Exploiting cut-off information to incorporate context effect: a discrete choice experiment on small fruits in an Alpine region

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1. Introduction

Economists, psychologists, and marketers have long investigated the decision processes used by people to make choices or to consider choice tasks (Simon, 1983; Hensher, 2006). In choice modelling, it has often been assumed that respondents consider all the attributes presented to them, as if all of these somehow influence their choice (Kaye-Blake et al., 2009). However, research in psychology and consumer behaviour has instead long suggested that individuals react to increasingly complex choice situations by adopting non compensatory models and simplifying strategies (Simonson and Tversky 1992; Swait and Adamowicz, 2001; DeShazo and Fermo, 2004; Scheibehenne et al., 2008). Deviations from the fully considered attribute assumption may be due to previous learning, cognitive difficulties in processing and integrating the information, constraints of time and cognitive abilities (Louviere et al., 2005, Kaye-Blake et al., 2009).

Among the several heuristics used by consumers to simplify their decision making, the use of threshold values is well recognised in literature (e.g. Swait, 2001; Elrod et al., 2004) and analysis of synthetic data shows that ignoring thresholds in datasets containing them leads to significant errors (Cantillo et al., 2006; Kaye-Blake et al., 2009). As defined by Swait (2001) thresholds can be considered as hard or soft cut-off. Hard cut-offs are attribute levels that must be reached, or alternatively not violated, to allow a valid choice. If a respondent prefers to violate the stated cut-off for single attributes rather than disregarding that particular alternative, thresholds have to be considered as soft cut-offs. So far, the Swait's soft cut-off approach has been applied in transport economics (Marcucci and Gatta, 2011), agricultural and natural resource economics (Bush et al., 2009), and in food economic (Aizaki et al., 2009; Ding et al., 2010).

In this study we apply the Swait's soft cut-off approach to investigate consumer preferences for small fruits (strawberries, blueberries and raspberries). The novelty is that we investigate the effect of cut-offs violations not only on consumer's utility but also on the variance of the error term. We parameterise the scale parameter using the number of cut-offs violations occurring in each choice card as an aspect of the decision context that affects the respondent's choice in term of accuracy. To the best of our knowledge, this is the first Choice Experiment (CE) to have focused on the analysis of cut-offs violations also as context effects. Moreover, differently from previous studies, the research focuses on consumer response towards sustainable production methods other than organic, methods which have been scarcely considered in the literature (Govindasamy and Italia, 1998; Louriero et al., 2001). These are integrated pest management (IPM), and a more innovative IPM technique that employs biocontrol agents extensively. In addition to this, we investigate consumer preferences for the adoption of mitigation farming practices that aim to reduce greenhouse gas emissions. Other investigated attributes are visual appearance, origin, and price. The research was carried out in Trentino (Italy), a small Alpine province where the production of these small fruits has been growing considerably reaching a remarkable importance at commercial level.

The remainder of the paper is structured as follows: section 2 describes shortly the context effect; section 3 explains our approach to incorporating context effect; section 4 describes the method employed, the experimental design, and the data; section 5 presents and discusses the results; and section 6 concludes.

2. Cut-offs violations as context effect

A rich literature exists in psychology and behavioural decision theory (e.g., Tversky and Shafir 1992; Dhar, 1997), but also some studies exist in economics (e.g., de Palma et al., 1994; De Shazo and Fermo, 2002), showing that consumers' choices are often influenced by decision context, which can be defined in different ways. Swait et al. (2002) provide a list of the most known context dependencies found in literature[1].

Since context may impact on the marginal utility estimates and consequent willingness to pay calculations (Louviere et al., 2005; Adamowicz and DeShazo, 2006), researchers should explicitly seek to incorporate context effects into choice modelling (Payne et al., 1999; Swait et al., 2002).

[1] It includes habit or experience dependence effects, social interdependence, accountability effects, menu-dependence, chooser-dependence, mental accounting, choice bracketing, motivation effects, decoy effects, reference prices, and complexity effects (Swait et al. 2002).

