{C}_j' - \hat{R}_j\hat{V}_{d,r}\hat{C}_j' - \hat{C}_j\hat{V}_{d,r}\hat{R}_j'\right]\hat{V}_{c,j}\right\},$$

where

$$\hat{C}_j = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\partial \ln f_{n,j}}{\partial \hat{\beta}_{c,j}}\right)\left(\frac{\partial \ln f_{n,j}}{\partial \hat{\beta}_d'}\right),$$

$$\hat{R}_j = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\partial \ln f_{n,j}}{\partial \hat{\beta}_{c,j}}\right)\left(\frac{\partial \ln f_{n,d}}{\partial \hat{\beta}_d'}\right).$$

5.3 Conclusions

In the context of the discrete/continuous model developed in this study, empirical application of the FIML approach has proven to be computationally cumbersome and problematic. The main challenges stem from (i) the nonlinearity of the system of short-run demand equations with a sizable number of coefficients, and

[60] Murphy and Topel (2002) showed that a two-step approach without correcting for standard errors would vastly exaggerate the precision of the second step estimates. One of their examples also shows that standard errors from the two-step procedure are similar to those obtained from FIML estimation.

(ii) multicollinearity and singularities that result from demand aggregation of individual energy services to match observed household fuel consumption data. However, as shown in the subsequent chapter, the block recursive system approach devised in this chapter proves to have strong statistical properties for three out of four cases in which statistical tests do not invalidate parametric restrictions across blocks of equations representing energy use and appliance choice.

Chapter 6: Estimation Results

This chapter presents the results of the empirical analysis of household energy consumption and technology choices using the model developed in Chapter 3. Section 6.1 summarizes the results of the short-run demand analysis; Section 6.2 presents results of technology choice analysis for clothes washing, water heating, space heating and clothes drying, respectively; Section 6.3 synthesizes the findings.

6.1 Short-Run Energy Demand

The system of short-run budget share equations (52) is estimated by dropping the electricity share equation. Among different combinations of budget share equations and specifications, the system of budget share equations for the numeraire and natural gas yields the highest log likelihood value. However, any combination of two equations should yield the same asymptotic results because the specification fully utilizes constraints for the translog system and estimates all parameters of the system.

Table 3 below presents the estimation results of four specifications using the iterated feasible generalized nonlinear least squares (FGNLS) procedure. Model 1a includes only price variables $\ln r_j$, the income variable $\ln y^*$, and demand interaction terms. Inclusion of demand interaction terms is guided by the features of energy service demands and significance of statistical tests. Four demand interaction terms are introduced: one between clothes washing and clothes drying, one between clothes washing and water heating, one between water heating and the "other" energy use category, and one between space heating and the "other" energy use category.[61]

Model 1b builds on Model 1a and adds household-demand interaction terms. Inclusion of household and demand interaction terms is based on similar principles. Four household and demand interaction terms are introduced, one between household size and water heating, one between building square footage and space heating, one between heating degree days and space heating, and one between the age of the house and the "other" energy use category.[62]

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., $\ln \phi_{i(cw)} = \gamma_1 \text{Standard}_i + \gamma_2 \text{EnergyStar}_i + e_{i(cw)}$, $E(e_{i(cw)}) = 0$, where $\ln r_{cw} = \ln(p_{l(cw)} / \varphi_{i(cw)}) = \ln p_{l(cw)} - \ln \varphi_{i(cw)}$. Average energy efficiency indicators

[61] Demand interaction between water heating the and "other" energy use category captures interactions between water heating and dishwashing; demand interaction between space heating and the "other" energy use category captures potential demand interaction between primary space heaters and secondary space heaters as 35 percent of households have a secondary space heating device. Secondary heating systems are not modeled explicitly due to the lack of technical specifics and are grouped in the "other" energy use category.

[62] Inclusion of other demographic interaction terms, such as with ownership, was tested. Interacting ownership with various energy services is not statistically significant in explaining the short-run demand for fuel.

