Modeling household energy consumption and adoption of energy efficient technology

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Abstract

This study develops a model to study household energy use behavior that can impose common preferences for feasible demand estimation with multiple discrete technology choices and multiple continuous energy consumption uses. The model imposes fixed proportions production and additivity of uses for plausible estimation feasibility while adopting a second-order translog flexible functional form to focus on flexibility in identification of consumer preferences that determine interactions among energy uses and between short-run and long-run choices. Using a unique household-level dataset from California, the model is applied to estimate short-run household demand for electricity and natural gas and the long-run technology choices with respect to clothes washing, water heating, space heating, and clothes drying. The estimation results support commonality of underlying preferences except in one case that is explained by an unavailable variable.

Keywords

Energy modeling; Household energy use; Technology adoption; Energy efficiency; Energy and climate policy; C30; D12; Q41; Q48

1. Introduction

Analysis of household energy consumption and demand elasticities has long been used to forecast energy demand for the purpose of energy planning and to assess the energy savings potential of energy efficiency programs (Halvorsen, 1978). Following the 1970s energy crisis, interest emerged in understanding consumer decisions with respect to the adoption of energy technology and conservation measures (McDougall et al., 1981). In recent years,
energy efficiency and consumer technology choice behavior have received renewed interest in the context of climate change policy and greenhouse gas (GHG) mitigation (e.g., Clarke et al., 2014; International Energy Agency, 2016; IPCC, 2014; Kriegler et al., 2014; Kyle et al., 2011).

The residential sector consumes about one-fifth of the total energy in the U.S. economy and is believed to have some of the most cost-effective opportunities to reduce GHG emissions (e.g., Interlaboratory Working Group, 2000). Various policy programs and instruments have been devised to encourage adoption of energy efficient technology, including market-based mechanisms (e.g., cap and trade), regulation (e.g., appliance energy efficiency standards), financial incentives (e.g., tax incentives for fuel-efficient vehicles, utility rebates for energy-efficient appliances), information programs (e.g., the Energy Star label), and behavioral interventions (e.g., nudging). Understanding household energy use and technology choice behavior therefore has important implications for evaluating the welfare effects of energy and climate policy.

With growing policy relevance, consumer energy efficiency behavior and the costs and benefits of policy interventions are still much debated. Rates of diffusion of cost-effective energy efficiency investments have been slow compared to “optimal” rates of technology diffusion determined by net present value of upfront investments and expected energy savings. This is the ‘energy paradox,’ or ‘energy efficiency gap’ that has been studied extensively (see Allcott and Greenstone, 2012; Anderson and Newell, 2004; Brown, 2001; DeCanio, 1998; Helfand and Wolverton, 2011; Howarth et al., 2000; Jaffe and Stavins, 1994; Levine et al., 1995; and others cited below). Various factors that potentially explain the energy efficiency gap are posited or empirically tested. These include factors that affect consumer technology adoption, such as hidden costs, heterogeneity, learning, uncertainty, irreversibility and option value (see reviews by Gillingham and Palmer, 2014, and Jaffe et al., 2003). The critical issue is consumer’s trade-offs between the upfront capital costs and expected but uncertain operating costs (e.g., Hassett and Metcalf, 1993; Hausman, 1979; Train, 1985). Market failures that inhibit socially optimal diffusion, in some cases illustrated as a principal-agent problem, include environmental externalities, innovation spillovers, incomplete information, and energy price distortions (e.g., Gillingham et al., 2009; Howarth and Sanstad, 1995; Jaffe et al., 2003; Jaffe and Stavins, 1994).

One major issue in the energy efficiency gap debate is potential modeling errors and misrepresentation of consumer energy use and technology choice behavior (Gerarden et al., 2015). Although recognized early that discrete consumer technology choice and continuous usage decisions are made by the same individuals, and are thus based on a common set of preferences and circumstances (Balestra and Nerlove, 1966; Dubin and McFadden, 1984; Hausman, 1979), analyses of household energy demand and appliance choice are typically modeled separately. ¹Hanemann (1984) demonstrated theoretically how discrete technology choice and continuous consumption decisions are derived from a common underlying model of utility maximization. Dubin and McFadden (1984) found that ignoring this joint

¹For example, a household with higher demand for air conditioning is more likely to purchase an energy-efficient air conditioner, which has higher capital cost but lower operating cost, compared to a household with low demand for air conditioning.
endogeneity when modeling energy demand yields biased and inconsistent estimates. However, joint modeling of energy technology choice and consumption decisions (as a “discrete-continuous model”) has been limited, and the studies that have done so have not imposed compatible structure such as demonstrated by Hanemann (1984), likely because of the complexity of the problem. To this point, empirical feasibility has been limited to cases without multiple types of technology choice and multiple forms of energy consumption (e.g., Bento et al.’s (2009) study of automobile choice and gasoline demand).

In this study, we develop a unified structural model of household discrete technology choice and continuous energy consumption using a second-order translog flexible form for indirect utility to derive compatible household specifications for multiple types of short-run fuel demand and multiple types of long-run technology choice. 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 and their interactions across both fuel types and end uses in a unified parametric structure. Short-run household demand for electricity and natural gas and long-run technology choices are estimated jointly with respect to clothes washing, water heating, space heating, and clothes drying. Using this consistent analytical framework, the results are used briefly to suggest some policy implications related to the ongoing debate about effectiveness of alternative policy instruments for encouraging household energy efficiency and GHG emission reductions. Due to space constraints, however, comprehensive welfare analysis is not included in this paper.

The model includes several unique features of consumer energy use imposing plausible fixed-proportions production of technologies and additive fuel uses while focusing on flexibility in substitution and demand estimation. Results demonstrate the importance and feasibility of joint empirical modeling of multiple discrete and continuous choices while considering demand interactions, aggregation, and substitution in a common underlying parametric structure at the household level. Using a unique and rich micro-level household survey dataset from California, the model is applied to examine the roles of income, prices, household characteristics, and energy and environmental policy in both short-run energy use and long-run technology choices. The results, based on observations of recent energy consumption and appliance holdings among 2408 households served by the Pacific Gas and Electric (PG&E) Company, demonstrate that the modeling framework is appropriate, robust, and useful for purposes of policy analyses of household energy consumption and technology choice.

The remainder of the paper is organized as follows. Section two presents the conceptual framework for joint modeling of household energy consumption and durable choice

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2 The discrete-continuous modeling approach has been applied to analyze short-run and long-run energy use in Europe (e.g., Dagsvik et al., 1987; Halvorsen and Larsen, 2001; Nesbakken, 2001; Vaage, 2000). But application of discrete-continuous modeling for energy use was sparse in the U.S. until recent years. Newell and Pizer (2008) used 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. Mansure et al. (2008) applied 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. Davis (2008) used a discrete-continuous model to estimate household demand for energy and water from a field trial of energy-efficient clothes washers and found that when simultaneity of appliance choice is ignored, estimates of price elasticities are biased away from zero. In addition, discrete-continuous modeling based on a common utility-theoretical framework has been used to model household vehicle choice and miles traveled (e.g., Bento et al., 2009; Feng et al., 2013).
decisions. Section three describes the data used for estimation. Section four presents the estimation strategy and the empirical results. Section five discusses results and policy implications, and concludes.

2. The model

This section presents the conceptual framework for joint modeling of short-run household energy consumption and long-run technology choice. The household is assumed to maximize utility from consuming two groups of goods, a composite of market goods ($E_0$) and energy services $E = \{E_1, \ldots, E_J\}$ such as clothes washing and space heating, in each time period,

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

where $\theta$ is a vector of household characteristics that influence household demand.

Demand for each energy service $E_j$ is met through utilization of household appliance $i$ with energy efficiency $\phi_{ij}$ that uses fuel type $l(i)$ as an input. Energy service production functions are assumed to follow fixed proportions as represented by

$$E_j = \phi_{ij} x_{l(i),j}, \quad j = 1, \ldots, J, \quad (2)$$

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

In the short-run, the household capital stock (e.g., appliances and housing) is fixed. The desired levels of energy services and the intensities with which fixed technologies are utilized are determined by short-run household optimization, which generates derived demands for fuels. In the long run, however, the household considers both capital costs and the future flow of operating costs associated with alternative technologies in the decision-making process.