In stated preference research, context effects have been investigated analyzing the influence of different survey design factors on individuals' decision-making behaviour such as the number of choice tasks, alternatives, attributes per alternative, and the range of attribute levels (Duquette et al., 2009). The effects of choice set complexity and decision environment have been investigated through an appropriate parameterisation of the scale factor. More in details, Swait and Adamowicz (2001) develop an entropy index associated to the experimental features and based on the distance between alternatives in a choice set and that captures the impact of choice set size and the attribute mix on scale differences. De Shazo and Fermo (2002) allow the scale parameter to be a function of some measures that capture either the amount of information or the correlation structure of the data. Arentze et al. (2003) scrutinise the influence of task complexity and the influence of presentation format and they find that task complexity impacts significantly on data quality, while the presentation method does not. Caussade et al. (2005) parameterize the scale factor as a function of five different design dimensions. However, the literature on the effects of violating a constant scale assumption on the measurement of willingness to pay is still scarce (Colombo et al., 2009).

Since context remains a broad concept (Carlsson, 2010), in this paper we explore the implications of considering cut-offs violations as context effect and their impact on the individuals' choice. In detail, we focus on understanding whether the number of cut-offs violations occurring in each choice card affects the variance of the error term. That is, we would like to investigate if it affects the respondent's ability to choose.

3. Incorporating context effect into the Swait model

According to the Swait's "soft cut-offs" model (2001), if the level of an attribute does not satisfy the stated threshold value, the respondent has two alternatives: to choose the no-buy option or to violate his/her stated threshold. Cut-offs violations signal that the respondent may prefer to suffer a penalty associated with cut-offs violation rather than giving up that particular alternative. According to this approach, information regarding thresholds can be introduced into the deterministic part of the utility function.

The attribute cut-offs stated by the respondents n for each attribute k and for the alternative i belonging to the choice set t =1,…,T can be expressed as lower (a_{ik}) and upper (b_{ik}) bounds, k=1,…,K-1, where $--\infty < a_{ik} \leq b_{ik} < \infty$, and lower and upper price c_i and d_i for p_i $\forall i \in C$, where $-\infty < c_i \leq d_i < \infty$. In order to represent the amount by which the cut-offs are violated in choosing alternative i, we need to associate two new variables to the cut-offs:

$\varphi_{ik} \geq 0$ for the lower limits and $\gamma_{ik} \geq 0$ for the upper limits ($\forall i \in C$, $k=1,\ldots, K$).

Then, for each attribute in each alternative, violations can be defined as

$\delta_i (\theta_{ik}^L - X_{ik}) - \varphi_{ik} \leq 0$ and $\delta_i (X_{ik} - \theta_{ik}^U) - \gamma_{ik} \leq 0$.

where δ_i is a choice indicator equal to 1 if respondents choose the alternative i and 0 otherwise, and θ_{ik}^L and θ_{ik}^U are two vectors defined as $\theta_{ik}^L = [a_{i1}\, a_{i2} \ldots a_{ik}\, c_i]'$, $\theta_{ik}^U = [b_{i1}\, b_{i2} \ldots b_{iK}\, d_i]'$.

The cut-offs violation for quantitative attributes preserves its quantitative nature, that is $\varphi_{ik} = \max(0, \theta_{ik}^L - X_{ik})$, $\gamma_{ik} = \max(0, X_{ik} - \theta_{ik}^U)$. The cut-offs violation for qualitative attributes causes marginal utility to drop discontinuously. This is done by transforming it into a dummy variable, that is φ_{ik} and γ_{ik} are equal to 1 or 0 depending on whether the stated cut-offs have been violated or not but in this way we loose the information about the intensity of the cut-offs violation.