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 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 some other home appliances, such as water heaters, has been modest during the same 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 a linear function of the age of water heater (“age_wh”) and an error term, i.e., $\ln \varphi_{i(wh)} = \lambda_1 \text{age\_wh}_i + e_{i(wh)}, E(e_{i(wh)}) = 0,$ The log likelihood ratio test between Model 1d 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.[63]

Model 1d is used as the main specification for subsequent discussions and the parametric estimates imposed in the second stage estimation of technology choice.[64]

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[63] 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.

[64] In the PG&E subsample, about 35.5 percent of households reported having a secondary heater, such as a portable electric heater, a fireplace, or a gas-fired floor or wall heater. The specifications reported

Table 3. 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*** (149.241)	0.92969*** (166.703)	0.81503*** (84.181)	0.80212*** (65.717)
a_1	intercept-*cw*	-0.03500* (-2.385)	-0.03577*** (-4.121)	0.06756*** (5.456)	0.10859*** (6.854)
a_2	intercept-*wh*	0.06316 (1.279)	0.02998 (0.893)	-0.02994 (-0.857)	-0.01002 (-0.226)
a_3	intercept-*cd*	-0.03620** (-3.101)	0.03689*** (4.138)	0.03209*** (3.774)	-0.00099 (-0.118)
a_4	intercept-*sph*	-0.03062 (-0.882)	0.02915 (1.214)	-0.02322 (-0.925)	-0.01592 (-0.619)
β_{01}	cross demand *numeraire-cw*	-0.01047*** (-8.144)	0.01596*** (14.497)	0.01142*** (7.430)	0.01094*** (6.680)
β_{02}	cross demand *numeraire-wh*	0.00265* (2.447)	0.00341* (2.498)	-0.00265 (-1.401)	-0.00222 (-1.226)
β_{03}	cross demand *numeraire-cd*	0.00158* (2.425)	0.00194*** (3.736)	0.00116 (1.764)	-0.00180** (-3.114)
β_{04}	cross demand *numeraire-sph*	-0.00072 (-0.667)	0.00643*** (4.798)	0.00271 (1.731)	0.00318* (2.022)
β_{05}	cross demand *numeraire-oth*	0.04241*** (32.445)	0.02293*** (12.234)	0.03754*** (14.173)	0.03999*** (14.105)
β_{11}	own demand *cw*	0.02324*** (7.540)	0.02383*** (30.328)	0.04820*** (15.794)	0.05129*** (15.795)
β_{12}	cross demand *cw-wh*	-0.00609*** (-6.231)	0.00056*** (3.471)	-0.00208 (-1.127)	-0.0023 (-1.156)

(Continued on next page)

in Table 3 explicitly model energy demand of only the primary heating device in the "*sph*" category and group energy demand of secondary heaters in the "other" category. A sensitivity test was performed by adding a set of secondary heater dummies in the space heating demand expression to see if demand interactions between the primary and the secondary heaters may be an issue. Results show that the secondary heater interaction terms are not statistically significant. This result is reasonable as less than 10 percent of the households in the subsample use their secondary heaters often.