2.1. Short-run fuel demand

The short-run utility maximization problem in Eq. (1) subject to the production function in Eq. (2) is completed by the budget constraint,

$$E_0 + \sum_{i=1}^{I} p_i x_i = E_0 + \sum_{j=1}^{J} p_{l(i),j} x_{l(i),j} \leq y^* \equiv y - \sum_{j=1}^{J} \rho_{l(j),j} x_{l(j),j}. \quad (3)$$

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3 We assume output nonjointness, i.e., no appliance produces more than one energy service, and input nonjointness, i.e., fuel allocated to one appliance does not affect production of other energy services.

4 Using these functional forms avoids estimating certain phenomena in unstructured reduced form relationships subject to large estimation errors when the specific physical relationships are known comparatively precisely.
where $i(j)$ is the technology currently in place for energy use $j$, $k(i(j))$ is denoted by $k(j)$ for convenience, $p_l \equiv p_{l(j),j}$ is the price of fuel $l$ regardless of the energy use, $x_l \equiv \sum_{j=1}^{J} x_{l(j),j}$ is the total household use of fuel $l$, $y^*$ is the amount of income ($y$) not already committed to fixed payments, including appliance payments represented as annualized capital costs $k_{i(j),j}$ of technology $i$ for end use $j$, where $p_{l(j),j}$ is annualized fixed cost rate of technology $i$ for end use $j$ that accounts for appliance lifetime and financing costs. The budget constraint in Eq. (3) implies that the implicit price of energy service $j$, i.e., the effective cost per unit of energy output for the $j$th energy use, is

$$r_j \equiv \left( p_{l(j),j} x_{l(j),j} \right) \left( \phi_{l(j),j} x_{l(j),j} \right) = p_{l(j),j} / \phi_{l(j),j}, \quad j = 1, \ldots, J. \quad (4)$$

Solving the utility maximization problem given the current appliance stock yields the conditional indirect utility function $V = V(r, y^*, \theta)$ where $r$ is a price vector including $r_0$, the price of the composite good, as well as the $r_j$’s across all energy end uses $j = 1, \ldots, J$. We adopt a version of the second-order translog flexible functional form for conditional indirect utility found in Berndt et al. (1977).

Demographic variables are incorporated by interacting them with price terms using “demographic translating” as discussed in Pollak and Wales (1992). In addition, a vector of household characteristics that may influence energy technology choices and disturbances associated with individual technology choices for energy service production are included. This functional form thus follows

$$V(r, y^*, \theta, \epsilon) = \exp \left\{ \bar{a} + \sum_{j=0}^{J} \alpha_j \ln \left( r_j / y^* \right) + \sum_{j=0}^{J} \sum_{j'=0}^{J} \beta_{jj'} \ln \left( r_j / y^* \right) \ln \left( r_{j'} / y^* \right) + \sum_{j=0}^{J} \ln \left( r_j / y^* \right) \Gamma_j \theta + \sum_{j=1}^{J} \sum_{j'=1}^{J} H_{i(j),j} \theta + \sum_{j=1}^{J} \epsilon_{i(j),j} \right\}, \quad (5)$$

where a zero subscript denotes the composite good; $\bar{a}$ collects constant terms across all energy goods that arise in the translog; $\alpha_j$, $j = 0, \ldots, J$, and $\beta_{jj'}$, $j, j' = 0, \ldots, J$, are scalar parameters; $\Gamma_j$, $j = 0, \ldots, J$, and $H_{i(j),j}$, $j = 1, \ldots, J$, are row-vector parameters of the indirect utility function; and $\epsilon_{i(j),j}$ is a disturbance. Both the parameter vector $H_{i(j),j}$ and the disturbance $\epsilon_{i(j),j}$ are associated with the specific technology $i$ chosen for energy use $j$. We assume separability in demand between the composite good and the choice of energy technology alternatives.

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5Flexible functional forms for indirect utility functions have desirable properties as they do not constrain price and income elasticities at a base point a priori. Popular functional forms include the almost ideal demand, translog, generalized Leontief, and generalized Cobb-Douglas systems. Using Bayesian procedures, Berndt et al. (1977) compared the latter three using Canadian data and found that the translog 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) estimated household energy conservation retrofit decisions and found that translog estimated coefficients were robust across specifications such as the generalized Leontief and the quadratic forms. A unique feature of this paper is to show that the translog system lends itself to estimation with a plausible structure of household energy demand interactions.
Using Roy’s identity, imposing normalization constraints for the translog system, rearranging terms, and aggregating household fuel use obtains the following budget share equations for fuel demand,

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

$$
= \sum_{j=1}^{J} \Psi(x_{l,j}, j > 0) \alpha_j + 2 \sum_{j'=1}^{J} \beta_j j' \ln(p_l(j'), j' / \phi_l(j'), j') - 2 \ln y^* \sum_{j'=0}^{J} \beta_j j' + \Gamma_j \theta + \mu_l,
$$

(6)

$$
I = 1, \ldots, L, \text{ where } \Psi(x_{l,j}, j > 0) \text{ is an indicator variable equal to one if energy use } j \text{ uses fuel } l \text{ and zero otherwise, and } \mu_l \text{ is an error term in fuel use decisions. Similarly, the budget share for the composite good } E_0 \text{ is expressed as}
$$

$$
\omega_0 = \frac{y^* - \sum_{j=1}^{J} p_l(j) \Psi_l(j, j)}{y^*}
$$

$$
= \alpha_0 + 2 \sum_{j'=1}^{J} \beta_0 j' \ln(p_l(j), j' / \phi_l(j), j') - 2 \ln y^* \sum_{j'=0}^{J} \beta_0 j' + \Gamma_0 \theta + \mu_0,
$$

(7)

where $$\mu_0$$ is an econometric disturbance.

### 2.2. Long-run technology choice

The household long-term optimization problem derives the capital stock decision equations. Assuming the household’s future price and income expectations are given by current prices and income, the long-term utility maximization problem associated with the utility function in Eq. (1) becomes

$$
\max_{E_0, E_1, \ldots, E_J, \theta} \{U_{E_0, E_1, \ldots, E_J}; \theta \}
$$

subject to

$$
E_0 + \sum_{j=1}^{J} p_l(j) \Psi_l(j, j') + \sum_{j'=1}^{J} \rho_{j'} \kappa_{j'} = y^*.
$$

After short-term optimization and imposing $$r_0 = 1$$ using the normalization constraint, the indirect utility function in Eq. (5) becomes

$$
V(r, y^*, \theta, \varepsilon) = \exp \left[ \tilde{\alpha}_0 - \ln y^* + \sum_{j=1}^{J} \alpha_j \ln r_j - 2 \ln y^* \sum_{j=0}^{J} \beta_j j' \ln r_j + \sum_{j=1}^{J} \sum_{j'=1}^{J} \beta_j j' \ln r_j \ln r_{j'} + \sum_{j=1}^{J} \ln r_j \Gamma_j - \ln y^* \sum_{j=0}^{J} \Gamma_j \theta + \sum_{j=1}^{J} \kappa_{j'} \right]
$$

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

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We assume the household energy technology choice for each individual energy use is stochastically independent of choices for other energy uses. Under this assumption, this model reduces to independent minimization of the implicit cost of individual energy uses. For this purpose, we define $y_j = y - \sum_{j'}=1 \rho_{ij}k_{ij}$ and $y_{ij} = y_j - \rho_{ij}k_{ij}$ 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 Eq. (4), we define $r_{ij} = p_{l(kj)}, j(kj), j$ as the effective cost per unit of energy service $j$ where $k(j)$ is the chosen technology.

