Applied Energy 240 (2019) 205–214

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Forecasting household consumption of fuels: A multiple discrete-continuous approach

Vito Frontuto

Department of Economics and Statistics "C. De Martiis", University of Torino, Lungo Dora Siena 100/A, I -10153 Torino, Italy

HIGHLIGHTS

- A Multiple Discrete Continuous Model (MDCEV) is implemented to study residential energy demand.
- Multiple discreteness allows to model a mixture of corner an interior solutions.
- Different policies and/or climate change scenarios are simulated.
- Demand is found to be inelastic with respect to prices for both transportation and space heating.

ARTICLE INFO

Keywords:
Multiple Discrete-Continuous Model
GEV models
Residential energy demand
Expenditure data

ABSTRACT

This paper uses a multiple discrete–continuous extreme value (MDCEV) model with perfect and imperfect substitutes to study residential energy demand. A non-linear utility function is employed within a Kuhn-Tucker multiple-discrete economic model of consumer demand, estimated on Italian expenditure data. The simulation algorithm measures demand elasticity with respect to price variations and the marginal effects of other covariates. Results show that household energy demand (space and water heating and transportation) is relatively inelastic with respect to prices (−0.55 and −0.67, respectively), meaning that pricing policies can induce a reduction in the demand for fuels less than proportional to the price variation. The model also allows to forecast the energy demand for space and water heating within a global warming scenario: an increase of 2 degrees Celsius would lead, for example, to a reduction in household energy consumption of 4.07%.

1. Introduction

In the last decades, governments have made efforts to achieve climate goals by fostering energy production from sustainable sources and by promoting energy efficiency. Among the available instruments, energy taxes have been widely used to reduce energy demand. This poses the need to quantify the reactions of agents to variations in energy prices and to forecast robustly the potential of mitigation policies. Although the economic literature on energy demand is rich and steadily expanding there are still a number of challenging gaps. Labandeira et al. [1] produced a rigorous meta-analysis on over four hundred studies finding such a wide range of elasticity measures to make them uninformative.

In order to improve the predictive capacity of economic models of energy demand, the attention has been recently moving to the demand of single end-use consumptions, that allow to analyse simultaneously investment and consumption decisions. For this reason, this paper presents an end-use energy demand model focusing on the residential sector. The latter accounts for one fourth of the worldwide final energy consumption [2] and with a global energy-saving potential of around 0.48 * 106 Ktoe per year, plays a crucial role in mitigating CO_2 emissions [3,4].

Households derive utility from a flow of services (such as comfortable temperatures in living environments, hot water) provided by durable goods which use energy as an input. Thus, choices of investing in durable goods imply a future demand for energy. The optimization problem faced implicitly by individuals is complex and requires weighing a significant amount of information.

Traditional discrete-continuous models consider the case of perfect substitute goods or "extreme corner solution problems" [5], in which by construction, the maximization process leads to the selection of only one alternative. However, individual choices (for example, financial investments, leisure time, and fuel and energy consumption) are often characterized by generalized corner solutions, or multiple discreteness, defined as situations in which multiple alternatives can be chosen simultaneously [6]. The methodological issue involved concerns the

E-mail address: vito.frontuto@unito.it.

https://doi.org/10.1016/j.apenergy.2019.01.262
Received 7 December 2017; Received in revised form 14 January 2019; Accepted 31 January 2019
Available online 15 February 2019

procedure used to model the choice of consumption bundles in which each quantity (or expenditure) can be either zero or positive. When only two goods are involved, the problem is typically solved by applying the so-called Tobit model or some adaptation of it [7]; these models have been applied widely in many fields (labour supply, investment decisions, infrequent purchases, and energy demand). When more than two goods are considered, the methodological issue becomes more difficult to deal with. Looking at Kuhn-Tucker's First Order Conditions, we observe that each demand function depends on the other quantities being zero or positive, thus originating $2^J - 1$ possible "regimes", where J indicates the number of goods, and at least one quantity must be greater than zero. Wales and Woodland [8] first attempt to deal with multiple discreteness by deriving the choice probabilities from the first order conditions and allowing for zero and positive consumption levels within a behaviourally consistent framework. Nevertheless, this approach requires the estimation of a complex likelihood function via multi-dimensional integration. Due to this computational issue, the Wales and Woodland model was considered impractical for many years until the Geweke-Hajivassiliou-Keane (GHK) simulator became available to evaluate the multivariate normal integral involved [9].

A very pragmatic and efficient alternative was proposed by Train et al. [10] with an application to telephone service demand. The idea consists of applying a Multinomial Logit model to a discrete representation of the opportunity set, in which the zeroes and positive outcomes are treated as discrete alternatives. Finally, Hendel [11] and Dube [12], the first to use the definition of "multiple discreteness", proposed to model consumption decisions among alternative goods as the result of a sequence of expected future utilities. In this context, the contribution of Bhat [13] is particularly significant, as it provides a straightforward procedure for recovering a closed form solution for the choice probabilities. He built the model on the generalized variant of the translated constant elasticity of substitution (CES) utility function with a multiplicative log-extreme value error term. The model, named the Multiple Discrete-Continuous Extreme Value (MDCEV) model, represents the multiple discrete version of a Multinomial Logit (MNL), and it collapses to the standard MNL when each individual decides to consume only one alternative [13].

Following the path opened by Bhat [13], Bhat et al. [14], and Pinjari and Bhat [15], this paper proposes an application of the MDCEV model to energy economics, introducing for the first time in that context the contemporaneous presence of imperfect and perfect substitute goods.

The model has a nested structure. In the first step of the decision path households decide whether to allocate, or not, a positive amount of money to each energy service (space heating, water heating, transportation, and a residual miscellaneous category including the electricity used to run the appliances owned by the household).[1]

The multiple discreteness introduced in the model allows the household to consume all or some of these services, except for the Hicksian goods – a subsistence goods a minimum level of which is always consumed.

In the second step, households select the fuels necessary for each energy service (oil, gas, gasoline, wood, and so on). This second choice is made among perfect substitutes and only one fuel can be chosen.

Finally, third step models the continuous demand or expenditure for each fuel conditional upon the previous discrete choices.[2]

[1] This was the most disaggregated categorization allowed by available data. The International Energy Agency categorizes energy demand as space heating, water heating, cooking, space cooling, lighting, and total appliance. The theoretical model developed here can, however, accommodate a more detailed disaggregation of residential energy demand, as well.

[2] It is important to stress that the whole model is estimated simultaneously; hence, the 'steps' in the decision path should not be considered as sequential estimations.