Thus, including the effect of penalties the model becomes:

$$\text{Max}U_{pi} = \sum_{i \in C} \delta_i U_i(X_{ik}) = \sum_{i \in C} \delta_i(\beta_{ik} X_{ik}) + \sum_{i \in C} \sum_{k} \delta_i(w_{ik}\varphi_{ik} + v_{ik}\gamma_{ik}) + \varepsilon_i \qquad (1)$$

$$\text{st.} \sum_{i \in C} \delta_i = 1,\ \delta_i = 0, 1,\ \sum_{i \in C} \delta_i\, p_i \leq Y_n,$$

$$\delta_i (\theta_{ik}^L - X_{ik}) - \varphi_{ik} \leq 0,\ \delta_i (X_{ik} - \theta_{ik}^U) - \gamma_{ik} \leq 0,\ \varphi_{ik} \geq 0,\ \gamma_{ik} \geq 0,\ \forall i \in T.$$

where

- U_{pi} is the penalized utility,
- X_{ik} is a vector of attributes describing the alternative i,

- φ_{ik} and γ_{ik} represent the amount by which the cut-offs are violated in choosing alternative *i* for the lower limits and for the upper limits respectively. Both are ≥0. If no violation occurs, (φ_{ik} and γ_{ik} equal to zero) one returns to the basic model without cut-offs.
- w_{ik} and v_{ik} are the marginal disutilities for individual n of violating respectively the lower and the upper stated cut-off value. In this specification, the w_{ik} and v_{ik} parameters should not be positive, indicating decreasing marginal utility when the attribute level does not reach the lower stated cut-off and/or exceed the upper stated cut-off. The magnitude of the estimated penalties w_{ik} and v_{ik} reveals compensatory or non-compensatory decision strategies.[2]
- ε_i is an error term usually assumed to be independently and identically Gumbel distributed. .

Under this assumption on the error term, the probability of choosing the alternative *i* in the choice set *t* is given by:

$$P_{nit} = \frac{\exp(\lambda \cdot V_{nit})}{\sum_{j=0}^{J} \exp(\lambda \cdot V_{njt})}, \tag{2}$$

where *V* represents the indirect utility function as a function of the attributes of the alternatives, and the parameter λ is a scale factor (inversely proportional to the common standard deviation) that does not vary across individuals and is usually normalised to one (DeShazo and Fermo, 2002).

Following Swait and Adamowicz (2001) and De Shazo and Fermo (2002), we employ a heteroskedastic multinomial logit model (HL). Instead of focusing on choice complexity linked to different design dimensions, we parameterise the scale parameter as a function of the number of cut-offs violations (C_{nt}) occurring in each choice card. The variable C_{nt} is choice-set and respondents' specific. This specification allows addressing the heteroskedasticity across responses to choice cards characterized by a different number of cut-offs violations.

The scale parameter λ must be strictly positive and it is usually specified as an exponential function (Caussade et al., 2005; Scarpa et al., 2011).

Then, the scale factor as a function of cut-offs violations occurring in each choice-set becomes:

$$\lambda_{nt}(C_{nt}) = \exp(\theta_1 Viol_{nt}) \tag{3}$$

Incorporating the parameterisation for the scale factor (3) in the choice probability (2) lead the following expression:

$$P_{nit} = \frac{\exp(\lambda_{nt}(C_{nt}) \cdot V_{nit})}{\sum_{j=0}^{J} \exp(\lambda_{nt}(C_{nt}) \cdot V_{njt})} \tag{4}$$

What we expect is that a larger number of cut-offs violation reduces the variance of the error component in the utility function. That means the larger the number of cut-offs violations the more precise is the choice of the respondent.

The logic behind this is the following. Consumers have in mind some minimum or maximum requirement but they often decide to violate them during their choices. The researcher cannot observe the decision process the respondent follows but probably he/she evaluates all alternatives relative to these thresholds to determine how far they are on a particular attribute before making the choice. If the number of violations is low the respondent has to put a lot of effort in making trade-offs. On the contrary, increasing the number of cut-offs violations may simplify the choice to consumers that therefore will make more accurate choices, leading to a lower variance in statistical models.

