The treatment of don't know responses in the consumers' perceptions: a survey in the agri-food sector

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Summary. In several studies the understanding of consumers' perceptions has become of paramount strategic value in order to understand consumption behaviour. In this area, we present a case study deriving from a survey aimed at measuring consumers' awareness with issues concerned with sustainability in the agri-food sector. Data are analyzed by using a statistical model, denoted as CUB and designed to understand the empirical evidence and infer the relationships among motivations, personal characteristics and expressed agreement of consumers. In addition, we propose two ways to take into account the presence of "don't know" responses and gain further information about the consumers' perceptions.

Keywords: agri-food; food chain sustainability; "don't know "responses; ordinal data; CUB models

Topic: Models of food consumption behavior and their predictive power

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1 Introduction

In order to investigate consumers' perceptions - for instance the perceived value of market supplied goods, the preferences about private or public services or the utility of consumer goods - researchers commonly use questionnaires where respondents are asked to express judgments on rating scales (see for example Lewis, 1983; Kemp and Willetts, 1995; Kemp and Fussell, 1995; Kemp, 1998; Lozza and Bosio, 2010). The data are then analyzed using statistical methods properly designed to deal with ordinal categorical data and aimed to give a quantitative measure to unobservable issues, usually called latent traits. The obtained response path is labeled according to the endpoint (ordinal response outcome) but it deserves its origin (cognitive state) on the base of latent variables.

Recent lines of research point out that the latent variable measurement should be made by using statistical models able to account for the psychological decision process leading the consumer to express the requested ratings. Generally, the strategy by means of which a respondent decides what to report as score is a weighted combination of several aspects. Simplifying, we can recognize two basic steps. On the one hand, the respondent performs an adequacy judgment on the potential response based on his/her background, interest, personal *feeling*, attractiveness, satisfaction, awareness. On the other hand, factors other than the personal feeling towards the latent trait being measured affect the response. For example, the respondent may evaluate the desirability of responding accurately (the *communicative intent* of Bradbum et al., 1979), and possible indecision, fuzziness and blurriness, advocated by the way in which the question has been submitted to the interviewee, may also be present (Simon, 1957; Converse, 1964; Tourangeau et al., 2000). The most commonly used statistical models for the measurement of latent variables tend to give full consideration to the first step, downgrading the second psychological mechanism to a sort of random process generated by the sampling procedure. Nevertheless, in spite of the low interest devoted by traditional statistical models to factors not directly related to the personal feeling towards the analyzed latent trait, several authors highlight that uncertainty should not be neglected when assessing a decision process (see for example Jonung, 1986; Luchini and Watson, 2013).

The first class of models which explicitly takes into account the above mentioned steps is the CUB framework introduced by Piccolo (2003), where two specific parameters are

intended to measure, respectively, *feeling* and *uncertainty* of respondents. CUB models aim at understanding the empirical evidence and inferring the relationships among motivations, personal characteristics and expressed agreement of respondents (Iannario and Piccolo, 2010).

Recently, this class of models has been extended (Manisera and Zuccolotto, 2014) to deal with "don't know" responses (*dk*) which could be caused by behavior, attitudes, beliefs, perceptions, or factual questions. The idea at the basis of this extension is that the *dk* answer should be used to refine the assessment of the uncertainty of respondents, instead of being considered as a missing value, as usual. Whether to include or not the *dk* option in a response scale is an open matter (after the seminal work of Converse, 1964, see, among others, Beatty and Herrmann, 1995; Lietz, 2010; Poe et al., 1988, while a review can be found in Krosnick, 2002), but we are convinced that, when the option is present, *dk* should be considered as a valid response to all extents. In fact, this option is selected when the respondent feels unable to answer a survey question. He/she may genuinely not have an opinion or belief to account or lack motivation to respond (Cannell and Henson, 1974), particularly if the questions are burdensome (Cannell et al., 1981). Alternatively, satisficing theory (Simon, 1957) suggests that respondents may report that they don't know as a strategy for providing acceptable (satisfactory) answers to survey questions without going through the process of accurate selection (Willis, 2008). Moreover, respondents may evaluate a potential response as inadequate because they are unable to choose between several response categories (this issue is strictly related to the structure of the response scale). Otherwise, they may believe that a potential substantive answer does not "count" because is not known precisely. Whatever the case, *dk*s can be fully considered as a valid information about respondents' indecision.

In our context, we also advocate "don't know" responses as a possible measure of item difficulty/complexity (in term of global understanding of item) and propose a method to refine the respondents' perceptions assessment based on the consideration of this item difficulty/complexity measure.

The aim of this paper is to present some results from a survey designed to analyze consumers' awareness in the food and environmental field. The investigated perceptions are related to social, environmental and cultural aspects of food, and we give a measure of the degree of responsibility of consumers with regard to issues concerned with

sustainability in the agri-food sector.

From a statistical point of view, the rating expressed by consumers' are analyzed by means of the above described extended statistical framework, holding that consumers' reports are not only based on factors strictly related to the communicative intent or the feeling towards the latent trait being analyzed. In doing that, we resort to CUB models in order to consider *feeling* and *uncertainty* as the main latent components that move the psychological process of selection among ordered outcomes and which summarize what the respondent perceives. We also add the information brought by *dk*s to this combined strategy. We address two different ways to account for *dk* responses and show how to extract important information from each alternative, also with a comparison to the usual choice of treating them as missing values.

After the discussion of the study design and the description of the details of our data set (Section 2), the rest of the paper is organized as follows. Section 3 presents the statistical analysis, focusing attention on both the findings in terms of perceptions' measurement and the additional information allowed by taking into account *dk* options with two different strategies. We report general discussion and conclusions in Section 4. The formal developments of the statistical models are reported in the Appendix.

