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Abstract

Solar-powered consumer electronics are a likely starting point for organic photovoltaic (OPV) market development. Therefore, a generic discrete choice experiments study can determine how Flemish consumers value solar-cell characteristics for solar-powered consumer electronics. Such characteristics include efficiency, lifetime, aesthetics, integratability, and price. We contribute to the literature by investigating preference heterogeneity in a solar-power niche market with an experimental design with a fixed reference alternative. The error components random parameter logit (ECRPL) with interactions provides a better fit than the latent class (LC) model for our choice data. The main effects had the expected signs. Consequently, aesthetics and integratability are OPV's assets. Nevertheless, heterogeneity puts the results that are valid for the average consumer into perspective. Based on our findings, OPV commercialization efforts should target the experienced, impatient user who highly values design and functionality.

Highlights:

- We investigate heterogeneous preferences for solar-powered consumer electronics.
- We present a generic DCE study with a fixed reference alternative
- The ECRPL best explains our choice data.
- Target the experienced, impatient user highly valuing design and functionality.

1. Introduction

Several authors have identified solar-powered consumer electronics as a likely starting point for organic photovoltaic (OPV) solar-cells' market development (Krebs et al., 2010b, Nielsen et al., 2010). OPVs are solar cells with an all-organic, solid-state active layer (Brabec et al., 2010). Among all alternatives to crystalline silicon-based solar-cells, OPVs are considered a strong solution to the problem of high cost and low throughput (Krebs et al., 2010c). OPVs might also provide a better solution than crystalline silicon solar cells to global warming if consumers adopt this promising renewable energy technology (RET). Energy payback times (EPBTs) of only one day are predicted for OPVs under favorable circumstances, but taking lifetime issues into account. Crystalline silicon solar cells have EPBTs of one to two years (Espinosa et al., 2012).

Nevertheless, consumers' willingness to adopt a product depends on how they value it. Therefore, we performed a generic, discrete choice experiments (DCE) study to see how Flemish consumers value solar-cell characteristics for solar-powered consumer electronics. We assessed generic preferences for such solar cells by setting attribute levels to cover the range of possible levels different solar-cell types achieve. This allows for assessing the match with OPV's (future) profile. We respond to OPV material scientists' call for guidance on how to claim a significant market share of a predefined market (Krebs et al., 2010a). We contribute to existing literature by incorporating unobserved heterogeneity into our modeling efforts. To this end, we investigated preferences using the error component random parameter logit (ECRPL) and the latent class (LC) logit models.

The remainder of this paper is divided into four sections. The methodology section reviews DCE use in RET literature, explains its intuition, and describes our approach. The results section provides the sample's descriptive statistics, after which we interpret the results obtained from the different models. The conclusion summarizes our main findings.

2. Methodology

2.1. DCEs covering renewable energy: A literature review

DCEs have frequently been applied to the topic of renewable energy, albeit from different angles. Table 1 presents the results of a literature review from 2006 to 2014. Contributions mainly examine the importance of the green electricity share in the electricity mix or the valuation of socioeconomic and environmental externalities of RETs. Solar power constitutes the exception to this rule. Photovoltaics and solar water heating have been investigated with an

77　eye on predicting the adoption time. Table 1 shows that solar-power niche markets have barely
78　been investigated, with little attention toward heterogeneity. Nevertheless, Yoo and Ready
79　(2014) showed that preferences for solar power are the most heterogeneous of all types of
80　renewable technologies.

81　[Insert Table 1]

82　## 2.2. DCEs modeling approach

83　The discrete choice-based elicitation format closely resembles an actual purchasing decision
84　(Ward et al., 2011). To formalize this decision process, DCE adopted the random utility theory
85　(RUT), which Thurstone (1927) originally developed. McFadden (1974) translated RUT into
86　the mathematical formulation of the conditional logit (CL) model.