With these definitions, the indirect utility function relevant to the technology choice for energy service $j$ implied by Eq. (5) can be denoted as

$$V_i \{i, y_{ij}, \theta, e_{ij}\} = \{V_r \{i, y_{ij}, \theta, e\} | i(\cdot) = i(j') \text{ for } j' = 1, \ldots, J; j' \neq j \}$$  (8)

where $V$ is the same indirect utility function with the same parameters as defined in Eq. (5). The indirect utility function $V_i$ 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. Using this decomposition for convenience, we represent the right-hand side of Eq. (8) alternatively as $V \{r, y_{ij}, \theta, e_{ij}\} = \exp(W_{ij}B_j + W_0 + e_{ij})$. The probability that the household chooses technology $i$ from the set $I_j$ of alternatives for energy service $j$ can then be represented as

$$P_{ij} = \Pr \{V_i \{i, y_{ij}, \theta, e_{ij}\} > V_i \{i', y_{ij}, \theta, e_{ij}\} \forall i' \neq i; i, i' \in I_j \}$$

$$= \Pr \{\exp(W_{ij}B_j + W_0 + e_{ij}) > \exp(W_{i'}jB_j + W_0 + e_{i'}) \forall i' \neq i; i, i' \in I_j \}$$

$$= \Pr \{W_{ij}B_j + W_0 + e_{ij} > W_{i'}jB_j + W_0 + e_{i'} \forall i' \neq i; i, i' \in I_j \}$$

$$= \Pr \{e_{ij} - e_{ij} < W_{ij}B_j - W_{i'}jB_j \forall i' \neq i; i, i' \in I_j \}$$

where

$$W_{ij} = \left\{ -\ln y_{ij}, \ln y_{ij}, \ln r_{ij}, -2 \ln y_{ij}, \ln r_{ij}, \ln r_{ij} \right\}$$

6We argue that this is a reasonable assumption because appliance purchase and replacement decisions are typically motivated by an old appliance wearing out, which occurs at random times. This assumption may be challenged for a subset of cases such as new home construction or retrofitting when multiple appliance choices are made simultaneously, or because green preferences of some individuals have effects across appliance choices. Although we cannot make direct inference, we postulate that higher education is a good proxy for green preferences because of better understanding of environmental concerns and solutions. In our results, college education is a significant predictor of choice of efficient technology (e.g., for clothes washing). We attempted to test for additional green preferences using proxies such as population percentages that voted for Green Party or Democratic Party candidates at the county level, but results were statistically insignificant. While this assumption of stochastic independence deserves further investigation as more sophisticated datasets become available, we suggest that it is appropriate to avoid the impractical estimation complications otherwise encountered with the already complex nature of multiple household energy uses.
\[ B_j = \left\{ \frac{1}{\sum \limits_{j = 0}^{J} \beta_j \Gamma_j \sum \limits_{j = 0}^{J} H_j(i, j)} \right\}. \]

As shown in Eq. (9), the \( W_j \) terms conveniently drop out of this expression. That is, only choice-related variables and technology choice disturbances are relevant. Assuming \( \epsilon_{ij} \forall i \in I_j \) are identically and independently distributed with zero means and follow extreme value (EV) type I distributions, the difference between the two disturbances follows the logistic distribution function. Following the well-known results developed by McFadden (1974), the EV error term distribution leads to a logit model of the discrete choice probability where the probability that technology \( i \) yields the highest indirect utility among all possible technologies is given by

\[
P_{ij} = \frac{\exp(W_{ij}B_j)}{\sum_{i' \in I_j} \exp(W_{ij}B_{i'})} = \frac{\exp(-\ln y_{ij}(1 + R_i + \ldots + R_j) + \ln r_{ij}(\alpha_j + R_j) + H_i\beta)}{\sum_{i' \in I_j} \exp(-\ln y_{ij} \cdot A_0 + \ln r_{ij} \cdot A_j + H_i\beta)},
\]

where \( R_j \equiv 2 \sum_{j = 1}^{J} \beta_j \ln r_{ij} + \Gamma_j \cdot A_0 \equiv 1 + 2 \sum_{j = 1}^{J} \beta_j \ln r_{ij} + \sum_{j = 0}^{J} \Gamma_j \cdot A_j \), and

\( A_j \equiv a_j + 2 \sum_{j = 1}^{J} \beta_j \ln r_{ij} + \Gamma_j \cdot A_j \). 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). Eq. (10) 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 Eq. (6). In addition, Eq. (10) shows how the household variables in \( \theta \) can influence the propensity that the household chooses technology \( i \) for energy use \( j \) in a mixed logit framework.

### 3. The data

Estimation uses micro-data from the 2003 Statewide Residential Appliance Saturation Study (RASS) in California, conducted by the California Energy Commission with sponsorship from the major investor-owned utilities in the state (KEMA-XENERGY et al., 2004). Sample frames are the electric customer population of the utilities. Based on a stratified random sampling of the population frames, the survey collected energy consumption and appliance holdings from households across various utility service areas and climate zones in California in 2002. Our analysis uses a subsample of 2408 households served by the Pacific Gas & Electric Company (PG&E) because PG&E provides both natural gas and electricity services to approximately 15 million people (44% of the California population) throughout
northern and central California.\(^7\) The subsample includes only households with both electricity and natural gas consumption in order to estimate tradeoffs between both short-run fuel uses and long-run technology choices among residents who have that choice without substantial capital costs to bring new gas service to a house.\(^8\)

The analysis of short-run fuel demand and long-run technology choice explicitly models four categories of energy services: clothes washing, water heating, space heating, and clothes drying.\(^9\) These energy uses are chosen for analysis mainly because of the availability and quality of technology cost and energy efficiency data. Together, these four energy uses represented 65% of the average household energy consumption in California in 2002. In the short-run demand analysis, all other energy uses are grouped in an “other” category.\(^10\)

The RASS dataset contains variables including household socioeconomic characteristics (e.g., income, household size and education level), housing characteristics (e.g., housing type, square-footage, and home ownership), appliance holdings by energy use (e.g., technology, vintage, and fuel type), and annual consumption of electricity and natural gas. The dataset also assigns individual households with climate zone and heating degree days (HDDs) and cooling degree days (CDDs) data, which help to determine households’ heating and cooling loads. Historic heating and cooling degree days between 1970 and 2003 were merged with the RASS based on climate zone.

The RASS dataset lacks some key variables required for the analysis: fuel prices \((p)\), appliance capital costs \((k)\), energy efficiency characteristics \((\phi)\), and household fixed payments to derive the expenditure variable \((\gamma)\). Historic electricity and natural gas tariffs were collected from PG&E and assigned to households based on service category definitions. Annual fuel expenditures are estimated using household annual fuel consumption and assigned energy prices. Energy efficiency measures of various appliances are based on databases of measurement data at the household level as well as market studies that estimated average energy efficiency levels of the existing appliance stock in California (Hanford et al., 1994; RLW Analytics, 2000, 2005; Wenzel et al., 1997). These databases also provide estimates of the average costs of various appliances and are used to develop the capital costs of the appliance choice alternatives. Household fixed payments are estimated based on a regression analysis of the relationship between household income and fixed payments using the Consumer Expenditure Survey. Details of the data sources and data management procedures are described in Li (2011).

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\(^7\)The RASS has 7295 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% of PG&E households), households with missing values for income, fuel consumption, and household variables used in the analysis (32.4%), and a few outliers of households with less than one member or 20 or more members (0.08%) or with a budget share for fuel consumption N 30% (0.07%).

\(^8\)The subsample of PG&E households with both electricity and natural gas service excludes 1500 households served with only electricity service and no natural gas service (15.5% of PG&E households).

\(^9\)An initial analysis was carried out to consider joint analysis of fuel choices for water heating and space heating given the possible correlation of fuel choices for these two energy services. However, a statistical test of the nested model could not reject the hypothesis that fuel choices for water heating and space heating are stochastically independent with a \(p\)-value of 0.395.

\(^10\)The majority of the 35% of energy use in the “other” category is for refrigeration, lighting, and electronics, which do not involve choices between gas and electric technologies. Air conditioning was not included as a separate category because it accounts for a small share of household energy use in the PG&E data in the relevant area of California due to climate conditions.
The technology choice analysis covers 1990–2003 with the exception of space heating choice analysis that covers 1980–2003 based on available technology cost data. The data include sufficient variation in fuel prices, consumption, household characteristics, and appliance choice for meaningful analysis.\textsuperscript{11} For example, the average price of electricity varies substantially from $0.10 to $0.14/kWh (in 2000 dollars) during the study period with high prices in the early 1990s, preceded by a 20 percent increase over the late 1980s and a decline of similar magnitude in the late 1990s before a 20 percent spike from 2000 to 2002 during the California energy crisis. The price of gas, after a long period of stability, is followed by substantial variation in both directions from $0.02 to $0.04/kWh-equivalent during the crisis (including a 70 percent increase from 1999 to 2001). Because of dramatic price variations during the energy crisis, this dataset provides an excellent natural experiment for identifying short-term energy price elasticities, as well as long-run conservation response and energy-efficient technology adoption behavior.