β_{13}	cross demand *cw-cd*	0.00042 (1.395)	0.00046** (2.749)	-0.00252** (-2.769)	-0.00085 (-0.719)
β_{22}	own demand *wh*	0.09579 (1.630)	0.01308 (0.352)	-0.01877 (-0.437)	0.00505 (0.147)
β_{25}	cross demand *wh-oth*	-0.09331 (-1.582)	-0.01231 (-0.331)	0.01938 (0.450)	-0.00501 (-0.147)
β_{33}	own demand *cd*	-0.00422** (-3.250)	0.00260*** (3.454)	0.00403*** (3.912)	-0.00057 (-0.344)
β_{44}	own demand *sph*	-0.11814 (-1.877)	-0.02305 (-0.579)	-0.0569 (-1.445)	-0.06193 (-1.559)
β_{45}	cross demand *sph-oth*	0.12151 (1.921)	0.02735 (0.685)	0.05789 (1.468)	0.0642 (1.615)
β_{55}	own demand *oth*	-0.06206 (-0.783)	-0.0249 (-0.496)	-0.07699 (-1.455)	-0.05884 (-1.200)
d_1	*hh_size-wh* interaction		-0.00038*** (-7.049)	-0.00037*** (-6.649)	-0.00038*** (-6.620)
d_2	*sqft–sph* interaction		0.00053*** (4.781)	0.00069*** (6.031)	0.00072*** (6.080)
d_3	*age–oth* interaction		-0.00069*** (-10.822)	-0.00074*** (-11.098)	-0.00075*** (-10.888)
d_4	*hhd–sph* interaction		0.00213*** (10.792)	0.00220*** (10.869)	0.00226*** (10.776)
γ_1	Standard-*cw*			-0.00515 (-0.428)	-0.00521 (-0.430)
γ_2	EnergyStar-*cw*			-0.00647 (-0.640)	-0.00714 (-0.694)
λ_1	technology change-*wh*				0.04578 (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.

The coefficients derived from the estimation are difficult to interpret on their own. Demand elasticities are more revealing. The income elasticities of demand for fuels are

$$(66)\qquad \hat{\varepsilon}_{yl} = \frac{\partial x_l / x_l}{\partial \ln y} = \frac{-2\sum_{j=1}^{5}\Psi(j)\hat{B}_j}{\sum_{j=1}^{5}\Psi(j)[\hat{\alpha}_j * \theta_j + 2\sum_{j'=1}^{5}\hat{\beta}_{jj'}\ln r_{ij'} - 2\ln y_n^*\hat{B}_j]}\ ,$$

where $B_j \equiv \sum_{j'=0}^{5}\beta_{jj'}$, $\Psi(j) \equiv \Psi(x_{n,l(j),j} > 0)$, the β_{jj} are own demand coefficients, and the $\beta_{jj'}$ are cross-demand coefficients, j = 1,…,5. The own price elasticities of demand for fuels are

$$(67)\qquad \hat{\varepsilon}_{pl} = \frac{\partial x_l / x_l}{\partial \ln p_l} = \frac{2\sum_{j=1}^{5}\Psi(j)\sum_{j'=1}^{5}\hat{\beta}_{jj'}}{\sum_{j=1}^{5}\Psi(j)[\hat{\alpha}_j * \theta_j + 2\sum_{j'=1}^{5}\hat{\beta}_{jj'}\ln r_{ij'} - 2\ln y_n^*\hat{B}_j]} - \frac{2\sum_{j=1}^{5}\hat{B}_j}{1 + 2\sum_{j''=0}^{5}\sum_{j'=1}^{5}\hat{\beta}_{j''j'}\ln r_{ij'}}.$$

The estimated income and own price elasticities are presented in Table 4 and 5 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 4. Estimated short-run income elasticities of demand for fuels

Model	Mean	Standard Deviation	Minimum	Maximum
Electricity				
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
Natural Gas				
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 5. Estimated short-run price elasticities of demand for fuels

Model	Mean	Standard Deviation	Minimum	Maximum
Electricity				
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
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

As shown in Table 4, the mean estimates of income elasticity for electricity are positive in all four specifications and less than unity. Model 1c yields the highest average estimate (0.503) and Model 1a has the smallest mean estimates (0.082).

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 5), 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 as they should be. 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.

Obtaining wrong signs for price elasticities for some households while obtaining plausible signs as a mean is quite common with the translog specification. In fact, being able to obtain negative own price elasticities for electricity demand for all households and negative own price elasticities for natural gas demand for 96.7 percent of the households (by Model 1d) is quite exceptional.

