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The prevalence of context-dependent adjustment of activity-travel patterns in energy conservation strategies: results from a mixture-amount stated adaptation experiment

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Abstract People's adaptive behaviour to increasing energy prices has been studied at length in transportation research. Prior research however has not addressed research questions concerning the contribution of travel-related changes in more encompassing energy conservation strategies. Moreover, context-dependency and choice under constraints has not been studied at any length. In this paper, we therefore report the results of a context-dependent elaboration of a mixture amount choice experiment to measure context-dependent responses to accumulative energy charges under budget constraints. Accounting for consumer heterogeneity in adaptive response behaviour, mixed logit analysis is used to analyse the extent and nature of adaptations of activity-travel behaviour and resource allocation in response to increasing energy costs. The results indicate that individuals are inclined to compensate for increased expenditures on energy due to price increases. Moreover, results show the existence of significant heterogeneity among respondents in terms of their adaptation strategies to various energy-saving choices.

Keywords Adaptation strategies · Choice experiments · Mixed logit analysis

Introduction

Empirical analysis of the effects of energy price fluctuations on people travel behaviour and energy consumption patterns has been a topic of considerable interest over the past

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40 years. Results of studies on in-home energy conservation (e.g., Staats et al. 1996; Sezgan and Koomey 2000; Geller 2002; McCalley and Midden 2002; Kua and Wong 2012; Zhang et al. 2012) indicate that the potential of energy-savings by changing behaviour is usually neglected. However, in-home energy consumption behaviour is a major determinant of energy usage in residential buildings. The impact of conservation might therefore be as high as savings from technological solutions.

The effect of energy price fluctuations on people's changing activity-travel behaviour has been addressed in travel behaviour research. Wardman and Grant-Muller (2011) found that higher fuel prices trigger people to reduce driving and increase fuel efficiency. Mustia et al. (2011) concluded that tax incentives, if properly structured, can play a valuable role in stimulating the introduction and initial sales of important energy efficient technologies such as hybrid and fuel cell vehicles. An overview of accumulated knowledge is given in a number of literature reviews and meta-analyses of travel demand elasticities (e.g., Graham and Glaister 2002, 2004; Hensher 2008; Litman 2005; Wardman and Grant-Muller 2011).

Although these studies have increased our knowledge of energy conservation mechanisms in transportation and residential settings, several important issues require further study. First, most studies have used either cross-sectional or panel revealed preference data (e.g., Swan and Ugursal 2009; Yang and Timmermans 2010; Jäggi and Axhausen 2012; Rentziou et al. 2012). A potential disadvantage of such data is that the preference/demand forecasting based on revealed choice may have limited applicability to dramatically changing or new phenomenon for which historical data of actual behaviour do not exist. Very few studies have used a stated adaptation format (e.g., Phifer et al. 1980; Lee-Gosselin, 1989, 1990; Doherty and Miller 2000; Doherty et al. 2002; Jäggi et al. 2012).

Second, previous stated preference/choice studies have two potential limitations. Studies did not consider any constraints that may influence individual preferences and choices. Moreover, most studies did not take any context effects into account, implicitly or explicitly assuming that consumer preferences and choices are invariant across different contexts. Preference or utility functions can only be assumed valid over a limited set of circumstances because variables that describe the background of the choice situation may differentially affect the evaluations of alternatives.

Third, most studies have addressed only a single saving option, focusing on either travel or in-home energy-savings. In reality, however, individuals may consider multiple energy-saving options at the same time and trade-off these options, subject to their time and money budgets. Thus, the stated adaptation experiment should ensure that any defined constraints are met. Conventional choice designs are not appropriate for such decision tasks as they do not involve any constraints on the attribute values nor trade-offs between different multiple-choice options.

To account for such effects, in this paper, an elaborated mixture amount design is used to study which combination of energy-saving strategies—defined as a combination of saving options—people choose in response to increased energy prices and whether the energy-saving choices are context-dependent. The advantage of mixture amount designs in assessing how individuals adapt their activity-travel patterns to save energy is that it forces people to make “trade-offs” across attributes in situations in which constraints are imposed on attribute levels. It provides a natural mechanism for introducing budget constraints into the choice task. The principles underlying this approach, the construction of the design and the formulation and estimation of relevant models will be discussed in detail. Moreover, we will extend standard mixture amount models to context-dependent models and apply these to the stipulated problem: if and how individuals change their activity-travel behaviour and set of resources when faced with increasing energy costs. Examples of resources in this context are home appliances and differently fuelled cars.

The paper is organized as follows. First, we will discuss the basic principles of mixture amount models and how they can be applied to the research issue at hand. This is followed by an explanation of the design of the stated adaptation experiment based on balanced incomplete block (BIBD) and simplex lattice designs and how context-dependency was included. Then, we will explain the sample and the online survey used in this study. Next, the results of mixed logit analyses are presented, followed by a discussion of model validation and choice predictions. The paper is completed with a summary and conclusions.

Models and experimental designs

Context-dependent mixture amount model

Stated preference models are based on the assumption that preferences or utilities can be uncovered by presenting subjects with profiles of hypothetical choice alternatives and asking them to express their preference for these profiles. When subjects are asked to choose between choice alternatives, simultaneously a mechanism that is assumed to represent the mapping of utilities into choices can be estimated. As discussed in the introduction, choice models usually do not take any budget constraints into account. The mixture amount model described in this paper represents an alternative design strategy that allows introducing budget and other constraints into preference or choice tasks. The objective of mixture models is to describe the relationship between the response variable of interest and mixture or allocation of a set of attributes. Mixture models impose constraints on attribute levels. In standard mixture designs, simplex-lattice designs and simplex-centroid designs are used to design an experiment in which choice percentages satisfy particular budget constraints (Draper and Pukelsheim 1998). When mixture components are subject to additional constraints, such as a maximum and/or minimum value for each component, designs other than the standard mixture designs, referred to as constrained mixture designs or Extreme-Vertices designs, are appropriate. In this case, the variable proportions can be rewritten as scaled fractions so that the scaled fractions sum to one.