The MDCEV model, now a MDCEV-GEV as it involves two set of errors, is particularly efficient in dealing with multiple and simultaneous choices among alternatives, along with the decision on whether and how much to consume of each. Moreover, this type of modelling differs from single discrete choice models because it allows us to introduce explicitly diminishing marginal returns (satiation) in consumption. The theoretical framework presented here thus allows to make a step forward in the use of MDCEV models in energy economics. With respect to previous literature [16,17], the simultaneous presence of perfect and imperfect substitutes enables us to model a wider bundle of energy services. Moreover, the empirical application is implemented on a large-sample national survey on households' expenditures (the *Italian Households Consumption Survey*) allowing us to infer population behaviour with a higher level of accuracy than previous works (e.g., [18]) based on small samples.

The paper is organized as follows: Section 2 introduces the theoretical model, and Sections 3 and 4 present the dataset and the results of the empirical model. Section 5 provides some scenario analyses through simulations, and Section 6 concludes.

2. The multiple discrete-continuous choice model

This section is strictly based on Bhat [13], Bhat et al. [14], and Pinjari and Bhat [15]. Following the general set up of a discrete-continuous choice model, the selection of the optimal portfolio simultaneously represents a discrete and a continuous choice. The discreteness is embodied in the decision regarding the appliances/equipment, and the continuous choice determines the expenditure in energy.

Suppose that there are K household services ($k = 1, 2,\ldots,K$; with k corresponding to the numerically labelled choices space heating, water heating, transportation, and so on) and J_k available fuels for each service ($j = 1, 2,\ldots,J$; with j corresponding to the numerically labelled choices electricity, oil, gas, and so forth). In this application, as in Yu et al. [18], the subsistence service is residual, and it represents the portion of income left after the energy expenditures allocation. The others $K - 1$ services are the alternatives of the multiple discrete choice: the household decides whether to spend a positive amount of money e_k, or zero for each $K - 1$ service. The utility function used is a special case, namely a linear expenditure system formulation of the Box-Cox version of a translated CES direct utility function [15], whose generic form, in terms of expenditure,[3] is:

$$U = \frac{1}{\alpha_1}\psi_1(e_1)^{\alpha_1} + \sum_{k=2}^{K}\frac{\gamma_k}{\alpha_k}\psi_k\left\{\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k}-1\right\}$$

$$\psi_k > 0, \quad 0 \le \alpha_k \le 1, \quad \gamma_k > 0 \tag{1}$$

The objective function is maximized subject to the budget constraint:

$$\sum_{k=1}^{K} e_k = E \tag{2}$$

where E is the total expenditure.

U is the utility derived from the expenditure of e for k services available to the consumer, ψ_k the baseline utility deriving from the consumption of service k and is function of observed characteristics associated to each alternative k. A higher baseline utility for k implies less likelihood of corner solutions for that service, in other words, positive consumption.

The α's are satiation parameters representing the rate of the diminishing marginal utility of spending money in category k. As α_k decreases, the satiation effect for good k increases, and, when $\alpha \to -\infty$,

[3] The utility function is expressed in terms of expenditures e_k. Starting from the model in quantities, we substitute $x_k = \frac{e_k}{p_k}$ and assume prices are normalized at 1.

there is immediate and full satiation. The parameters γ_k can be also interpreted as satiation parameters: they shift the position of the point at which the indifference curves are asymptotic. The indifference curve becomes steeper as the value of γ increases.

Different assumptions on the satiation parameters can generate alternative utility function specifications. When γ is equal to 1 for each service, we end up with the so-called $\alpha - profile$ utility function, and, when $\alpha \to 0$, we have the $\gamma - profile$ utility function; when either γ is equal to 1 or $\alpha \to 0$, there is no satiation, and the function collapses to the case of perfect substitutes (single discreteness):

$$U = \sum_{k=1}^{K} \psi_k(e_k) \tag{3}$$

Intuitively, when there is no satiation and the unit good prices are all the same, the consumer will invest all his/her expenditures on the good with the highest baseline (and constant) marginal utility (i.e., the highest ψ_k value).

Consistent with the single discrete-continuous model of Hanemann [5], we assume that the utility is decomposed into a deterministic component (V) and a random term (ε) introduced as a multiplicative element in ψ; therefore:

$$\psi(e_k, \varepsilon_k) = V_k(z_k)e^{\varepsilon_k} = \exp(\beta' z_k + \varepsilon_k) \tag{4}$$

where z_k is a vector of exogenous covariates influencing the utility related to the specific energy service k, β is the vector of the corresponding alternative specific coefficients, and ε_k is the error component.

In order to accommodate the presence of a second step in the decision process, we decompose the k services in two groups: the first includes services for which no finer representation can be done (set B), and the second collects the services for which the consumer can make a “subsequent” choice in terms of fuel. Substituting Eq. (4) into Eq. (1), the utility function becomes:

$$\begin{aligned}\tilde{U} = {}& \frac{1}{\alpha_1}[exp(\beta' z_1 + \varepsilon_1)]e_1^{\alpha_1} + \sum_{k\neq B}\frac{\gamma_k}{\alpha_k}[exp(\beta' z_k + \varepsilon_k)]\left\{\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right\} \\ & + \sum_{k=B}\frac{\gamma_k}{\alpha_k}[exp(max_{j\in N_k}\{W_{jk}\})]\left\{\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k} - 1\right\}\end{aligned} \tag{5}$$

where N_k is the set of different fuels used in each service.[4] W_{jk} can be modelled in a linear form, as in Bhat et al. [14], or allow for non-linearities. In general, the utility associated with fuel j in the service k can be written as:

$$W_{jk} = \delta' s_{jk} + \eta_{kj} \tag{6}$$

where s_{jk} is the vector of variables influencing the utility related to the specific fuel j in service k, δ is the vector of corresponding alternative specific coefficients, and η_{kj} is the error component.

The Lagrangean function for the maximization of the utility function subject to the budget constraint is:

$$\mathscr{L} = \tilde{U} - \lambda\left[\sum_{k=1}^{K} e_k - E\right] \tag{7}$$

where λ is the Lagrangean multiplier, and the first order Kuhn-Tucker conditions are:[5]

$$\begin{aligned}
&\psi_1(e_1)^{\alpha_1-1} - \lambda = 0 \qquad since \quad e_1^* > 0\\
&\psi_k\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k-1} - \lambda = 0 \qquad if \quad e_{k\notin B}^* > 0\\
&\psi_k\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k-1} - \lambda < 0 \qquad if \quad e_{k\notin B}^* = 0\\
&exp(max_{j\in N_k}\{W_{jk}\})\left[\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k-1}\right] - \lambda = 0 \qquad if \quad e_{k\in B}^* > 0\\
&exp(max_{j\in N_k}\{W_{jk}\})\left[\left(\frac{e_k}{\gamma_k}+1\right)^{\alpha_k-1}\right] - \lambda < 0 \qquad if \quad e_{k\in B}^* = 0
\end{aligned} \tag{8}$$

The second set of conditions have been decomposed to accommodate the presence of a within-service decision. The Lagrange multiplier is recovered from the first first-order condition, and, after some manipulation, we end up with:

$$\begin{aligned}
&V_1 = \beta' z_1 + (\alpha_1 - 1)ln e_1^*\\
&V_k = \beta' z_k + (\alpha_k - 1)ln\left(\frac{e_k^*}{\gamma_k}+1\right) \qquad if \quad k \notin B\\
&V_k = Max_{j\in N}\{\delta' s_{jk} + \eta_{jk}\} + (\alpha_k - 1)ln\left(\frac{e_k^*}{\gamma_k}+1\right) \qquad if \quad k \in B
\end{aligned} \tag{9}$$

where the Vs represent the deterministic part of the utility function, as in a standard Random Utility Model (RUM). The standard assumptions for identification in the MDCEV model hold also in the MDCEV-GEV extension. In particular, α must be bounded between 0 and 1, and γ must be greater than zero.

