Resolvable and near-epistemic uncertainty in stated preference for olive oil: An empirical exploration

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Abstract

We elicit subjective probabilities of choice using a choice experiment designed to study preferences of German consumers for high quality Italian extra-virgin olive oils. We develop an econometric framework to address the issues of resolvable and near-epistemic uncertainty. Focussing on behaviourally meaningful quantities linked to changes in oil attributes, such as marginal probabilities and marginal willingness to pay, we found estimates of these quantities to be robust to both types of uncertainty from both discrete and fractional elicitation formats of the response variable. The frequency and presence of potentially near-epistemic responses are explained by socio-economic covariates, but their effects are not always in the same direction as in models of heteroskedastic choice, suggesting the existence of different sources. Rounding behaviour in subjective probabilities statements conforms with previous findings in the literature.

Keywords: elicited choice probability, nonparametric estimations, subjective random utility model, choice experiments, extra virgin olive oil, rounding behaviour.

JEL Classifications: C83, C25, Q17.

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Introduction

In this paper we contribute to the econometric and conceptual analysis of stated probability of selection, with special attention to the econometric treatment of (near) 'epistemic' uncertainty (e.g. responses with uncertainty so high as to be 'random') (Bruine de Bruin et al., 2002) and the separate concept of 'resolvable' uncertainty. This latter concept was introduced empirically by Blass et al. (2010), but previously conceptualised in a broader context by Manski (2004). Our study is motivated by a high-profile call for more research in this interdisciplinary area (Bruine de Bruin and Fischhoff, 2017; Manski, 2017). While we develop our approach in the context of choice experiments for extra virgin olive-oil, we argue it can be used in most, if not all, analyses of probabilistic choice.

Statements of intentions are fundamentally different from real choices and are subject to hypothetical bias. Blass et al. (2010) note that—although probably not the main cause of such bias (see Harvey and Hubbard, 2013, for a discussion in the context of public goods and animal welfare)—resolvable uncertainty is one of its causes, and it is due to differences in information sets faced by subjects between two types of choice: stated and real. The focus is on filling the information gap between knowledge available to subjects at the time choice statements are collected and at the time of making a real purchase. Specifically, we seek to detect, account for and explain resolvable uncertainty in stated food choice, by elicitating subjective probabilities.

In studies of stated food choice respondents are asked to make choices based on descriptions of purchase scenarios. But such descriptions are seldom complete, if ever. They fail to provide respondents with the complete information they would search for before committing to a real choice.

In the special issue of the Journal of Risk and Uncertainty dedicated to preference elicitation, Manski eloquently stated (Manski, 1999, page 51), that:

> '... expected choice questions generally do not elicit pure statements of preference from respondents. They elicit respondents' preferences mixed with their expectations of future events that may affect choice behavior.'

In the same issue, Fischhoff et al. (1999) suggest that whatever detail is needed for the decision and is missing, the respondent is likely to 'make up', with subjective expectations (imaginations) substituting for missing information. And, as with all expectations, it will be wrapped in uncertainty. From the researcher's viewpoint this 'resolvable uncertainty' adds to the existing uncertainty of a standard random utility framework.

Surveys of food purchase intentions systematically fail to provide complete information scenarios to respondents: not all information needed by respondents in real choice can possibly be provided during a controlled experiment. This implies that, by the time they get round to an equivalent real choice, subjects expect to have ‘resolved’ part of the total uncertainty experienced when asked to state their intention. However, even in real choice, part of this uncertainty still remains unresolved, at least from the viewpoint of the analyst. Hence, even under best conditions (e.g. absence of strategic behaviour), data on hypothetical choice are more uncertain than data on real choices. This is often demonstrated empirically in estimations of choice models from combined revealed and stated preference data (Adamowicz et al., 1994) by a relatively lower scale parameter (i.e. a higher variance) of the Gumbel error for stated preference data.

Psychologists argue that using subjective probabilities of choice can identify the degree of resolvable uncertainty respondents experience. We use this approach and propose an econometric characterization of these data. Specifically we explore how they relate to the standard uncertainty treatment in the conventional practice of choice experiments.

Our empirical example is a choice between bottles of Italian extra-virgin olive oil (henceforth olive oil) as recorded from a sample of over one thousand German residents. Quality olive oil is one of the main Italian food exports to Germany, which is the second largest importer of this product after the U.S.A., with 13% of the total exported production of pure olive oil, which in 2015 was worth USD218 million (ISTAT). The oil comes in a wide range of qualities, in terms of certifications of production processes, taste, packaging and place of origin. Differences in olive oil quality are determined by factors similar to differences in wine quality. Olive tree varieties, place of growth, soil conditions, timing and mode of production are all factors that give specific taste features to olive oil. As such, it offers a good context for exercising subjective expectations over resolvable uncertainty due to incomplete product description, which is typical of complex food stated preference experiments.