For example, suppose there are q independent variables that are constrained to a q dimensional dependent space. In fitting regression functions, the response is assumed to be represented by a polynomial in x_i . Then

$$x_i \geq 0 \quad (i = 1, 2, \dots, q), \quad \sum_{i=1}^q x_i = 1 \quad (1)$$

Scheffe (1958) introduced the simplex lattice design: the $\{q, m\}$ designs are a class of mixture designs consisting of $\binom{m+q-1}{m}$ points. The proportions taken by each component are $m+1$ equally spaced values from 0 to 1, $x_i = 0, 1/m, 2/m, \dots, 1$, for $i = 1, 2, \dots, q$. The general first-degree polynomial for expressing dependent variable U in terms of the i variables $x_1, x_2, \dots, x_q$ is:

$$U = \sum_{i=1}^q \beta_i x_i. \quad (2)$$

The second-degree model overcomes parameter redundancy by deliberately including only the linear and cross-product terms (Tian and Fang 1999; Raghavarao and Wiley 2009):

$$U = \sum_{i=1}^q \beta_i x_i + \sum_{\substack{i,i'=1 \\ i < i'}}^q \beta_{ii'} x_i x_{i'} \quad (3)$$

Preferences for mixtures may also depend on the total amount that needs to be allocated to the mixture. This is the realm of mixture amount models. Suppose that the total amount of the mixture is A_{max} , and that the actual amount of the i th component in the mixture is A_j ($j = 1, \dots, J$). Assume that j different levels indicated by $a_j = a_1, a_2, \dots, a_J$ ($J \geq 2$) can be considered. Then, the basic utility function (not including any socio-demographic and context effects) for the combination of amount level j and mixture i can be expressed as:

$$U_{ij}^{Basic} = \alpha a_j + \alpha' a_j^2 + \sum_{i=1}^{q-1} \beta_i a_j x_i + \sum_{i=1}^q \beta'_i x_i + \sum_{\substack{i,i'=1 \\ i < i'}}^q \beta_{ii'} x_i x_{i'} \quad (4)$$

where a_j and a_j^2 represent the first and second order of the amount of energy-saving for amount j . We assume that the relationship between utility and amount of savings potentially is a nonlinear function as represented by the first two terms of Eq. (4). The next term depicts the interaction effects of amounts and mixtures on utility. Note that we do not use all $a_j x_i$ terms, because $\sum x_i = 1$. The last terms pick up any single effect on the utility of the mixtures and a combination of the mixtures. This mixture amount model with utility function (4) only involves main effects that pertain to the attributes of alternatives.

To allow examining whether context affects choice probabilities, the mixture amount utility function can be extended with terms that represent the effects of context variables. Total utility then includes two parts: basic utility and impact of context.

Suppose there are, in addition to the base, K context and socio-demographic variables. We use effect coding to represent the effects of these context and socio-demographic variables. Then, the main effects of context variable k with L_k levels can be represented by $L_k - 1$ indicator variables. Interactions of variables can be represented by multiplying the corresponding coding. We use U_j^k to represent the effect of one particular context or socio-demographic variable k on the basic utility. The function of U_j^k is expressed in Eq. (5).

$$U_{ij}^k = \sum_{l=1}^{L_k-1} \left(\gamma_{kl} w_{kl} a_j + \gamma'_{kl} w_{kl} a_j^2 + \sum_{i=1}^{q-1} \delta_{kli} w_{kl} a_j x_i + \sum_{i=1}^q \delta'_{kli} w_{kl} x_i + \sum_{\substack{i,i'=1 \\ i < i'}}^q \delta_{kii'} w_{kl} x_i x_{i'} \right) \quad (5)$$

where w_{kl} is to the l th level indicator of the k th context variable, and γ_{kl} is the estimated effect of l th level, k th context or socio-demographic variable on utility. Equation (5) expresses the influence of context variables in terms of interactions with the basic variables. Equation 5 can be extended to incorporate combinations of any two of the K context variables as interactions with the main variables:

$$\begin{aligned} U_j^{kk'} &= \varphi_{kik'l'} w_{kl} w_{k'l'} a_j + \varphi'_{kik'l'} w_{kl} w_{k'l'} a_j^2 + \sum_{i=1}^{q-1} \eta_{kik'l'i} w_{kl} w_{k'l'} a_j x_i \\ &+ \sum_{i=1}^q \eta'_{kik'l'i} w_{kl} w_{k'l'} x_i + \sum_{\substack{i,i'=1 \\ i < i'}}^q \eta'_{kik'l'ii'} w_{kl} w_{k'l'} x_i x_{i'} \end{aligned} \quad (6)$$

where w_{kl} and $w_{k'l'}$ refer to the l th level indicator of the k th variable and l' th level indicator of the k' th variable. The effects of socio-demographic variables can be implemented in the same way.

Finally, the total utility function is shown in Eq. (7). It includes the basic utility U_j^{Basic} , all contexts effects, socio-demographic interactions U_j^k and the interaction effects with certain combinations of socio-demographic or context variables $U_j^{kk'}$.

$$U_j^{Total} = U_j^{Basic} + \sum_{k=1}^K U_j^k + \sum_{\substack{k,k'=1 \\ k < k'}}^K U_j^{kk'} \quad (7)$$

Household energy conservation design

To analyze if (how much) and how consumers save on their expenditures to compensate for dramatically increasing energy prices, we estimated their preferences for different (combinations of) energy conservation strategies, using a stated adaptation approach. We extended simplex lattice and BIBD designs to create a model that allows estimating context dependency in a mixture amount model. We will explain the process step by step.

Step 1 identify mixture components

The aim of the experiment is to examine whether respondents are willing to save on their expenditures such as to fully or partially compensate for a higher energy bill and how they save by choosing among different energy-saving options. Subjects can save energy by considering any combination of changing their activity-travel pattern such that they spend less on fuel and reduce energy consumption at home. Based on the literature review (Berry et al. 1995; Brownstone and Train 1998; Balcombe et al. 2004; Abrahamse et al. 2005; Holmgren 2007; Hennessy and Richard 2011), we defined three energy-saving options: (i) buying a more efficient car (ii) using slow modes more often and (iii) using more efficient appliances and facilities at home. The three options cover long term, short term, out-of-home and in-home energy conservation possibilities. The mixture of the attributes is denoted by $x_1 + x_2 + x_3$, ($0 \leq x_1, x_2, x_3 \leq 1$ and $x_1 + x_2 + x_3 = 1$).

Step 2 identify the amounts

Energy prices in the Netherlands have significantly increased from 1996 to 2010. Gas prices increased by around 72 % in the Netherlands, while the price of electricity increased by almost 50 % for domestic use. To make the scenarios realistic, we considered three amounts of energy-saving a_1 (25 euro), a_2 (40 euro) and a_3 (55 euro).