2 The survey: motivation, design and relevant data

In the recent decades, several organizations and movements (among others, Slow Food, Greenpeace, Friends of the Earth Europe, Corporate Europe Observatory, International Federation of Organic Agriculture Movements, Food Tank) have spread their philosophy about food, agriculture, environment, culture, health around the world. Terms like sustainability, biodiversity, genetically modified organisms and food, 'green' agriculture, food security are now part of our language. The message is that it is important to link the pleasure of good, quality and healthy food with forms of production that do not damage the environment (land, water and biodiversity) and guarantee accessible prices for consumers and fair conditions and pay for producers. The attention is also on the distribution of products, the sustainability of packaging and the reuse of resources, the keeping and protection of local food cultures and traditions, the consequences of food choices on the planet. The importance of these themes is also confirmed by Expo

2015, the Universal Exhibition that Milan, Italy, will host from May 1 to October 31, 2015, where "*more than 140 participating countries will show the best of their technology that offers a concrete answer to a vital need: being able to guarantee healthy, safe and sufficient food for everyone, while respecting the Planet and its equilibrium*" (http://www.expo2015.org). At Expo 2015 the dialogue between international players is encouraged on the three major challenges that can be summarized in the following three points: the right to food that is healthy, safe and sufficient; the environmental, social and economic sustainability of the food chain and the preservation of taste and of food culture. All these arguments are used to propose effective policy recommendations for governments (for example, at the European level), but also to raise awareness in the community. Obviously, these issues are very important also (or especially) from an economic point of view, and are used by producers as well as marketing managers to address consumers' preferences: for example, the environmental considerations have also been integrated into the marketing approach called green marketing, which involves changes to the product (for example, with sustainable packaging) or the production process as well as advertising (for example, advertising campaigns promoting the companies' commitment in ecological behaviour and how this affects their products).

In view of these considerations, a survey concerned with consumers' awareness in the food and environmental field has been carried out in 2014 as part of a Master's degree thesis in Management at the University of Brescia, Italy. The idea was to focus on the *consumers of tomorrow*, so the questionnaire was mainly administer to young people. The number of interviewees is 421. Their main characteristics are summarized in Table 1. The sample is mainly composed of females (59%), the education level is mostly (68%) equal to or higher than high school diploma, 52% of the respondents are students (university students, likely) and 70% are under 30 years old (the average age is 28.4 years, with a standard deviation of 13.0 years).

In the case study presented in this paper, we analyze a single question of the survey that asked respondents to rate their agreement with seven assertions by using a 5-point Likert scale, as recommended by Maddala (1983). The assertions (Table 2) were related to several aspects of the so-called agri-food sector: social (such as the relationship between producers and consumers), environmental (such as the protection of biodiversity) and cultural aspects (such as the protection of traditional knowledge). For all statements

Table 1: Summary statistics concerning the 421 respondents of the survey

Gender
Male (41%), female (59%)
Education
Lower than high school diploma (32%), high school diploma (30%),
Bachelor's degree (23%), Master's degree or higher (15%)
Job
Employee (18%), student (52%), other (30%)
Age (years)
≤ 20 (29%), 21-30 (43%), 31-50 (19%), > 50 (9%)
Attention on food quality
Not at all (1%), very little (13%), somewhat (57%), to a great extent (29%)
Are you the person who goes grocery shopping?
No (40%), yes (60%)
Do you have children?
No (74%), yes (26%)
Do you know any food certifications?
No (or I just know they exist) (18%) yes (82%)
Do you spend time to read labels when you goes grocery shopping?
Not at all (11%), very little (40%), somewhat (40%), to a great extent (9%)
Do you know 'Slow food'?
No (41%), yes (59%)

considered, the response *dk* was also available in the questionnaire.

Figure 1 shows the barplots of the seven analyzed statements. Most respondents agree with all the statements: the median is 4 for all the statements, and the percentage of ratings equal to 4 or 5 ranges from 57% (Supporting local communities) to 72% (Sustainability). The percentage of *dk* responses is rather low, ranging from 1.43 (Sustainability) to 9.98 (Biodiversity), as also reported in Table 2. The statements receiving the highest percentages of *dk* responses are quite long and are the latest in the scale. We can conjecture that respondents chose the *dk* response for many reasons, among which we can include a certain difficulty in understanding the statement, apathy or boredom

Table 2: Statements analyzed (with items' names in brackets) and corresponding percentage of *dk* responses

It is important:	*dk* (%)
- to protect the traditional knowledge in the agri-food sector (Tradition)	4.04
- to protect the environment during the food production (Environment)	1.43
- to consider food as a pleasure and and source of culture (Culture)	2.14
- to promote a good confidence relationship between producers and consumers (Confidence)	2.14
- to pay attention to protect biodiversity, during production (Biodiversity)	9.98
- that companies support local communities, in production and supply chain management (Local)	9.26
- to involve local communities and consumers to several initiatives to raise awareness towards the agri-food sector (Involvement)	6.89

at the end of the scale, the presence of some 'sophisticated' words.