2.1. Error distribution

The MDCEV-GEV model accommodates the presence of two error terms: ε_k for the MDCEV portion of the model and η_{kj} for the GEV one; consequently, it requires some assumptions on distributions and potential correlation between the two. ε_k is assumed to follow a first-type Gumbel distribution, and η_{kj} (Eq. (6)) is decomposed into two components: $\eta_{kj} = \lambda_k + \lambda_{kj}$, where the first element is an unobserved component common to the alternatives and the second is an extreme value identically distributed with a scale parameter θ_k. The terms in λ_{kj} are independent of ε_k, but correlated among them, and a general correlation structure is assumed, as follows:

$$F_k(\lambda_{k1}, \lambda_{k2}, \cdots, \lambda_{kJ}) = exp[-G_k(e^{\lambda_{k1}}, e^{\lambda_{k2}}, \cdots, e^{\lambda_{kJ}})] \tag{10}$$

where G_k is a non-negative, homogeneous function. In general, the violation of the Independence of Irrelevant Assumption (IIA) can be allowed by modelling a mixture logit or GEV structure for both the MDCEV (ε) and the within-service choice (η).

From these assumptions, the marginal choice probabilities to participate in the first M alternatives in choice set K can be written as:

$$P(e_1^*, e_2^* e_3^*, \cdots, e_K^*, 0, 0, \cdots, 0) = |J|\left[\frac{\prod_{k=1}^{M} e^{V_k+\eta}}{\left(\sum_{k=1}^{K} e^{V_k+\eta}\right)^M}\right](M-1)! \tag{11}$$

where J is the Jacobian whose determinant is defined as:

$$|J| = \left[\prod_{k=1}^{M} r_k\right]\left[\sum_{k=1}^{M}\frac{1}{r_k}\right], \qquad with \qquad r_k = \left(\frac{1-\alpha_k}{e_k^*+1}\right) \tag{12}$$

and the Vs are recovered from the first first-order condition:

$$\begin{aligned}
&V_1 = \beta' z_1 + (\alpha_1 - 1)ln e_1^*\\
&V_k = \beta' z_k + (\alpha_k - 1)ln\left(\frac{e_k^*}{\gamma_k}+1\right) \qquad if \quad k \notin B\\
&V_k = \beta' z_k + \theta_k lnG_k(e^{s_{k1}}, e^{s_{k2}}, \cdots, e^{s_{kJ}})(\alpha_k - 1)ln\left(\frac{e_k^*}{\gamma_k}+1\right) \qquad if \quad k \in B
\end{aligned} \tag{13}$$

[4] N can vary across categories.

[5] As mentioned previously, in the following expression, the prices are normalized to one.

The GEV structure for the discrete choice (function G) permits the use of different specifications for different services: in particular, Nested Logit and Multinomial Logit (or mixtures). In the case of Multinomial Logit, the last row of Eq. (13) becomes:

$$V_k = \beta' z_k + \theta_k ln \sum_{j \in N_k} exp\left(\frac{\delta' s_{jk}}{\theta_k}\right) + (\alpha_k - 1) ln\left(\frac{e_k^*}{\gamma_k} + 1\right) \tag{14}$$

The probability of choosing fuel j conditional on the allocation of positive expenditure to service k is obtained from Eq. (6):[6]

$$P(j|e_k^* > 0; j \in N_k) = \frac{e^{\delta' s_{jk}} \cdot G_{jk}(e^{\delta' s_{1k}}, e^{\delta' s_{2k}}, \cdots, e^{\delta' s_{jk}})}{\frac{1}{\theta_k} \cdot G_k(e^{\delta' s_{1k}}, e^{\delta' s_{2k}}, \cdots, e^{\delta' s_{jk}})} \tag{15}$$

The unconditional probability that an individual chooses to participate in consumption of fuel *1* for service *2* for an amount e_{12}^*, fuel *2* for service *3* for an expenditure e_{23}^*, and so forth, can be written as:

$$P(e_1^*, e_{12}^*, e_{23}^*, \cdots, 0, 0, \cdots, 0) = P(e_1^*, e_2^*, e_3^*, \cdots, e_K^*, 0, 0, \cdots, 0) \cdot P(1|e_2^* > 0) \cdot P(2|e_3^* > 0) \cdots \tag{16}$$

The multiple category choice and the discrete fuel choice are linked by the contemporaneous presence of parameters δ and θ in Eq. (15). When θ is equal to *1,* the joint model reduces to the standard MDCEV model, for which there are $K + \sum A_j$ alternatives, where A_j is the number of alternatives in N_j [13]. In the empirical application presented in the next sections, we will test the hypothesis of $\theta \neq 1$ to verify the validity of the model of contemporaneous presence of perfect and imperfect substitutes. The estimation of the joint model (Eq. (16)) is implemented using the maximum likelihood inference approach.[7]

3. Data

The MDCEV-GEV model has been tested using expenditures data for Italian households from the Households Consumption Survey (HCS) for the year 2010.[8] The scope of the survey, conducted by the Italian Institute of Statistics, is to collect information about consumption behaviours of Italian families. Data on expenditures for goods and services are collected from each household considered as single individual or a group of people living in the same house and participating in consumption decisions. The choice to adopt the year 2010, even if more recent data are available, is given by the lower variability of the latter. Given the complexity of the model presented in Section 2, we need considerable variation to identify parameters of the fuel choice via maximum likelihood estimation. For the most recent years it has not been possible to collect information, in particular prices and temperatures, presenting an adequate geographical and seasonal variability.

As in all national surveys, energy expenditures, recorded for each fuel, are not differentiated among services. This lack of information is a common empirical issue for researchers interested in end-use consumption analysis; unless a primary study is conducted, researchers generally accept a trade-off with sample representativeness. In principle, the issue can be solved by directly metering individual appliances or equipment. Nevertheless, metering data are costly and therefore are not available for different end-uses and large samples. When direct metering of appliances is not an option because the technology is not available or too expensive, the statistical procedure referred to as a conditional demand analysis (CDA) can be implemented [19,20,21,22]. The procedure compares households owning an appliance to the others and interprets the differences in consumption as a measure of the appliance's unit energy consumption (UEC). The main idea of the econometric model is that estimated coefficients of the dummy variables are interpreted as mean electricity consumption related to these appliances. In their application of the discrete-continuous demand model, Dubin and McFadden [23] calculate the total electricity consumption and an electric utilization base rate using UEC (annual consumption in kWh) fitted by regressing electricity consumption on household appliance dummies. These estimates are declared to be biased, and they require standard error corrections, but they can be used to build a measure of expenditure shares. Actually, this procedure could provide unreliable information on the efficiency of single appliances but, as shown in Dubin and McFadden [23] and used in Nesbakken [24], Vaage [25] and Larsen and Nesbakken [26] in the single discrete-continuous model and Jeong et al. [16] in MDCEV models, it can be useful in auxiliary regressions to recover the share of energy demand for each domestic service.