4. Estimation strategy and results

The discrete-continuous model developed in Section 2 consists of a system of simultaneous equations with continuous demand and discrete choice endogenous variables and a set of explanatory variables consisting of prices, income, and household characteristics. This system notably has a recursive econometric structure between the discrete and continuous components whereby energy consumption depends on observed appliance choice but not vice versa as the vast majority of observations on appliance choice pertain to decisions made in a different time period. This yields a block recursive system of equations in which blocks of equations can be estimated separately with consistency, and with asymptotic efficiency if disturbances are uncorrelated between blocks.

We use a two-step limited information maximum likelihood (LIML) approach to estimate the model. The first step estimates the system of short-run demand Eqs. (6) and (7) using iterated feasible generalized nonlinear least squares (FGNLS) to produce asymptotically consistent estimates. Under normality, these estimates are theoretically equivalent to maximum likelihood (ML) estimates (Greene, 2008).\textsuperscript{12} One equation is dropped from the system for identification because the adding-up condition imposes a singular covariance matrix. All parameters are estimated directly after imposing integrability conditions, which provides important identifying structure.

As a second step, the technology choice equations in Eq. (10) are first estimated separately by maximum likelihood (ML) without imposing structural constraints. Because choices of different appliances are made at different points in time, correlation among the disturbances is likely minor, in which case separate estimation does not sacrifice efficiency aside from ignoring parametric constraints among equations (see footnote 6). Separate energy technology choice equations are estimated for clothes washing, water heating, space heating

\textsuperscript{11}A table of summary statistics is available from the corresponding author.

\textsuperscript{12}While full-information maximum likelihood (FIML) estimation can theoretically achieve asymptotic efficiency when disturbances are correlated between blocks, in practice it is more complicated to implement in the case of discrete-continuous modeling (see Blanchard, 1983; Greene, 2008; Murphy and Topel, 2002). In addition, if some part of the model is incorrectly specified, then specification errors propagate through the system with FIML estimation, and possibly make LIML a more reliable approach, i.e., the adverse implications of a specification error are confined to the particular equation in which specification error is present.
and clothes drying. A binary logit choice model is estimated for clothes washing and clothes drying as both cases involve two choice alternatives in the dataset; a multinomial logit choice model is estimated for water heating and space heating.

Then the equations in Eq. (10) are re-estimated imposing parametric constraints on parameters $A_0$ and $A_j$ implied by ML estimates of the short-run demand Eqs. (6) and (7), which summarize the role of parameters that appear in both the short- and long-run models. The vector of the remaining parameters is estimated, producing the ML estimators of the remaining parameters and the associated covariance matrix of the parameters. Then, the covariance matrix is corrected to account for the covariance matrix estimator of the short-run parameters to obtain a proper consistent estimator of the covariance matrix.

4.1. Short-run energy demand

Using the iterative FGNLS procedure, the system of budget share equations for the numeraire and natural gas are estimated with four specifications of demand interactions as reported in Table 1.\(^{13}\) Model 1 includes only price variables, $\ln r_j$, the income variable $\ln y^*$, and demand interaction terms as a benchmark.\(^{14}\) Model 2 builds on Model 1 by adding basic household-demand interaction terms. Inclusion of additional household terms in Model 2 is guided by plausible features of energy service demands and significance of statistical tests. For example, heating degree days and dwelling square footage are believed to influence space heating demand whereas household size is more likely to influence water heating demand.

A log likelihood ratio test between Models 1 and 2 rejects the null hypothesis that the household-demand interaction terms are jointly zero with a $p$-value far $<0.001$. Further statistical tests show that each of these additional variables is highly significant individually with $p$-values far $<0.001$. In addition to energy price and income, strong determinants of household energy demand are shown to be household size, dwelling age, square footage, and heating degree days.

Model 3 builds on Model 2, but 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 energy efficiency standards ($S_i$) and the EnergyStar information program ($E_i$) aside from an error term, i.e., $\ln r_{cw} = \ln (p_{cw}/\varphi_{cw}) = \ln p_{cw} - \ln \varphi_{cw}$ where $\ln \varphi_{cw} = \gamma_1 S_i + \gamma_2 E_i + e_{cw}$. $E(e_{cw}) = 0$. Several policy changes and substantial improvements in energy efficiency of clothes washers occurred during the study period (see Section 4.2). Compared with Model 2, Model 3 improves fit

\(^{13}\)Specification tests show that among different combinations using two of the three budget share equation specifications, the system with equations for the numeraire and natural gas yields the highest log likelihood value, although all three modeling alternatives should yield equivalent parametric results asymptotically.

\(^{14}\) Some second-order translog interaction terms have clear plausibility while others do not. For example, clothes washing tends to generate demand for water heating and clothes drying, while clothes drying does not generate demand for water heating, nor does space heating tend to generate demand for clothes washing, water heating, and clothes drying. Interactions of water heating and space heating with the “other” category are also potentially important because other secondary means are sometimes used for those purposes, but not for clothes washing or drying. Accordingly, $\beta_{14}=\beta_{15}=\beta_{23}=\beta_{24}=\beta_{34}=\beta_{35}=0$ was tested and not rejected with a $p$-value of 0.585. Therefore these interactions are omitted in the final reported results in Table 1. On the other hand, a test for omission of remaining second-order interactions is sharply rejected with a $p$-value $< 0.001$. Further, a number of the remaining individual second-order estimated coefficients are significant with $p$-values of 0.05, 0.01, or 0.001 in Table 1.
significantly with much higher log likelihood and pseudo-$R^2$ values as confirmed by a $p$-value < 0.001. This result suggests measurement error from using the average energy efficiency of the clothes washer stock as reported in the literature.

Changes in the energy efficiency performance of water heaters, space heaters and clothes dryers were modest during the study period. However, a specification test is performed to see whether use of average energy efficiency indicators for other energy uses is statistically equivalent to modeling energy efficiency as an estimable function of appliance age to capture technological progress. In Model 4, the energy efficiency of water heaters is modeled as a linear function of the age of water heaters ($A_i$) and an error term, $\ln(\phi_{wh}) = \lambda_1A_i + e_{wh}$. The log likelihood ratio test of Model 4 compared to Model 3 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. Model 4 is thus used as the preferred specification for subsequent discussions and parametric estimates imposed in the second stage estimation of technology choices.

The estimated income and own-price elasticities of the short-run model are presented in Table 2. The average estimated income elasticity for electricity is positive and less than one in all four specifications. For Model 4, the preferred specification, estimated income elasticities have an average of 0.418 for electricity with variation between 0.319 and 1.697 among observations. As expected, the results show that electricity is a superior good. The average estimated 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 4, the average estimated 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.

The average estimates of own-price elasticity for electricity are all negative except for Model 1, which is rejected by statistical tests. For Model 4, the estimated own price elasticities for electricity have an average of $-0.134$ with a range entirely in negative territory between $-1.091$ and $-0.068$ across all observations, which is somewhat unusual with second-order flexible forms. The average estimates of price elasticity for natural gas are consistently negative. Similar to estimates of income elasticity for natural gas, however, the ranges of estimates among individual households include both negative and positive values. In Model 4, estimated own price elasticities for natural gas average $-0.119$ with a range between $-0.177$ and 0.837, although very few households (3.3%) fall in the positive range.

The average short-run income and price elasticities of energy consumption derived from the short-run demand model are all in reasonable ranges. While a few of the price elasticities

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15 An additional specification test shows that using average energy efficiency indicators for space heating and clothes drying systems is not statistically different from explicitly modeling the energy efficiency of these systems.
16 Cross price elasticities between electricity and natural gas are unlikely to be important as substitution between the fuels is limited in the short run.
17 Of the U.S. studies of electricity demand reviewed by Taylor (1975), short-run income elasticity estimates ranged from 0.02 to 0.14. All of 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 short-run income elasticities for electricity ranging from 0.137 to 0.429 and the short-run income elasticities for natural gas
of natural gas demand of individual households are in an implausible positive range, they are no more than typically obtained with the flexibility of the translog model.\textsuperscript{18}

\section{Energy technology choices}

\subsection{Clothes washer choices—}
In the PG&E subsample, 88.6\% of the households have top-loading washers and 11.4\% have front-loading washers. Front-loading clothes washers are predominantly newer; 88\% of the front-loading washers were purchased after 2000. In comparison, only 46\% of the top-loading washers were purchased after 2000. Front-loading washers are distinctively more energy efficient, consuming at least 60\% less energy and 40\% less water than top-loading washers. With higher efficiency performance, the front-loading costs were higher by $322 to $374 in 2000 dollars between 1996 and 2004.