Step 3 design the choice sets

Given the three components and the three amounts, we used the $\{3, 3\}$ simplex lattice design to create 10 mixtures:

$$\begin{aligned} &\{1, 0, 0\}, \{0, 1, 0\}, \{0, 0, 1\}, \{2/3, 1/3, 0\}, \\ &\{0, 2/3, 1/3\}, \{1/3, 0, 2/3\}, \{1/3, 1/3, 1/3\}, \\ &\{1/3, 2/3, 0\}, \{2/3, 0, 1/3\}, \{0, 1/3, 2/3\}. \end{aligned}$$

The second-degree canonical model has 6 parameters. Therefore, seven mixtures were used for the allocation, while three remaining mixtures were used as holdouts (Table 1). Commonly used design principles in stated choice experiments, including D-optimal designs (e.g. Rose and Bliemer 2005; Jaeger and Rose 2008), can be used to create the choice sets. In this study, a balanced incomplete block design was used to construct a design of 21 profiles allocated to 7 choice sets of 3 profiles each. Note that in this design, each mixture appears an equal number of times, while systematically varying the order in which they appear in the choice set. A no-choice option was added to each choice set. Table 2 presents the choice sets for the three-attribute design with three amounts. Table 3 gives an example of a choice set.

Step 4 identify context variables

To gain more insight into possible context dependency of energy-saving behaviour, different contexts were constructed and varied in the experiment. The approach, suggested by Oppewal and Timmermans (24), was generalised to the mixture-amount experiment. Assuming we have two context variables w_1 (season) and w_2 (amount of luggage if any to carry), each with two levels: w_{11} (-1: late autumn or winter), w_{12} (1: other season), w_{21} (-1: heavy luggage) and w_{22} (1: no heavy luggage), these contexts were coded as $\{-1, -1\}$, $\{-1, 1\}$, $\{1, -1\}$ and $\{1, 1\}$.

The total design, thus, contains $4 \times 7 = 28$ treatments and 8 holdouts. To reduce respondent burden, each respondent was presented only two contexts.

Data

The web-based questionnaire system developed by and for our group was used to program the survey, which included two parts. The first part concerned a set of questions related to personal and household characteristics including age, gender, household composition, and net-income. 11 socio-demographic variables were included in the questionnaire. Table 4 provides an overview of the main socio-demographic variables. The second part of the survey concerned the energy-saving allocation experiment. Respondents were informed that energy costs increased 55 euro per month due to increasing energy prices. They can save 25 euro, 40 euro or 55 euro per month by buying a more efficient car, use slow modes more often or using more efficient appliances at home. If they do not save 55 euro on these options, they have to save the remaining amount on other activities. Then, they were asked to choose the options they like best.

The sample was recruited from the panel of a professional questionnaire company in December 2011. Respondents were selected based on two criteria: (1) they must have a driver's licence; (2) they must have at least one car in their household. Of the 1,037 respondents who were sent an invitation to participate, 319 completed the questionnaire. Two respondents were discarded because their questionnaires were invalid. One respondent who was younger than 18 years of age and one who completed the questionnaire in less than 5 min were not included in the analysis. Thus, reported results are based on 317 respondents.

Figures 1 and 2 present an overview of sample composition and household characteristics. Half of the respondents earn over 1,875 € per month while 37 %, respectively 12 % earn 625 €–1,875 € and less than 625 € per month. Most respondents are married or live

Table 1 Three attribute mixture design

Mixture	Attribute 1	Attribute 2	Attribute 3
1	1	0	0
2	0	1	0
3	0	0	1
4	2/3	1/3	0
5	0	2/3	1/3
6	1/3	0	2/3
7	1/3	1/3	1/3
Holdout mixture design			
1	1/3	2/3	0
2	2/3	0	1/3
3	0	1/3	2/3

Table 2 Choice sets for three-attribute mixture design with three amounts

Choice set	Profile a	Profile b	Profile c	Base alternative
1	$a_1(1)$	$a_2(2)$	$a_3(4)$	No choice
2	$a_1(2)$	$a_2(3)$	$a_3(5)$	No choice
3	$a_1(3)$	$a_2(4)$	$a_3(6)$	No choice
4	$a_1(4)$	$a_2(5)$	$a_3(7)$	No choice
5	$a_1(5)$	$a_2(6)$	$a_3(1)$	No choice
6	$a_1(6)$	$a_2(7)$	$a_3(2)$	No choice
7	$a_1(7)$	$a_2(1)$	$a_3(3)$	No choice
Holdout set				
1	$a_1(1)$	$a_2(2)$	$a_3(3)$	No choice
2	$a_1(2)$	$a_2(3)$	$a_3(1)$	No choice

p.s. $a_j(i)$ denotes the i -th mixture with amount a_j , $i = 1, 2, \dots, 7$; $j = 1, 2, 3$

together (75 %). The remaining respondents are single or live with their parents (9.1 %). In contrast to previous research, which indicated that young people tend to be overrepresented in Internet surveys (Verhoeven 2010), the age distribution of this sample shows an almost equal share of younger people and elderly. Most respondents live in a terrace house or another type of single-family house (78 %), while 18 % lives in a flat or apartment. Moreover, the distribution of household energy expenditure indicates that electricity and gas expenditures vary from 50 to more than 1,400 euro per month.

Analysis and results

In this section, we describe the results of a mixed logit model that was estimated to analyse energy-saving choice behaviour. The normal distribution was assumed for the main effects not only because it is intuitively more appealing, but also because it leads to better model fit. Nlogit 4.0 was used to estimate the model. The estimation is based on 317 observations with 4,438 choice. The log likelihood is -4450.186 . To reduce model complexity, insignificant variables were excluded in two stages. First, we successively excluded

Table 3 Example of the choice set (in euro)

Choice set 1	Buying a more efficient car	Using slow modes more often	Saving at home	Saving from other activities	Your choice
Option 1	25	0	0	30	
Option 2	0	40	0	15	
Option 3	36.67	18.33	0	0	
Option 4	None of these				

variables whose $P[|Z| > z]$ values were less than 0.6. After five rounds, we found all $P[|Z| > z]$ values to be less than 0.6. Next, the insignificant interaction variables were successively excluded, until a model with only significant (at the 0.1 level) interaction variables remained. The results for this model are presented in Table 5. This procedure is acknowledged to be heuristic. We, therefore, deliberately used a low significance level to keep as much variables as possible for further estimations. However, the procedure ignores possible covariances. Differences in Rho-sqrd and Adjusted Rho-sqrd are small (approximately 0.29).