Following the procedure proposed by Jeong et al. [16], we run a CDA for electricity and natural gas and after standard error corrections we measured expenditures in the space and water heating services.[9] These shares are then employed in the MDCEV model (expenditures in Eq. (1)). In terms of the other fuels (i.e., wood, LPG, and oil), we assume that they can be used only for space and water heating services.

This procedure implicitly assumes static expectations forcing the choices pertaining to the purchase of appliances and their use to be simultaneous. As suggested by Dubin and McFadden [23], "these assumptions are just approximately true", and we should consider dynamic representations of expectations and decision processes. Nevertheless, according to Dubin and McFadden [23], the discrete and continuous choices can be assumed to be simultaneous if there are perfect markets for durables. In order to limit the potential bias caused by the fact that some households may not have had the opportunity to choose their heating system, we selected a subsample of households who settled in their home in the year of its construction or households who had been living in their current house for at least 15 years. In the first case, we assumed that families participated in decisions regarding heating systems during the building stages; in the second case, considering that the average lifespan of a heating system is 15 years, we presumed that the family had the opportunity to replace it and hence to choose their preferred system. In line with this assumption, we did not use households living in buildings with centralized heating systems in the estimation.

The Households Consumption Survey contains data on many aspects of the living conditions of Italian families. From this rich dataset, we extrapolated the information which seemed to describe energy demand accurately, in particular:

(1) Households' characteristics: head of family gender and age, household size, presence of children (less than 14 years old).
(2) House attributes: dwelling type and age, location, number of rooms, renewal or maintenance work during the last year, type of right of use.
(3) Energy consumption: monthly energy expenditures on electricity, gas, wood, oil, LPG, gasoline, and diesel.
(4) Ownership of vehicles: number of cars owned.
(5) Wealth and Income: number of houses owned and monthly total expenditures.

Table 1 provides participation rates for each service. In particular, column 2 reports the total number of individuals demanding a positive amount of each service, and in column 3 the average expenditures are reported.

[6] In the case of MNL we have: $P(j|e_k^* > 0; j \in N_k) = \frac{exp\left(\frac{\delta' s_{jk}}{\theta_k}\right)}{\sum_{g \in N_k} exp\left(\frac{\delta' s_{jk}}{\theta_k}\right)}$. For a detailed description of the error distributions, see Bhat et al. [5].

[7] The model has been estimated using Gauss Aptech.

[8] The dataset -"Indagine corrente sui consumi delle famiglie"- is provided upon request by the Italian Institute of Statistics (ISTAT). The data manipulation and analysis are exclusive responsibility of the author.

[9] The results of the conditional demand analysis are available upon request.

Table 1
Participation rates and mean expenditure by categories.

Expenditure category	Total number (%) of individuals	Mean expenditure*
Residual	12,169 (100%)	2219.67
Miscellaneous	12,169 (100%)	44.59
Space and Water Heating	12,097 (99.4%)	89.58
Transportation	8992 (73.89%)	180.85

* The mean expenditure is measured only for individuals with non-zero consumption.

As required by the theoretical model, expenditures in the residual category are always positive. The estimated average expenditure per month is 2220 Euros.

The miscellaneous category collects the expenditures in electricity not included in space and water heating (lighting, electronic devices, and so on): all families in the sample own at least one electric device for which a positive amount of money is spent (on average, 44.59 Euros per month). Almost all households in the sample own space and water heating equipment (99.4%), and, on average, they spent around 90 Euros per month on this equipment.

Table 2 reports the descriptive statistics relative to the penetration of different space and water heating systems in Italy. The dimensions and capillarity of the gas distribution network appears to be the most relevant driver in the adoption of different technologies utilizing this fuel, for which the supply is more complex and expensive.

In the case of transportation services, one household out of three prefers the use of non-motorized vehicles or public transportation to avoid paying for fuel (gasoline, diesel, or a combination of the two). This appears to be a counterintuitive result, at least in an industrialized country such as Italy, but we must interpret it in the light of the presence in the sample of a large number of elderly people living in cities, which implies a reduction in the use of motorized vehicles (see Table 3).

The set of alternatives in the transportation service refers to the two most diffused fuels, gasoline and diesel, and a third alternative built as the combination of the two. Among these fuels (see Table 3), the favourite one is gasoline (48.53%). Almost 11.38% of households are using diesel vehicles, as is true of families reporting the consumption of both gasoline and diesel (with more than one vehicle). One household out of four (26.11%) reports zero expenditure for transportation, confirming the result on participation rates in Table 1.

Table 4 presents some descriptive statistics for the covariates used in the empirical application of the model. The average Italian family is composed of 2/3 people with children (28% of cases); they live in popular/medium apartments (75%) with four to five rooms (60–70 square meters) and mainly in towns or cities (80%). The head of the family is male in the 70% of the cases, and 11% of the heads of household achieved a high school degree. Those owning their homes amount to more than three out of four (78%), and, in most cases, they live in old houses and did not invest in renewal or maintenance work during the last year. The mean monthly total expenditure is around

Table 2
Participation rates and mean expenditures for space and water heating fuels.

Expenditure category	Total number (%) of individual participating	Mean Expenditure*
Oil	220 (1.81%)	237.35
Natural Gas	11,317 (93%)	84.13
Lpg	368 (3.02%)	126.73
Wood (solid)	192 (1.58%)	169.97

* The mean expenditure is measured only for individuals with non-zero consumption.

Table 3
Participation rates and mean expenditures for transportation.

Expenditure category	Total number (%) of individual participating	Mean Expenditure*
Gasoline	6102 (48.53%)	166.24
Diesel	1385 (11.38%)	148.18
Mixed	1505 (12.37%)	270.17
Zero Expenditure	3177 (26.11%)	*

* The mean expenditure is measured only for individuals with non-zero consumption.

Table 4
Households' Descriptive Statistics.