3 Measurement of the perception

The measurement of the perception has been made by means of CUB models, a framework which basically assume that the psychological mechanism leading a respondent to express a judgment on a rating scale from 1 to m is driven by two fundamental components: the feeling he/she has towards the judged issue and the uncertainty intrinsically connected with the choice of the rating. In CUB models, the discrete random variable R defined over the support $\{1, \cdots, m\}$, and denoting the expressed rating has a discrete probability distribution, given by the combination of two random variables, V and U, accounting respectively for feeling and uncertainty. Details about this probability distribution and the assumptions supporting its definition are reported in the Appendix,

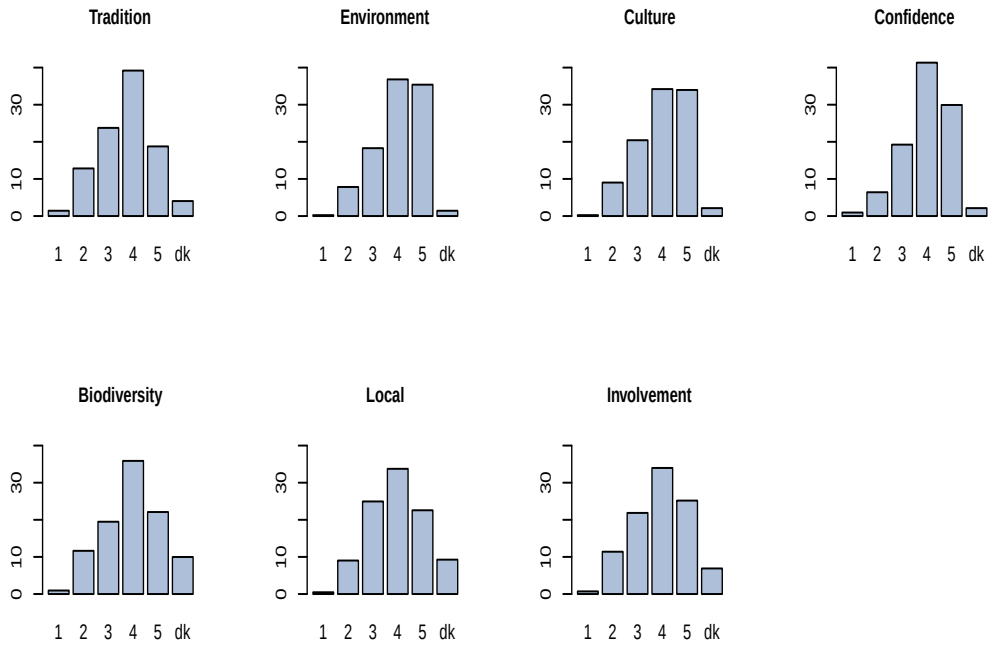

Figure 1: Barplots of the seven statements analyzed

where the formulation of CUB models is fully described. Here it is enough to point out that $P(R = r)$, $r = 1, \cdots, m$, depends on two parameters, $\xi \in [0, 1]$ and $\pi \in (0, 1]$, able to measure the overall degree of feeling and uncertainty of respondents with respect to a given item. Since they are inversely related to feeling and uncertainty, $1 - \xi$ and $1 - \pi$ are usually called feeling and uncertainty parameters, respectively. A development of the basic CUB model consists in considering that ξ and π may depend on subjects' (*i.e.* the respondents) and/or objects' (*i.e.* the items) covariates. In other words, it is possible to define ξ and π as functions of some respondents' and/or items' characteristics (called, respectively *individual effect* and *item effect* covariates), in order to obtain measures of feeling and uncertainty that can differ among respondents, items, or both. The functions commonly used to link ξ and π parameters with all covariates may be different; generally linear links between logistic function and covariates are favourite. The linear combinations depend on vector parameters that are usually denoted with γ and η (respectively, the parameters associated to subjects' and objects' covariates in the function for ξ) and with β and ν (respectively, the parameters associated to subjects' and objects' covariates in the function for π). The values of these parameters give an

idea of the role and weight of each covariate in determining the measures of feeling and uncertainty.

We have preliminarily fitted a standard CUB model to the ratings expressed on the seven items, with listwise deletion - for each item - of subjects who selected the *dk* option. The seven items have a very similar positioning on the uncertainty-feeling plane since they are characterized by a medium-high level of feeling (between 0.66 and 0.75) and a very low level of uncertainty (lower than 0.05). Thus, respondents exhibit a good awareness about the investigated issues, both in terms of the agreement with the statements and the certainty about the expressed opinions. The most-agreed-with items are Environment, Culture and Confidence, and the least-agreed-with one is Tradition (Figure 2).

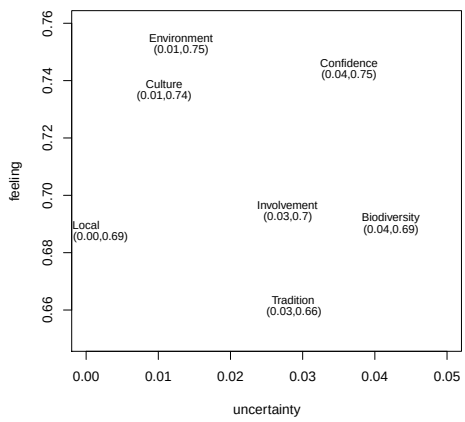

Figure 2: Measures of feeling and uncertainty for the seven items: plot of the seven CUB models on a smaller portion of the parameter space.

The main statistical proposal of this paper regards the treatment of *dk* responses. As mentioned above, we are convinced that the choice of the *dk* option should not be considered, as usually done in the main part of the statistical literature, as a missing value. It can basically inform about two main issues: the complexity of a given item, in terms of the difficulty encountered in formulating a judgment (due to reasons related to both the content and the sentence formulation) and the uncertainty of the respondent in deciding a rating for the item. These two ways of considering the information brought by *dk*s allow us to define two different strategies to analyze data from two different perspectives:

(A) on the one hand, focusing on those subjects who have actually expressed a rating, the fraction of *dk*s can be used as objects' covariate in a CUB model, in order to refine their feeling and/or uncertainty measures by taking into account the complexity of the item being evaluated;

(B) on the other hand, extending the consideration to all the respondents (included those who have selected the *dk* option), the fraction of *dk*s of a given item is used to adjust the measure of overall uncertainty of that item.