Taylor (1975) reviewed the econometric literature on the demand for electricity. Among the U.S. studies he reviewed, the short-run income elasticity estimates ranged from 0.02 to 0.14. All the studies he cited used either state- or city-level data. Using the U.S. state-level energy demand data, Maddala et al. (1997) estimated average short-run income elasticities for electricity ranging from 0.137 to 0.429 and the short-run income elasticities for natural gas ranged from 0.048 to 0.307, depending on the estimation approach used. Using household level expenditure data, Branch (1993) estimated an average income elasticity of 0.23 for electricity. In an analysis of energy demand among British households, Baker et al. (1989) estimated a mean income elasticity of 0.131 for electricity and a mean income elasticity of 0.115 for natural gas.

Thus, the mean income elasticities for electricity demand estimated here are not only consistent with theoretical expectations, but are also roughly in line with previous econometric studies, although on the high end of the range of previous estimates. The mean income elasticities for natural gas estimated here are negative whereas the mean estimates in previous studies are positive. However, the range of estimated income elasticities here is wide enough to include the mean estimates of the previous studies referenced above. The difference in mean elasticities may be due to the relatively high income status of households in the area of California served by PG&E. For example, Baker et al. (1983) noted that the top decile of the income distribution in their study has a small and negative median income elasticity for natural gas demand. Overall, household demands for fuels are found to be fairly inelastic with respect to income in the short run, as is expected given the fixed nature of appliances in the short run.

Taylor (1975) reported short-run price elasticities for electricity in the range of -0.13 and -0.90 among the studies he reviewed. Maddala et al. (1997) reported short-run price elasticity estimates in the range of -0.158 and -0.214 for electricity and -0.092 and -0.177 for natural gas. Examining nonlinear pricing structures, Reiss and White (2005) estimated a mean annual electricity price elasticity of -0.39 for California households. Aside from the Model 1a estimates for electricity demand, the mean estimates of price elasticities for both electricity and natural gas reported here are consistent with estimates in the literature, although the mean electricity price elasticity is on the low end of estimates among other studies.

Reiss and White (1995) reported differences in estimated price elasticities for different income groups among California households finding that lower income households are more responsive to electricity price changes. In my analysis, the estimated income and price elasticities based on Model 1d do not vary significantly across different income groups or between home owners and renters even though the model has the flexibility to represent such relationships.

6.2 Energy Technology Choices

Clothes Washer Choices

The binary logit model of clothes washer choices is estimated using the method of maximum likelihood. Various specifications are tested in the first stage analysis. Table 6 reports the estimation results of four specifications with a robust covariance matrix estimator. 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. The energy efficiency standards implemented during the study period induced changes in the energy efficiency of clothes washers on the market. The Energy Star program was launched in the middle of the study period. These programs likely enhanced consumers' awareness of energy performance of clothes washers.

Model cw1a and Model cw2a 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 according to equation (61). 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 6 presents the results of the constrained estimation as Model cw2b*.

As shown in Table 6, 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. (Recall that *ln_incCW* is the negative of household expenditure minus the annualized capital cost of the clothes washer alternative.) The expected operating cost, derived using average energy efficiency indicators (Model cw1a and Model cw1b), also significantly influences clothes washer choices.

Table 6. Estimated coefficients of the clothes washer choice model

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

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.[65]

The fitted probabilities from the various estimation specifications are compared with the data. Table 7 below presents the predicted probabilities of Model cw1a, Model cw1b, Model cw2a and Model cw2b. Compared with the data in the sample, predicted probabilities also show that the specifications that model consumer perception of energy efficiency as a function of policy variables fit the data much better than using average energy efficiency indicators.

[65] In the specifications reported in Table 6, dummy variables are used to indicate the presence of energy efficiency standards and the Energy Star program. Numerical values of the clothes washer energy efficiency standards and Energy Star criteria were also tested. A potential problem with this specification is the change of efficiency standards from using the "energy factor" to use of the "modified energy factor" during the study period. The two measures are not comparable. Regression results using the numerical values show that energy efficiency standards have a negative and significant effect in the choice of energy-efficient front-loading washers. These results were counter-intuitive and thus discarded.