87　The assumption of independently, identically distributed (IID) error terms allows for the
88　convenient closed form of the CL model. The simplicity of the closed form comes at a cost,
89　given that the CL model translates the IID assumption into substitution patterns that are
90　restricted by the independence of irrelevant alternatives (IIA). Fully relaxing the IIA
91　assumption without adopting different distributions for the error terms or different structures
92　in decision-making, forces the use of mixed logit type models. Moreover, these types of models
93　allow for unveiling unobserved heterogeneity. Mixed logit models have unconditional
94　probabilities P_{ij} equal to the integral of standard logit conditional probabilities $L_{ij}(\beta)$ over a
95　density of parameters $f(\beta)$ (see Equation 1). This density may be continuous or discrete (Train,
96　2003).

97　An error component random parameter logit (ECRPL) model assumes a continuous
98　distribution of attribute parameters and allows for calculating preferences at the individual
99　level. Error components are often normally distributed as $N(0,\sigma^2)$. The variance captures the
100　magnitude of the correlation between the nested alternatives. Formulating the model in this
101　way has been shown to provide the best fit when dealing with a reference alternative (Hess and
102　Rose, 2009).

103　A LC model assumes a discrete distribution of attribute parameters and assesses the average
104　preferences for homogenous segments while using a class membership function (Train, 2003).

105
$$P_{ij} = \int L_{ij}(\beta) * f(\beta) * d\beta \qquad (1)$$

106

4

2.3. Performing a DCE study

2.3.1. Setting up DCEs

Relevant attributes and levels were identified using focus-group discussions and expert interviews, given the lack of prior studies. A full description of the attribute development process, the motivations for the respective chosen levels, and the method for ensuring optimal understanding, can be found in Lizin et al. (2012). This process led to the conceptualization of five attributes, each consisting of four levels (see Table 2). In summary, the upper bounds for quantitative attribute levels and lower bounds for qualitative attribute levels are those for polycrystalline silicon cells. On the contrary, the lower bounds for quantitative attribute levels and upper bounds for qualitative attribute levels are values that OPV solar cells might attain. This allows for capturing all solar-cell technologies with levels between these bounds.

Based on these attributes and levels, a generic, forced choice, main-effects design for a CL was created in SAS, with a relative D-efficiency of 80.14 using zero priors by means of the alternative swapping procedure (Kuhfeld, 2010). Such a design may be reused with limited efficiency loss for estimating a random parameter logit model (Bliemer and Rose, 2010). However, statistical efficiency should not dominate respondent efficiency (Ferrini and Scarpa, 2007). Respondent efficiency is usually increased by limiting the number of attributes and levels, ensuring realism and credibility, and optimally conveying the meaning of attributes.

We felt the need to go further for our case study. Focus-group discussions revealed that most people are knowledgeable of solar cells' application in solar panels, which are generally made of polycrystalline silicon. However, most people are unaware of the different types of PV solar cells used in alternative applications. To deal with respondents' limited experience polycrystalline silicon levels serve as a point of reference by means of a fixed reference alternative. In theory, such an alternative can represent an opt-out option (Kontoleon and Yabe, 2003). In our case, as respondents were largely unaware of which type of solar cell they possessed, the constant alternative does not represent an opt-out nor even a perceived status quo (Domínguez-Torreiro and Soliño, 2011). Neither does it provide a reference alternative, as this would also require respondent awareness. The fixed alternative merely serves to provide a contextual reference (Schläpfer and Fischhoff, 2012). Respondents were consequently forced to choose between the provided alternatives. Hence, the results are meaningful for people having decided they want to buy a solar-powered consumer electronics device. This led to a design consisting of 16 choice sets, each presenting four alternatives. Given the large number

139 of choice sets, we decided to block the design over two surveys. To counter for order effects
140 bias, the choice sets' order was randomized 10 times for both survey versions.

141   [Insert Table 2]

142   **2.3.2. Questionnaire development, conduct and processing**

143 We developed a questionnaire based on Bateman et al.'s (2002) guidelines. Accordingly, we
144 divided it into four sections: The survey's purpose; attitudinal questions and use of the device;
145 the choice sets; and socio-demographic questions. Prior to the final roll-out, the questionnaire
146 was pilot-tested on a group of 30 respondents to verify language understanding.