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[2] Estimated coefficients which tend toward zero imply that the attribute cut-offs play no role and the model becomes a compensatory model. Finite values of the penalties signal the presence of hybrid decision strategies in which cut-offs are considered to be soft or violable (Swait, 2001). Nevertheless, the model does not allow for a clear identification of decision rules.

4. Survey design

We designed a labelled CE with three alternatives (strawberries, blueberries and raspberries) and the "none-of-these option", by following the typical steps of a CE survey: selection of attributes and definition of levels, selection of the experimental design, construction of the choice set, testing and piloting and measurement of preferences via field survey administration. The investigation of stated threshold as decision heuristics requires the direct elicitation of these thresholds during the survey (Swait, 2001) and therefore a special section of the survey is designed to elicit alternative specific cut-offs.

4.1 Identification of attributes and levels

Through a review of the literature we identified a list of attributes emerging to be very important in consumers' choice to purchase and pay a premium for fresh fruit with credence attributes. They are visual and smell components, pesticide free, local production, certification, origin, health, and organic. We added climate change mitigation practices to this list,[3] given the increasing importance of the climate change issue. From this extended set of attributes, participants in two focus groups selected production method, visual appearance, origin, presence of low greenhouse gases (GHG) emissions as being important for small fruits.

Levels of non-monetary attributes (Table 1) and their description to the respondents were defined with the help of experts. For the production methods, four types were identified: Conventional, Integrated Pest Management (IPM), Innovative[4] and Organic. For visual appearance, three levels were identified: bad, mediocre and good. Three levels were also identified to test the impact of origin: abroad, Italy, and Trentino. For GHG emission practices the levels were the adoption of low emission practices in growing methods (presence) or not (absence)[4]. Price levels reflect the range of market prices registered in local supermarkets and grocery stores during the years 2008 and 2009. They were selected to be wide enough to cover the potential WTP (Hensher, 2006). Six price levels were identified varying from € 2.40 to € 4.15 for 125g box of blueberries and raspberries and from € 0.95 to € 2.95 for 250g box of strawberries.

Table 1. Attributes and levels employed in the CE

Attribute	**Level**
Method of production	Conventional (base level)
	Integrated Pest Management[a](IPM)
	Innovative[b] (INNOV)
	Organic (ORG)
Appearance	Bad (base level)
	Mediocre
	Good
Origin	Abroad (base level)
	Italy
	Trentino
Low GHG emission	No (base level)
	Yes
Prices of Blueberries and Raspberries (125g box)	2.40, 2.75, 3.10, 3.45, 3.80, 4.15
Prices of Strawberries (250g box)	0.95, 1.35, 1.75, 2.15, 2.55, 2.95

[a] IPM denotes a reduction in chemical treatments of 13-23 % compared to Conventional

[b] INNOV denotes a reduction in chemical treatments of 60-83 % compared to Conventional

[3] They refer to the implementation of agricultural practices that aim to produce low greenhouse gas (GHG) emissions (carbon dioxide and methane) and therefore to reduce the impact of farming on climate.

[4] The "innovative" method is a IPM that intensifies the use of biocontrol agents and agronomic techniques as much as possible till reaching a further reduction of the number of chemical treatments with respect to IPM control.

4.2 Generating the experimental design

We used a Bayesian D-efficient design as it is state-of-the-art with respect to the design of labelled stated CE (Jaeger and Rose, 2008). Due to the large full factorial design, we initially employed a computer generated orthogonal fractional factorial design that generated 36 choice sets divided into four equal blocks of 9 choice sets each. The survey was administered to an initial sample of 120 respondents (preliminary survey). The coefficients' estimates obtained from a multinomial logit (MNL) model were employed to create a Bayesian D-efficient block design using Ngene software. The final design has a Bayesian D-error of 0.2316 and is attribute level balanced.

4.3 The construction of choice sets

Each of the 9 choice cards presented 3 labelled alternatives and the "none-of-these" option (Figure 1). This option was also added to meet the property of exhaustiveness (Train, 2003, pp:15), to give more realism to the questionnaire and to forecast how category volumes would vary as products become more or less attractive (Johnson and Orme, 1996).