Clothes washers are regulated under federal energy efficiency standards. The first federal energy efficiency standard for top-loading clothes washers, which required a minimum energy factor (EF) of 1.18, was adopted by the U.S. Department of Energy in 1994. The standard was updated at the beginning of 2004 to a modified energy factor (MEF) of 1.04 for both front- and top-loading washers. California has implemented state standards following the federal schedule. The voluntary, information-based Energy Star program for residential clothes washers was established in 1997, which required a 2.5 EF for the Energy Star label, which was changed to an MEF of 1.26 in 2001.\textsuperscript{19}

The estimated binary logit model of clothes washer choice and specification tests are reported in Table 3. \textit{Free Income}, which incorporates the initial cost of clothes washer alternatives, is significant across all specifications (Models 5–7). \textit{Free Income} is measured as the logarithm of household income not already committed to fixed payments minus the annualized capital costs of the choice alternative. Estimates show it to be a significant predictor of clothes washer adoption. For instance, in Model 7 the coefficient of \textit{Free Income} implies that a $100 increase in household income would increase the propensity of front-loading washer adoption by 2.1\%; a $100 reduction in the capital cost of energy-efficient front-loading washer (such as through rebates) would increase the propensity of its adoption by only 1.1\%. However, a smaller effect is plausible because the model considers an income increase to be permanent compared to a one-time capital cost reduction.

\textit{Operating Cost} represents the expected operating cost as the logarithm of costs derived from average energy efficiency indicators. Model 5 results imply that \textit{Operating Cost} plays a significant role in determining clothes washer choices and, specifically, that an increase in expected operating cost encourages adoption of more efficient front-loading clothes washers. Models 6 and 7 represent an alternative specification of perceived operating cost affected by

\textsuperscript{18}As further evidence supporting the translog specification, we note that estimation without second-order terms produces elasticity estimates outside of plausible ranges, including positive price elasticities of demand for both electricity and natural gas at data means, and ranging as high as 2406.8 for natural gas, as well as income elasticities ranging from −371.6 to 193.8 among individuals for natural gas compared to estimates in Table 2.

\textsuperscript{19}The standard of measurement changed from an “energy factor” to a “modified energy factor” to account for the amount of dryer energy used to remove the remaining moisture content in washed items. Because the two metrics are not directly comparable, a binary index is used in the estimation.
three factors: Fuel Price (in logarithmic form), the Energy Standard (a binary variable representing whether the clothes washer meets the U.S. Department of Energy efficiency standard), and Energy Star (a binary variable representing presence of the Energy Star label). The positive coefficient on Fuel Price implies that a higher energy price increases the propensity to choose more efficient front-loading clothes washers. In Model 7, the coefficient for Fuel Price implies that a 20 percent increase in energy price will increase the propensity of frontloading washer adoption by 0.7%. However, Fuel Price is not statistically significant. This could be due to either measurement errors of the actual energy prices faced by households, perceived uncertainty of consumers about future energy prices when making technology choices, or failure of consumers to perceive changes in fuel prices when they occur. The energy Efficiency Standard and Energy Star rating are shown to be significant predictors of household clothes washer choices. Specifically, according to Model 7, the energy Efficiency Standard increases the propensity of adoption of front-loading washers by 10%, and the Energy Star rating increases the propensity by 18%, respectively. When consumer perception of energy efficiency is modeled as a function of policy variables (the energy Efficiency Standard and Energy Star rating) in Models 6 and 7, the model fit improves significantly compared to using average energy efficiency indicators. This suggests that energy efficiency information provided by policies related to the Energy Star label and energy efficiency standard strongly influence consumer technology choices in favor of the energy-efficient front-loading washers.

Household characteristics also have significant effects on the choice of clothes washers. Compared to Model 6, Model 7 includes three household variables: Home Ownership (a binary variable), Household Size (the number of individuals in the household), and College (a binary variable for college education). Home ownership and college education increase the propensity of front-loading washer adoption by 5.7% and 4.0%, respectively. Household Size also has a positive effect but appears to be less significant. The positive and significant effect of Home Ownership indicates a potential principal-agent problem in residential energy consumption behavior, and that of College education likely reflects educated consumers’ abilities to understand energy efficiency or preferences for environmentally friendly products.

Model 8 considers imposing parametric commonality of preferences between short-run demand and long-run appliance choice through constraints on the coefficients of Free Income and Fuel Price variables from the short-run demand in Model 4 (as discussed in the model development section). A log ratio test of the constrained Model 8 compared to the unconstrained Model 7 rejects the null hypothesis of common parameters between the short-run demand model and the long-run clothes washer choice model with a p-value < 0.001. This is a very different outcome from the results for the other three end-use models analyzed below. The rejection of parametric equivalence between the short-run demand model and the clothes washer choice model raises concern that clothes washer choice behavior may be misspecified in the preference function. One possible explanation is that in California where water supply is constrained, the water saving benefits of front-loading washers may be an additional factor that drives clothes washer choice. Unfortunately, water price and consumption data were not available in this dataset to test this hypothesis. With absence of household data, a crude indicator was considered to represent water use restrictions. Results
were not significant, likely because restrictions were intermittent, and sometimes imposed only as voluntary appeals for conservation in support of the public good. Further investigation is warranted where better data are available.

As far as effects of imposing parametric commonality, the estimated coefficients of variables that predict front-loading washer adoption change as follows. Compared to the coefficients in Model 7, the estimated coefficients in the restricted model for the energy efficiency standard and Energy Star label are lower by 8% and 17%, respectively, and the effects of household variables are stronger by 7.7% for home ownership and 7.3% for college education, respectively, and have greater statistical significance. These effects represent the importance of imposing parametric commonality to avoid overstating the response to energy policy.

4.2.2. Water heater choices—The water heater technology choice analysis considers natural gas tank systems (95.6%), natural gas tankless systems (1.3%), and electric tank systems (3.1%). Analysis is restricted to these three choices by availability of historic capital cost data, but they represent over 99% of household primary water heating systems among PG&E households. Among the choice alternatives, the average purchase price of gas tankless systems is significantly higher than that of gas tank systems (by about $500–800), although the price gap has declined over time, and the average installation cost of gas tank water heaters is about $150 higher than for electric tank water heaters. Although electric tank systems had lower capital costs and higher energy efficiency, the average price of electricity was about five times higher than that of natural gas during the period.

Household appliance energy efficiency surveys in California suggest the average energy efficiency measured by energy factor (EF) was 0.57–0.58 for gas tank systems and 0.89–0.90 for electric tank systems (RLW Analytics, 2000, 2005). 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. Energy efficiency for water heating systems changed only modestly in the last few decades and there were no major changes in energy efficiency policies during the study period. Therefore, using average energy efficiency indicators is unlikely to introduce significant measurement errors in the choice analysis.

The first two columns of Table 4 report results for two specifications of the multinomial logit model of water heater choice. Model 9 evaluates the effect of Free Income, which incorporates the initial capital cost of water heaters, and the effects of expected Operating Cost of alternative water heaters. Model 9 also includes the three household variables used in the clothes washer analysis.

In contrast to the clothes washer choice analysis, neither Free Income nor Operating Cost are statistically significant determinants of water heater choice. This is likely because of limited variation in efficiency and relative costs in the sample. One reason is that gas tank systems have consistently combined lower installation costs (compared to tankless systems) with lower operating costs (compared to electric systems). Because these conditions have

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20 Solar, propane, and electric heat pump systems account for only 0.4, 0.2, and 0.2% of the RASS data, respectively.

*Energy Econ.* Author manuscript; available in PMC 2019 June 04.
prevailed throughout the sample period, the effects of income and operating cost differences are likely captured by the highly significant constant terms. However, Home Ownership is a significant predictor that increases the propensity of choosing a gas tank system by an estimated 7% compared to renters. This can be explained by the fact that a home owner is more likely to pay for the operating cost of a water heater than a renter.