A stable set of estimates was searched for by systematically increasing the number of Halton draws from 100 to 3,000 with step size 100. As shown in Fig. 3, the results do not show stability. Substantial fluctuations in estimated coefficients for especially x , y , z and xz continue to appear even after 3,000 Halton draws. It suggests that more fundamental research into parameter estimation of complex mixed logit model is still needed. Similar problems have been reported when the mixed logit model was introduced in transportation research, but a literature review suggests the potential problem has been left under estimated. Here, we interpreted the results based on variables' overall performance and their average value of coefficients.

The parameters values and $P[|Z| > z]$ -values are presented in Table 5. The goodness-of-fit of the model in terms of average Rho-squared is 0.295. The $P[|Z| > z]$ -value for most main effects is less than 0.05, except for energy-saving by buying an energy efficient car (AX), energy-saving by using slow modes more often (AY), using more slow transport modes (Y) and interaction between buying an energy efficient car and saving energy at home (XZ). Overall, there is quite some heterogeneity among respondents.

The positive estimated coefficient for the amount variable A suggests a positive relationship between utility (choice probability) and the amount of energy-savings by buying a more efficient car, by using slow modes more often, and by saving energy at home. Hence, it seems that respondents are willing to save by these options to compensate for increasing energy bills. As expected, the quadratic term has a negative sign, suggesting a decreasing utility with increasing amount of savings. Further, results show that respondents are less interested in choosing single saving options. Comparing the energy-saving options they have, buying an energy-efficient car is the least preferred option. Combinations of buying an efficient car and using slow modes more often or using slow modes more often and saving energy at home are the most preferred options.

The second part of Table 5 shows the effects of the context variables and the two socio-demographic variables. Season is found to influence utility and, thus, the choice probabilities of the various options. As winter was coded -1 , respondents seem more inclined to save on energy in winter than in other seasons (C1A). In addition, the utility of buying a more efficient car increases in winter (C1X), but the utility of the combination of using

Table 4 Socio-demographic variables

Variables	Name	Description	Type
Personal and household	Gender	Gender	Binary: 0-men/1-woman
	Age	Age	Continuous
	Net-income	Personal net-income per month in three levels	Ordinal: low; middle; high
	No. of members	Number of people in the household	Continuous
	Household composition	Composition of household in 5 levels	Ordinal
Property	Type of house	House type in 5 levels	Ordinal
	Ownership status	Household ownership	Binary: 0-own/1-rent
	E&G expenditure	Expenditure on electricity and gas	Continuous
	Public transport card	Public transport discount card ownership	Binary: 0-none/1-yes
	Number of cars	Number of cars in the household	Continuous
Other	Time spend	Minutes spend on the questionnaire	Continuous

slow transport modes more often and saving energy at home decreases in winter (C1YZ). As for the other context variable, results suggest that people are more willing to save energy if they have to travel with heavy luggage (coded as -1). The coefficients for buying a more efficient car (C2X) and the effects of a combination of buying a more efficient car and saving energy at home (C2XZ) are negative and significant, suggesting these two options are preferred when people travel with heavy luggage. Furthermore, comparing these two coefficients, results indicate that individuals prefer the combination of options (XZ) more than the single option X in this situation. However, the coefficient for heavier use of slow modes is significant and positive, indicating that this option is the most disliked single option in the case of heavy luggage, which may be expected. Also, the combination of using slow modes more often and saving energy at home is not appreciated. Finally, looking at the interaction between season and luggage, the parameter for C1C2Y indicates that both contexts affect the utility of travelling more often by slow modes simultaneously.

The remaining part of Table 5 shows the estimated coefficients of the socio-demographic variables. The three income groups were dummy coded. The negative estimate for the amount variable A for the low income group (IIA) suggests a negative relationship between utility (choice probability) and the amount of savings by buying a more efficient car, by using slow modes more often, and/or by saving energy at home. The coefficient for discount card variables shows that the utility of respondents who have public travel discount (PTD, coded as 1) increases with the amount of savings. Compared with respondents who do not have a public transport card, they increased their utility significantly with the energy-saving combination XY (buying a more energy efficient car and increased use of slow transportation modes) and XZ (buying a more energy efficient car and saving energy at home).

The total impact on the utility function for context and two socio-demographic parameters is shown in Fig. 4. Among these four variables, we found out that consumer choices were mainly influenced by net-income. The context variables used in this study have relatively less impact on consumers' energy conservation strategy compared with effects of personal net-income and transport card ownership. As demonstrated by Fig. 4,

Fig. 1 Sample composition

Fig. 2 Household characteristics

total utility increases for consumers who have a public transport discount card and this impact is increasing with the accumulation of the amount saved. Furthermore, the total effects of public transport discount card on utility are higher for profiles 5–7 for all travel budget levels. In contrast, utility decreases for consumers, who have lower income, and with increasing amounts saved. Effects of context variables, compared to socio-variables, on the total utility of the various profiles are more complicated. Generally speaking, with an increasing amount saved, the effect of season on consumer energy-saving is higher. Further, context effects on total utility vary across profiles. Both context variables have eminent effects on consumer choice of profiles 1 and 6, and smaller effects on profiles 2 and 5.

Model evaluation and predictive performance

The most telling test of model performance is the ability to correctly predict the choices for a test sample, which was not used in model estimation. For this purpose, holdout choice sets were designed and data were collected for model validation.

To assess the validity of the model, its predictive performance for the training data was compared with its performance for the test data, based on 1,000 Halton draws. Table 6 presents the results for the training data set. It shows the cross-tabulation of actual and predicted choices. The row is the actual choice, while the column represents predicted choice. It shows that for the training data the model correctly predicts 30.6 % of all observed choices. The percentage correct predictions is 32.67 % for choice 1, 36.85 % for choice 2, 28.17 % for choice 3, and 13.31 % for the last choice option. Further, compared to training data set, the prediction ability of the model is slightly less for the holdout data, except for choice 3. Table 7 indicates that the model correctly predicts 32.14 % of choice 3, 31.33 % of choice 2 and 26.01 % of choice 1. These values are higher than random choice among four options (25 %). The percentage of correct prediction is lower for 4, but consistent with the training data.

Discussion and conclusion

In this paper, we discussed the principles of mixture-amount experiments and proposed an extended context-dependent mixture amount model to study the problem of energy-saving strategies (combinations of transportation related options and technology) under price increases. A sample of 315 respondents provided the choice data for estimating a mixed logit model. The experiment considered budget constraints and context dependency. Although the percentage of correct prediction could be higher, the suggested approach shows evidence of face validity and is particularly relevant for choices under resource constraints.

