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Revealing additional preference heterogeneity with an extended random parameter logit model: the case of extra virgin olive oil

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Abstract

Methods that account for preference heterogeneity have received a significant amount of attention in recent literature. Most of them have focused on preference heterogeneity around the mean of the random parameters, which has been specified as a function of socio-demographic characteristics. This paper aims at analyzing consumers' preferences towards extra-virgin olive oil in Catalonia using a methodological framework with two novelties over past studies: 1) it accounts for both preference heterogeneity around the mean and the variance; and 2) it considers both socio-demographic characteristics of consumers as well as their attitudinal factors. Estimated coefficients and moments of willingness to pay (WTP) distributions are compared with those obtained from alternative Random Parameter Logit (RPL) models. Results suggest that the proposed framework increases the goodness-of-fit and provides more useful insights for policy analysis. The most important attributes affecting consumers' preferences towards extra virgin olive oil are the price and the product's origin. The consumers perceive the organic olive oil attribute negatively, as they think that it is not worth paying a premium for a product that is healthy in nature.

Additional key words: preference heterogeneity; attitudinal factors; discrete choice model; extra-vigin olive oil; willingness to pay.

Introduction

Preference elicitation methods have been extensively used by economists and market researchers to determine consumers' willingness to pay (WTP) for specific product attributes. Discrete choice modeling is a preference elicitation method that has been widely used in previous research (Lusk & Shroeder, 2004; Ding *et al.,* 2005; among many others). Initially almost all researchers applying discrete choice models assume that error variances are homogeneous over individuals by the application of Multinomial Logit (MNL), Conditional Logit (CL), and Nested Logit (NL). However, evidence of preference heterogeneity in both revealed preference data (Hensher, 2008) and stated preference data (Hess & Rose, 2009) is increasing. Failure to account for preference heterogeneity may not only result in poor model performance (*i.e.,* generating an incorrect standard error and biased parameter estimates) but also affect elasticities, WTP measures and substitution patterns, all of which could lead to problems in the reliability of model results (Hynes *et al.,* 2008; Hess *et al.,* 2010).

Therefore, methods that account for preference heterogeneity have received a significant amount of attention in recent literature (Campbell *et al.,* 2010;

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Abbreviations used: BCAT (Catalonian Manufacturer Label); CAT (Catalonia); CE (choice experiments); CFA (Confirmatory Factor Analysis); CL (Conditional Logit); GHR-RPL (Greene-Hensher-Rose Random Parameter Logit model); HL (Health); IIA (independence from irrelevant alternatives); LCM (Latent class model); MNL (Multinomial Logit); NL (Nested Logit); ORG (organic); ORG-AGE (interaction variable of organic with age); ORG-KNW (interaction variable of organic with knowledge); PDO (protected designations of origin); PRIV (Private Label); RPL (Random Parameter Logit Model); RUM (Random Utility Modeling); RUT (Random Utility Theory); SD (standard deviation); SLL (simulated log-likelihood); SML (simulated maximum likelihood estimator); TRT (trust); TS (town size); UNIV (university education level); WTP (willingness to pay).

Greene & Hensher, 2013). Among the most relevant we can cite: 1) the use of segmentation strategies (Shen, 2010); 2) the inclusion of interaction effects to explain sources of heterogeneity (Mtimet & Albisu, 2006); 3) the use of random parameter estimates, assuming preference coefficients to be randomly distributed across individuals (Revelt & Train, 1998); and 4) the combination of interaction effects and random parameters (Hensher & Greene, 2003), or segmentation strategies and random parameters (Greene & Hensher, 2013).

Among these approaches, the estimation of a Random Parameter Logit Model (RPL) (Revelt & Train, 1998) to obtain WTP estimates for food attributes has become increasingly popular. The RPL model relies on the relaxation of the three main limitations of conventional logit models: 1) it allows for random preference variation across individuals through the distribution of random parameters; 2) it relaxes the assumption of independence from irrelevant alternatives (IIA), and 3) it allows for correlation among unobserved factors over time (Train, 2003).

However, the RPL also has some limitations. Indeed, although the RPL model uses continuous (*i.e.,* normal, log-normal or triangular) distributions for individual tastes to account for preference heterogeneity, it does not identify the heterogeneity source. Additionally, the RPL estimated parameters ($\beta_{ki} = \beta_k + \sigma_k\vartheta_{ki}$), depend on the so-called individual specific heterogeneities (ϑ_{ki}) which follows a normal distribution with zero mean and a standard deviation of one (Hensher & Greene, 2003), and σ_k, the standard deviation of the distribution of the estimated parameter around its mean. Therefore, if the product $\sigma_k\vartheta_{ki}$is small, the estimated parameters across individuals will be very similar. Furthermore, Lenk & DeSarbo (2000) and Scarpa & Thiene (2005) have shown that although the RPL model provides an interesting way to account for preference heterogeneity, it might be inadequate if different groups of individuals with different group-specific preferences exist[1]. To overcome such limitations, Greene *et al.* (2006) extended the Random Parameter Logit model (GHR-RPL) to account for heterogeneity around both the mean and the variance of the parameter distributions and illustrated the implications on the moments of the WTP.

The traditional approach to identify the preference heterogeneity is to directly include the individual observable socio-demographic characteristics in the utility function. However, Morey & Rossmann (2003) showed that this procedure could be very restrictive as it assumes that some segments, which seem to have the same characteristics, have the same preferences. Although improving the model goodness-of-fit, Scarpa & Thiene (2011) also argued that this approach was relatively poor in giving some insight about the source of heterogeneity. McFadden (1986) and Ben-Akiva *et al.* (2002) discussed the important role of attitudes and beliefs to understand and estimate individuals' preferences, and to what extent they were conceptually important in choice decision protocols. However, in spite of the potential benefit of introducing attitudinal factors to explain individuals' preferences heterogeneity, up to our knowledge, only a few papers have addressed this issue (Moore, 2008; Stolz *et al.,* 2011a,b).