	Blueberries 125g	Raspberries 125g	Strawberries 250 g
Method of Production	Integrated	Organic	Conventional
Appearance	Mediocre	Good	Bad
Origin	Abroad	Trentino	Italy
Low greenhouses gas emission	No	No	Yes
Price	2.75	3.45	1.75
Your CHOICE is	⬆	⬆	⬆
	None of these products		

Figure 1. Example of a choice card

Since showing cards always in the same order, with the alternatives and attributes at the same place in the card might introduce bias in the estimates and may impact on overall model parameters (Kjaer et al., 2006), a mechanism that automatically randomizes sequence, rows and columns of the choice cards was employed. Before showing the nine choice cards to respondents, a "cheap talk" script following Cummings and Taylor (1999) was provided to respondents to reduce hypothetical bias. In addition, since people may change the value they attach to the products according to the eating occasion they face (Connor et al., 2001), a reminder text was shown to the respondent to encourage him or her, in the choice of product to behave as he/she does everyday and not occasionally or on special occasions. Finally, to avoid pro-social behaviour (List et al., 2006), we performed the CE in a natural setting (store) and not in a laboratory.

4.4 Cut-offs elicitation

According to both Swait (2001) and Hu (2008) cut-offs reporting should be collected before the choice task so they are free of contextual experience and are based on consumers' past experience and not on information provided in the CE (attribute levels) itself. We followed this suggestion and we asked respondents to select the level of method of production, origin, and appearance they consider to be the minimum requirement for purchasing each small fruit before starting the choice task. For the price, they were asked to choose the maximum level they were willing to pay. The elicited cut-offs are therefore alternative specific.

4.5 Survey administration and data analysis

To collect data, we used a touch-screen computer-assisted self-interviewing system (CASI), a recently developed method that has many benefits compared to the traditional paper-and-pencil method (Metzger et al., 2000; Cooley et al., 2001; Brown et al., 2008). After a pre-test survey (32 interviews) carried out in June 2009, data for the final survey was collected during July and August 2009 by trained interviewers in different towns of Trentino province and in different types of food store. To capture all types of grocery shoppers, interviews were conducted from weekdays to weekends and from morning to evenings. Respondents were intercepted at the entrance of each supermarket, using a systematic sampling probabilistic design by drawing randomly at an approximate rate of one out of 5. Eligibility to participate required a respondent to answer affirmatively to two screening questions: i) being a primary food shopper in the household (make at least 50% of food purchases), and ii) eating and buying small fruits (blueberries, raspberries, strawberries). Once participants had passed the screening questions, they started the survey. Out of the 516 people approached, 37% declined to be interviewed immediately, and another 7% declined after they had listened to the introduction, before the screening questions. In addition, five participants did not complete the survey, so we excluded their responses. The final sample usable for estimation resulted in 280 completed questionnaires and in 2520 choices.

Given the qualitative nature of our non-monetary attributes, we employed effect coding to codify attribute levels. Effect coding has been preferred to dummy coding, since the coefficients will not be correlated with the constants and there will be no confounding effects (Bech and Gyrd-Hansen, 2005). Given the high number of parameters involved in the Swait model specification (51 in the full model), we analysed the data applying a multinomial logit model (MNL) and a heteroskedastic logit model (HL). Both models were estimated using BIOGEME (Bierlaire, 2003; http://biogeme.epfl.ch).

5. Results

Two estimated models are presented in this paper. The first model implements the base Swait's model, while the second model includes context effects as specified in Eq. (5). The parameter estimates of the two models and the usual measures of fit (log-likelihood and the adjusted R^2 measure) are reported in Table 2. Being a labelled CE, the utility function includes alternative specific variables for method of production, appearance and origin. This specification allows us to determine whether the sample has different and/or particular preferences for the three small fruits. Regarding low GHG emissions and cost, we assume them a priori to be common to the three types of small fruits. In fact, we assume that a respondent who is price sensitive and/or environmentally friendly would be so independently of the product presented.