	Freq.	Percentage	Cum.		
Households					
Children	3393	27.88	*		
High Education	1435	11.79	*		
Gender Head	8521	70.02	*		
Northern Italy	4626	38.01	38.01		
Central Italy	4220	34.68	72.69		
Southern Italy	2377	19.53	82.22		
Islands	946	7.77	100.00		
Houses					
Home Owners	9581	78.73	*		
Other Houses (ownership)	1049	8.62	*		
New House	521	4.25	*		
Renewals	659	5.42	*		
Town	9803	80.55	80.55		
Group of Houses	1696	13.94	94.49		
Countryside	670	5.51	100.00		
Manor	1261	10.37	10.37		
Detached House	1313	10.79	21.15		
Popular House	9294	76.37	97.53		
Rural House	301	2.47	100.00		
	Obs.	Mean	St. dev.	Min.	.Max.
Rooms	12,169	4.50	1.52	1	20
Components	12,169	2.57	1.26	1	12
Total Expenditures	12,169	2,486.95	1405	248.54	10,149.32
Number of Cars	12,169	1.30	0.83	0	6
Log Price Nat. Gas	12,169	2.006	0.52	1.89	2.12
Log Price Gas Cylinder	12,169	4.61	0.24	4.18	5.03
Log Price Oil	12,169	4.74	0.11	4.51	4.98
Log Price Wood	12,169	3.48	0.705	2.56	4.49
Log Price Gasoline	12,169	4.76	0.14	4.65	4.99
Log Price Diesel	12,169	4.63	0.16	4.50	4.91
Nat. Gas network density	12,169	0.56	0.32	0.144	1.297

* The mean expenditure is measured only for individuals with non-zero consumption.

2487 Euros, and, on average, there is more than one car in each family.

In addition to the data from the national survey, we used data on climate conditions and fuel prices. The data on temperature are expressed in degrees Celsius and collected from EUROSTAT. We gathered the average price for each fuel for each Italian region from the local Offices of Commerce, and the average prices for electricity and natural gas from EUROSTAT and the Department of Energy of the Italian Ministry of Economic Growth, respectively. Ever since early demand models, scholars have discussed the potential endogeneity bias introduced by adopting an incorrect price specification. In demand models at the consumer level, price is not necessarily endogenous in the traditional sense since demand does not usually affect market prices. Nevertheless, omitted product attributes can create correlation between prices and the unobservable components of utility: the price can be higher for products with desirable attributes observed by consumers but not measured by the econometrician. However, both marginal and average prices are potentially endogenous, and the use of least squares techniques may lead to estimate incorrect price elasticities. As many authors before [23,16,27], among others), we preferred the use of average prices[10] to avoid the reverse causality problem in using the latter, as suggested by Hewitt and Hanemann [28]. The reverse causality issue arises due to the simultaneous determination of the price of fuel and the demand for it; this could happen in particular in the case of block-rate tariffs. Moreover, Ito [29] found strong evidences that consumers respond to average prices rather than marginal or expected marginal prices. On average, people are not able to fully understand the marginal rate of non-linear prices and tend to react more consciously to variations in average price rather than marginal prices [30].

4. Results

The empirical application presented in this section uses the γ-profile utility function specification in which the satiation parameter α tends to zero and the utility function assumes the Linear Expenditure System (LES) structure. Higher values of the γ parameter induce a steeper indifference curve, thus implying a stronger preference, and hence lower satiation, for the good.

$$\widetilde{U} = \frac{1}{\alpha_1}[exp(\beta' z_{res} + \varepsilon_{res})]ln(e_{res}) + \gamma_{misc}[exp(\beta' z_{misc} + \varepsilon_{misc})]ln\left(\frac{e_{misc}}{\gamma_{misc}} + 1\right) + \sum_{m=sh-wh,tr} \gamma_m [exp(max_{j\in N_j}\{W_{jm}\})]ln\left(\frac{e_m}{\gamma_m} + 1\right) \quad (17)$$

Tables 5–7 present the results of the MDCEV-GEV model. For the sake of presentation, the service participation choice and the within service fuel choice are presented separately in order to distinguish the two sets of results.

As shown in Table 5, the satiation parameters (γ) are all significantly different from one, allowing us to reject the linear utility structure employed in standard discrete choice models. Moreover, this result confirms the adequacy of the MDCEV model in this context, which is able to accommodate diminishing marginal utilities (satiation) in the consumption of each alternative.

Both the residual and the miscellaneous services are considered to be Hicksian goods; hence, the associated satiation parameters are constrained to be equal to one. The γ parameters reflect higher satiation for the transportation service and very low satiation for the space and water heating service, which appears to behave as a subsistence and thus relatively inelastic category.

All the baseline utility constants are strongly significant and negative, implying that the baseline propensity to consume non-energy services is higher than the one for the energy services and a higher proportion of households are spending a positive amount of money in the residual category than in the energy services. As pointed out by Yu et al. [17] and Ferdous et al. [31], these constants capture the generic propensity to spend on each category (see Table 5).

The estimated parameters in Table 5 indicate the effect of the covariates on the likelihood of allocating positive or negative amounts of money in each service. The estimated parameters pertaining to household characteristics confirm the results from the literature, and, in particular, the one implementing MDCEV models. The number of household components has a negative effect on space and water heating, meaning that bigger families have a higher propensity to spend for non-energy services. The rationale of this result may rest on many factors: (i) expenditure in the residual category (mainly food and clothes) is strongly influenced by family composition, (ii) energy expenditure is more influenced by other factors (i.e., dwelling type or the number of motorized vehicles), (iii) larger families tend to invest in less energy-intensive heating systems, and (iv) there is a growing literature on energy deprivation suggesting that larger families are more likely to be energy deprived, as they tend to react to financial stress by reducing energy consumption more than the consumption of other goods. As in Yu et al. [17], the number of family components has no effect on the baseline utility preference for consumption in the transportation service. Households living in large houses have a negative and significant baseline utility preference parameter for consumption in space and water heating. This result could appear counterintuitive, but it is not if we consider that the baseline parameter must be read against the residual category reference. The reason why these families seem to be more prone to spend on services other than energy could be: (i) they are richer families owning efficient heating systems, and (ii) if we can assume that richer families live in bigger houses, the relevance of energy expenditure is relatively small, as it represents a small portion of the monthly total consumption.

Further housing characteristics included in the MDCEV model are house position, as in within or outside the city centre, and dwelling type. If the position and characteristics of the house seem to have no effect on demand for transportation service, this information is particularly important for the space and water heating service. The coefficients of the three types of houses (detached, popular, and rural) built against the reference case (manors), interpretable as proxies for their real estate value, display significant and negative effects, meaning that it is more likely to have positive expenditures in the space and water heating service in the reference case. Therefore, less noble houses are associated with a lower propensity to consume energy for space and water heating. Moreover, the position of the house (suburbs and countryside) has a positive effect on demand for space and water heating with respect to houses located in urban areas (the reference category).

Information concerning home ownership and expenditures to renew the house was added to the model, but we failed to reject the null hypothesis of their estimated coefficients being different from zero. In particular, the non-statistical significance of the variable identifying the substitution of heating systems in the years before the survey is consistent with previous literature on space and water heating for Italy [32].