Strategy (A) is a new proposal of this paper, while strategy (B) has been formerly proposed by Manisera and Zuccolotto (2014). It is worth pointing out that strategy (A) and (B) are not competing, as they work under two completely different approaches. In the former the interest is just devoted to respondents who have formulated a rating, in the latter the whole sample is considered. In the following two paragraphs we will present the results obtained by means of the two strategies, and show that their combined use allows us to gain relevant information about the analyzed latent trait. The second strategy is also compared to the results deriving by means of an imputation technique, *i.e.* by treating *dk* responses as missing values, that is the usual way to face *dk*s when the analysis has to be carried out considering the entire sample of respondents.

3.1 Strategy (A): refining perception estimates by using *dk* responses to account for item complexity

In this subsection we analyze the seven statements by means of strategy (A), consisting in fitting data with CUB models, having both subjects' and objects' covariates. Specifically, we aim at including the fraction of *dk* responses among the objects' covariates, in order to use *dk*s as indicators for item complexity. The aim of this analysis is to gain better insights on the feeling and uncertainty of subjects who have expressed a rating. In detail, we want to discover whether personal characteristics and the item complexity affect the overall feeling and uncertainty of the subjects who rated their agreement with the seven items. This *multi-item* approach with subjects' and objects' covariates is formally described in the Appendix.

Table 3 reports the obtained results with the estimated parameters and the related

standard errors. We do not find significant covariates for uncertainty, thus its level is constant among the items. This means that the uncertainty measure is not affected by personal characteristics and item complexity. Its value is confirmed to be very low ($1 - \hat{\pi} = 0.004$), as in the general analysis. In practice, $\hat{\pi}$ is not significantly different from 1 and the CUB model is *de facto* a shifted Binomial one. Note that, differently from the analysis presented in Figure 2, in this case $\hat{\pi}$ provides an overall uncertainty measure, relative to all the items. For the feeling component, the significant covariates have turned out to be: a transformation of *Age* (the logarithm of *Age* minus its average) and Age^2 as *individual effect* covariate, and level of *difficulty* (*Diff*) measured by the fraction of *dk* responses of each item as *item effect*. Specifically, for a given item t and a subject i, we have

$$logit\left(\xi_i^{(t)}\right) = -1.250 - 0.495 * Age_i + 1.1223 * Age_i^2 + 22.057 * Diff_t$$

meaning that the feeling is affected by the age of respondents and the difficulty of the item. Figure 3 shows the combined effect of the two covariates. As age increases, the level of awareness firstly increases, then start decreasing. So, young and elderly people tend to have the same feeling, while the highest levels of awareness are reached by respondents between 30 and 40 years old. As far as it concerns the item difficulty, it is negatively related to feeling. So, the more difficult the item, the lower the expressed agreement. This can reasonably be interpreted as a higher difficulty to agree with the most complex (in terms of content and/or wording) items.

Table 3: Results for strategy (A)

Components	Covariates	CUB model parameters	Wald-test
Uncertainty	constant	$\hat{\pi} = 0.996$ *(0.012)*	83.565
Feeling	constant	$\hat{\gamma}_0 = -1.250$ *(0.046)*	−26.856
	Age	$\hat{\gamma}_1 = -0.495$ *(0.062)*	−7.973
	Age^2	$\hat{\gamma}_2 = 1.223$ *(0.121)*	10.086
	Diff	$\hat{\eta}_1 = 22.057$ *(4.246)*	5.194

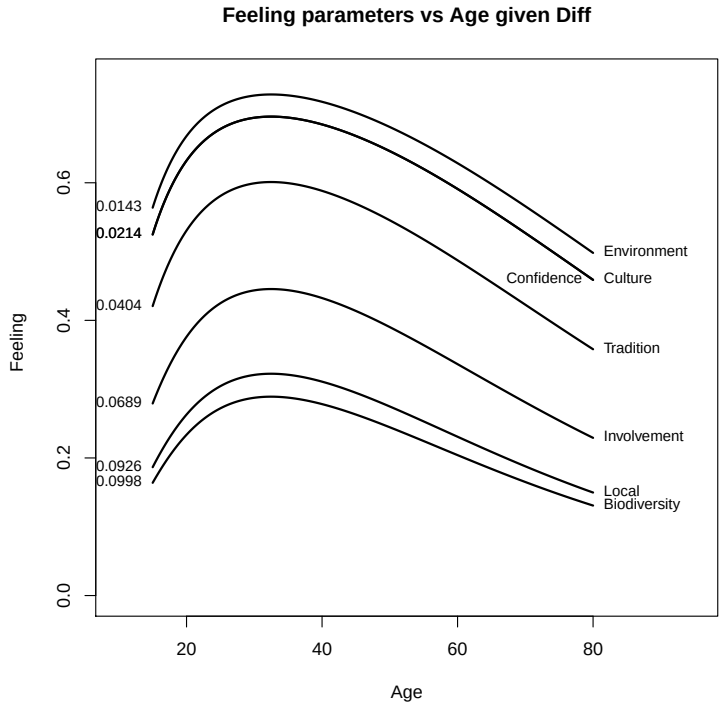

Figure 3: Effects of age and item difficulty on the respondents' feeling

3.2 Strategy (B): using *dk* responses to adjust consumers' uncertainty

With strategy (B) we aim at considering the whole set of respondents, included those who have selected the *dk* option. Traditionally this is made by treating *dk*s as missing values and replacing them with values obtained by means of some imputation technique. Instead, we resort to the method proposed by Manisera and Zuccolotto (2014) that, without needing any imputation, adjusts the uncertainty measure already computed for respondents who have expressed a rating, to take into account the presence of respondents who have selected the *dk* option.