The aim of this paper is to assess consumer's preferences heterogeneity for extra-virgin olive oil[2] in Catalonia (North-East Spain). Spain is the first producer and exporter country of extra-virgin olive world-wide. Additionally, olive oil constitutes a fundamental component of the Spanish diet. As a consequence, the vast majority of Spanish consumers are knowledgeable about this product, and all of them are aware of market prices and product characteristics. Catalonia is the second region within Spain in terms of total olive oil consumption (the Catalonian per capita consumption was 9.93 liter in 2011). Moreover, Catalonia has a quite heterogeneous population with an adequate combination of urban (Barcelona is the second largest town in Spain) and rural environments which seems to be adequate for the purpose of this study.

To tackle with this objective, the methodological framework adopted is based on the estimation of the GHR-RPL model. More precisely, we intend to account for preference heterogeneity in two ways: (i) by identifying further behavioral information associated with the mean of the random parameter distributions by the parameterization of its heterogeneity through attitudinal factors such as health awareness, environment awareness, organic olive oil trust, subjective norms, organic olive oil purchasing

[1] The use of the Latent class model (LCM) could also lead to inefficient estimates because it might oversimplify the population's preferences, especially when a small number of classes are defined and the distribution of preferences is continuous within classes (Allenby & Rossi, 1998).

[2] Extra-virgin indicates that the olive oil has been produced by using mechanical means only, without any chemical treatment and contains no more than 0.8% free acidity. It is considered as the highest quality olive oil.

intention and knowledge, and (ii) by providing more information about the variance, allowing it to be expressed as a function of individual specific observed characteristics. The performance of the GHR-RPL with attitudinal factors is evaluated against three alternative RPL models: 1) the conventional RPL model without accounting for heterogeneity around the mean (RPL1); 2) the RPL model taking into account the heterogeneity around the mean of the random parameters as a function of socio-demographic characteristics (RPL2); 3) same than RPL2 but in this case heterogeneity is a function of attitudinal factors (RPL3). The paper also illustrates the implications of each model on the moments of the WTP distribution.

Methodology

The extended random parameter logit model (GHR-RPL)

The choice information used in Random Utility Modeling (RUM) can come from the observations of actual choices in a real setting (revealed preferences) or from choices made in hypothetical settings (stated preferences) (Louviere & Hensher, 1982; Louviere, 2001). From the latter type of choice information, choice experiments (CE) are derived. The CE is in accordance with both the Random Utility Theory (RUT) (McFadden, 1974) and the Lancaster's consumer theory (Lancaster, 1966). The RUT assumes that decision makers are rational and that individuals make choices to maximize their utility, taking into account budget constraints. In parallel, Lancaster's consumer theory presumes that the utility of a defined good can be segregated into product attribute utilities and proposes that consumers make choices based on attribute preferences. Therefore, the utility is derived from the attributes and attribute levels. The respondents are asked to make repeated choices between hypothetical alternatives described by combinations of attributes and their levels and are asked to choose their preferred alternative.

McFadden (1974) proposed an econometric framework to estimate discrete choice models based on random utility models. The individual utility of a particular option can be expressed as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad [1]$$

where V_{ij} is a deterministic or observed component that is a function of alternative product characteristics (X_{ij}) and ε_{ij} is the stochastic or non-observed component. Individual *i* will choose alternative *j* if it provides him a higher utility than any k^{th} available alternative. The probability of consumer *i* choosing alternative *j* out of the total set of options is expressed as follows:

$$P_{ij} = Prob\left[U_{ij} > U_{ik}\right] = Prob\left[V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}\right] \ \forall \ j \neq k \in C_n \quad [2]$$

where is the choice set and the observed component V_{ij} is expressed as follows:

$$V_{ij} = \beta_0 + \sum_k \beta_k * X_{kj} + \beta_{price} * P_j \quad [3]$$

where β_0 is an alternative-specific constant for alternative *j*, β_k the marginal utility of attribute X_{kj} and β_{price} is the marginal utility of the price P_j of alternative *j* for consumer *i*.

Different assumptions about the stochastic component generate different models. If the stochastic component ε_{ij} has a type I extreme value distribution, we obtain the familiar Multinomial Logit model as a conditional logit model, where the probability of consumer *i* choosing option j from a specific choice set (C_n) is expressed as follows:

$$P_{ij} = \frac{e^{\mu V_{ij}}}{\sum_{k=1}^{J} e^{\mu V_{ik}}} \quad \forall \ j \in C_n \quad [4]$$

This model is based on the following quite restrictive assumptions: 1) the consumers are assumed to be homogeneous, which implies that all coefficients for all attributes considered in the utility function are assumed to be the same across the sample; 2) the property of independent of IIA holds; and 3) errors are independent over time (Hensher *et al.,* 2005; Van Loo *et al.,* 2011).

To overcome some of these restrictive assumptions, several alternatives have been proposed in the literature. One of the most used in the literature is the RPL model. The RPL model is based on the assumption that parameters in Eq. [2] are distributed across individuals according to a statistical distribution. This model accounts for preference heterogeneity among individuals and it is flexible enough to accommodate alternative specifications, although it does not explain the source of this heterogeneity (Train, 2003).

Under the RPL model, the probability that an individual *i* chooses alternative *j* in a particular choice set C_n is expressed as follows:

$$Prob_i\left\{j \text{ is chosen}\right\} = \int L_{ij}\left(\beta_{ij}\right) f\left(\beta_i / \theta\right) d\beta_i, \text{ with } k \in C_n \quad [5]$$

where $f(\beta_i / \theta)$is the density function of the β_i coefficients; θ refers to the moments of the parameter distributions (the mean and the standard deviation of β_i) and

$$L_{ij}\left(\beta_{ij}\right) = \frac{e^{V_{ij}}}{\sum_{k=1}^{J} e^{V_{ik}}} = \frac{e^{\beta_{ij}X_{ij}}}{\sum_{k=1}^{J} e^{\beta_{ik}X_{ik}}} \quad [6]$$

As mentioned above, the model is flexible enough to specify any distribution for the estimated parameters (such as normal, log-normal, triangular, uniform, etc.).