5.1 The base model

Model 1 represents the base against which we compare our proposed model and it is a simple MNL model that implements Swait's model incorporating the respondents' alternative specific stated cut-offs and assuming a non compensatory utility model (LL= -2775.36, $n_{\text{parameters}}$=50, $n_{\text{observations}}$= 2520). Results show that most estimated coefficients of the variables meet our expectation as regards the sign of the coefficients, except for IPM production and Italian origin for strawberries which proved to be negative. The coefficient estimates of ASCs – that indicate the utility of each option in relation to the "none of these" option – result to be not significant.

In general, for all three products, high quality, organic production, low GHG emissions and price are found significant, while mediocre quality was insignificant. For blueberries and raspberries, Trentino origin is of great importance in influencing the decision to purchase, while Italian origin played no role. Quite the opposite is found for strawberries: the Trentino origin coefficient is found insignificant, while the one relating to Italian origin is found to be significantly negative (β = -0.360). Integrated production is also found to decrease the probability of purchasing strawberries, while not having any significant impact on the other two small fruits.

Looking at the alternative-specific penalties, the results show that for our sample, most statistically significant cut-offs violations have a negative sign (cost, Italian and Trentino origin, and IPM production) but different intensity. In details, violating cost implies the greatest disutility in the choice of both blueberries (v = -0.734) and raspberries (v = -0.762) and the penalty coefficient is almost four times greater than its impact on choice probability. Violating Italian origin leads to greatest penalization for strawberries (w = -1.131) and the second one for raspberries (w = -0. 517). This result is quite unexpected. Given the model results of no or negative influence of Italian origin on the probability of purchasing raspberries and strawberries respectively, we expected that its violation would also play no role. Finally, it is interesting to note that for our sample, violating organic production and good appearance are found to be not significant for all the small fruits, while the innovative production related penalty is found to be significantly positive for strawberries only. Moreover, penalties are found to have greater magnitude when the low level, rather than the high one, of each attribute is violated.