A second-step constrained estimation is reported as Model 10 by imposing parametric constraints from the short-run demand estimates of Model 4 in Table 1. A log likelihood ratio test of the constrained Model 10 compared to the unconstrained Model 9 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. In this case, imposing parametric commonality does not change the magnitude and significance level of effects of the variables included in the model. This result suggests a substantial compatibility with theoretical results that imply common preference parameters should drive both short-run energy use and long-run appliance choice. This result can be interpreted as a robustness check on the model.

4.2.3. Space heating system choices—The space heating technology choice analysis considers natural gas central forced-air systems (96.3%), natural-gas radiator systems (0.4%), and electric central forced-air systems (3.3%). The energy efficiency of space heating equipment, expressed as a percentage of energy output per unit of input, is usually assumed to be 1.00 (100%) for electric space heating equipment (RLW Analytics, 2005). Appliance surveys in California find an average energy efficiency of gas-based central forced-air heating equipment of 0.78 and an average energy efficiency of gas radiator systems of 0.80 (RLW Analytics, 2000). In addition to the heating units, system choice alternatives also involve heating distribution systems of differing efficiency. The average distribution efficiency is 0.7 for central forced-air systems and 0.9 for hydronic radiator systems (Hanford et al., 1994; Wenzel et al., 1997). The average installation cost of a gas central forced-air heater is about $150–200 higher than an electric central forced-air heater. The average installation cost of a radiator system is significantly higher by about $1500 than a gas central forced-air system (all in 2000 dollars). In addition, the distribution system of a hydronic radiator system costs about $1.22 more on a per square foot basis than central forced-air distribution systems.

Similar to the water heater choice model, two specifications of the multinomial logit model are estimated as reported in the middle two columns of Table 4. Model 11 evaluates the role

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21 Of the 7295 PG&E households in the RASS dataset, 7053 households report a primary space heating device. Of the primary space heating systems, 90% use natural gas, 8% use electricity, and 2% use bottled gas, solar, or wood. The three choices included in the long-run technology choice analysis account for 74% of homes with primary space heating systems. Attempts to include natural gas floor and wall systems and electric resistance systems were blocked by missing values for income, fuel consumption and household variables. Other types of systems (central heat pumps, through-the-wall heat pumps, portable electric heaters, and an unspecified “other” category of natural gas systems), representing only 3.3% of choices, are excluded due to the lack of reliable capital cost data. Because the excluded observations are minor and removed for reasons unlikely to be related to space heating system choice, their exclusion likely does not cause serious bias in the estimation results.

22 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 and fossil fueled boilers must meet a minimum energy efficiency of 0.80.

*Energy Econ.* Author manuscript; available in PMC 2019 June 04.
of Free Income, which accounts for the capital costs of choice alternatives, and expected Operating Costs of technology alternatives. Using average energy efficiency estimates to derive the operating costs is reasonable in this case as the energy efficiency of individual space heating systems did not change dramatically during the study period. Model 11 also includes the Home Ownership and College household variables as well as Dwelling Age and Heating Degree Days to represent household characteristics more pertinent to space heating. Heating Degree Days measures the historic mean heating degree days between 1985 and the year of system installation.

Similar to the water heater choice analysis, household Free Income and expected Operating Cost are not statistically significant determinants of space heating technology. Again, the role of these variables is likely captured in the significant constant terms because relative installation costs and efficiency changed little during the estimation period. On the other hand, Dwelling Age significantly affects the choice of electric systems and Heating Degree Days significantly affects the choice of natural gas radiators relative to gas forced-air systems.

Older houses are more likely to have electric central forced-air heating systems than natural gas central forced-air systems. A 10-year increase in house vintage increases the likelihood of having an electric forced-air system by 8%. This seems plausible given the fact that natural gas has gained popularity over time with its cost-effectiveness as a residential fuel source. A 10 percent increase in the average heating degree days of a residence increases the likelihood of having a gas-fired radiator system by 7%. 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 that lowers operating cost. Electric central forced-air systems are less preferred in colder areas, as one would expect, but the estimated effect is not statistically significant. Home Ownership is not a significant predictor of space heating system choice. 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 so that the current home owner likely has little if any role in the decision.

A second step constrained estimation is reported as Model 12 by imposing parametric constraints from the short-run demand estimates in Model 4 of Table 1. A log likelihood ratio test of the constrained Model 12 compared to the unconstrained Model 11 for space heating cannot reject the null hypothesis of parametric equivalence between the short-run demand model and the long-run space heating system choice model with a p-value of 0.634. Similar to water heater choice modeling, imposing parametric commonality does not change the magnitude and significance level of effects of the variables included in the model. Again, the results show a substantial compatibility with theoretical results that imply common preference parameters should drive both short-run energy use and long-run appliance choice. These results offer a further robustness check on the overall model.

### 4.2.4. Clothes dryer choices

Among the data used for estimation, 40.9% of households have gas clothes dryers and 59.1% have electric clothes dryers. The energy performance of the two types of clothes dryers is fairly similar. In 2000, average energy
efficiency in California was 2.67 for gas clothes dryers and 3.01 for electric clothes dryers as measured by the energy factor (RLW Analytics, 2000). The technology costs are also fairly similar. On average, gas clothes dryers cost about $30 more than electric clothes dryers.

The last two columns of Table 4 report the estimation results. Model 13 considers Free Income after commitments to annualized capital cost and expected Operating Costs of technology alternatives. Again, as for water heating and space heating technology choices, Free Income not committed to capital costs and expected Operating Cost are not significant determinants of clothes dryer choices likely due to little change in perceived energy efficiency of alternatives during the sample period. Model 13 also includes the three household variables used for clothes washing technology choice analysis. Home Ownership and Household Size are significant predictors of clothes dryer choices. Home ownership and an additional household member increase the propensity of electric dryer adoption by 10.3 and 2.5%, respectively.

Model 14 presents constrained estimates by imposing parametric commonality with the short-run demand estimates of Model 4 in Table 1. In this case, the log likelihood ratio test of parametric equivalence of Model 14 compared to Model 13 is mildly rejected at the 10 percent level, but cannot be rejected at more conservative levels of 1, 2, and 5% with a p-value of 0.051. One possible misspecification of the clothes dryer choice model has to do with electricity voltage in the laundry area of a dwelling. Most electric dryers require 240-volt service, twice the strength available in many older homes in California. If the laundry area is not equipped with a 240-volt outlet, the alternative to a natural gas clothes dryer requires installation of a 240-volt outlet to run an electric clothes dryer. If natural gas service is already available, a household may choose a gas clothes dryer to avoid the significant additional costs of obtaining new 240-volt electrical service to the house and installation of a 240-volt service panel if these features are not available, as is the case with many older homes. Unfortunately, electricity voltage information is not available in the RASS data and could not be included for further tests.

As far as the effects of imposing parametric commonality compared to Model 13, the restricted model produces estimates that increase both the magnitude and statistical significance of effects of household variables, which is similar to the case of adoption of front loading washing machines. Home ownership and each additional household member increase the propensity of electric dryer adoption by 11.3 and 2.6%, respectively.

5. Discussion and conclusions

This paper presents a flexible empirical framework that can be used to study welfare effects of policy intended to improve energy efficiency and reduce emissions from household energy use and appliance choice behavior. The major contribution is to show that commonality of preferences across short-run energy use demands and long-run appliance choices can be imposed for feasible estimation when both multiple forms of energy and multiple energy uses are involved. Previously this has been achieved only for a single type of durable and a single energy use, e.g., Bento et al.’s (2009) study of automobile selection and gasoline use. We accomplish this by imposing a plausible fixed-proportions structure on
production with additive aggregation while focusing on flexibility in substitution and demand for services through a common underlying indirect utility function that satisfies integrability.

Available space precludes detailed welfare analysis in this paper. However, the results demonstrate that both short-run continuous energy demands and long-run discrete appliance choice equations can be estimated from a common underlying utility maximization model with second-order flexibility such as provided by the translog specification. The results are unique in testing for common applicability of preference parameters to explain the relationship of short-run demands and long-run appliance choice. Statistical tests cannot reject statistical equivalence of a common preference structure among short-run demands for two alternative fuels in four end uses and long-run technology choices for water heating, space heating and clothes drying at the 1, 2, and 5 percent significance levels. Given the richness and flexibility of the estimated model, these results provide considerable validation. Further, non-commonality of the clothes washer choice model is plausibly explained by model misspecification due to lack of data on water price and intermittent water use restrictions (both voluntary and mandatory) in California.