Table 7. Predicted probabilities of clothes washer choice from alternative models

Model	Mean	Standard Deviation	Minimum	Maximum
Data	0.113787	0.317619	0.000000	1.000000
Model cw1a	0.113787	0.028822	0.003341	0.144919
Model cw1b	0.113787	0.043405	0.006094	0.332771
Model cw2a	0.113787	0.102490	0.000108	0.285870
Model cw2b	0.113787	0.106290	0.000228	0.348701

Model cw2b* is the constrained model with parametric commonality imposed from the first step analysis of the short-run demand model. 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 developed in Chapter 3. However, 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.

However, as shown in Table 6, estimated coefficients are fairly consistent across specifications except for the common parameters.[66] 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.

The Energy Star program emerges as the most significant factor influencing the adoption of front-loading clothes washers, followed by energy efficiency standards. Based on Model cw2b, the establishment of Energy Star criteria for clothes washers increased the propensity of front-loading washer adoption by 17.4 percent. In comparison, the establishment of energy efficiency standards for clothes washers increased front-loading clothes washer adoption by 8.4 percent. The propensity of front-loading washer adoption is 7.4 percent higher for a home owner than a renter. A household with at least a college education is 6.5 percent more likely to adopt a front-loading washer.

On the other hand, the economic factors are found to be less significant factors influencing clothes washer choice decisions. Model cw2b provides insights on the effects of economic factors. The estimated coefficients imply that a $100 reduction in

[66] Since the parametric commonality is rejected, the coefficient interpretation focuses on Model_cw2b specification.

the purchase cost of front-loading washers (e.g., through appliance rebates) on average would increase the propensity of its adoption by 0.5 percent. A $50 income tax credit for the purchase of energy-efficient front-loading washers on average would increase its adoption by 1 percent. Although the coefficient is statistically significant, the estimated impacts of an income tax credit and capital cost reduction are minimal, especially compared with the Energy Star program and energy efficiency standards. A 20 percent increase in the electricity price would increase the front-loading washer choice propensity by 0.5 percent. Again, the price effect is found to be statistically insignificant.

Water Heater Choices

The multinomial logit model of water heater choices illustrated in equation (61) is also estimated using the method of maximum likelihood. Table 8 reports three specifications. 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 is carried out by imposing parametric constraints from the short-run demand analysis on Model wh1b. Results of the constrained estimation are presented in column 3 of Table 8 as 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 developed in Chapter 3 is robust as common parameters explain both consumer water heater choice behavior and short-run use behavior.

In contrast to the clothes washer choice analysis, the household expenditure variable (*ln_incWH*) is not a statistically significant determinant of water heater choices.[67] The expected operating cost (*ln_oCostWH*) is also a statistically insignificant predictor of water heater choices.

[67] Another set of unreported specification tests shows that when the expenditure variable *ln_incWH* is separated into two terms (the log of income not already committed to fixed payments and the log of the capital cost of technology alternatives), the model fit does not change significantly and both the income variable and capital cost variables are statistically insignificantly.

Table 8. 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.

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. Furthermore, 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.

The results of the water heater choice analysis should be interpreted with some caution. Due to data availability, the analysis evaluates household choices among broad categories of water heater systems, rather than choices among different brands and models of a technology. Thus, energy efficiency performance may vary widely within these groups. The weak predictability of the expenditure and operating cost variables likely reflects the fact that the decision regarding the water heating system may not be made by consumers but rather depend heavily on an earlier stage of building construction. Once pipes and other infrastructure are installed, households are less likely to change, say, from a gas tank system to a tankless system than from a less efficient tank system to a more efficient tank system, because such a system-wide change involves a major renovation effort, which can be costly.[68] The logistics as well as the high cost of retrofitting an existing home with a tankless system may be an important deterrent.