Different specifications for data on temperature, as proxies for climate conditions, have been tested (i.e., Heating Degree Days, Cooling Degree Days, and so forth), but the regional annual average temperature in degrees Celsius was the measure with the best statistical performance. As expected, an increase in temperature causes a decrease in demand for space and water heating service. This result seems to suggest that households will benefit from climate change, as they will be able to reduce space heating expenditures. Nevertheless, the rising temperature will result in an increase in the use of cooling equipment, such as air conditioning and refrigerators, with a subsequent increase in electricity consumption (as shown in Section 5).

The number of cars in the household has a strong positive effect on increasing the participation in transportation expenditures: more cars in the same family means a higher propensity to consume in the transportation category. The price of gasoline is introduced to measure the elasticity of demand for transportation with respect to price variations. The estimated coefficient is reasonably negative, meaning that higher prices reduces the likelihood of observing families with non-zero expenditures in the transportation service.[11]

4.1. Multinomial logit model for space and water heating

Table 6 presents the results of the Multinomial Logit model for the choice of the space and water heating system. The choice is among fuels to run the system: Oil, Gas, LPG, and Wood. The base alternative is oil, considered to be the *dirty technology*. Very few households use

[10] The prices are expressed in Euros per Gigajoule for fuels used for space and water heating, and in Euros per litre for fuels used in transportation.

[11] We assume, and this is confirmed by the estimated γ in Table 4, that consumers are able to contract the consumption of transportation fuels by switching, even temporarily, their modes of transport. Contrarily, consumers are less capable of reducing energy demand for space and water heating purposes, and, consequently, the choice pertains more to the fuel to use rather than the quantities. This is the reason why we used the price of gasoline in the MDCEV component of the model instead of the prices of fuels for space and water heating.

Table 5
MDCEV Results.

	(I) Residual	(II) Miscellaneous	(III) Space and Water Heating	(IV) Transportation
Household's components	–	–	−0.4278*** (0.13)	−0.014 (0.01)
Rooms	–	–	−0.304*** (0.08)	–
Temperature (C)	–	–	−0.010*** (0.00)	–
Suburbs	–	–	0.3544** (0.17)	−0.0087 (0.05)
Countryside	–	–	0.8862*** (0.31)	−0.0388 (0.08)
Detached House	–	–	−0.7144*** (0.23)	–
Popular House	–	–	−1.1327*** (0.35)	–
Rural House	–	–	−0.0733 (0.18)	
Number of Cars	–	–	–	0.4484*** (0.02)
Price Gasoline	–	–	–	−0.2652*** (0.02)
Constant	–	−1.966*** (0.05)	–	−3.707*** (0.12)
$\gamma_{spaceandwater}$	–	–	0.096*** (0.01)	–
γ_{tra}	–	–	–	19.484*** (1.41)
Mean Log-Likelihood at Convergence				−18.1212
N. obs.				12,196

Standard errors in parenthesis, $***p \leq 0.01$, $**\ p \leq 0.05$, $*p \leq 0.1$.

Table 6
Multinomial Logit model for space and water heating - Results.

	(I) Oil	(II) Natural Gas	(III) Other Gas (cylinder)	(IV) Wood
Household's Components	–	0.3721*** (0.13)	0.4287*** (0.15)	0.4506*** (0.17)
Rooms	–	0.2975*** (0.10)	0.2424*** (0.09)	0.2569*** (0.09)
Suburbs	–	−0.3805** (0.18)	0.6275** (0.27)	0.2608 (0.19)
Countryside	–	−1.12*** (0.41)	0.7885*** (0.30)	0.4545** (0.22)
Detached House	–	0.5935** (0.26)	−0.494* (0.27)	−0.4553 (0.32)
Popular House	–	1.086*** (0.39)	0.1717 (0.14)	0.1646 (0.17)
Rural House	–	−0.1581 (0.19)	−0.1017 (0.22)	0.2872 (0.27)
Price Gas		−0.0271** (0.01)	–	–
Price Wood	–	–	–	−0.309*** (0.11)
Price Gas Cylinders	–	–	−0.0683*** (0.02)	–
Density Nat. Gas Network		0.1942*** (0.07)	−0.8624** (0.37)	−0.4962 (0.34)
θ				0.68* (0.18)

Standard errors in parenthesis, $***\ p \leq 0.01$, $**\ p \leq 0.05$, $*p \leq 0.1$.

electricity for space and water heating; hence, the electricity alternative was not included in the analysis.

The composition of the family has a strong positive effect on the probability of choosing other fuels over Oil. Accordingly, the variable reporting the number of rooms, used as proxy of house dimensions, is positive for each alternative, meaning that households living in big houses tend to prefer more efficient and sustainable space heating systems.

The house location plays a different role for the fuel alternatives: natural gas is generally preferred in city areas rather than in suburbs and the countryside. This result is quite intuitive and confirmed by the positive coefficient associated with the density of the Natural Gas network (i.e., denser networks increase the probability of installing natural gas heating systems). On the contrary, other fuels not requiring specific networks for their distribution are used more frequently in suburbs and the countryside compared to in city areas, and their penetration is negatively correlated to the density of the natural gas network.

Lastly, all prices, expressed as Euros per Gigajoule, present negative and significant coefficients, suggesting that the probability of installing a specific heating system decreases when the price of the fuel used to feed the system increases. It is relevant to notice that the estimated parameters of the MNL logit model are part of the conditional probability of Eq. (16) and can accordingly be used to estimate the elasticity of demand for fuels.

4.2. Multinomial logit model for transportation

The HCS is designed to collect information on household consumption and almost completely ignores transportation mode choices. For these reasons, scarce information is present on transportation preferences and behaviour. We arranged the Multinomial logit model for this energy category by exploiting all of the data available. The choice is among three alternatives: gasoline, diesel, and a combination of the two. Observations with zero expenditure for these categories are not entered in the within category mode choice.

The alternative specific constants are negative, meaning that people prefer the use of gasoline to diesel or a mixture of the two (see Table 7). This is particularly true for families with a higher number of components and more highly educated family heads. If we consider that the survey is based on the family (rather than the individual) as a reference

Table 7
Multinomial Logit model for transportation - Results.

	(I) Gasoline	(II) Diesel	(III) Mixed
Household's Components	–	0.0244*	0.1076***
		(0.01)	(0.03)
High Education (head)	–	0.1455***	0.0975**
		(0.05)	(0.04)
Number of Cars	–	−0.0715**	0.2042***
		(0.02)	(0.05)
Gender Head	–	0.2133***	−0.1454***
		(0.06)	(0.05)
Detached House	–	0.0546	0.0564
		(0.06)	(0.05)
Popular House	–	0.0703	0.0069
		(0.05)	(0.04)
Rural House	–	0.0332	−0.2357**
		(0.09)	(0.11)
North	–	0.2957***	0.3105***
		(0.08)	(0.09)
Central	–	0.3787***	0.3928***
		(0.10)	(0.10)
Islands	–	−0.2634***	−0.3592***
		(0.08)	(0.11)
Constant	–	−1.1423***	−1.7027***
		(0.31)	(0.45)
θ	–	–	0.4716*** (0.26)

Standard errors in parenthesis, $***p \leq 0.01$, $**\ p \leq 0.05$, $*p \leq 0.1$.

unit, this is a coherent result: more people prefer a differentiated system of transportation and, in general, own a higher number of vehicles. The gender of the family head displays a different sign for the diesel and the mixed categories, meaning that men more likely own diesel cars with respect to women and the reference category.