Without further welfare analysis that is beyond the scope of this paper, the estimated model has several important implications for energy and climate policy.

1. Short-run, price-induced household energy efficiency is modest. A 10 percent increase in electricity price reduces consumption by an average of only 1.3% while a 10 percent increase in natural gas price reduces consumption by only an average of 1.2%. As a check on validity of the basic short-run results, these effects are within the range of short-run price elasticities reported in the literature.

2. Significant effects of capital and expected operating costs of alternative technologies can be identified only where major changes in relative efficiency among appliances have occurred in the sample period. In the case of clothes washers, income level is a significant predictor of energy-efficient technology choice. However, Home Ownership has significant estimated effects on household choices of clothes washers, clothes dryers, and water heating systems, which suggests that home owners tend to internalize the cost of energy use whereas renters are significantly less likely to make energy efficiency investments—a finding similar to some previous studies (e.g., Davis, 2011; Gillingham et al., 2012; Myers, 2013). In contrast, however, space heating systems are usually decided by home builders. Retrofits, on the other hand, appear to require structural modifications with prohibitive costs. The implication is that policy programs for residential energy efficiency must carefully consider market failures associated with principal-agent problems and distinguish principal decision makers and market segments.

3. When parametric commonality is imposed between the short-run demand models and the long-run choice models, the magnitude and significance level of the effects are similar in the case of water heating but estimated magnitudes and
significance levels of household variables are larger for clothes washing and clothes drying while the magnitude and significance of policy variables (energy efficiency and Energy Star ratings) are smaller for clothes washing. The implication is that correctly estimating energy-saving behavior between policy controls and inherent household characteristics may require imposing parametric commonality of preferences.

iv. For clothes washer choices, the information-based Energy Star program emerges as the most significant factor influencing adoption of efficient front-loading washers; it increases the propensity of choice by 17%. In an empirical analysis of consumer refrigerator purchase decisions, Houde (2014) also found that consumers appear to respond positively and significantly to the Energy Star label. Performance efficiency standards are also found to be a significant predictor, increasing the propensity of choice by 8%. In the case of clothes washers, however, the estimates may also be capturing improved water efficiency as well.

v. Surprisingly, financial incentives for energy-efficient appliances, such as income tax credits and rebate programs included in the income variables are found to be far less effective. A $100 reduction in the purchase cost of a front-loading washer increases the propensity of adoption by only 0.5%. Such estimated income effects are even less for water heating and space heating choices.

Several limitations of this study should be borne in mind. (i) Actual household energy expenditures for electricity and natural gas were not available and had to be estimated from standard tariff schedules, which likely introduces measurement errors that tend to reduce statistical significance of energy price and operating cost variables. (ii) The analysis assumes consumers form expectations of future operating costs based on current energy prices, which could be modified with more sophisticated price expectation mechanisms. (iii) The technology choice model evaluates choices among broad categories of energy systems. More detailed work should consider price and performance information for specific appliance brands and models. Our analysis of broad appliance categories had to eliminate some categories due to lack of reliable technology cost and performance data. (iv) Estimation of the simultaneous equations of short-run demand for multiple fuels and long-run technology choices with multiple energy usages required limiting the sample to households that have observed values for each variable to attain convergence in estimation, which also introduces potential selection bias in estimation.23 (v) Recent developments in behavioral economics that identify impediments such as loss aversion or inattention to energy information when making energy investment decisions could be used to consider alterations of the neoclassical

23This also required elimination of some households that had zero energy uses to avoid non-convergence of demand system estimation. This reduces the selection problem. Both this exclusion and the imposition of parametric commonality make measuring a correction for it impractical. On the other hand, by imposing commonality of preferences through the indirect utility function, the joint modeling of technology choice and energy demand takes into account the variation in household factors (such as dwelling age, square footage, ownership, household size, education level, and heating degree days) that drive jointness between technology choice and energy use, e.g., the tendency of a consumer expecting to consume more to choose a more efficient appliance, as in the typical selection bias found in quasi experimental settings (e.g., Davis, 2008). Aside from the clothes washing analysis, results support a parametric equivalence that provides strong validation that the model captures the important determinants of both. Further, even though commonality is rejected is rejected statistically for clothes washing, we suggest that the commonality model may be preferred on economic grounds given the results for the other three energy uses.  

Energy Econ. Author manuscript; available in PMC 2019 June 04.
model we estimate (e.g., see Allcott, 2011; Allcott and Taubinsky, 2015; Gillingham and Palmer, 2014). (vi) Application of full information ML estimation to discrete-continuous models remains an empirical challenge except for choice problems less complex than the household appliance-choice-energy-usage problem (e.g., the auto-choice-fuel-efficiency problem estimated by Bento et al., 2009). Also, like most existing studies, we use a two-step limited information ML approach and simply test compatibility in a two-step context.

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Table 1

Coefficient estimates of the short-run demand equations.

| Coefficient | Model 1 | Model 2 | Model 3 | Model 4 |
|-------------|---------|---------|---------|---------|
|             | No household variables | With household variables | With clothes washer efficiency | Clothes washer & water heater efficiency |
| **Intercepts** |         |         |         |         |
| $a_0$ Numeraire | 1.07892 $^{***}$ (149.241) | 0.92969 $^{***}$ (166.703) | 0.81503 $^{***}$ (84.181) | 0.80212 $^{***}$ (65.717) |
| $a_1$ Clothes Washing | -0.03500 $^{*}$ (-2.385) | -0.03577 $^{***}$ (-4.121) | 0.06756 $^{***}$ (5.456) | 0.10859 $^{***}$ (6.854) |
| $a_2$ Water Heating | 0.06316 (1.279) | 0.02998 (0.893) | -0.02994 (-0.857) | -0.01002 (-0.226) |
| $a_3$ Clothes Drying | -0.03620 $^{**}$ (-3.101) | 0.03689 $^{***}$ (4.138) | 0.03209 $^{***}$ (3.774) | -0.00099 (-0.118) |
| $a_4$ Space Heating | -0.03062 (-0.882) | 0.02915 (1.214) | -0.02322 (-0.925) | -0.01592 (-0.619) |
| **Demand interaction terms** |         |         |         |         |
| $\theta_1$ Household Size | -0.00038 $^{***}$ (-7.049) | -0.00037 $^{***}$ (-6.649) | -0.00038 $^{***}$ (-6.620) |         |
| $\theta_2$ Square Footage | 0.00053 $^{*}$ (4.781) | 0.00069 $^{***}$ (6.031) | 0.00072 $^{***}$ (6.080) |         |
| $\theta_3$ Dwelling Age | -0.00069 $^{***}$ (-10.822) | -0.00074 $^{***}$ (-11.098) | -0.00075 $^{***}$ (-10.888) |         |
| $\theta_4$ Heating Degree Days | 0.00213 $^{***}$ (10.792) | 0.00220 $^{***}$ (10.869) | 0.00226 $^{***}$ (10.776) |         |
| $\gamma_1$ Standard | -0.00515 $^{**}$ (-4.28) | -0.00515 (-4.28) | -0.00521 $^{***}$ (-4.30) |         |
| $\gamma_2$ Energy Star | -0.00647 (-0.640) | -0.00647 (-0.640) | -0.00714 (-0.694) |         |
| $\lambda_1$ Technology Change |         |         |         | 0.04578 (0.146) |
| **Second-order own effects** |         |         |         |         |
| $\beta_{21}$ Clothes Washing | 0.02324 $^{***}$ (7.540) | 0.02383 $^{***}$ (30.328) | 0.04820 $^{***}$ (15.794) | 0.05129 $^{***}$ (15.795) |
| $\beta_{22}$ Water Heating | 0.09579 (1.630) | 0.01308 (0.352) | -0.01877 (-0.437) | 0.00505 (0.147) |
| $\beta_{23}$ Clothes Drying | -0.00422 $^{*}$ (-3.250) | 0.00260 $^{***}$ (3.454) | 0.00403 $^{***}$ (3.912) | -0.00057 (-0.344) |
| $\beta_{24}$ Space Heating | -0.11814 (-1.877) | -0.02305 (-0.579) | -0.0569 (-1.445) | -0.06193 (-1.559) |
| $\beta_{25}$ Other | -0.06206 (-0.783) | -0.0249 (-0.496) | -0.07699 (-1.455) | -0.05884 (-1.200) |
| **Second-order cross effects** |         |         |         |         |
| $\beta_{01}$ Numeraire | -0.01047 $^{***}$ | 0.01596 $^{***}$ | 0.01142 $^{***}$ | 0.01094 $^{***}$ |
| $\beta_{02}$ Clothes Washing | ( - 8.144) | (14.497) | (7.430) | (6.680) |
| $\beta_{03}$ Numeraire | 0.00265 $^{*}$ | 0.00341 $^{*}$ | -0.00265 | -0.00222 |
| $\beta_{04}$ Water Heating | (2.447) | (2.498) | (-1.401) | (-1.226) |
| Coefficient          | Model 1 No household variables | Model 2 With household variables | Model 3 With clothes washer efficiency | Model 4 Clothes washer & water heater efficiency |
|----------------------|--------------------------------|----------------------------------|----------------------------------------|--------------------------------------------------|
| $\beta_{03}$ Numeraire | 0.00158*                        | 0.00194***                      | 0.00116                               | $-0.00180^{**}$                                      |
| Clothes Drying       | (2.425)                         | (3.736)                         | (1.764)                                | ($-3.114$)                                        |
| $\beta_{04}$ Numeraire | $-0.00072$                      | 0.00643***                      | 0.00271                                | 0.00318*                                          |
| Space Heating        | $(-0.667)$                       | (4.798)                         | (1.731)                                | (2.022)                                           |
| $\beta_{05}$ Numeraire | 0.04241***                      | 0.02293***                      | 0.03754***                             | 0.03999***                                        |
| Other                | (13.445)                        | (12.234)                        | (14.173)                               | ($-1.200$)                                        |
| $\beta_{12}$ Clothes Washing | $-0.00609^{****}$             | 0.00056***                      | $-0.00252^{**}$                       | $-0.0023$                                         |
| Water Heating        | $(-6.231)$                       | (3.471)                         | ($-2.769$)                             | ($-1.156$)                                        |
| $\beta_{13}$ Clothes Washing | 0.00042                          | 0.00034***                      | $-0.00265$                             | $-0.00085$                                        |
| Clothes Drying       | (1.395)                         | (2.749)                         | ($-1.401$)                             | ($-0.719$)                                        |
| $\beta_{33}$ Water Heating | $-0.09331$                      | $-0.12331$                      | 0.01938                                | $-0.00501$                                        |
| Other                | $(-1.582)$                       | ($-0.331$)                      | (0.450)                                | ($-0.147$)                                        |
| $\beta_{06}$ Space Heating | 0.12151                         | 0.02735                         | 0.05789                                | 0.0642                                           |
| Other                | (1.921)                         | (0.685)                         | (1.468)                                | (1.615)                                           |
| Observations         | 2408                            | 2408                            | 2408                                   | 2408                                              |
| Log Likelihood       | 14.827                          | 15.414                          | 15.516                                 | 15.519                                            |
| $R^2$-Numeraire      | 0.385                           | 0.579                           | 0.604                                  | 0.604                                             |
| $R^2$-Natural Gas    | 0.414                           | 0.777                           | 0.788                                  | 0.788                                             |