In this context, we can reasonably think that the interviewees have at least heard about the general topics in the analyzed statements, so the *dk* responses come from their inability to express the requested rating and not from a complete ignorance about the issues in the questionnaire. For this reason, the case study fits well the assumptions required by the above cited adjustment procedure. Let $\hat{\pi}$ and $\hat{\xi}$ be the parameter estimates for a CUB model fitted to the dataset with listwise deletion of all the subjects with *dk*

responses, the cited procedure requires to determine the adjusted estimated parameter $\hat{\pi}_{adj} = \hat{f}\hat{\pi}$, where $1 - \hat{f}$ is the relative frequency of *dk* responses. Since, in presence of *dk* responses, $\hat{\pi}_{adj} < \hat{\pi}$, the adjusted measure of uncertainty $1 - \hat{\pi}_{adj}$ is systematically increased with respect to $1 - \hat{\pi}$, as an effect of *dk*s. It is worth noting that the measure for the feeling $1 - \hat{\xi}$ is not affected by the adjustment, which is a reasonably desirable property, as the choice of the *dk* option is able to inform only about the uncertainty of the respondent and not about his/her feeling.

This very simple adjustment is motivated by a probabilistic framework, whose details are fully described in the Appendix.

In order to compare this strategy with the usual practice of treating *dk* responses as missing values, we also report the results obtained by imputing the *dk* responses according to the 'iCUB ' single imputation method proposed in Cugnata and Salini (2014).

The 'iCUB ' imputation method is a CUB approach-based iterative algorithm useful when missing values are in more than one item in the data set. In this iterative procedure, a CUB model is fitted to one item at a time, with all the remaining items used as covariates for both ξ and π. In practice, the missing values of each item are imputed with random ratings generated by a CUB model with the estimated coefficients. The iterations stop when the imputations stabilize, according to a measure of stability related to the difference between the imputed values of two consecutive iterations (Cugnata and Salini, 2014). In this case study, the *dk* responses of each of the seven items in Table 2 are imputed using the iCUB procedure with covariates given by the remaining six items. After imputation, standard CUB models are fitted to the complete data set.

The circles in Figure 4 show, for the seven statements, the estimates for the feeling and uncertainty parameters with listwise deletion of *dk* responses (note that only a limited portion of the parameter space is represented), obtained from the preliminary analysis whose results are displayed in Figure 2.

The adjustment (increase) of the uncertainty estimates accounting for the presence of the *dk* responses, according to the procedure proposed by Manisera and Zuccolotto (2014) - strategy (B) - is represented in Figure 4 by the black arrows. As expected, the statements with the highest percentage of *dk* responses also have the highest increase in the uncertainty estimate; the longest arrows are observed for Biodiversity (*dk* =

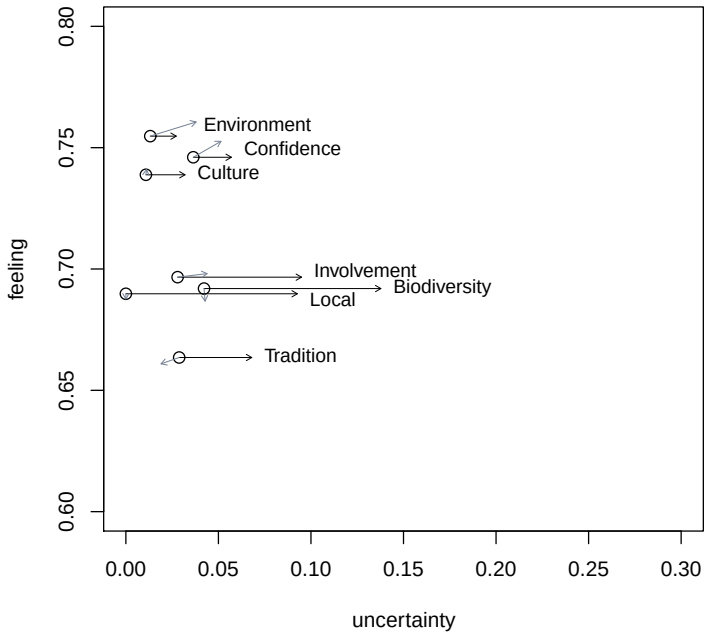

Figure 4: Uncertainty (x-axis) and feeling (y-axis) estimates for each statement with listwise deletion of *dk* responses (circles) and corresponding adjustment of the estimates for the *dk* responses using (1) stategy (A) (black arrows) and (2) the 'iCUB ' imputation method of missing values (grey arrows).

9.98%), Local (dk = 9.26%) and Involvement (dk = 6.89%). The adjustment is very important for the comparison of different statements. For example, before adjustment, the uncertainty estimates for the items Local and Involvement seem different, but the different percentages of *dk* responses lead to similar adjusted uncertainty parameters.

The adjustment of the CUB estimates obtained by the iCUB imputation method is shown by the grey arrows in Figure 4. Although results show that this adjustment is negligible most of the times, and slighter than that achieved using strategy (A), it is worth noting that it concerns both feeling and uncertainty estimates and does not necessarily increases the uncertainty estimate (for example, Tradition). In our view, the change in the feeling estimate and the possible decrease in the uncertainty estimate is not consistent with the psychological meaning and nature of *dk* responses. In fact, the iCUB procedure has been proposed for the treatment of missing values and here is used just for comparison purposes. In addition, when the aim is to analyze a set of

items composing a scale, as in this study, the use of one item as a response variable and the remaining items of the scale as covariates in the CUB model implemented in the iCUB procedure, is connected with a multicollinearity problem, because the items are correlated by construction. This requires a fine tuning in the use of iCUB procedure in order to avoid instability in the estimates. An alternative proposal in Cugnata and Salini (2014) considers one item with missings at a time, neglecting the relationships with other items. A CUB model is estimated on the subset of the observed data, and then the missing values are imputed with random ratings drawn from the estimated CUB distribution. In our view, this procedure should be repeated an appropriate number B of times in order to avoid sample bias and the final estimates of feeling and uncertainty should then be obtained by averaging over the B estimates. However, this leads to the expected result of a substantially null adjustment of the initial CUB estimates.