147 After modifications, the actual survey was conducted on various intercity train travels
148 throughout the entire Flemish region during the 2011 and 2012 summer holiday periods. This
149 ensured the presence of many (about 53 percent) infrequent train users. However, there still
150 may have been an eco-friendly bias because people unwilling to use the train were left out.

151 This type of sampling can be classified as intercept sampling. Additionally, quota screening
152 was used to closely resemble the 2010 gender distribution (49.35 percent male) obtained when
153 using probability sampling. Motivated by solar cells' technical nature and the intrinsic
154 cognitive burden on respondents associated with DCEs, the target population was limited to
155 anyone between the ages of 18 and 64 living in the Flemish region who understood the native
156 language. We assumed that anybody in this age group at a given point in time would buy a
157 solar-powered consumer electronics device. A simple pen-and-paper distribution method was
158 used for taking the survey, with additional guidance from trained surveyors. The surveyors'
159 ability to help people through the process in a personalized way was crucial in making this
160 decision (Arrow et al., 1993). Task familiarity was further augmented by providing a written,
161 filled-in choice set example. In total, 450 fully filled-in questionnaires were collected.

162   **2.3.3. Econometric analysis**

163 The first step in the econometric analysis of the DCE data was to identify the most qualified
164 expression for the indirect utility function, without and with interaction effects. This was done
165 using the CL model. All tested attributes demonstrated at least one significantly different slope.
166 The price attribute was coded linearly to allow straightforward calculations of willingness to
167 pay. Dummy coding was used because of ease of interpretation, relative to effects coding.
168 Qualitative attributes must be nonlinearly coded. The constant alternative's levels were the

169   omitted base levels. Consequently, the direct utility V_{ij} was defined in Equation 2 with

170   abbreviated subscripts for the respective estimated parameters (see Table 2).

171   $V_{ij} = \beta_{pr}X_{pr} + \beta_{15y}X_{15y} + \beta_{10y}X_{10y} + \beta_{5y}X_{5y} + \beta_{15\%}X_{15\%} + \beta_{10\%}X_{10\%} + \beta_{5\%}X_{5\%} +$

172   $\beta_{ug}X_{ug} + \beta_{ni}X_{ni} + \beta_{vni}X_{vni} + \beta_{pint}X_{pint} + \beta_{int}X_{int} + \beta_{vint}X_{vint}$ (2)

173   Socio-economic variables can only be included as interaction terms because they are constant

174   across choice occasions for any individual (Hanley et al., 2001). In that case, V_{ij} takes the form

175   shown in Equation 3, with $(S_z * X_q)$ as the interaction effects and $\beta_\#$ as the interaction effects'

176   parameter weights. The identified interaction effects are: High energy awareness ($S_{energyaware}$);

177   high environmental awareness ($S_{envaware}$); high impatience ($S_{impatient}$); and high experience with

178   PV application ($S_{experienced}$). Energy awareness was measured as an index consisting of

179   questions measuring energy-saving behavior. Environmental awareness was measured as an

180   index consisting of questions gauging pro-environmental behavior. Impatience was measured

181   on a single Likert scale assessing how inconvenient respondents think it is to charge electrical

182   devices. Those who considered charging very inconvenient were considered impatient users.

183   The output of the final models is discussed in the results section.

184   $V_{ij} = \beta_{pr}X_{pr} + \beta_{15y}X_{15y} + \beta_{10y}X_{10y} + \beta_{5y}X_{5y} + \beta_{15\%}X_{15\%} + \beta_{10\%}X_{10\%} + \beta_{5\%}X_{5\%} +$

185   $\beta_{ug}X_{ug} + \beta_{ni}X_{ni} + \beta_{vni}X_{vni} + \beta_{pint}X_{pint} + \beta_{int}X_{int} + \beta_{vint}X_{vint} + \beta_1 X_{5\%}S_{energyaware} +$