People are inclined to compensate for increased expenditures due to increasing energy prices. Moreover, results indicate that there are significant differences across individuals in their sensitivity to different energy-saving options, except for the combination of using slow transportation modes more often and saving energy at home. There is also evidence that their adaptation behaviour depends on context: season and luggage. Although energy-saving preferences vary in different contexts, total utility increases for buying a more efficient car in both context situations (winter and heavy luggage). Results also show reasonable saving adaptation. Respondents dislike the option of using slow transport modes more often in the situation when they have to carrying heavy luggage. In winter, they dislike the saving options of saving energy at home and travel more often by slow mode.

Socio-demographic variables appear to be correlated with energy-saving preferences. The low-income group is less likely to compensate for increasing expenditures by buying a more efficient car, using slow modes more often, and/or saving energy at home. Consumers with a public transport card have greater utility gains from saving energy. Moreover, public transport card owners prefer combinations of energy-saving options, which include buying a more efficient car.

These findings can help both planners and policy makers in developing a more thorough understanding on individual/household energy-savings as it relates to transportation and in-home energy-saving. Giving the increasing concern for smart cities, it is important for both city planners and policy makers alike to understand that individuals/households play a

Table 5 Results of the mixed logit model

Variable	Variable description	100	
		Coef	$P[Z > z]$
A	First order energy-saving	0.12	0.00
A2	Second order energy-saving	0.00	0.00
AX	Energy-saving by buying a more efficient car	0.00	0.60
AY	Energy-saving by using slow modes more often	0.01	0.15
X	Buying an energy efficient car	-1.60	0.00
Y	Using slow modes more often	-0.47	0.21
Z	Saving energy at home	-0.69	0.05
XY	Interaction between buying a more efficient car and using slow modes more often	1.21	0.01
XZ	Interaction between buying a more efficient car and saving energy at home	-0.51	0.33
YZ	Interaction between using slow modes more often and saving energy at home	2.43	0.00
St.dev(A)	Random parts of the basic function	0.03	0.00
St.dev(A2)		0.00	0.00
St.dev(AX)		0.02	0.00
St.dev(AY)		0.06	0.00
St.dev(X)		3.13	0.00
St.dev(Y)		2.66	0.00
St.dev(Z)		1.67	0.00
St.dev(XY)		1.99	0.01
St.dev(XZ)		4.60	0.00
C1A	Interaction between season and first order energy-saving	-0.02	0.00
C1A2	Interaction between season and second order energy-saving	0.00	0.00
C1AX	Interaction between season and saving by buying a more efficient car	0.01	0.03
C1AY	Interaction between season and saving by using more slow modes	0.01	0.00
C1X	Interaction between season and an energy efficient car	-0.57	0.02
C1YZ	Interaction among season, using slow modes more often and saving energy at home	0.61	0.05
C2A	Interaction between luggage and first order energy-saving	-0.01	0.02

Table 5 continued

Variable	Variable description	100													
		Coef		IP[Z > z]		Coef		IP[Z > z]		Coef		IP[Z > z]			
C2A2	Interaction between luggage and second order energy-saving					0.00						0.01			
C2X	Interaction between luggage and saving by buying a more efficient car					-0.35						0.00			
C2Y	Interaction between luggage and saving by using slow modes more often					0.52						0.00			
C2XZ	Interaction among luggage, buying a more efficient car and saving energy at home					-0.60						0.08			
C1C2Y	Interaction among season, luggage and using more slow modes					0.15						0.04			
IIIA	Interaction between low income and first order energy-saving					-0.07						0.00			
IIIA2	Interaction between low income and second order energy-saving					0.00						0.00			
PTDA	Interaction between PTDA and first order energy-saving					0.04						0.00			
PTDA2	Interaction between PTDA and second order energy-saving					0.00						0.00			
PTDXY	Interaction among PTD, buying a more efficient car and using slow modes more often					1.81						0.01			
PTDXZ	Interaction among PTD, buying a more efficient car and saving energy at home					2.63						0.00			
Rho-sqrd						0.286									
Rho-sqAdj						0.284									
Variable		200		300		400		500		600		700		800	
		Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]
A		0.13	0.00	0.13	0.00	0.12	0.00	0.14	0.00	0.14	0.00	0.14	0.00	0.14	0.00
A2		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AX		0.00	0.65	0.00	0.82	0.00	0.60	-0.02	0.05	-0.03	0.00	-0.02	0.05	-0.02	0.04
AY		0.00	0.90	0.01	0.12	0.01	0.41	0.01	0.16	0.01	0.33	0.01	0.08	0.02	0.02
X		-1.60	0.00	-1.66	0.00	-1.39	0.00	-1.06	0.01	-0.92	0.03	-1.42	0.00	-0.96	0.04
Y		-0.13	0.73	-0.16	0.68	-0.28	0.47	-0.83	0.04	-0.32	0.45	0.01	0.98	-0.79	0.05
Z		-0.78	0.03	-0.54	0.12	-0.26	0.48	-0.76	0.04	-0.99	0.01	-0.66	0.08	-0.84	0.03
XY		0.75	0.16	1.06	0.04	1.18	0.02	1.63	0.00	1.58	0.00	1.71	0.00	1.62	0.00
XZ		-0.58	0.39	-0.73	0.20	-0.47	0.42	-0.73	0.23	-0.68	0.26	-0.95	0.13	-1.08	0.09
YZ		2.31	0.00	2.24	0.00	2.51	0.00	2.66	0.00	2.71	0.00	2.65	0.00	2.68	0.00