Table 2. Estimates of the cut-off models with and without context effect

Attributes	1) MNL Coeff. (t-stat)	2) HL Coeff. (t-stat)
IPM_Prod_Blueberries	-0.057(-0.45)	-0.029(-0.27)
IPM_Prod_Raspberries	-0.196(-1.35)	-0.170(-1.38)
IPM_Prod_Strawberries	-0.322(-2.48)***	-0.250(-2.24)**
INNOV_Prod_Blueberries	0.033 (0.30)	0.026(0.27)
INNOV_Prod_Raspberries	0.164(1.30)	0.140(1.30)
INNOV_Prod_Strawberries	-0.032(-0.29)	-0.032(-0.34)
ORG_Prod_Blueberries	0.288(2.40)**	0.247(2.40)**
ORG_Prod_Raspberries	0.300(2.56)***	0.262(2.62)***
ORG_Prod_Strawberries	0.312(2.87)***	0.254(2.71)***
Mediocre_Blueberries	0.238(1.59)	0.195(1.49)
Mediocre_Raspberries	0.055(0.32)	0.065(0.46)
Mediocre_Strawberries	0.086(0.61)	0.072(0.61)
Good_Blueberries	0.396(2.85)***	0.323(2.56)***
Good_Raspberries	0.841(5.42)***	0.716(4.80)***
Good_Strawberries	0.645(5.15)***	0.542(4.55)***
Italian_Blueberries	0.079(0.40)	0.070(0.40)
Italian_Raspberries	-0.174(-1.10)	-0.166(-1.19)
Italian_Strawberries	-0.360(-2.81)***	-0.322(-2.91)***
Trentino_Blueberries	0.445(2.34)**	0.374(2.14)**
Trentino_Raspberries	0.397(2.60)***	0.325(2.31)**
Trentino_Strawberries	0.151(1.32)	0.088(0.84)
Low_GHG	0.065(1.91)*	0.054(1.85)*
Price	-0.203(-3.08)***	-0.159(-2.66)***
Blueberries_ASC	-0.016(-0.06)	-0.019(-0.08)
Raspberries_ASC	0. 104 (0.43)	0. 087 (0.43)
Strawberries_ASC	-0.248(-1.42	-0.225(-154)
Cut-off penalties		
VIPM_Blueberries	-0.144(-1.06)	-0.098(-0.83)
VINNOV_Blueberries	0.114 (1.15)	0.084(1.01)
VORG_Blueberries	-0.129 (-1.54)	-0.104(-1.14)
VMediocre_Blueberries	-0.203(-1.10)	-0.169(-1.06)
VGood_Blueberries	-0.107(-1.28)	-0.088(-1.24)
VItalian_Blueberries	-0.182(-0.67)	-0.149(-0.60)
VTrentino_Blueberries	-0.979(-1.32)	-0.078(-1.26)
VPrice_Blueberries	-0.734(-5.02)***	-0.593(-4.35)***
VIPM_Raspberries	-0.250(-1.66)*	-0.202(-1.57)
VINNOV_Raspberries	0.109(1.10)	0.094(1.14)
VORG_Raspberries	-0.036(-0.44)	-0.030(-0.44)
VMediocre_Raspberries	0.553(2.76)***	0.487(2.84)***
VGood_Raspberries	-0.038(-0.43)	-0.025(-0.33)
VItalian_Raspberries	-0.517(-2.63)***	-0.446(-2.54)**
VTrentino_Raspberries	-0.983(-1.16)	-0.072(-1.01)
VPrice_Raspberries	-0.762(-5.49)***	-0.633(-4.85)***
VIPM_Strawberries	-0.228(-1.65)*	-0.185(-1.55)
VINNOV_Strawberries	0.208(2.30)**	0.163(2.07)**
VORG_Strawberries	-0.033(-0.43)	-0.031(-0.50)
VMediocre_Strawberries	-0.191(-1.17)	-0.159(-1.14)
VGood_Strawberries	-0.036(-0.48)	-0.031(-0.49)
VItalian_Strawberries	-1.131(-7.45)***	-0.985(-6.56)***
VTrentino_Strawberries	-0.121(-1.77)*	-0.101(-1.76)*
VPrice_ Strawberries	-0.085(-0.66)	-0.093(-0.85)
Scale parameter		
Context effect		0.117(1.84)*
LL funct	-2775.36	-2773.85
R-sq Adj Const. only	0.191	0.191
# parameter	50	51

***, **, * significant at 1%, 5% and 10% level

5.2 The heteroskedastic Swait model

The second model represents our proposed model incorporating the number violations as an element of choice context (Table 2). The hypothesis is that number of cut-offs violations impacts on scale parameter. Incorporating the number of violations that occurs in a choice card in the model improves the model fit (from LL= -2775.36 to LL=- 2773.85). The Likelihood ratio test reveals that we can reject the null hypothesis that they play no role on the scale parameter (χ^2 statistic=3.02, df=1, p-value: <0.01).

Results show a systematic effect of the cut-offs violations on the variance of utilities as the number of violations increases. The number of cut-offs violations has a positive and significant effect on the ability to choose, contributing to increase the consistency of the respondent's decision process by reducing the error variance. This suggests that the increasing number of violations lead respondent to select an alternative with more precision.

5.3. Willingness to pay estimates

Focusing on the above results, we investigate if the number of cut-offs violations affects as context effect the marginal willingness to pay amounts. WTPs are calculated as the usual ratio of attribute's coefficient to the negative of the price coefficient. However, since in our study the variables are effect coded, the estimated coefficients have to be multiplied by 2 to get the actual WTPs (Bech and Gyrd-Hansen 2005). For attribute where consumer stated a cut-off, the WTPs includes the penalties estimates and becomes equal to $\frac{-2\times(\beta_{ik}+w_{ik})}{(\beta_{Cost}+v_{Cost})}$ (Bush et al., 2009).