When the i^{th} individual (i = 1...N) faces a choice among J alternatives (j = 1...J) in each of the T choice sets (t = 1...T), the utility of individual i associated with each alternative in each choice situation can be expressed as follows (Train, 2003):

$$U_{ijt} = \beta_{ij} X_{ijt} + \varepsilon_{ijt} \quad [7]$$

The simplest specification treats the coefficients as varying among the individuals but being constant for the choice situation of each person. Under the RPL model, the individual parameter estimates β_{ij} are expressed as follows:

$$\beta_{ij} = \beta_j + \sigma_j \vartheta_{ij} \quad [8]$$

where β_j is the sample mean for alternative j, σ_j is the standard deviation of the distribution of the partworth around the mean and ϑ_{ij} are individual specific heterogeneities with a mean of zero and a standard deviation of one (Hensher & Greene, 2003). The product characteristics (X) are observable, and we can estimate β_j and σ_j and test (Hensher *et al.,* 2005) which alternative parametric distribution for β_j and σ_j (*e.g.,* normal, log-normal, uniform or triangular) provides the best approximation of sample preferences.

Greene et *al.* (2006) suggested extending the RPL model to capture additional alternative unobserved variation, by first estimating deep parameters to account for heterogeneity around the mean of the distribution and, second, adding further behavioral information associated with the variance of the random parameter distribution, through the parameterization of its heteroscedasticity. Hence, Eq. [8] can be re-written as follows:

$$\beta_{ij} = \beta_j + \delta_j Z_i + \sigma_{ij} \vartheta_{ij} \quad [9]$$

where the vector Z_i is a set of choice-invariant characteristics that produce individual heterogeneity in the mean of the randomly distributed coefficients; δ_j are parameters that capture the mean shift; σ_{ij} is specified as $\sigma_{ij} = \sigma_i \exp[\omega_j\ hr_i]$, where ω_j are parameters that capture the variance heterogeneity of the random parameters in the systematic utility; and hr_i are individual specific characteristics.

The individual choice probabilities can be approximated using the three-step procedure suggested by Train (2003): 1) for any given value of θ, draw a value of β_i from $f(\beta_i / \theta)$ and label it β_i^r with $r = 1...R$[3]; 2) calculate the logit formula $L_{ij}(\beta_i^r)$ with this draw; and 3) repeat steps 1) and 2) many times and average the results. This average is the simulated probability:

$$\widehat{P_{ij}} = \frac{1}{R}\sum_{r=1}^{R} L_{ij}\left(\beta_i^r\right) \quad [10]$$

where R is the number of draws. The simulated probabilities are inserted into the log-likelihood function to obtain a simulated log-likelihood (SLL):

$$SLL = \sum_{i=1}^{I}\sum_{j=1}^{J} d_{ij} Ln\widehat{P_{ij}} \quad [11]$$

where $d_{ij} = 1$ if the individual i chooses j and zero otherwise. The simulated maximum likelihood estimator (SML) is the value of θ that maximizes SLL.

The WTP for product attributes is the price change associated with a unit increase in a given attribute and can be calculated as the negative ratio of the partial derivative of the utility function with respect to the attribute of interest, divided by the derivative of the utility function with respect to the variable "Price" (Van Loo *et al.,* 2011):

$$WTP_{Attribute} = -\frac{\dfrac{\partial U_{ijt}}{\partial Attribute}}{\dfrac{\partial U_{ijt}}{\partial Price}} = -\frac{\beta_{Attribute}}{\beta_{Price}} \quad [12]$$

The mean and standard deviations of the WTP are derived by generating a distribution of 1000 WTP estimates using the parametric bootstrapping method proposed by Krinsky & Robb (1986). This approach significantly reduces the problem related to potential changes of sign caused by the extreme values of the behavioral WTPs distributions. In other words, we are increasing

[3] Halton draws are used because they have been shown to provide a more efficient distribution of draws for numerical integration, in comparison to random draws (Bhat, 2003; Train, 2003).

the probability of prices to be randomly distributed across the individuals following an unconstrained distribution.

To test for differences in WTP distributions derived from the different estimated RPL models, the nonparametric combinatorial test mentioned in Poe *et al.* (2005) will be used. This test consists of calculating all differences between the WTPs estimated from two RPL models for all possible combinations of the bootstrapped values. The proportion differences that are negative are considered as the *p*-value associated with the one side test that the WTP estimated from the first model overestimate the WTP estimated from the second model.

Empirical application

Data for this study were collected from a survey carried out on a random sample among Catalonian consumers of olive oil with quotas by postal code[4]. A total of 425 persons participated in face-to-face interviews, 401 of which participated in the choice experiment. The data collection was conducted in September 2009 during different shopping hours and at different types of food retail stores. Two filter questions were included at the beginning of the questionnaire to guarantee that the sample represented our objective population. The first one was about if the respondent was responsible for food shopping within the household. The second was if the respondent had bought olive oil during the previous three months. Only respondents who answered yes to the two questions were selected for the survey.

The questionnaire used was divided into four sections. The first section was designed to elicit information on respondents' buying and consumption habits concerning different types of olive oil. The second section was designed to obtain information about different attributes considered by respondents when buying extra-virgin olive oil, with special attention paid to attitudes towards the organic attribute. The third section addressed the choice experiment. The last section was designed to obtain information about the socio-demographic characteristics and lifestyles of the respondents. Attitudes were measured using eleven-point Likert scales (from 0 to 10, where 0 indicates total disagreement and 10 indicates total agreement)[5].