Table 5 continued

Variable	200		300		400		500		600		700		800	
	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$	Coef	$IP[Z] > z]$
St.dev(A)	0.03	0.00	0.04	0.00	0.04	0.00	0.04	0.00	0.01	0.08	0.04	0.00	0.04	0.00
St.dev(A2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
St.dev(AX)	0.03	0.00	0.05	0.00	0.03	0.00	0.06	0.00	0.08	0.00	0.06	0.00	0.05	0.00
St.dev(AY)	0.08	0.00	0.08	0.00	0.05	0.00	0.03	0.00	0.05	0.00	0.05	0.00	0.02	0.00
St.dev(X)	2.86	0.00	3.28	0.00	3.23	0.00	3.44	0.00	2.35	0.00	3.12	0.00	2.90	0.00
St.dev(Y)	1.41	0.00	2.22	0.00	2.75	0.00	3.21	0.00	3.10	0.00	3.07	0.00	3.18	0.00
St.dev(Z)	1.76	0.00	1.28	0.00	1.91	0.00	1.96	0.00	2.16	0.00	1.93	0.00	2.05	0.00
St.dev(XY)	2.81	0.00	3.46	0.00	3.46	0.00	3.28	0.00	2.47	0.00	3.33	0.00	3.24	0.00
St.dev(XZ)	4.14	0.00	4.23	0.00	4.47	0.00	5.14	0.00	5.63	0.00	5.24	0.00	5.25	0.00
C1A	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00
C1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
C1AX	0.01	0.03	0.01	0.03	0.01	0.02	0.02	0.01	0.01	0.04	0.01	0.05	0.01	0.03
C1AY	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
C1X	-0.58	0.02	-0.61	0.02	-0.68	0.01	-0.71	0.01	-0.63	0.02	-0.58	0.03	-0.66	0.01
C1YZ	0.59	0.06	0.60	0.05	0.60	0.05	0.65	0.04	0.61	0.06	0.66	0.04	0.67	0.03
C2A	-0.01	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.01	-0.01	0.01	-0.01	0.01
C2A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.02
C2X	-0.38	0.00	-0.37	0.00	-0.37	0.00	-0.40	0.00	-0.40	0.00	-0.41	0.00	-0.40	0.00
C2Y	0.49	0.00	0.54	0.00	0.50	0.00	0.51	0.00	0.54	0.00	0.50	0.00	0.53	0.00
C2XZ	-0.74	0.03	-0.56	0.11	-0.68	0.06	-0.60	0.10	-0.81	0.03	-0.66	0.07	-0.77	0.04
C1C2Y	0.15	0.04	0.18	0.02	0.17	0.03	0.17	0.03	0.18	0.02	0.14	0.07	0.16	0.04
IIA	-0.07	0.00	-0.09	0.00	-0.09	0.00	-0.09	0.00	-0.10	0.01	-0.10	0.00	-0.11	0.00
IIA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDA	0.05	0.00	0.04	0.00	0.05	0.00	0.05	0.00	0.04	0.01	0.06	0.00	0.05	0.00
PTDA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDXY	2.46	0.00	2.50	0.00	2.43	0.00	2.17	0.01	1.48	0.06	1.41	0.09	2.16	0.01

Table 5 continued

Variable	200		300		400		500		600		700		800	
	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]
PTDXZ	1.98	0.02	3.07	0.00	2.90	0.00	2.65	0.01	1.58	0.09	2.42	0.01	3.20	0.00
Rho-sqrd	0.288		0.293		0.295		0.295		0.295		0.296		0.295	
Rho-sqAdj	0.287		0.291		0.293		0.293		0.293		0.294		0.293	
Variable	900		1,000		1,100		1,200		1,300		1,400		1,500	
	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]
A	0.13	0.00	0.14	0.00	0.14	0.00	0.14	0.00	0.14	0.00	0.14	0.00	0.14	0.00
A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AX	0.00	0.78	0.00	0.63	-0.01	0.23	-0.01	0.24	0.00	0.63	0.00	0.70	0.00	0.73
AY	0.01	0.21	0.00	0.57	0.01	0.13	0.01	0.30	0.01	0.08	0.01	0.34	0.01	0.40
X	-1.76	0.00	-1.50	0.00	-1.54	0.00	-1.44	0.00	-2.01	0.00	-1.72	0.00	-1.65	0.00
Y	-0.75	0.06	-0.48	0.24	-0.64	0.12	-0.43	0.29	-0.27	0.50	-0.25	0.54	-0.32	0.44
Z	-0.72	0.05	-0.67	0.07	-0.80	0.03	-0.77	0.04	-0.77	0.04	-0.67	0.08	-0.67	0.08
XY	1.36	0.01	1.21	0.02	1.39	0.01	1.37	0.01	1.43	0.01	1.57	0.00	1.53	0.01
XZ	-0.63	0.30	-0.66	0.29	-0.66	0.29	-0.92	0.15	-0.87	0.16	-0.48	0.45	-0.35	0.58
YZ	2.70	0.00	2.63	0.00	2.66	0.00	2.65	0.00	2.62	0.00	2.68	0.00	2.70	0.00
Std.dev(A)	0.03	0.00	0.03	0.00	0.04	0.00	0.04	0.00	0.04	0.00	0.02	0.00	0.02	0.00
Std.dev(A2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std.dev(AX)	0.01	0.04	0.04	0.00	0.05	0.00	0.04	0.00	0.00	0.49	0.03	0.00	0.03	0.00
Std.dev(AY)	0.06	0.00	0.07	0.00	0.05	0.00	0.06	0.00	0.07	0.00	0.06	0.00	0.06	0.00
Std.dev(X)	3.71	0.00	3.07	0.00	2.95	0.00	3.12	0.00	3.29	0.00	3.34	0.00	3.42	0.00
Std.dev(Y)	2.95	0.00	2.91	0.00	3.02	0.00	3.01	0.00	2.61	0.00	3.02	0.00	2.98	0.00
Std.dev(Z)	2.05	0.00	2.03	0.00	1.75	0.00	2.16	0.00	2.19	0.00	2.02	0.00	2.09	0.00
Std.dev(XY)	3.54	0.00	3.36	0.00	4.14	0.00	3.62	0.00	4.24	0.00	3.92	0.00	3.94	0.00
Std.dev(XZ)	4.93	0.00	5.15	0.00	5.26	0.00	5.55	0.00	4.93	0.00	5.81	0.00	5.94	0.00
C1A	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00