4 General discussion and concluding remarks

In this paper we presented the results of a case study aimed at inspecting the consumers' awareness with issues concerned with social, environmental and cultural aspects in the agri-food sector. Data stem from a survey where consumers' opinions were recovered by asking respondents to rate their agreement on some specific statements.

From a statistical point of view, the resulting ordinal data were analyzed by means of a class of models able to describe two main features of the respondents' perceptions: the feeling towards the judged statement, and the uncertainty in choosing the correct answer in the rating scale. The analysis has been completed by taking into account the information brought by the presence of "don't know" responses in the dataset, following two different, not competing, strategies.

The main results of the analysis can be summarized as follows.

The agreement of respondents with the proposed statements is generally high. The confidence relationship between producers and consumers, the protection of environment and the idea of food as pleasure and culture are the most-agreed-with items. Thus, the awareness of respondents covers all the aspects (social, environmental and cultural) taken into account by the survey. The highest levels of agreement are reached by respondents between 30 and 40 years old, meaning that much should still be done to increase the

awareness of the new generations.

Respondents exhibited low uncertainty in rating their agreement in the requested scale. However, the statements dealing with biodiversity, local communities and supply chain management have been considered more difficult to judge, perhaps due to the complex content and wording. This difficulty has affected the fraction of respondents that surrendered to the "don't know" option. Considering this fraction as a measure of the difficulty of the item, we showed that this difficulty resulted to be inversely related with the level of agreement. In other words, respondents were cautious in judging the most complex issues. After the adjustment of the uncertainty measure by taking into account the "don't know" responses, the statements dealing with biodiversity, local communities and supply chain management also exhibited the highest level of uncertainty.

Appendix

CUB models

Let $\boldsymbol{r} = (r_1,\, r_2,\, \ldots,\, r_n)'$ be the collection of integers assigned by n raters which express their *score* on a Likert scale to a given item; here, $r_i \in \{1, 2, \ldots, m\}$ for a given m. Then, $\boldsymbol{r}$ is an *observed sample* of size n generated by a *random sample* $(R_1,\, R_2,\, \ldots,\, R_n)$, where each R_i, $i = 1, 2, \ldots, n$ is an independent CUB random variable characterized by the parameter vector $\boldsymbol{\theta} = (\pi, \xi)'$. More specifically, π and ξ are related to the *uncertainty* and *feeling* of the mixture distribution (Iannario and Piccolo, 2012).

Formally, for each item, the CUB mixture has been defined for each respondent by:

$$Pr(R_i = r|\, \boldsymbol{\theta}) = \pi_i\, b_r(\xi_i) + (1 - \pi_i)\, p_r^U\,. \tag{1}$$

We set $b_r\,(\xi_i) = \binom{m-1}{r-1}\xi_i^{m-r}\,(1-\xi_i)^{r-1}$ and $p_r^U = 1/m$, for $r = 1, 2, \ldots, m$, $i = 1, 2, \ldots, n$ the probability mass functions of the shifted Binomial and the discrete Uniform random variables, respectively. Motivations for the selection of these probability distributions are detailed in Iannario and Piccolo (2015). For the inferential issues, the log-likelihood function is defined by:

$$\log \mathcal{L}(\boldsymbol{\theta}) = \sum_{i=1}^{n} \log\left[Pr(R_i = r \mid \boldsymbol{\theta})\right].$$

For $m > 3$ categories, the CUB distribution in (1) may include *subjects'* and *objects'* covariates (predictors related to respondents or questioned items) as proposed by Piccolo and D'Elia (2008).

Maximum likelihood estimators of parameters have been implemented via EM algorithm (Piccolo, 2006). Some validation and fitting measures are reported in Iannario (2009).

Strategy (A): CUB models for *multi-item* framework

For the implementation of a *multi-item* strategy, with the reference to i-th subject we denote the p covariates explaining *uncertainty* as: $\boldsymbol{y}_i = (y_{i0}, y_{i1}, \ldots, y_{ip})$ and the q covariates explaining *feeling* as: $\boldsymbol{w}_i = (w_{i0}, w_{i1}, \ldots, w_{iq})$, respectively. We assume that we have data from T items, with a different number of respondents n_t for each of them. We are setting: $y_{i0} = w_{i0} = 1, \forall\, i = 1, 2, \ldots, n_t$, for convenience. We also include for each item $t = 1, 2, \ldots, T$, the K covariates related to the object as $\boldsymbol{z}_t = (z_{t1}, z_{t2}, \ldots, z_{tK})$, each row vector of the models replicated n_t times should be generated as:

$$(r_i^{(t)} \,|\, 1, y_{i1}, y_{i2}, \ldots, y_{ip} \,|\, 1, w_{i1}, w_{i2}, \ldots, w_{iq} \,|z_{t1}, z_{t2}, \ldots, z_{tK})\,.$$

for $i = 1, 2, \ldots, n_t$ and it is available for each item $t = 1, 2, \ldots, T$.

We link parameters to subjects' and items' characteristics by means of:

$$logit(\pi_i^{(t)}) = \boldsymbol{y}_i\,\boldsymbol{\gamma} + \boldsymbol{z}_t\,\boldsymbol{\nu}; \qquad logit(\xi_i^{(t)}) = \boldsymbol{w}_i\,\boldsymbol{\gamma} + \boldsymbol{z}_t\,\boldsymbol{\eta},$$

for $i = 1, 2, \ldots, n_t$; $t = 1, 2, \ldots, T$, where $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)'$ and $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, \ldots, \gamma_K)'$ are parameters measuring the impacts of subjects' features on π_{it} and ξ_{it}, and $\boldsymbol{\nu} = (\nu_1, \nu_2, \ldots, \nu_K)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_K)'$ are parameters measuring the impacts of the items characteristics on *uncertainty* and *feeling* components, respectively.