Table 1. Attributes and attribute levels in the Choice Experiment for extra-virgin olive oil

Attributes	Levels
Production system	Conventional (CONV) Protected Denomination of Origin (PDO) Organic (ORG)
Origin	Spain (ESP) Catalonia (CAT) Imported (IMP)
Brand	Spanish manufacturer (BESP) Catalonia manufacturer (BCAT) Private label (PRIV)
Price (€ L^{-1})	3.70 6 7.5

The choice experiment design

To implement the choice experiment, attributes and attribute levels were first selected on the basis of a three-step process: 1) a literature review of consumers' extra-virgin olive oil purchase and consumption habits; 2) two focus groups (of 8 people each) to identify main consumption patterns and attitudes toward extra-virgin olive oil, with special focus on the organic attribute; and 3) observation in retail outlets of real prices and informal interviews with consumers about their reasons for choosing a specific olive oil. As a result, four main attributes were identified: price, production system, origin of the product, and origin of the brand (see Table 1). To avoid the level effect between attributes (De Wilde *et al.,* 2009), each attribute was defined as having three levels.

Taking into account the number of attribute levels, a total of 81 (3^4) hypothetical bottles of extra-virgin olive oil were obtained. This led to a large number of choice sets affecting respondents' decisions and a consequent decrease in response reliability (Chung *et al.,*

[4] In this study, the objective population is assumed to be geographically distributed as the global Catalonian population. To avoid misrepresentation of the smaller provinces, 40% of the sample is assigned to Barcelona while 20% is assigned to each of the three remaining provinces.

[5] This scale is very comprehensive for respondents in Spain as it coincides with the traditional grading system at schools.

	Alternative A	Alternative B	Alternative C	Alternative D
System of production	Extra-virgin olive oil with Protected Designation of Origin (PDO)	Conventional extra-virgin olive oil	Organic extra-virgin olive oil	None of them
Origin of olive oil	Spain	Catalonia	Imported	
Brand	Spanish Manufacturer	Private label	Catalonian Manufacturer	
Price	3.70 € L^{-1}	7.50 € L^{-1}	6 € L^{-1}	

Figure 1. Example of choice sets.

2010). To reduce the number of combinations that participants had to evaluate, an orthogonal factorial design was generated, resulting in 9 product profiles and 9 choice sets. Each choice set consisted of three alternatives plus the "none of them" option. We employed the strategy proposed by Street & Burgess (2007) to obtain a 100% efficient main effects design. Fig. 1 shows one of the choice sets offered to respondents.

The empirical models

As mentioned in the introduction, the methodological approach followed in this paper has been the estimation of the Greene *et al.* (2006) GHR-RPL model that accounts for heterogeneity around both the mean and the variance of the distributions of the estimated parameters. Results from this model are going to be compared with three alternative RPL models: RPL1, RPL2 and RPL3, already mentioned in the introduction. Likelihood ratio tests will be used to compare the goodness-of-fit performance of alternative models. However, the comparison between RPL2 and the GHR-RPL is not straightforward as both models are non-nested. The Vuong's (1989) test has been used for this purpose.

Suppl. Table S1 [pdf online] shows the description of the deterministic components of respondents' utility that are common for the four models. Except for the price, which is assumed to be continuous, the rest of the variables are considered categorical and coded as either dichotomous of effect-coded dummy variables.

RPL models allow a higher level of flexibility in specifying some coefficients to be fixed or randomly distributed across respondents. In this study, and based on the Wald test statistic, four parameter estimates associated to PDO, ORG, CAT, and PRICE are defined to be random and following unconstrained[6] normal distributions[7]. In contrast to the approach taken by Revelt & Train (1998), the price coefficient is not assumed to be invariant across individuals. As noted by Train & Weeks (2005), assuming a fixed price coefficient implies that the standard deviations of unobserved utility are the same for all observations. Therefore, estimation practices that ignore this source of variation may lead to erroneous interpretation and policy conclusions (Scarpa *et al.,* 2008).

Suppl Table S1 [pdf online] also includes the main respondents' socio-demographic characteristics that are considered to generate potential sources of heterogeneity (gender, age, education level, town size, and olive oil purchasing frequency). Finally, six attitudinal factors related to consumers' perceptions about organic olive oil (health awareness, environment awareness, trust, subjective norms, organic olive oil pur-

[6] Greene *et al.* (2006) commented that the impact of accommodating heterogeneity around the mean and variance of random parameter distributions does not guarantee an advantage to using any constrained distributions.
[7] Due to space limitation the full procedure followed to identify random parameters has not been included but it is available from authors upon request.

Table 2. Attitudinal factors results from the confirmatory factor analysis (CFA)

Ind	Factors	Means	Standard deviation	Variance	Cronbach's alpha	References
	Health awareness (HL)			81.96	0.898	Adapted from Munuera & Gozález-Adalid (2005) and Roitner-Schobesberger *et al.* (2007)
HL_1	The consumption of organic olive oil reduces human exposure to chemical residues.	6.867	1.764			
HL_2	Organic olive oil is healthy for children.	6.862	1.660			
HL_3	The product is suitable for a healthy diet.	7.088	1.636			
	Environment awareness (ENV)			91.27	0.957	
EV_1	The production of organic olive oil helps indirectly to reduce water pollution by waste chemicals and pesticides.	6.923	1.680			
EV_2	The production of organic olive oil helps indirectly to conserve agricultural soil.	6.933	1.716			
EV_3	The production of organic olive oil improves environmental sustainability	6.893	1.809			
	Trust (TRT)			69.79	0.860	Adapted from Krystallis & Chryssohoidis (2005), and Roitner-Schobesberger *et al.* (2007)
TR_1	I trust the product because of its certification by an organization or regulatory board of organic farming.	6.447	1.601			
TR_2	I trust the product because it is sold exclusively in specialty stores.	6.668	1.646			
TR_3	I have confidence in the information provided on the product label.	6.202	1.710			
TR_4	I have confidence that a product certified as organic really is organic.	6.103	1.866			
	Purchase intention (PINT)			76.91	0.858	Adapted from Lea & Worsley (2005)
PI_1	If I have more information and confidence, I buy organic olive oil.	5.923	2.179			
PI_2	I buy more if the product is cheaper.	5.770	2.219			
PI_3	If organic olive oil is more readily available, I most often buy it.	5.655	2.246			
	Knowledge (KNW)			87.63	0.861	
KN_1	Lack of information about the benefits of organic products.	6.905	1.834			
KN_2	Lack of information about the label that identifies products as organic.	6.872	1.889			
	Subjective norms (SBN)			86.61	0.926	Chen (2007)
SN_1	My kids prefer organic olive oil.	2.342	2.475			
SN_2	My family prefers organic olive oil.	2.465	2.422			
SN_3	Persons who are important to me prefer organic olive oil.	2.578	2.436			