Space Heating System Choices

The multinomial logit model of space heating choices is evaluated similar to the water heater choice model. Table 9 reports the results of three specifications. 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 is also carried out by imposing parametric constraints from the short-run demand analysis on Model sph1b. The constrained results (Model sph1b*) are reported in Column 3 of Table 9.

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[68] Unfortunately, data on retrofitting cost from a tank water heating system to a tankless water heating system was not available.

Table 9. 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 developed in Chapter 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

Similar to the clothes washer choice analysis, a binary logit model of clothes dryer choices is evaluated using the method of maximum likelihood. Table 10 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 is carried out by imposing parametric constraints from the short-run demand analysis on Model cd1b. The results (Model cw1b*) are reported in Column 3 of Table 10.

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.

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.

Table 10. Estimated coefficients of the clothes dryer choice model

Regressor	Model		
	cd1a	**cd1b**	**cd1b***
ln_incCD	-333. 829* (-2.51)	-165.752 (-1.21)	
ln_oCostCD	0.604 (0.87)	-0.087 (-0.12)	
Own		-0.430** (-2.65)	-0.471** (-2.92)
Household size		-0.106*** (-3.51)	-0.111*** (-3.98)
College		-0.029 (-0.32)	-0.080 (-0.92)
Constant	-0.636 (-0.61)	1.138 (1.01)	1.155 (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.

In addition, in the case of clothes dryer choices, a household's education level does not appear to be a significant factor influencing technology choice decisions.

6.3 Conclusions

This chapter presents an empirical application of the household energy demand and technology choice model developed in Chapter 3 by estimating the short-run household demand for electricity and natural gas and the long-run technology choices of clothes washers, water heaters, space heating systems, and clothes dryers among California households.

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. Technology choice analysis of the four energy uses shows varying effects of technology capital cost, expected operating cost, and household characteristics. The policy implications of the empirical findings are discussed in the following chapter.

Chapter 7: Policy Implications for Household Energy Efficiency

Findings from the empirical analysis using the unified modeling framework of discrete technology choice and continuous energy consumption 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

Household-level energy durable choice decisions have long-lasting impacts on energy consumption and greenhouse gas emissions as major home appliances typically have lifetimes from ten to twenty years. The diffusion rates of apparently cost-effective energy efficiency investments are often low. This phenomenon is referred to as the "energy paradox."

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. For instance, ownership is found to be a significant factor influencing the choices of clothes washers, water heaters and clothes dryers, but is not a significant determinant of space heating system choices, which have longer life. Unlike home appliances such as clothes washers, decisions for home-wide systems such as for space heating and cooling are more complex and are often made as an integral part of building design and construction. Once the system is determined, retrofitting can be expensive. In the situation of home-wide system choices, policy intervention should thus be best designed to target developers and contractors, such as through building codes.

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.[69] 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 programs 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.

The 20 percent increase in electricity price represents the estimated long-run electricity price increase that might be due to a carbon cap-and-trade program under the proposed HR 2454 bill (the American Clean Energy and Security Act of 2009, also referred to as the "Waxman-Markey Bill"). This effect appears to be insignificant

[69] 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.

and much smaller than the effects of energy efficiency standards or information-based programs such as the voluntary Energy Star program.

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, producting higher R^2 and log likelihood values, and suggesting potential measurement errors by using average energy efficiency data on the appliance stock.

Chapter 8: Conclusions

Residential consumer energy consumption is a critical aspect of energy and climate change policy and an important application of consumer theory. This study develops an internally consistent theoretical framework that can be used for practical analysis of various aspects of household energy use behavior.