186   $\beta_2 X_{ug}S_{envaware} + \beta_3 X_{ni}S_{envaware} + \beta_4 X_{vni}S_{envaware} + \beta_5 X_{ni}S_{impatient} +$

187   $\beta_6 X_{vni}S_{impatient} + \beta_7 X_{5y}S_{experienced}$ (3)

3. Results

3.1. Descriptive statistics

190   Table 3 shows the descriptive statistics. We were dealing with a younger, moderately

191   environmentally aware, fairly energy-aware audience. Only 6.73 percent had not taken action

192   to lower their energy bill, and 86.55 percent had used solar-powered consumer electronics,

193   mainly solar-powered calculators in the past. This comes as no surprise, as calculators were the

194   first solar-powered consumer product (Apostolou and Reinders, 2014).

195   Furthermore, respondents were divided concerning the inconvenience of having to charge their

196   electronic devices. Using a five-point Likert scale (ranging from -2 to 2), we found that 40

197   percent found charging to be inconvenient, another 40 percent thought it not bothersome, and

198   20 percent were neutral. The respondents were also asked to motivate their response. The first

199   group's most frequently found motivations were: They did not like having to monitor the

battery's status, so often forgot to recharge; no outlet or charger compatible to the device was available; and the full freedom of operation was lost while charging. The second group's most popular answers were: It is a habit; and it does not require much effort.

Household size, family income, and educational level were three potential predictor variables for domestic energy use (Sardianou, 2007). Their respective means and distributions are also provided. For completeness, we also present the respondents' geographic distribution (within Flanders).

[Insert Table 3]

3.2. <u>Parameter estimates</u>

Table 4 presents the results of the final ECRPL with interactions. Models were run using 1,000 Halton draws, assuming normal distributions for random parameters and accounting for correlation between random parameters. The suitability of this distributional assumption was verified using kernel density estimation (Hensher and Greene, 2003).

All attributes were significant factors in determining consumers' choice. Furthermore, all main effect coefficients showed the expected *a priori* signs for the average consumer. More specifically, the average respondent preferred a solar cell with the highest efficiency, the highest lifetime, the nicest aesthetics, and a decent integratability at the lowest price.

Observed heterogeneity was captured by creating interaction effects with socio-demographic characteristics (SDCs). Their signs and values put the results, which were valid for the mean main effect coefficients, into perspective. On the one hand, the highly environmentally aware respondents had an aversion for better-looking products. Perhaps they associated better appearances with higher environmental burdens. Similarly, the experienced user did not show a strong dislike for five-year lifetimes. On the other hand, the highly energy-aware individuals showed a stronger than average dislike for low efficiencies, while the impatient user was also more sensitive to aesthetically pleasing products. In spite of the various significant interactions, all main effects showed significant unobserved heterogeneity in the ECRPL model. Most heterogeneity was found for the attribute levels that were most likely for OPVs; in other words. for cells with an efficiency of 5 percent and a lifetime of five years. Finally, a significant shared error component was found to be highly significant, confirming cross-correlation between the hypothetical alternatives.

[Insert Table 4]

8

231 In the LC model, respondents were divided into homogenous segments based on SDCs and the
232 highest class decision rule. Following Birol et al. (2006), we assumed that the respondent
233 characteristics used to obtain significant interactions most affected segment membership. In
234 order to choose the most suitable number of segments, information criteria were investigated
235 while increasing the number of segments. The lower the value of the BIC and the Bozgodan
236 AIC (AIC3) (Andrews and Currim, 2003), the better the model fit. In our case, both criteria
237 pointed to the same conclusion. Consequently, a model with four segments was considered
238 optimal. The results of the LC model are provided in Table 5.

239 From the results, respondents belonging to classes 1 to 4 were best characterized by: (1) a high
240 sensitivity toward nicer aesthetics; (2) high preference for good integratability; (3) high
241 aversion for low efficiencies and high prices; and (4) great dislike for low lifetimes and
242 efficiencies. Additionally, the fourth segment was not influenced in their choice by the price,
243 and segments 2 and 3 seem to be heterogeneous in their preferences for lifetime levels. The
244 second part of the table reports the segment membership coefficients relative to the normalized
245 fourth segment. Only high environmental awareness and impatience dummies were significant
246 segmenting variables for the first segment.