chasing intention and knowledge) were also included in the utility functions (Table 2). These six attitudinal factors were defined by 18 items using a set of scales defined in the literature and measured through the application of a Confirmatory Factor Analysis (CFA). The internal consistency reliability, measured by Cronbach's α (Chen, 2007), was greater than 0.7 in all cases. The variance extracted was greater than 50% in all cases, indicating that latent variables were adequately represented by the defined items.

Results

Sample characteristics

From the 401 respondents who completed the survey, 40% came from Barcelona (the main town) and 60% came from elsewhere in the Catalan region. Approximately 80% of respondents were women, consistent with Gil *et al.* (2002), as the objective population was made up of those responsible for shopping within households. The average age of the respondents was 49 years old (with a standard deviation [SD] of 15.39). With respect to the education level, 27.3% of the respondents had completed only primary studies, 46.8% had completed secondary studies or professional education, and nearly 25.6% had obtained a university degree. Finally, 70% of the respondents were married, and the average household size was approximately 3 members. All respondents bought olive oil regularly. In fact, most of the respondents used to purchase olive oil weekly or every two weeks and nearly 30% purchased it monthly or quarterly. Olive oil and conventional extra-virgin olive oil are oil types most commonly bought; only 9.25% of respondents buy extra-virgin olive oil with a protected denomination of origin designation and less than 1% buys organic olive oil. Finally, the mean price paid for one liter of conventional extra-virgin olive oil was 3.42 euro (SD = 0.80).

Empirical results

The four models mentioned above were estimated by the SML method. Table 3 shows the estimated parameters for the four models as well as their relevant goodness-of-fit measures. As can be observed, the GHR-RPL model provides the best goodness-of-fit in terms of the McFadden R-square and the Akaike Information Criterion (AIC). Likelihood ratio tests (Table 4), partially corroborate such results as the GHR-RPL outperforms both RPL1 and RPL3 models. When comparing RPL2 and GHR-RPL, the result from the Vuong's test indicates that the difference in goodness-of-fit measures between these two models is not statistically significant[8]. Finally, Fig. 2 shows the estimated marginal utilities from the four RPL models[9]. The four utility distributions have very similar shapes. That is, the introduction of additional sources of heterogeneity, even in the GHR-RPL model, makes both the mean and the standard deviation to change but not the global shape of the distribution.

As regards the estimated parameters for the four RPL models[10], in all cases, the no-option coefficient is negative and significant, indicating that most of the respondents tried to participate in the choice experiment by choosing one of the proposed olive oil alternatives instead of the no-option alternative. Table 4 also shows that all parameter estimates associated with the attribute levels considered in the utility function are statistically significant and with the expected sign, with the only exception of the estimated parameters associated to the levels of the attribute Origin of Brand: "BCAT" (Catalonian Manufacturer Label), which is not significant in any of the four models, and "PRIV" (Private Label), which is only significant in RPL3 and GHR-RPL, where heterogeneity around the mean is defined as a function of attitudinal factors.

Table 5 presents the moments of the WTP distributions derived from the four estimated models, as well as their confidence intervals. Results for the GHR-RPL model indicate that Catalonian consumers are willing to pay a 60% premium for a Catalan olive oil over an olive oil from another Spanish region and a 30% for a PDO extra virgin olive oil over the conventional counterpart. In contrast, the mean WTP for the organic attribute and imported olive oil are both negative. That is, consumers reveal that they have to be rewarded to shift from the conventional to organic olive oil, as well as, from purchasing olive oil of national origin to imported olive oil.

Additionally, results displayed in Table 6 from the non-parametric combinatorial test reveal that it is not

[8] In any case, this result has to be interpreted with caution as the Vuong's test has low power in finite samples (Desmarais & Harden, 2013).

[9] A kernel density function has been used to graph the non-parametrically distribution of the marginal utility of the respondents in both models.

[10] In relation to interaction terms, for space limitation purposes, Table 3 just shows the statistically significant interaction parameters.

Table 3. Estimated coefficients and goodness-of-fit measures. Values in parentheses represent the parameters' standard errors