8.1 Summary and Main Contributions

This study develops a unified discrete technology choice and continuous demand model (the "discrete/continuous model") which can be used to examine household short-run energy consumption and long-run technology choice behavior. The model, derived from underlying utility maximization using a second-order translog indirect utility function, provides a transparent and cohesive structure with considerable flexibility to investigate consumer preferences and the role of economic factors, household characteristics, and policy interventions in household energy use and technology choice decisions.

An empirical application of the model is carried out using a rich and unique micro-level energy consumption and appliance holdings dataset of California households. I estimate the household short-run demand for electricity and natural gas and long-run technology choices for four energy uses—clothes washing, water heating, space heating, and clothes drying—using the modeling framework.

Results of the empirical analysis show that the discrete/continuous model developed in this study is quite robust in explaining household energy consumption and technology choice behavior across energy forms and appliance choices. Income and price elasticities derived from the short-run analysis appear to be sensible and within the range of estimates documented in the literature. With the exception of the clothes washer choice model for which misspecification is a potential concern, the estimated parameters from the short-run demand analysis are all statistically equivalent to the parameters obtained in the long-run technology choice model (weakly so for clothes drying), validating the appropriateness of the modeling framework for both the continuous and discrete choices.[70]

This study is the first known application of the second-order translog flexible functional form or of any second-order flexible form to energy demand analysis that encompasses both discrete and continuous choices in a unified parametric structure. This model addresses several unique features of consumer energy use and allows analysis of demand interactions, demand aggregation, and fuel substitution.

In addition, the model extends the existing discrete/continuous models (e.g., Dubin and McFadden 1984) by modeling demands for multiple fuels and technology choices for different categories of energy uses. Existing studies mostly deal with demand for a single fuel (e.g., electricity or natural gas) and technology choices for a single energy use. The joint modeling of demand for both electricity and natural gas

[70] Parametric equivalence is rejected for the expenditure variable in the clothes washer choice model. The non-equivalence of the parameter between the short-run demand model and the long-run choice model for clothes washers is likely due to a misspecification of the clothes washer choice model by omitting the water price and water efficiency of alternative clothes washer choices, which are significant factors that potentially drive clothes washer choices in California.

permits the identification of tradeoffs both in the short run and the long run as well as between short-run and long-run considerations.

Another unique contribution of this study is the empirical insights that allow evaluation of the effectiveness of 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 residential short-run and long-run energy efficiency.

8.2 Future Research

Several assumptions used in the model and analysis can be relaxed and tested. First, the analysis assumes that consumers form expectations of future operating costs of energy technology alternatives based on the current energy prices. Preliminary analysis suggests that households may indeed have some form of price expectations while making energy durable choices. This assumption can be further investigated empirically by introducing more general expectation mechanisms in the model structure.

Second, the analysis assumes that consumers respond to average energy prices in making both short-run energy use and long-run technology choice decisions. The assumption is made partially due to data limitations. If actual household energy tariffs and billing data are available, this assumption can be tested. Nonlinear pricing for energy is an important feature of energy demand in most applications. The empirical evidence of consumer response to marginal versus average energy prices is mixed and worth further investigation.

Third, research that utilizes the full information maximum likelihood approach to estimate discrete/continuous models remains an unconquered empirical challenge. Like most existing studies, this study adopts a two-step limited information maximum likelihood approach. Despite the merits of the second-order translog flexible functional form of consumer preference functions, estimation of the system of demand functions is computationally cumbersome and problematic due to nonlinearity of the likelihood function. In this study, the typical problem of nonlinearity is further complicated by multicollinearity when energy uses by appliance type are not observed and must be aggregated for estimation. A structural approach that estimates the entire system of equations with full information is a challenge, but is worth further pursuit, particularly if energy uses by appliance types can be observed.

Fourth, the clothes washer choice model rejects the parameter commonality between the short-run demand model and the long-run choice model for clothes washers. One possible explanation is the omission of effective water price and water efficiency of alternative clothes washers, which is possibly a significant issue in California. The specification could be further investigated by including representation of water cost if appropriate data can be identified.

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