The average WTP values for each small fruit are reported in Table 3 and they refer to the usual packaged boxes of small fruits found in supermarkets: a 125g box for blueberries and raspberries and a 250g box for strawberries.

Table 3 Willingness-to-pay values for small fruits by different models (Euro/box)

	1) MNL			2) HL		
Attribute	**Blueberries**	**Raspberries**	**Strawberries**	**Blueberries**	**Raspberries**	**Strawberries**
IPM_Production	-0.12	-0.41	-5.33***	-0.08	-0.43	-3.14**
Innov_Production	0.07	0.34	1.74	0.07	0.35	1.65
Organic Production	0.61**	0.62**	3.07***	0.66**	0.66***	3.19***
Mediocre Appearance	0.51	1.26	0.85	0.52	1.39	0.91
Good Appearance	0.85***	1.74***	6.35***	0.86***	1.81***	6.82***
Italian Origin	0.17	-1.43	-14.69***	0.19	-1.55	-16.44***
Trentino Origin	0.95**	0.82**	0.29	0.99**	0.82**	-0.16
Low_GHG	0.14*	0.13*	0.64*	0.14*	0.14*	0.68*

The highest WTPs are found for strawberry and raspberry good appearance (6.35 Euro/box and 1.74 Euro/box respectively) and strawberry organic production (3.07 Euro/box), while the lowest WTP is for low GHG emissions practices (0.13 Euro/box for blueberries and raspberries, while 0.64 Euro/box for strawberries).

It is interesting to note that while alternative production methods that employ IPM and BCAs do not present significant premium price, negative WTPs is found for strawberry of Italian origin and produced according to IPM. This may suggest the importance these attributes have for those individuals who prefer them, reflecting the fact that the absence of these features leads to a great disutility in the case of strawberries. The case of the Italian origin may reflect the lack of information associated to "abroad" origin. Indeed, in the survey the "abroad" origin has not been specified, leading consumers to convey their own information. The negative WTP may indicate that some consumers may perceive strawberries coming from abroad better than Italian, maybe associating to the word "abroad" higher qualitative standards.

Comparing the WTP estimates of the two models shows that in general heteroskedasticity arisen by the number of cut-offs violations does not lead to big changes into the WTP values. However, WTP estimates tend to be slightly higher for HL, except for IPM production for strawberries, suggesting that not accounting for heteroskedasticity associated to cut-offs violations may bias the WTPs downwards. This result is different to that reported by DeShazo and Fermo (2002) who find that not controlling for heteroskedasticity may bias estimates up to 33%, but it is similar to Caussade et al. (2005).

6. Conclusions

In this paper, we contribute to the literature by proposing a cut-off approach that incorporates cut-offs violations as context effect. We conduct an exploratory analysis about the effect of the number of cut-offs violations on consumers' choice variance. Results show that violations occurring in choice task impacts on consumers' choice by reducing the variance of the error term. Incorporating cut-offs violations improves model fitting, and slightly influences the estimated values of attributes' coefficients in terms of magnitude. However, when preferences are translated into WTP measures, we do not find systematic effects on willingness to pay values.

As research limitations, we need to underline that the proposed model is not a fully heteroskedastic model. The formulation addresses only one type of heteroskedasticity: the scale parameter differs across responses to choice cards characterized by different number of violations. Other forms of heteroskedasticity remain unaddressed.

Moreover, we assumed that self-reported thresholds are fixed, exogenous to the choice and not affected by measurement error. Future research could be devoted to model cut-offs as dynamic - respondent may change cut-offs over time due to experience, learning, or due to more information availability (Huber and Klein, 1991; Swait, 2001) and how to solve the related issue of endogeneity associated with attribute cut-offs. Secondly, due to the large number of parameters to be estimated, we employed a MNL model under the homogenous preferences assumption. Therefore, the next step would be to test the proposed model by controlling for preference heterogeneity among the respondents.

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