In this framework, the log-likelihood function is defined by:

$$\log \mathcal{L}(\boldsymbol{\theta} \mid \mathcal{S}_n) = \sum_{t=1}^{T} \sum_{i=1}^{n_t} \log \Big[Pr(R = r_i^{(t)} \mid \boldsymbol{y}_i,\, \boldsymbol{w}_i,\, \boldsymbol{z}_t; \boldsymbol{\theta}) \Big]$$

where $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\nu}, \boldsymbol{\eta})'$ is the whole set of parameters to be estimated and $\mathcal{S}_n = (\tilde{\boldsymbol{r}} \,|\, \tilde{\boldsymbol{Y}} \,|\, \tilde{\boldsymbol{W}} \,|\, \tilde{\boldsymbol{Z}})$ is the sample information in which $\tilde{\boldsymbol{r}} = vec(\boldsymbol{R})$; $\tilde{\boldsymbol{Y}} = (\boldsymbol{1}_T \otimes \boldsymbol{Y})$; $\tilde{\boldsymbol{W}} = (\boldsymbol{1}_T \otimes \boldsymbol{W})$; $\tilde{\boldsymbol{Z}} = (\boldsymbol{Z} \otimes \boldsymbol{1}_n)$. In this context, $\boldsymbol{1}_T$ and $\boldsymbol{1}_n$ are unit vectors of length T and $n = n_1 + n_2 \ldots + n_t$, respectively.

Of course, when parameters related to objects are significant, their interpretation is relevant and reflects a genuine *multivariate* approach.

Strategy (B): adjustment of the uncertainty measure

In the following we will denote with Y the latent trait which is being analyzed in a population, by means of a questionnaire composed of items with Likert-scaled responses. With reference to a given item, following Manisera and Zuccolotto (2014), we assume that the population is divided into two groups according to a dichotomous variable A, independent of Y, which takes values 0 or 1 with probability f and $1-f$, respectively. Variable A indicates whether a respondent, although having experienced the events that can have generated the latent trait Y, feels unable (A=1) to face the decision process leading up to the expression of the requested rating. In the following we will deal with the case of *dk* option available in the questionnaire, and we assume that subjects choose the *dk* option if and only if they belong to the group with $A = 1$, as in the simplified mapping of the state-response composed by two cognitive states, described by Beatty and Herrmann (1995). In other words, for a given subject i, we have

$$a_i = 1 \Leftrightarrow m_i = 1 \tag{2}$$

for all $i = 1, \cdots, n$, where a_i is the value of A in subject i and m_i is the indicator function assuming value 1 if the subject marks the *dk* option.

Conditioning on $A = 0$, the probability distribution of R is $Pr(R = r|A = 0; \theta_0)$, which depends on the set of parameters θ_0, characterizing all subjects with $a_i = 0$. For the subjects with $a_i = 1$, the probability distribution of R corresponds to the probability distribution governing the responses of subjects unable to express the rating, when the *dk* option is missing and they are forced to answer the question regardless their reluctance (Bishop et al., 1986). Following the wide set of motivations supplied by Manisera and Zuccolotto (2014) and the evidence present in the literature about probed answers, we assume for $P(R = r; |A = 1)$ the discrete Uniform distribution p_r^U, *i.e.*

$$R|A = 1 \sim U(1, \cdots, m).$$

Under this assumption, the marginal distribution of the response R is given by

$$Pr(R = r; \theta) = f Pr(R = r|A = 0; \theta_0) + \frac{1-f}{m}. \tag{3}$$

Since, for a subject i, $Pr(R = r_i, A = a_i; \theta) = Pr(A = a_i)Pr(R = r_i|A = a_i; \theta)$, given a random sample of n subjects, $\mathbf{x} = (\mathbf{x}_1, \cdots \mathbf{x}_n)'$, where $\mathbf{x}_i = (r_i, a_i)$, the log-likelihood function is

$$\begin{aligned}
\mathcal{L}(\theta|\mathbf{x}) &= \sum_{i:a_i=0} \log[fPr(R = r_i|A = 0; \theta_0)] + \sum_{i:a_i=1} \log\left(\frac{1-f}{m}\right) \\
&= \log[f^{n_{lw}}(1-f)^{n_{dk}}] + \sum_{i:a_i=0} \log[Pr(R = r_i|A = 0; \theta_0)] + \sum_{i:a_i=1} \log\left(\frac{1}{m}\right) \\
&= \ell_1(f) + \ell_2(\theta_0) + c
\end{aligned}$$

where $n_{dk} = \sum_{i=1}^{n} m_i$ and $n_{lw} = n - n_{dk}$. The parameters f and θ_0 can be estimated separately:

- the estimate $\hat{f}$ of f is obtained by maximizing the function $\ell_1(f)$, and it is easy to show that this leads to compute $\hat{f}$ as the relative frequency of the expressed ratings
$$\hat{f} = \frac{n - n_{dk}}{n} \tag{4}$$
- the estimate $\hat{\theta}_0$ of θ_0 is obtained by maximizing the function $\ell_2(\theta_0)$, that is, by fitting the model assumed for the expressed ratings to sample data with listwise deletion of *dk* responses.

Manisera and Zuccolotto (2014) have shown that if $Pr(R = r_i|A = 0; \theta_0)$ is assumed to follow a CUB model with parameters $\theta_0 = (\pi, \xi)'$, *i.e.*

$$R|A = 0 \sim \text{CUB}\ (\xi, \pi)$$

the marginal distribution (3) also follows a CUB model with parameters $\theta = (\pi_{adj}, \xi)'$, where $\pi_{adj} = f\pi$. In practice, this means that the marginal distribution of the ratings taking the *dk* responses into account is again a CUB with higher uncertainty.