Table 5 continued

Variable	900		1,000		1,100		1,200		1,300		1,400		1,500	
	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $
C1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C1AX	0.01	0.03	0.01	0.03	0.02	0.02	0.01	0.05	0.01	0.03	0.01	0.03	0.01	0.03
C1AY	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
C1X	-0.61	0.02	-0.62	0.02	-0.68	0.01	-0.60	0.02	-0.60	0.02	-0.65	0.01	-0.63	0.02
C1YZ	0.67	0.04	0.60	0.06	0.66	0.04	0.64	0.04	0.62	0.05	0.64	0.04	0.65	0.04
C2A	-0.01	0.01	-0.02	0.00	-0.02	0.00	-0.02	0.01	-0.02	0.00	-0.02	0.00	-0.02	0.01
C2A2	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01
C2X	-0.43	0.00	-0.36	0.00	-0.41	0.00	-0.42	0.00	-0.38	0.00	-0.41	0.00	-0.41	0.00
C2Y	0.54	0.00	0.54	0.00	0.51	0.00	0.54	0.00	0.58	0.00	0.52	0.00	0.52	0.00
C2XZ	-0.82	0.03	-0.78	0.03	-0.75	0.04	-0.80	0.03	-0.76	0.04	-0.77	0.04	-0.79	0.03
C1C2Y	0.17	0.03	0.17	0.03	0.18	0.03	0.18	0.02	0.15	0.07	0.17	0.03	0.17	0.03
I1A	-0.11	0.00	-0.09	0.00	-0.09	0.00	-0.10	0.00	-0.10	0.00	-0.11	0.00	-0.11	0.00
I1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDA	0.06	0.00	0.05	0.00	0.04	0.00	0.04	0.00	0.05	0.00	0.06	0.00	0.06	0.00
PTDA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDXY	2.43	0.00	2.08	0.01	2.28	0.01	2.63	0.00	1.79	0.04	1.82	0.04	1.84	0.04
PTDXZ	2.92	0.00	2.78	0.00	3.28	0.00	2.96	0.00	3.01	0.00	2.89	0.00	2.74	0.01
Rho-sqrd	0.296		0.296		0.298		0.296		0.296		0.296		0.296	
Rho-sqAdj	0.294		0.294		0.296		0.294		0.294		0.294		0.294	
Variable	1,700		1,800		1,900		2,000		2,100		2,200		2,300	
	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $	Coef	$IP[Z] > z $
A	0.13	0.00	0.14	0.00	0.13	0.00	0.13	0.00	0.14	0.00	0.14	0.00	0.14	0.00
A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AX	-0.01	0.25	-0.02	0.03	-0.01	0.18	0.00	0.74	-0.01	0.33	-0.01	0.37	-0.01	0.33
AY	0.01	0.09	0.01	0.29	0.01	0.14	0.01	0.36	0.01	0.14	0.01	0.27	0.01	0.14

Table 5 continued

Variable	1,700		1,800		1,900		2,000		2,100		2,200		2,300	
	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]	Coef	IP[Z > z]
X	-1.43	0.00	-1.15	0.01	-1.23	0.01	-1.63	0.00	-1.34	0.00	-1.67	0.00	-1.49	0.00
Y	-0.39	0.35	-0.40	0.33	-0.36	0.39	-0.24	0.56	-0.53	0.23	-0.48	0.24	-0.57	0.17
Z	-0.62	0.09	-0.83	0.03	-0.71	0.06	-0.61	0.11	-0.64	0.09	-0.84	0.03	-0.89	0.02
XY	1.53	0.00	1.32	0.01	1.35	0.01	1.37	0.01	1.53	0.01	1.32	0.02	1.35	0.01
XZ	-0.97	0.13	-0.45	0.46	-0.94	0.15	-0.39	0.53	-0.65	0.31	-0.34	0.58	-0.57	0.38
YZ	2.77	0.00	2.66	0.00	2.68	0.00	2.59	0.00	2.72	0.00	2.65	0.00	2.74	0.00
St.dev(A)	0.05	0.00	0.03	0.00	0.04	0.00	0.03	0.00	0.03	0.00	0.02	0.00	0.03	0.00
St.dev(A2)	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
St.dev(AX)	0.05	0.00	0.07	0.00	0.05	0.00	0.04	0.00	0.05	0.00	0.04	0.00	0.05	0.00
St.dev(AY)	0.05	0.00	0.05	0.00	0.06	0.00	0.07	0.00	0.04	0.00	0.06	0.00	0.05	0.00
St.dev(X)	3.30	0.00	2.38	0.00	2.77	0.00	3.13	0.00	3.23	0.00	3.22	0.00	3.16	0.00
St.dev(Y)	3.41	0.00	2.95	0.00	2.81	0.00	2.72	0.00	3.12	0.00	3.02	0.00	3.20	0.00
St.dev(Z)	1.98	0.00	1.92	0.00	2.18	0.00	1.91	0.00	2.00	0.00	2.09	0.00	2.21	0.00
St.dev(XY)	3.82	0.00	3.72	0.00	3.92	0.00	3.59	0.00	3.69	0.00	3.94	0.00	3.82	0.00
St.dev(XZ)	5.65	0.00	5.08	0.00	5.43	0.00	4.96	0.00	5.66	0.00	5.46	0.00	5.63	0.00
C1A	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00
C1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C1AX	0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.03	0.01	0.02	0.01	0.03	0.01	0.03
C1AY	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
C1X	-0.62	0.02	-0.65	0.01	-0.62	0.02	-0.63	0.02	-0.64	0.01	-0.66	0.01	-0.67	0.01
C1YZ	0.63	0.05	0.61	0.05	0.60	0.06	0.58	0.07	0.64	0.04	0.62	0.05	0.63	0.05
C2A	-0.01	0.01	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.01	0.01	-0.01	0.01
C2A2	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01
C2X	-0.43	0.00	-0.42	0.00	-0.41	0.00	-0.37	0.00	-0.41	0.00	-0.43	0.00	-0.41	0.00
C2Y	0.53	0.00	0.50	0.00	0.54	0.00	0.53	0.00	0.55	0.00	0.48	0.00	0.52	0.00
C2XZ	-0.77	0.04	-0.72	0.05	-0.74	0.05	-0.77	0.04	-0.76	0.04	-0.81	0.03	-0.72	0.05