247   [Insert Table 5]

248 To compare the ECRPL and LC model fit, we used a test Ben-Akiva and Swait (1986)
249 suggested, given that we are no longer working with nested models. The test confirms that the
250 more parsimonious ECRPL is the best-fitting model. The information criteria point to a similar
251 conclusion.

252   **3.3. WTP estimates**

253 Since ECRPL is the best-fitting model, we used it to compute the welfare measures. WTP
254 estimates were calculated at the means, using the Delta method, while correcting for the
255 interactions with SDCs. Table 6 shows the results of the estimations. WTP measures reveal
256 how much people are willing to pay for a change from the base level to the displayed attribute
257 level. The WTP measures are given as €/Wp. For instance, the WTP estimate for a lifetime of
258 five years indicates that the average respondent should be compensated by 10.33 €/Wp for a
259 loss in lifetime of 15 years. Additionally, kernel density plots showing WTP estimate
260 distributions reconfirm that the widest WTP distributions were found for the attribute levels
261 most likely for OPV, i.e. cells with an efficiency of 5 percent and a lifetime of five years.

262   [Insert Table 6]

4. Conclusion and discussion

Discrete choice experiments (DCEs) have been widely applied to assess the importance of the green electricity share in the electricity mix or the valuation of socioeconomic and environmental externalities. Solar-power niche markets have barely been investigated, or with little attention to heterogeneity. Nevertheless, Yoo and Ready (2014) showed that preferences for solar power are more heterogeneous than preferences for all other types of renewable technologies. Moreover, by investigating preferences for solar-powered consumer electronics, we answered OPV material scientists' call for guidance on how to gain market share (Krebs et al., 2010a).

To fill these gaps, we investigated Flemish consumer preferences for solar-powered consumer electronics by using generic DCEs with a fixed reference alternative representing a polycrystalline silicon solar cell. This alternative was included in the experimental design to provide the respondents with a reference frame. Focus-group discussions showed that respondents were largely unfamiliar with PV cell types and performances, but used solar panels (which are mostly of the polycrystalline silicon type) as a point of reference.

We estimated preferences using the error component random parameter logit (ECRPL) model (which was well-suited to deal with fixed reference alternatives), and the latent class (LC) model. A test Ben-Akiva and Swait suggested, confirmed that the ECRPL model with interactions provided a better fit than the LC model for our choice data. Mean main effects exhibited the expected signs for the efficiency dummies (-), lifetime dummies (-), aesthetics dummies (+), integratability dummies (+), and price (-). Hence, aesthetics and integratability should be seen as OPV assets.

However, the mean main effect coefficients should be interpreted with caution, as our analysis indicates that preferences are very heterogeneous. Respondents with specific characteristics had inverse preferences. In particular, respondents with high environmental awareness attached less importance to better-looking products. Furthermore, experienced users liked lifetimes of five years more than others. Alternatively, the main effects were reinforced for some type of respondents. Those with high energy awareness typically had a higher preference for low efficiencies than respondents with moderate or low levels of energy awareness. Impatient respondents, who strongly disliked waiting while their device charged, also had stronger preferences for good-looking products compared to more patient respondents. Therefore, we

concur with Apostolou and Reinders (2014) in stating that functionality depends on the user's charging habits.

Based on our findings, we would advise organic photovoltaic (OPV) commercialization efforts to aim for the experienced, impatient user who highly values a functional design. Moreover, the ECRPL also allowed us to grasp unobserved heterogeneity by estimating the standard deviations of the normally distributed parameters. All random parameters showed significant unobserved heterogeneity, in spite of the various significant interactions with socio-demographic characteristics. Moreover, the magnitude shows that the most heterogeneity was present in the attribute levels likely for OPV in its early development stages; in other words, cells with an efficiency of 5 percent and a lifetime of five years. This may point to a segment of consumers that perceives lower requirements for consumer electronics to be satisfactory, signaling the viability of an OPV-powered consumer electronics niche market. We finish with a word of caution that these are exploratory results that should be reconfirmed by probabilistic sampling.