The variable indicating the number of cars confirms the expectations and displays a positive coefficient for the mixed alternative, in which more vehicles are involved. On the contrary, the variable related to the number of cars has a negative effect on the probability of using only diesel cars with respect to gasoline.

Finally, household location was introduced to offer a geographical representation of preferences for transportation modes across Italian macro-areas: in the North and Central areas, there is a stronger preference for diesel and mixed consumption with respect to gasoline, with Southern Italy used as the reference category. On the contrary, people living in the Islands prefer gasoline-powered vehicles.

4.3. Logsum parameters

The Logsum parameters (θ) create a link between the MDCEV and the within- category choice model. The Logsum parameter for space heating is estimated to be 0.68 (the t-statistic testing to see if the parameter is different from 1 is 1.73), and the Logsum parameter for transportation is estimated to be 0.471 (the t-statistic testing to see if the parameter is different from 1 is 1.964). These results suggest that the presence of common unobserved attributes affecting the utilities of space and water heating equipment and utilities of transportation modes, thus confirming the strategy of modelling the decision process as a MDCEV-GEV.

5. Elasticities of demand for energy services: A scenario analysis

The forecasting procedure proposed by Pinjari and Bhat [15] can be applied to several policy simulations or scenario analyses. In Table 8, the predicted and observed mean expenditures for energy services are reported, along with the participation rates in each category.

The model predicts an average expenditure for the residual category of 2272 Euros, while the observed average is 2219 Euros per month, and it predicts an average of 44.50 Euros for the miscellaneous category

Table 8
Predicted and observed expenditures and participation rates.

Expenditure category	Predicted Average Expenditure (Euro)	Observed Average Expenditure (Euro)
Residual	2272 (1257)	2219 (1,319)
Miscellaneous	44.50 (24.63)	44.59 (31.65)
Space and Water Heating	74.88 (48.31)	89.58 (81.51)
Transportation	107.74 (180.89)	180. 85 (110.56)
	Predicted Participation Rate	Observed Participation Rate
Residual	100%	100%
Miscellaneous	100%	100%
Space and Water Heating	100%	99.4%
Transportation	80.49%	73.89%

with respect to 44.59 Euros of observed average expenditures. The simulation procedure predicts very precisely the residual and the miscellaneous category, but it is less precise in the simulation of the space and water heating and transportation categories.

However, according to Pinjari and Bhat [15], the comparison between predicted and observed data should not be used as a validation of the procedure; in fact, the forecasting procedure, which uses at least half of the sample over which predictions are performed, includes estimation data. This is the reason why it is better to use the predictions to investigate the sensitivity of the model to policy scenarios and changes in covariates. In light of this, we report in Table 9 on four different simulations: (i) price variations for natural gas and gasoline, (ii) the effect of temperature variations, (iii) the increase in the natural gas network density, and (iv) the increase in the number of cars.

The demand for space and water heating is relatively inelastic with respect to price variations, namely the demand decreases by −0.55% for a 1% increase in the natural gas prices. As already mentioned, an elasticity lower than one means that the demand varies less than proportionally with respect to the price variation. This result is definitely in line with the level of long-run elasticities present in the literature (−0.568 according to [1]).[12]

Demand for gasoline is even more sensitive to price variation: an increase of 1% in the price for gasoline leads to a demand decrease of 0.67%. The effect remains stable for larger variations: for an increase of 20%, the model predicts a reduction of 13% in transportation expenditures. In both cases, the forecasting procedure seems to suggest that there is room for policy makers to reduce energy consumption through price instruments.

The second scenario refers to climate change. In particular, variations in temperatures, e.g., increases from 0.2 to 2 degrees Celsius are presented. The temperature variations are effective in reducing demand for the space and water heating service. In particular, the demand for fuels used for space and water heating reacts sensibly: for an increase of 0.2 degrees Celsius, the model predicts a reduction in energy consumption of 0.41%. In the long-run, with an increase in temperature of 2 degrees Celsius, a decrease of 4.07%, or 45 Euros per year, is expected. Nevertheless, as previously observed, this reduction can be overbalanced by the increase in electricity consumption to run air conditioning systems and refrigerators.

The spatial distribution of natural gas, expressed as the natural gas network density, displays a positive effect on the demand for space and water heating services. An increase of 1% in the network density (i.e., areas covered by the natural gas network over total area) determines an increase of 0.18% in space and water heating expenditures. This result, along with the price elasticity of demand, suggests that policy makers

[12] For a detailed literature review see Brons [34] and Labandeira et al. [1].

Table 9
Simulated demand elasticities and participation rates.

Expenditure Category	Variationin Av. Exp + 1% Nat. Gas (Euro)	Variationin Av. Exp + 1% Gasoline	Variationin Av. Exp + 0.2 Celsius Degrees	Variationin Av. Exp + 1% Nat. Gas Network Density	Variation Av.Exp in Car +1
Space and Water Heating	−0.55%	–	−0.41%	0.18%	–
Transportation	–	−0.67%	–	–	331%
Predicted Participation Rates					
Space and Water Heating	100%	–	100%	100%	–
Transportation	–	80.30%	–	–	94.93%

have the opportunity to induce substitution among fuels through price and networks density variations.

In general, the forecasting procedure is useful for predicting changes in the demand for the modelled services, both in terms of participation rates (discrete component) and expenditures (continuous component) due to changes in covariates. In this paper price variations and temperature increases are used to predict the elasticities of demand for energy services and the main results are in line with previous literature, confirming the reliability of the MDCEV-GEV model.

6. Conclusions

The paper has presented an alternative approach to the standard single discrete-continuous models by accommodating multiple discreteness, thus increasing the ability of these type of models to describe complex phenomena such as individual energy consumption choices. The joint MDCEV-GEV model, allowing for the presence of perfect and imperfect substitute goods, is the core advancement over previous works in energy economics.

The results of the empirical application to Italian household expenditures validate the assumption of the joint estimation of the MDCEV-GEV model. The likelihood ratio tests on scale parameters, θ, confirm the goodness of the model specification, rejecting the null hypothesis of a linear utility structure.