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References

Beatty, P., Herrmann, D., 1995. A framework for evaluating "don't know" responses in surveys, in: Proc of the section on Survey Research Methods. Am Stat Assoc, Washington DC, pp. 1005–1010.

Bishop, G.F., Tuchfarber, A.J., Oldendick, R.W., 1986. Opinions on fictitious issues: The pressure to answer survey questions. Public Opinion Quarterly 50, 240–250.

Bradbum, N.M., Sudman, S., Blair, E., 1979. Improving Interview Method and Questionnaire Design. Jossey-Bass Publishers, San Francisco.

Cannell, C., Miller, P., Oksenberg, L., 1981. Research on interviewing techniques. Sociological Methodology 1, 50–79.

Cannell, C.F., Henson, R., 1974. Incentives, motives, and responses bias. Annals of Economic and Social Measurement 3, 307–317.

Converse, P., 1964. The nature of belief systems in mass publics, in: Apter, D. (Ed.), Idealogy and Discontent. Free Press, pp. 206–261.

Cugnata, F., Salini, S., 2014. Comparison of alternative imputation methods for ordinal data. Communications in Statistics. Theory and Methods In press.

Iannario, M., 2009. Fitting measures for ordinal data models. Quaderni di Statistica 11, 39–72.

Iannario, M., Piccolo, D., 2010. A new statistical model for the analysis of customer satisfaction. Quality Technology & Quantitative Management 7, 149–168.

Iannario, M., Piccolo, D., 2012. CUB models: Statistical methods and empirical evidence, in: Kenett, R.S., Salini, S. (Eds.), Modern Analysis of Customer Surveys. Wiley, New York, pp. 231–258.

Iannario, M., Piccolo, D., 2015. A generalized framework for modelling ordinal data statistical methods and applications. *Submitted*, .

Jonung, L., 1986. Uncertainty about inflationary perceptions and expectations. Journal of Economic Psychology 7, 315 – 325. URL: http://www.sciencedirect.com/science/article/pii/0167487086900231, doi:http://dx.doi.org/10.1016/0167-4870(86)90023-1.

Kemp, S., L.S., Fussell, S., 1995. Experiments on rating the utility of consumer goods: Evidence supporting microeconomic theory. Journal of Economic Psychology 16, 543 – 561. URL: http://www.sciencedirect.com/science/article/pii/0167487095000262, doi:http://dx.doi.org/10.1016/0167-4870(95)00026-2.

Kemp, S., 1998. Rating the values of government and market supplied goods. Journal of Economic Psychology 19, 447 – 461. URL: http://www.sciencedirect.com/science/article/pii/S016748709800018X, doi:http://dx.doi.org/10.1016/S0167-4870(98)00018-X.

Kemp, S., Willetts, K., 1995. Rating the value of government-funded services: Comparison of methods. Journal of Economic Psychology 16, 1 – 21. URL: http://www.sciencedirect.com/science/article/pii/016748709400036A, doi:http://dx.doi.org/10.1016/0167-4870(94)00036-A.

Krosnick, J., 2002. The causes of no-opinion responses to attitude measures in surveys: They are rarely what they appear to be, in: Groves, R., D.D.E.J.L.J. (Ed.), Survey nonresponse. Wiley, New York, pp. 1005–1010.

Lewis, A., 1983. Public expenditure: Perceptions and preferences. Journal of Economic Psychology 3, 159 – 167. URL: http://www.sciencedirect.com/science/article/pii/0167487083900715, doi:http://dx.doi.org/10.1016/0167-4870(83)90071-5.

Lietz, P., 2010. Research into questionnaire design - a summary of the literature. International Journal of Market Research .

Lozza, E., C.S., Bosio, A., 2010. Perceptions and outcomes of a fiscal bonus: Framing effects on evaluations and usage intentions. Journal of Economic Psychology 31, 400 – 404. URL: http://www.sciencedirect.com/science/article/pii/S0167487010000152, doi:http://dx.doi.org/10.1016/j.joep.2010.01.008.

Luchini, S., Watson, V., 2013. Uncertainty and framing in a valuation task. Journal of Economic Psychology 39, 204 – 214. URL: http://www.sciencedirect.com/science/article/pii/S0167487013001013, doi:http://dx.doi.org/10.1016/j.joep.2013.08.001.

Maddala, G.S., 1983. Limited dependant and qualitative variables in econometrics. Cambridge University Press, New York.

Manisera, M., Zuccolotto, P., 2014. Modelling "don't know" responses in rating scales. Pattern Recognition Letters 45, 226–234.

Piccolo, D., 2003. On the moments of a mixture of uniform and shifted binomial random variables. Quaderni di Statistica 5, 85–104.

Piccolo, D., 2006. Observed information matrix for MUB models. Quaderni di Statistica 8, 33–78.

Piccolo, D., D'Elia, A., 2008. A new approach for modelling consumers' preferences. Food Quality and Preference 19, 247–259.

Poe, G., Seeman, I., McLaughlin, J., Mehl, E., Dietz, M., 1988. Don't know boxes in factual questions in a mail questionnaire. Public Opinion Quarterly 19, 212–222.

Simon, H., 1957. Models of Man. John Wiley & Sons, New York.

Tourangeau, R., Rips, L., Rasinski, K., 2000. The psychology of survey response. Cambridge University Press, Cambridge.

Willis, G., 2008. Cognitive aspects of survey methodology (CASM), in: Lavrakas, P. (Ed.), Encyclopedia of survey research methods. SAGE Publications, Thousand Oaks, CA, pp. 104–107.