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475 **Table 1: Discrete choice experiments eliciting consumers' valuation of (the effects of) renewable energy**

RES	Reference	Topic	Observed heterogeneity	Unobserved heterogeneity
Biomass	Jensen et al. (2010)	Valuation of E85 fuel originating from different biomass types	X	RPL
Biomass	Soliño (2010)	Valuation of a forest biomass promotion program	X	/
Biomass	Susaeta et al. (2011)	Valuation of woody biomass' positive externalities	X	RPL
Hydro	Han et al. (2008)	Valuation of environmental impacts of large dam construction	X	/
Hydro	Kataria (2009)	Valuation of environmental improvements for hydropower regulated rivers	X	RPL
Solar	Islam and Meade (2013)	Estimation of preferences for factors influencing solar panel adoption	/	GMXL
Solar	(Islam, 2014)	Estimation of preferences for factors influencing solar panel adoption	/	LC
Solar	Lizin et al. (2012)	Valuation of solar cell characteristics for powering consumer electronics	X	/
Solar	Yamaguchi et al. (2013)	Estimation of preferences for factors influencing solar panel and solar hot water adoption	/	/
Tidal	Lee and Yoo (2009)	Valuation of environmental damage caused by the construction of a tidal power plant	/	/
Tidal	Vazquez and Iglesias (2015)	Valuation of environmental and socio-economic externalities of a tidal power plant	X	/
Wind	Drechsler et al. (2011)	Optimal spatial allocation of wind turbines	/	/
Wind	Ek and Persson (2014)	Optimal establishment of wind farms	X	RPL&LC
Wind	Meyerhoff et al. (2010)	Valuation of landscape externalities of onshore wind turbines	X	LC
Wind	Strazzera et al. (2012)	Social acceptability of wind turbines	X	LC
Mix	Amador et al. (2013)	The influence on WTP of the renewable energy share in the electricity mix		
Mix	Bergmann et al. (2006)	Preferences over environmental and employment impacts that may result from renewable energy projects	X	/
Mix	Bergmann et al. (2008)	Valuation of environmental and employment impacts that may result from renewable energy projects	X	RPL
Mix	Borchers et al. (2007)	The influence on WTP of the specific energy source of origin	X	NL

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Mix	Cicia et al. (2012)	The influence on WTP of the specific energy source of origin	X	LC
Mix	Gracia et al. (2012)	The influence on WTP of the specific energy source of origin	X	RPL
Mix	Kaenzig et al. (2013)	The influence on WTP of the renewable energy share in the electricity mix	/	HB
Mix	Kosenius and Ollikainen (2013)	Valuation of environmental and societal trade-offs of renewable energy sources	X	NL
Mix	Ku and Yoo (2010)	Valuation of environmental and employment impacts that may result from renewable energy projects	/	MNP
Mix	Longo et al. (2008)	Valuation of short-term security of energy supply resulting from RES	X	RPL
Mix	Scarpa and Willis (2010)	Preferences for various micro-generation technologies	/	RPL
Mix	Tabi et al. (2014)	Preferences for green electricity	/	HB
Mix	Willis et al. (2011)	In-sample heterogeneity for various micro-generation technologies	X	RPL
Mix	Yoo and Ready (2014)	Preference heterogeneity for renewable energy share in the electricity mix	X	RPL&LC&LCRPL

Legend: RPL = random parameter logit model, LC = latent class model, LCRPL= latent class random parameter logit, NL = nested logit model, MNP = multinomial probit model, GMXL = generalized mixed logit; HB= hierarchical Bayes model / = type of heterogeneity remained untreated, X = observed heterogeneity was treated

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Table 2: The meaning of attributes and their levels