Furthermore, the results highlight that there is an unobservable common driver behind the choice of consuming different energy services which determines the substitution patterns among both services and fuels. One added value of this model is that it enables to capture this component by analysing simultaneously the whole set of energy-based services, something that cannot be done with standard models that estimate energy demand separately for each service. The forecasting procedure developed in Section 5 has provided a robust estimation of price elasticities of energy demand, which is crucial to comprehend how variations in energy prices may impact on energy consumption at the household level. Demand for space and water heating and transportation turns out to be relatively inelastic with respect to price variations; -0.55 and -0.67 are the respective elasticities. The analysis can also be used to simulate the impact of Climate Change on household energy demand, which results to be sensitive to temperature increases in a range between $+0.2$ and $+2\,^{\circ}$C.

These results suggest to policy makers where corrective pricing policies are more effective, both in terms of socio-economic and environmental impact. For example a smaller lever is required to reduce gasoline consumption with respect to natural gas consumption. At the same time, the results identify the energy services whose the demand is more sensitive to climate change. Being able to estimate the reaction in specific fuel use associated to different climate change scenarios. This may in turn allows policy makers to design in advance policies able to reduce negative socio-economic impacts.

The model is suitable to be used in engineering-economic or computable general equilibrium (CGE) models to rigorously depict the dynamics of household energy demand. The effectiveness showed in this application suggests that there is scope for wider use in applied research and policy analysis.

Possible extensions are twofold. First, from a methodological point of view, a Nested Logit structure for space and water heating could be used as in Dubin [33]. The Nested Logit model could be a first step in relaxing the IIA assumption of the multinomial logit here implemented. Incorporating heteroskedasticity in the multiple-discrete component or in the single discrete choice component using a mixture of distributions would allow the IIA assumption to be definitively discarded (in particular, for the space heating and transportation categories), resulting in a more flexible structure of the variance-covariance matrix, which in turn would enhance our capacity to model substitution among fuels. Second, from the empirical point of view, further refinements in the analysis of energy demand will become possible with future diffusion of more detailed dataset, ideally classifying the different end-use consumptions now bundled in the miscellaneous category according to IEA's classes.

References

[1] Labandeira X, Labeaga JM, Lopez-Otero X. A meta-analysis on the price elasticity of energy demand. Energy Policy 2017;102:549–68.
[2] IEA. Statistics Report. Paris (France): OECD/IEA; 2016.
[3] IEA. 25 Energy Efficiency Policy Recommendations 2011 Update. Paris (France): OECD/IEA; 2011.
[4] Pablo-Romero MP, Pozo-Barajas R, Yiguez R. Global changes in residential energy consumption. Energy Policy 2017;101:342–52.
[5] Hanemann MW. Discrete/continuous models of consumer demand. Econometrica 1984;52(3):541–61.
[6] Hanemann MW. A methodological and empirical study of the recreation benefits from water quality improvements. Ph.D. dissertation. Department of Economics, Harvard University; 1978.
[7] Tobin J. Estimation of relationship for limited dependent variables. Econometrica 1958;26(1):24–36.
[8] Wales T, Woodland AD. Estimation of consumer demand systems with binding non-negativity constraints. J Econ 1983;21(3):263–85.
[9] Kim J, Allenby GM, Rossi PE. Modeling consumer demand for variety. Market Sci 2002;21(3):229–50.
[10] Train K, McFadden DL, Ben-Akiva M. The demand for local telephone service: A fully discrete model of residential calling patterns and service choices. Rand J Econ 1987;18(1):109–23.
[11] Hendel I. Estimating multiple-discrete choice models: An application to computerization returns. Rev Econ Stud 1999;66:423–46.
[12] Dube J-P. Multiple discreteness and product differentiation: Demand for carbonated soft drinks. Market Sci 2004;23(1):66–81.
[13] Bhat CR. A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions. Transport Res B-Met 2005;39(8):679–707.
[14] Bhat CR, Srinivasan S, Sen S. A joint model for the perfect and imperfect substitute goods case: Application to activity time-use decisions. Transport Res B-Met 2006;40(10):827–50.
[15] Pinjari AR, Bhat CR. Computationally efficient forecasting procedures for Kuhn-Tucker consumer demand model systems: Application to residential energy consumption analysis. Technical paper, Department of Civil and Environmental Engineering, University of South Florida; 2011.
[16] Jeong J, Kim C, Lee J. Household electricity and gas consumption for heating homes. Energy Policy 2011;39:2679–87.
[17] Yu B, Zhang J, Fujiwara A. Representing in-home and out-of-home energy consumption behavior in Beijing. Energy Policy 2011;39:4168–77.
[18] Yu B, Zhang J, Fujiwara A. Analysis of the residential location choice and household energy consumption behavior by incorporating multiple self-selection effects. Energy Policy 2012;46:319–34.
[19] Parti M, Parti C. The total and appliance-specific conditional demand for electricity in the household sector. Bell Jl Econ 1980;11(1):309–21.
[20] Aigner DJ, Sorooshian C, Kerwin P. Conditional demand analysis for estimating residential end-use load profiles. Energy J 1984;5(3):81–98.

[21] Marit Dalen H, Larsen BM. Residential end-use electricity demand: development over time. Energy J 2015;36(4):165–81.
[22] Matsumoto S. How do household characteristics affect appliance usage? Application of conditional demand analysis to Japanese household data. Energy Policy 2016;94:214–23.
[23] Dubin JA, McFadden D. An econometric analysis of residential electric appliance holdings and consumption. Econometrica 1984;52(2):2722–30.
[24] Nesbakken R. Price sensitivity of residential energy consumption in Norway. Energy Econ 1999;21:493–515.
[25] Vaage K. Heating technology and energy use: A discrete/continuous choice approach to Norwegian household energy demand. Energy Econ 2000;22(6):649–66.
[26] Larsen BM, Nesbakken R. Household electricity end-use consumption: Results from econometric and engineering models. Energy Econ 2004;26(2):179–200.
[27] Alberini A, Gans W, Velez-Lopez D. Residential consumption of gas and electricity in the U.S.: The role of prices and income. Energy Econ 2011;33(5):870–81.
[28] Hewitt J, Hanemann W. A discrete/continuous choice approach to residential water demand under block rate pricing. Land Econ 1995;71:173–92.
[29] Ito K. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. Am Econ Rev 2014;104(1):537–63.
[30] de Bartolome CAM. Which tax rate do people use: average or marginal? J Public Econ 1995;56(1):79–96.
[31] Ferdous N, Pinjari AR, Bhat CR, Pendyala RM. A comprehensive analysis of household transportation expenditures relative to other goods and services: An application to United States consumer expenditure data. Transportation 2010;37:363–90.
[32] Alberini A, Bigano A. Looking for free-riding: Energy efficiency incentive and Italian homeowners. Note di Lavoro 2013.024, Fondazione Eni Enrico Mattei (FEEM); 2013.
[33] Dubin J. Consumer durable choice and demand for electricity. Amsterdam: North-Holland; 1985.
[34] Brons M, Nijkamp P, Pels P, Rietveld P. A meta-analysis of the price elasticity of gasoline demand. A SUR approach. Energy Econ 2008;30(5):2105–22.