Table 5 continued

Variable	1,700		1,800		1,900		2,000		2,100		2,200		2,300	
	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]
C1C2Y	0.16	0.05	0.17	0.03	0.16	0.04	0.18	0.03	0.16	0.04	0.17	0.03	0.18	0.02
IIA	-0.11	0.00	-0.10	0.00	-0.09	0.00	-0.09	0.00	-0.10	0.00	-0.09	0.00	-0.10	0.00
IIA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDA	0.06	0.00	0.05	0.00	0.05	0.00	0.06	0.00	0.05	0.00	0.06	0.00	0.05	0.00
PTDA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDXY	1.80	0.04	1.85	0.03	2.01	0.02	2.04	0.02	1.71	0.05	2.37	0.01	2.09	0.02
PTDXZ	3.04	0.00	2.71	0.01	2.81	0.01	2.59	0.01	2.91	0.00	2.61	0.01	2.60	0.01
Rho-sqrd	0.298		0.296		0.296		0.296		0.297		0.297		0.297	
Rho-sqAdj	0.296		0.294		0.294		0.294		0.295		0.295		0.295	
Variable	2,400		2,500		2,600		2,800		2,900		3,000			
	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]	Coef	IP[Z] > z]		
A	0.14	0.00	0.13	0.00	0.13	0.00	0.14	0.00	0.14	0.00	0.14	0.00	0.14	0.00
A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AX	-0.01	0.18	-0.01	0.29	0.00	0.74	0.00	0.80	0.00	0.80	-0.02	0.17	-0.01	0.38
AY	0.01	0.07	0.01	0.46	0.01	0.26	0.01	0.37	0.01	0.37	0.01	0.18	0.01	0.11
X	-1.46	0.00	-1.65	0.00	-1.15	0.01	-1.91	0.00	-1.22	0.02	-1.22	0.02	-1.83	0.00
Y	-0.55	0.18	-0.22	0.60	-0.05	0.90	-0.53	0.20	-0.37	0.37	-0.37	0.37	-0.51	0.22
Z	-0.78	0.04	-0.62	0.10	-0.38	0.31	-0.72	0.06	-0.84	0.03	-0.84	0.03	-0.76	0.04
XY	1.26	0.02	1.16	0.04	1.40	0.01	1.45	0.01	1.37	0.01	1.37	0.01	1.48	0.01
XZ	-0.80	0.22	-0.44	0.48	-0.71	0.28	-0.85	0.19	-0.63	0.36	-0.63	0.36	-0.48	0.45
YZ	2.73	0.00	2.64	0.00	2.61	0.00	2.73	0.00	2.67	0.00	2.67	0.00	2.74	0.00
Std.dev(A)	0.03	0.00	0.03	0.00	0.05	0.00	0.00	0.69	0.02	0.25	0.02	0.25	0.03	0.00
Std.dev(A2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std.dev(AX)	0.05	0.00	0.04	0.00	0.03	0.00	0.02	0.03	0.06	0.00	0.06	0.00	0.04	0.00
Std.dev(AY)	0.03	0.00	0.07	0.00	0.06	0.00	0.06	0.00	0.05	0.00	0.05	0.00	0.05	0.00

Table 5 continued

Variable	2,400		2,500		2,600		2,800		2,900		3,000	
	Coef	IP[ZI > zI]	Coef	IP[ZI > zI]	Coef	IP[ZI > zI]	Coef	IP[ZI > zI]	Coef	IP[ZI > zI]	Coef	IP[ZI > zI]
Std.dev(X)	3.03	0.00	2.92	0.00	3.07	0.00	3.70	0.00	2.75	0.00	3.39	0.00
Std.dev(Y)	3.10	0.00	2.72	0.00	2.69	0.00	3.07	0.00	2.89	0.00	3.13	0.00
Std.dev(Z)	2.07	0.00	2.09	0.00	1.88	0.00	2.13	0.00	2.14	0.00	2.10	0.00
Std.dev(XY)	3.63	0.00	4.08	0.00	3.80	0.00	4.18	0.00	3.71	0.00	3.67	0.00
Std.dev(XZ)	5.41	0.00	5.18	0.00	5.23	0.00	5.54	0.00	5.67	0.00	5.52	0.00
C1A	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00	-0.02	0.00
C1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C1AX	0.01	0.02	0.01	0.04	0.01	0.04	0.01	0.03	0.01	0.02	0.01	0.03
C1AY	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
C1X	-0.69	0.01	-0.59	0.03	-0.60	0.02	-0.62	0.02	-0.69	0.01	-0.64	0.02
C1YZ	0.62	0.05	0.62	0.05	0.65	0.04	0.61	0.05	0.63	0.04	0.63	0.05
C2A	-0.01	0.01	-0.02	0.00	-0.01	0.01	-0.02	0.00	-0.01	0.01	-0.02	0.00
C2A2	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00
C2X	-0.42	0.00	-0.37	0.00	-0.42	0.00	-0.41	0.00	-0.45	0.00	-0.40	0.00
C2Y	0.51	0.00	0.52	0.00	0.52	0.00	0.53	0.00	0.51	0.00	0.51	0.00
C2XZ	-0.70	0.06	-0.74	0.05	-0.71	0.05	-0.75	0.05	-0.79	0.04	-0.79	0.04
C1C2Y	0.17	0.03	0.17	0.03	0.16	0.04	0.16	0.05	0.18	0.02	0.16	0.04
I1A	-0.09	0.00	-0.09	0.00	-0.11	0.00	-0.10	0.00	-0.09	0.00	-0.09	0.00
I1A2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDA	0.05	0.00	0.05	0.00	0.06	0.00	0.06	0.00	0.06	0.00	0.04	0.00
PTDA2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PTDXY	2.31	0.01	2.21	0.01	1.78	0.04	1.80	0.05	1.94	0.03	1.99	0.02
PTDXZ	2.93	0.00	2.69	0.01	3.04	0.00	2.87	0.00	2.90	0.01	2.67	0.01
Rho-sqrd	0.298		0.296		0.296		0.296		0.297		0.297	
Rho-sqAdj	0.296		0.294		0.294		0.294		0.295		0.295

Fig. 3 Fluctuations in main parameters with increasing number of Halton draws

Fig. 4 Effects of context and socio-demographic variables on total utility and profiles for different saving options

Table 6 Correct predictions for the training sample

	1	2	3	4	Total
1	425	416	319	141	1,301
2	410	541	350	167	1,468
3	328	362	322	132	1,143
4	151	170	135	70	526
Total	425	416	319	141	1,301
% correct predictions	32.67	36.85	28.17	13.31	30.60

pivotal role in the reduction of both transportation-related and in-home energy consumption. Policy makers should be aware that individual/household energy-saving should include out-of-home energy consumption which is mostly travel-related, in-home energy

Table 7 Correct predictions for the validation sample

	1	2	3	4	Total
1	97	119	118	39	373
2	120	141	144	46	450
3	80	96	99	33	308
4	36	43	44	14	137
Total	333	399	405	131	1,268
% correct predictions	26.01	31.33	32.14	10.22	27.68

consumption and ownership of a more efficient car. For transportation planners and policy makers, these results may help them understanding that energy price policy (such as increasing fuel tax or CO₂ tax) might trigger multiple conservation strategies to reduce energy consumption. Moreover, the results indicate that combined energy-saving strategies such as changing of transport modes and ownership of a more efficient car are easier to be accepted than single saving options. Policies should also be sensitive to the influence of context and socio-demographic variables.

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