Attribute	Meaning	Levels	Estimated parameters	Base level
Price	The selling price of fully integrated solar cells is commonly expressed in terms of Euro/Watt peak (€/Wp). The Wp is an industry-wide agreed-upon unit of power, which is found by measuring the power output under standard testing conditions (El Chaar et al., 2011).	3.5, 2.5, 1.5, and 0.5 €/Wp	β_{pr}	/
Efficiency	Fully integrated solar cells' efficiency equals the percentage of sunlight reaching a solar cell that is converted to electricity under standard testing conditions (Brabec, 2004).	20, 15, 10, and 5 percent	$\beta_{15\%}, \beta_{10\%}, \beta_{5\%}$	$\beta_{20\%}$
Lifetime	Fully integrated solar cells' lifetime is defined as the period of time during which the cells maintain at least 80 percent of their initial efficiency (Jørgensen et al., 2008).	20, 15, 10, and 5 years	$\beta_{15y}, \beta_{10y}, \beta_{5y}$	β_{20y}
Aesthetics	Aesthetics is defined as a measure of how appealing a product is to the eye.	very ugly, ugly, nice, and very nice	$\beta_{ug}, \beta_{ni}, \beta_{vni}$	β_{vug}
Integratability	Integratability is defined as how easily solar cells can be integrated into any consumer electronics product. It is an overarching attribute, taking into account weight, thickness and flexibility, and serves as a proxy for functionality.	hardly integratable, poorly integratable, integratable, and very integratable	$\beta_{pint}, \beta_{int}, \beta_{vint}$	β_{hint}

Table 3: Descriptive statistics

Statistic [min,max]	Sample Mean, (SD)
Total number of respondents (#)	450
Age (years) [18,65]	37.43 (13.90)
Energy saving measures installed (#) [0,6]	2.28 (1.24)
Environmentally friendly behavior index [5,35])	24.19 (3.80)
Charging inconvenience., 5-point Likert [-2,2])	0.0 (1.13)
Experience with solar-powered devices. (#) [0,8]	1.72 (1.33)
Male (%)	48.7
Household size	1	14.8%
	2	27.7%
	3	20.4%
	4	23.8%
	5	8.1%
	>5	5.2%
Monthly net family income (€)	0-1,000	2.8%
	1,001-2,000	26.6%
	2,001-3,000	23.5%
	3,001-4,000	25.1%
	4,001-5,000	14.7%
	5,001-6,000	3.7%
	>6,000	3.6%
Education level	Elementary	2.3%
	Secondary	40.1%
	College	31.3%
	University	21.2%
	Post-university	5.1%
Geographic distribution	Antwerp	22.7%
	East Flanders	15.5%
	Flemish Brabant	15.1%
	Limburg	33.9%
	West Flanders	12.8%

Table 4: ECRPL with interactions output

Main and interaction effects	Mean		Standard deviation	
	Coef.	s.e.	Coef.	s.e.
$\beta_{15\%}$	-0.57***	0.12	0.78***	0.17
$\beta_{10\%}$	-1.67***	0.15	1.53***	0.23
$\beta_{5\%}$	-3.33***	0.28	2.66***	0.31
β_{15y}	0.10	0.13	1.07***	0.15
β_{10y}	-0.71***	0.15	1.35***	0.17
β_{5y}	-2.93***	0.26	2.40***	0.25
β_{ug}	1.24***	0.22	1.00**	0.39
β_{ni}	1.87***	0.28	1.69***	0.27
β_{vni}	1.91***	0.26	1.69***	0.26
β_{pint}	0.39***	0.15	0.87***	0.29
β_{int}	1.65***	0.17	1.54***	0.45
β_{vint}	1.52***	0.16	1.48***	0.57
β_{pr}	-0.25***	0.03	/	/
β_1	-0.51*	0.30	/	/
β_2	-0.46*	0.26	/	/
β_3	-0.58**	0.29	/	/
β_4	-0.66**	0.28	/	/
β_5	0.59**	0.24	/	/
β_6	0.49**	0.23	/	/
β_7	0.63**	0.29	/	/
Error component	0	(fixed)	2.23***	0.24