Variables[x]	RPL1	RPL2	RPL3	GHR-RPL
CONV[a]	0.425 (—)	0.273 (—)	0.537 (—)	0.495 (—)
PDO[b]	0.254*** (0.041)	0.237** (0.105)	0.283*** (0.044)	0.303*** (0.039)
ORG[b]	–0.679*** (0.054)	–0.510*** (0.133)	–0.820*** (0.058)	–0.798*** (0.053)
ESP[a]	0.107 (—)	0.133 (—)	0.072 (—)	0.04 (—)
CAT[b]	0.503*** (0.046)	0.493*** (0.106)	0.556*** (0.047)	0.581*** (0.040)
IMP	–0.610*** (0.042)	–0.626*** (0.042)	–0.628*** (0.043)	–0.621*** (0.045)
BESP[a]	–0.047 (—)	–0.018 (—)	0.074 (—)	0.077 (—)
BCAT	–0.009 (0.039)	–0.024 (0.039)	0.005 (0.039)	0.006 (0.052)
PRIV	–0.056 (0.038)	–0.042 (0.038)	–0.079** (0.039)	–0.083* (0.059)
PRICE[b]	–0.907*** (0.043)	–1.006*** (0.067)	–0.923*** (0.038)	–0.987*** (0.029)
No-option	–6.528*** (0.178)	–6.831*** (0.191)	–6.888*** (0.198)	–6.933*** (0.112)
Standard deviations of parameter distributions				
PDO	0.326*** (0.055)	0.339*** (0.052)	0.436*** (0.047)	0.265*** (0.053)
ORG	0.732*** (0.057)	0.800*** (0.057)	0.803*** (0.064)	0.683*** (0.172)
CAT	0.681*** (0.050)	0.682*** (0.051)	0.710*** (0.052)	0.542*** (0.074)
PRICE	0.803*** (0.041)	0.795*** (0.033)	0.769*** (0.039)	0.700*** (0.046)
Heterogeneity in mean (Attitudinal factors)				
PDO-ENV	—	—	—	–0.153* (0.079)
PDO-KNW	—	—	–0.131*** (0.044)	–0.136*** (0.050)
PDO–SBN	—	—	–0.207*** (0.045)	–0.230*** (0.042)
ORG–ENV	—	—	—	0.177* (0.096)
ORG-KNW	—	—	0.128*** (0.057)	0.164*** (0.051)
ORG-SBN	—	—	0.306*** (0.055)	0.301*** (0.053)
CAT-PINT	—	—	0.138** (0.056)	0.141** (0.062)
CAT-SBN	—	—	–0.096** (0.046)	–0.124*** (0.039)
PRICE–TRT	—	—	—	–0.163*** (0.045)
PRICE-PINT	—	—	0.206*** (0.032)	0.204*** (0.030)
PRICE-KNW	—	—	—	–0.063** (0.030)
PRICE-SBN	—	—	0.097*** (0.036)	0.139*** (0.030)
	Heterogeneity in mean (socio-demographic factors)			**Heterogeneity in variance**
PDO-UNIV	—	—	—	0.636*** (0.109)
PDO-TS	—	—	—	—
PDO-GEN	—	—	—	–0.538*** (0.167)
PDO-MONTH	—	–0.154** (0.071)	—	0.275*** (0.153)
PDO-QUART	—	—	—	–0.454*** (0.213)
PDO-AGE	—	0.183** (0.086)	—	1.213*** (0.200)
ORG-MONTH	—	0.218*** (0.089)	—	—
ORG-QUART	—	0.160*** (0.087)	—	—
ORG-AGE	—	–0.326*** (0.109)	—	–0.377** (0.181)
CAT-UNIV	—	—	—	0.635*** (0.084)
CAT-MONTH	—	—	—	–0.489*** (0.134)
CAT-QUART	—	0.136*** (0.076)	—	0.230** (0.103)
CAT-AGE	—	—	—	0.321*** (0.099)
PRICE-UNIV	—	0.120*** (0.044)	—	0.128*** (0.045)
PRICE-TS	—	0.186*** (0.071)	—	–0.248*** (0.091)
PRICE-AGE	—	—	—	0.205*** (0.068)

Table 3 (cont.). Estimated coefficients and goodness-of-fit measures. Values in parentheses represent the parameters' standard errors

Variables[x]	RPL1	RPL2	RPL3	GHR-RPL
Goodness-of-fit measures				
Log likelihood (LL)	–3,075.64	–3,018.20	–2,982.07	–2,928.41
McFadden R^2	0.383	0.395	0.402	0.413
AIC	1.72	1.70	1.68	1.66
N. parameters	12	40	36	60

[x] See Tables 1 and 2, and Suppl Table 1 [pdf online] for variable definitions. [a] This represents the base level. [b] Random parameters following normal distributions. ***, ** and * indicate that the corresponding parameter is statistically significant at the 1%, 5% or 10% level, respectively.

Table 4. Results from likelihood and Vuong tests for model selection

Likelihood ratio (LR) test for nested models				
	LR statistic	**Critical χ^2 (5%)**	**Degrees of freedom**	**Result**
RPL1 *vs* RPL2	114.88	16.93	28	RPL2 preferred
RPL1 *vs* RPL3	187.146	13.85	24	RPL3 preferred
RPL1 *vs* GHR-RPL	254.45	34.76	48	GHR-RPL preferred
RPL3 *vs* GHR-RPL	107.32	13.85	24	GHR-RPL preferred

Vuong's test for non-nested models			
	Vuong's statistic[1]	**Degrees of freedom**	**Result**
RPL2 *vs* GHR-RPL	6.10	20	No significant differences

The Vuong's test has a standard normal distribution (critical value 1.96 at the 5% level of significance).

possible to reject at the 5% level of significance that the estimated WTPs obtained from the four models are statistically similar for all attribute levels except for the organic attribute level in the RPL2. The WTP value for such attribute is also negative but lower than in the other three models. This result indicates that when heterogeneity around the mean and the variance is explicitly considered, although the goodness-of-fit of estimated models improve, no significant differences are found in relation to WTP measures. This could be used as an argument in favor of the use of using simpler models especially when the main reason for using the CE is to assess consumers' WTP.

Discussion

As mentioned above, accounting for mean and variance heterogeneity of random parameters estimates has been proved to be relevant as the GHR-RPL model clearly outperforms the other models being significant a large number of specific parameters associated with mean and variance heterogeneity. Therefore, in the next paragraphs we concentrate in discussing results obtained from such model.