Notes: Asterisks denote significance of p-values:

* for $p < 0.05$

*** for $p < 0.001$, and

**** for $p < 0.0001$.

Values in parentheses are t-statistics.
Table 2
Estimated short-run price and income elasticities of demands for fuels.

| Model   | Price elasticity | Income elasticity |
|---------|------------------|-------------------|
|         | Price elasticity | Income elasticity |
|         | Mean             | Range             | Mean             | Range             |
|         | Electricity demand |                     | Natural gas demand |                     |
| Model 1 | 0.245 (0.143)    | 0.150 to 2.831    | 0.082 (0.084)    | −0.262 to 2.115   |
| Model 2 | −0.133 (0.060)   | −0.534 to −0.106  | 0.344 (0.080)    | 0.256 to 0.870    |
| Model 3 | −0.064 (0.083)   | −0.750 to −0.036  | 0.503 (0.066)    | 0.427 to 1.004    |
| Model 4 | −0.134 (0.141)   | −1.091 to −0.068  | 0.418 (0.179)    | 0.319 to 1.697    |

Note: Elasticities are based on the four models of Table 1. Values in parentheses are standard errors.
Table 3

Estimated coefficients of the clothes washer choice model.

| Regressor         | Model 5       | Model 6       | Model 7       | Model 8       |
|-------------------|---------------|---------------|---------------|---------------|
| Free Income       | 104.578 ***   | 155.477 ***   | 123.609 ***   |                |
|                   | (4.62)        | (4.47)        | (3.45)        |                |
| Operating Cost    | 1.430 ***     | 0.448 (0.50)  | 0.448 (0.50)  |                |
| Fuel Price        | 0.339 (0.40)  | 0.448 (0.50)  | 0.448 (0.50)  |                |
| Efficiency Standard| 1.154 **      | 1.114 **      | 0.888 *       |                |
|                   | (2.75)        | (2.65)        | (2.13)        |                |
| EnergyStar        | 2.001 ***     | 2.022 ***     | 1.925 ***     |                |
|                   | (7.18)        | (7.15)        | (8.39)        |                |
| Home Ownership    | 0.642 (1.94)  | 0.847 *       |                |                |
| Household Size    | 0.045 (0.99)  | 0.062 (1.38)  |                |                |
| College           | 0.447 **      | 0.798 ***     |                |                |
|                   | (2.73)        | (5.10)        |                |                |
| Constant          | −3.180 *      | −4.105 *      | −5.911 ***     |                |
|                   | (−1.97)       | (−2.39)       | (−11.71)      |                |
| Observations      | 2408          | 2408          | 2408          | 2408          |
| Log likelihood    | −835          | −719          | −712          | −734          |

Notes: Asterisks denote significance of p-values:

- *** for p < 0.001
- ** for p < 0.01, and
- * for p < 0.05

Values in parentheses are t-statistics. A top-loading clothes washer is the base case.
Table 4

Estimated coefficients of the water heater, space heating, and clothes dryer choice models.

| Regressor       | Water heating choice Model 9 | Model 10 | Space heating choice Model 11 | Model 12 | Clothes dryer choice Model 13 | Model 14 |
|-----------------|-----------------------------|----------|-------------------------------|----------|-------------------------------|----------|
| Home Ownership  | −0.806 (−1.59)              | −0.694 (−1.39) | −1.061 (−1.32)              | −0.956 (−1.20) | −0.430** (−2.64)              | −0.471** (−2.92) |
| Household Size  | 0.152 (1.53)                | 0.163 (1.67)   | −0.258 (−0.78)              | −0.259 (−0.78) | −0.106*** (−3.54)             | −0.111*** (−3.98) |
| Dwelling Age    | −0.810 * (−2.13)            | −0.682 (−1.85) | −0.252 (−0.38)              | −0.101 (−0.16) | −0.029 (−0.32)                | −0.080 (−0.92)   |
| Heating Degree Days | 2.884** (−2.42)           | 2.859* (−2.39)  | 10.950*** (−3.17)           | 11.737*** (−3.44) | 1.171 (1.07)                  | 1.155*** (6.34)   |
| College         | −3.411*** (−5.17)           | −3.815*** (−6.63) | −10.950*** (−3.17)         | −11.737*** (−3.44) | 1.171 (1.07)                  | 1.155*** (6.34)   |
| Constant        | −1.260*** (−4.27)           | −1.269*** (−4.28) | −0.109 (−0.26)              | −0.054 (−0.13) | −0.054 (−0.13)                | −0.054 (−0.13)   |
| Observations    | 2408                        | 2408          | 2408                         | 2408      | 2408                          | 2408     |
| Log likelihood  | −483                        | −484          | −398                         | −399      | −1615                         | −1618    |

Notes: Asterisks denote significance of p-values:

* for p < 0.05
** for p < 0.01
*** for p < 0.001
'' for p < 0.01, and

''' for p < 0.001.

Values in parentheses are t-statistics. That base cases are a natural gas tank system for water heating, a natural gas forced-air system for space heating, and a gas-fired clothes dryer for clothes drying.