Log-Likelihood = -3421
Pseudo R². (adj.) = 0.297 (0.291)
AIC = 7037.5

Note:* p<0.10; ** p<0.05; *** p<0.01; See Table 2 for more information about the main effects parameters

$\beta_1 = X_{5\%}S_{energyaware}$; $\beta_2 = X_{ug}S_{envaware}$; $\beta_3 = X_{ni}S_{envaware}$; $\beta_4 = X_{vni}S_{envaware}$; $\beta_5 = X_{ni}S_{impatient}$;

$\beta_6 = X_{vni}S_{impatient}$; $\beta_7 = X_{5y}S_{experienced}$

Table 5: Four segment LC model output

Attributes	Class 1 (0.224)		Class 2 (0.32)		Class 3 (0.256)		Class 4 (0.199)	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
$\beta_{15\%}$	-0.47**	0.20	-0.13	0.15	-0.32**	0.13	-1.02***	0.19
$\beta_{10\%}$	-0.97***	0.30	-0.37**	0.18	-1.74***	0.22	-2.21***	0.30
$\beta_{5\%}$	-1.88***	0.37	-0.38**	0.18	-4.13***	0.44	-3.18***	0.48
β_{15y}	-0.38	0.24	0.31**	0.14	0.91***	0.21	-1.00***	0.22
β_{10y}	-0.17	0.19	-0.11-	0.17	-0.11	0.23	-2.15***	0.29
β_{5y}	-0.83***	0.26	-0.49*	0.25	-2.46***	0.28	-3.72***	0.47
β_{ug}	1.28***	0.45	0.30**	0.15	1.23***	0.27	0.33	0.32
β_{ni}	3.87***	0.46	0.50***	0.18	1.64***	0.24	0.63**	0.30
β_{vni}	3.71***	0.44	0.51***	0.16	1.41***	0.23	0.58*	0.31
β_{pint}	0.19	0.20	0.49***	0.18	-0.05	0.20	0.04	0.31
β_{int}	1.08***	0.22	1.49***	0.17	0.93***	0.21	0.67**	0.33
β_{vint}	1.21***	0.24	1.49***	0.18	0.76***	0.20	0.58*	0.30
β_{pr}	-0.23***	0.08	-0.09**	0.05	-0.45***	0.07	-0.12	0.11
Segment function: respondents' social and economic characteristics								
Constant	-0.34	0.43	0.04	0.42	0.41	0.34	0	(fixed)
$S_{energyaware}$	0.24	0.38	-0.54	0.39	0.12	0.35	0	(fixed)
$S_{envaware}$	-1.06**	0.42	0.03	0.42	-0.004	0.37	0	(fixed)
$S_{impatient}$	1.25***	0.42	0.37	0.37	0.31	0.35	0	(fixed)
$S_{experienced}$	-0.12	0.40	0.37	0.40	-0.39	0.40	0	(fixed)

Log likelihood = -3532.27
Pseudo-R^2 (adj) = 0.274 (0.260)
AIC = 7198.5

Note: $p<0.10$; * $p<0.10$; ** $p<0.05$; *** $p<0.01$

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Table 6: WTP estimates using the Delta method

	WTP (€/Wp)	95% CI
$WTP_{15\%}$	-2.25***	[-3.48;-1.02]
$WTP_{10\%}$	-6.58***	[-13.43;-7.23]
$WTP_{5\%}$	-14.02***	[-18.15;-9.89]
WTP_{15y}	0.41	[-0.64;1.45]
WTP_{10y}	-2.80***	[-4.09;-1.50]
WTP_{5y}	-10.33***	[-13.43;-7.23]
WTP_{ug}	4.10***	[2.34;5.87]
WTP_{ni}	7.81***	[5.43;10.18]
WTP_{vni}	7.57***	[5.18;9.96]
WTP_{pint}	1.54**	[0.32;2.75]
WTP_{int}	6.52***	[4.60;8.44]
WTP_{vint}	6.01***	[3.93;8.09]

Note:* p<0.10; ** p<0.05; *** p<0.01;

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