Results from Table 3 suggest that the organic production system does not seem to influence consumer preferences. The negative utility of organic olive oil is noticeable. This result can be explained by the fact that in Spain, olive oil is already perceived as a healthy product by Spanish consumers, as it occupies a prominent position in the Mediterranean diet. In line with Calatrava (2002), the organic attribute does not add any additional value to Spanish consumers, especially when Spanish consumers are not sufficiently concerned about environmental issues. In fact, environmental concerns do not seem to be a key factor in explaining consumer's olive oil choices (Vega-Zamora *et al.,*

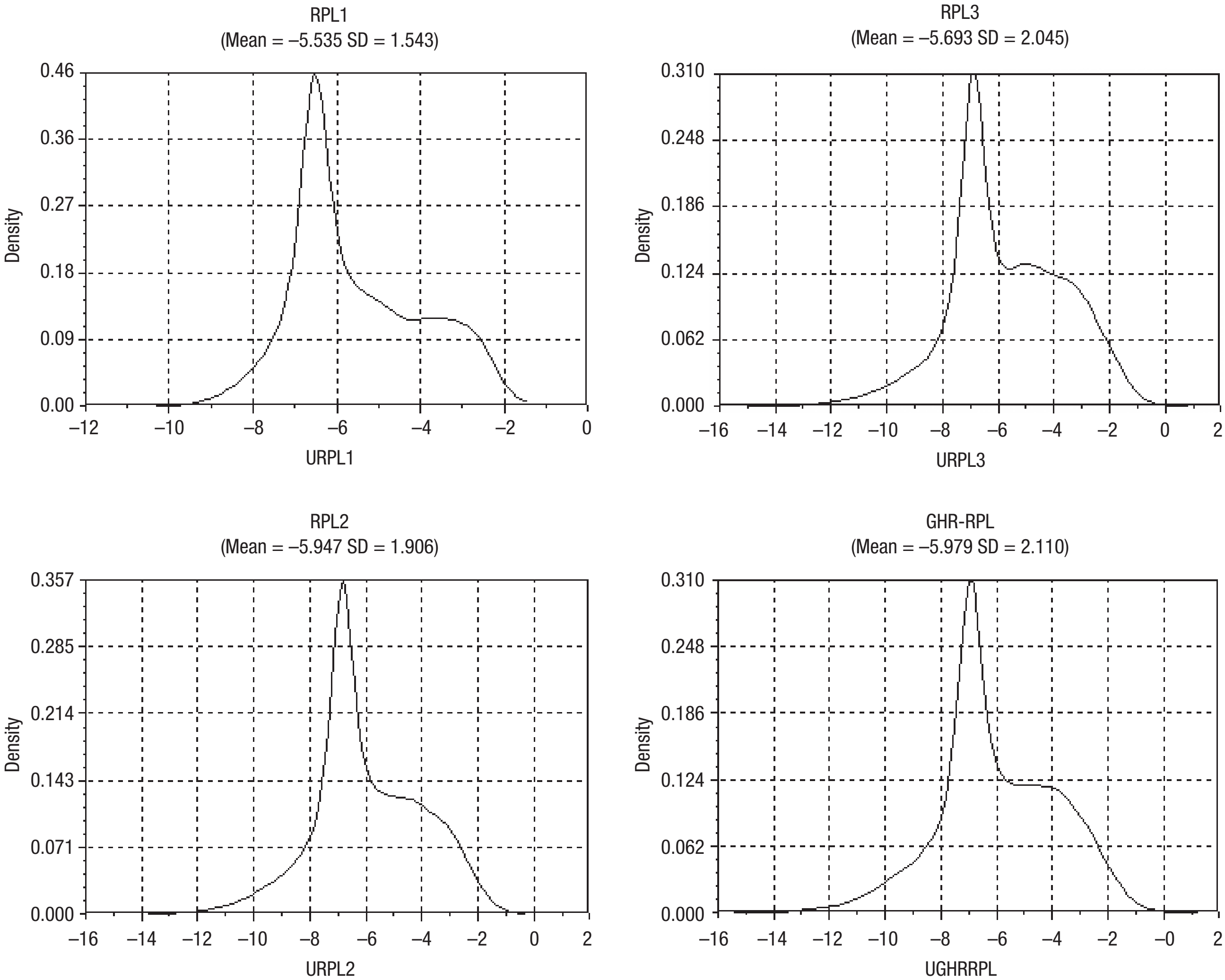

Figure 2. Kernel density estimates for marginal utility distribution of RPL models

Table 5. Willingness to pay (WTP) for the attribute levels. In parenthesis, standard deviation

	RPL1		RPL2		RPL3		GHR-RPL	
	WTP	CI	WTP	CI	WTP	CI	WTP	CI
PDO	0.281 (0.048)	[0.191, 0.375]	0.238 (0.104)	[0.038, 0.438]	0.308 (0.048)	[0.216, 0.403]	0.306 (0.041)	[0.227, 0.388]
ORG	–0.748 (0.075)	[–0.910, –0.610]	–0.510 (0.133)	[–0.785, –0.264]	–0.886 (0.066)	[–1.018, –0.755]	–0.808 (0.056)	[–0.919, –0.70]
CAT	0.557 (0.051)	[0.458, 0.656]	0.488 (0.109)	[0.272, 0.712]	0.603 (0.051)	[0.499, 0.702]	0.590 (0.041)	[0.507, 0.675]
IMP	–0.671 (0.051)	[–0.778, –0.575]	–0.625 (0.058)	[–0.744, –0.519]	–0.678 (0.050)	[–0.775, –0.580]	–0.631 (0.047)	[–0.728, –0.547]

CI: confidence interval at 5% significance level.

Table 6. Hypothesis test of equality WTPs (*p* values) across the treatments

Hypothesis	WTP_{PDO}	WTP_{ORG}	WTP_{OCAT}	WTP_{OIMP}
RPL1 *vs* RPL2	0.357	0.064	0.279	0.280
RPL1*vs* RPL3	0.347	0.081	0.263	0.426
RPL1 *vs* GHR-RPL	0.341	0.255	0.311	0.288
RPL2 *vs* RPL3	0.256	0.005	0.172	0.203
RPL2 *vs* GHR-RPL	0.253	0.022	0.194	0.433
RPL3 *vs* GHR-RPL	0.494	0.184	0.417	0.247

2011). This finding contradicts results reported in other studies such as: Gracia & Magistris (2008), for Italy; Soler *et al.* (2002) and Vega-Zamora *et al.* (2013), for Spain; or Tsakiridou *et al.* (2006), for Greece. However, in all mentioned studies, consumers only had to choose between organic olive oil and its conventional counterpart, whereas in our study, we have considered the trade-offs not only with other olive oil attributes but with other attribute levels within the production system, such as the PDO (Protected Designation of Origin).

In line with Gracia & Magistris (2007), consumer's preferences in Catalonia towards the organic olive oil are positively affected by their more positive attitude towards environmental benefits provided by the organic production system. Equally important is the effect of subjective norms associated with the consumption of organic olive oil in mitigating the disutility related to its consumption (Chen, 2007). An interesting result that arises from this study is that consumer's attitudes towards health benefits provided by organic olive oil (HL) and trust (TRT) do not seem to have a significant effect on consumers' marginal utilities towards the organic olive oil. This may be related to the consumer's positive perception about the healthiness of the extra virgin olive oil regardless the type of production system (PDO, organic, or conventional) (Calatrava, 2002; Vega-Zamora *et al.,* 2011). In any case, results also suggest that more information on the properties of the organic olive oil could be relevant to increase the consumers knowledge about this product and then to increase the probability to buy it (the coefficient of the interaction ORG-KNW is positive and significant), in line with the results found in of Gracia & Magistris (2008). Moreover, the negative and significant coefficient of the interaction ORG-AGE to explain variance heterogeneity suggests this information should be mainly address to younger consumers.

Contrary to the organic attribute, Catalonian consumers show a strong preference for PDO extra virgin olive oil. Scarpa & Del Guidice (2004) arrived to the same conclusion in Italy. This result is consistent with prior expectations as results from the survey indicated that 9.26% of Catalonian consumers use to buy PDO extra virgin olive oil while less than 1% buy occasionally organic olive oil. PDO extra virgin olive oil is very knowledgeable among Catalonian and Spanish consumers. There exist 28 PDO brands in Spain; five of them are located in Catalonia. Additionally, the production of this type of olive oil continues to grow being the domestic market its main destination and, to a lesser extent, the EU (Ruiz-Castillo, 2008). In any case, such positive preference is not homogeneous among Catalonian consumers. PDO olive oil is highly preferred by the older population with higher education levels and showing a higher purchasing frequency of olive oil. Results from Table 3 also show that the interaction terms PDO-ENV, PDO-KNW, and PDO-SBN are negative and statistically significant. Therefore, the results reveal that consumer's preferences in Catalonia towards PDO olive oil are negatively correlated with factors affecting attitudes towards organic olive oil such as subjective norms, consumers' concerns about the environmental benefits of organic olive oil and knowledge.

The price coefficient (–0.987) is significant and has a negative sign, becoming the most restrictive factor for purchasing extra virgin olive oil (Scarpa & Del Giudice, 2004; Parras-Rosa *et al.,* 2008; Menapace *et al.,* 2011). Moreover, the corresponding standard deviation is significant indicating relevant Catalonian consumers' preferences heterogeneity. However, this negative utility is mitigated, to a certain extent, in consumers who are more likely to purchase organic olive oil (*i.e.* the interaction term PRICE-PINT is statistically significant and positive). Furthermore, the statistically significance of the variance heterogeneity coefficients show that price heterogeneity within the model varies taking into account the effect of some sociodemographic factors such as the university education level (UNIV), age (AGE) and town size (TS). However, while the effect of two first variables is positive that of the last one is negative, indicating that older, more educated consumers and those living in rural areas are less sensitive with respect to price.

Apart from price, the origin is one of the most important attributes affecting consumers' preferences toward extra-virgin olive oil. In fact, the estimated parameters associated to the origin levels (IMP and CAT) (–0.621 and 0.581, respectively) are relatively high, only below those associated to PRICE and ORG (–0.781). This finding is consistent with previous studies on the importance of geographical origin in consumer decision making (Scarpa & Del Guidice, 2004; Scarpa & Thiene, 2005; Schnettler *et al.,* 2008; Menapace *et al.,* 2011). Catalan olive oils are preferred over other Spanish or imported oils, while olive oil produced in other Spanish regions is preferred over imported olive oil. The positive preference associated with the Catalan olive oil increases for consumers who are more likely to buy organic olive oil. This result was also found by Cicia *et al.* (2002) who evaluated the preferences of regular consumers of organic food towards the purchasing intention of extra virgin olive oil. They concluded that regular organic food consumers pay more attention to the origin of the product which is taken as a proxy of organic olive oil quality. Furthermore, and consistent with the results we discussed above about marginal utilities associated to PDO olive oil, older consumers with higher education level have a stronger preference for the local origin as well as for respondents who buy extra-virgin olive oil less frequently. In fact, results from the survey indicated that this consumer segment used to buy olive oil in large quantities from local cooperatives.

The lack of significance associated with the local brand attribute level (BCAT) indicates that in the case of extra-virgin olive oil, respondents are more interested in the origin of the product than in the origin of the brand, although this result could be related to the fact that many consumers do not acknowledge the origin of the brand (that is, whether the manufacturer is located or not in Catalonia). Results also show that, on average, consumers do not value private labels for this specific product.

Finally, it is worth mentioning that this study has been based on the use of generic alternatives and hypothetical responses to choice experiment questions. Lusk & Schroeder (2004) showed that hypothetical choices could overestimate the marginal willingness to pay for extra-virgin olive oil. Therefore, results from this study could be extended to non-hypothetical environments in which consumers face choices involving real products and real money in a series of choice scenarios.

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