The paper is organised as follows: in the next section we review the relevant literature. Then we move to a section that describes the theory leading to the hypotheses we test and the assumptions invoked in testing them, as well as the testing methods. This is followed by a section describing the survey data and experimental design. Discussion of our results precedes the conclusions.

Literature Review and Research Questions

The explicit elicitation of self-reported uncertainty measures in stated preference, and their effect on econometric estimates of interest, has long been the subject of empirical and conceptual investigations (e.g. more recently Balcombe et al., 2008; Balcombe and Fraser, 2011; Kobayashi et al., 2012). Some discrete choice studies have made progress in trying to elicit uncertainty using subjective expectations, and how to address it econometrically (Lundhede et al., 2009, 2015; Kassahun et al., 2016; Dekker et al., 2016). However, the focus has been mostly on uncertainty surrounding either outcome scenarios or choice attribute values, which have been econometrically handled either with heteroskedastic choice models, focussing on choice determinism, or with hybrid choice models, to deal with endogeneity. The latter models rely on complex assumptions necessary for combining various parametric models in a single sample likelihood. Consequently, they tend to have low credibility (in the sense of Manski, 2013), and suffer from other shortcomings in terms of their use in public policy (see Chorus and Kroesen, 2014; Vij and Walker, 2016, for a discussion). We intentionally do not review this literature here as it is mostly grounded on choice data analysis and choice experiments, while we intend to focus on elicitation of subjective probability of choice, which is necessary to identify the often neglected concepts of (near)epistemic and resolvable uncertainty.

Manski (1990) argued persuasively in favour of the use of individual elicited probabilities in surveys designed to assess subjective evaluations that a given event will occur. For example, raining, loss of one's job, death, schooling outcomes, etc. Economists were initially reluctant of asking survey subjects to reveal their subjective probabilities and expectations.

However, in experimental economics this has become an area of active research and has produced sufficiently persuasive evidence to dissipate these initial concerns. For example, Delavande and Kohler (2009); Attanasio (2009); Delavande et al. (2011*b*,*a*) showed that probability can be elicited in survey research in developing countries and be used effectively to produce robust estimates. Provencher et al. (2012) showed that such subjective expectations can be used to improve estimates relating to environmental goods and found these to have good convergence validity with other methods. In a food choice context similar to ours, Lusk et al. (2014) illustrated how accounting for subjective beliefs can materially modify policy prescriptions and marketing guidance derived from choice model estimates.[1]

In light of this evidence, stated preference surveys could be designed to obtain subjective probabilities rather than preferred choices, thereby enabling researchers to adequately account for subjective expectation on unresolvable uncertainty and also to rely on less stringent—and hence more credible assumptions—than those required conventionally to analyse stated choice data.

The literature on stated preference experiments eliciting subjective choice probabilities is scant. The seminal paper by Blass et al. (2010) showed how robust random utility models can be estimated using data on consumer preferences for the reliability of electricity services in Israel. Shoyama et al. (2013) elicited subjective choice probabilities to model public preference for land-use scenarios in the Kushiro watershed (northern Japan) and found some differences between these willingness to pay (WTP) estimates obtained from conventional preferred alternative data. A further nonmarket valuation study comparing preference estimates from the two elicitation methods (discrete choice and subjective probabilities) under varying information provision is that by Herriges et al. (2011), who found significant differences between the

[1] Subjective choice probabilities have also been used by labour economists who study choice of major by college students and income expectations across American households (Arcidiacono et al., 2012; Wiswall and Zafar, 2015); and they are also routinely used to test the properties of risk preferences in economic experiments (Cerroni et al., 2012; Harrison et al., 2014; Harrison and Martínez-Correa, 2017).

two formats in terms of implied preferences for two hypothetical lake scenarios. Their work emphasizes how they differ in terms of treatment of risk preferences and welfare measures. More recently, Pedersen et al. (2019) used this approach to model employment location choices by senior medical students in Denmark. All these initial studies call for further work in this context.

Importantly for interdisciplinary collaborations, this field of enquiry can benefit from and contribute to a fruitful exchange between psychologists and economists, as illustrated by the arguments reported by Bruine de Bruin and Fischhoff (2017) and Manski (2017). Specific research dealing with the epistemological interpretation of focal central probability statements, such as fifty-fifty statements in binary choice tasks, which are commonly encountered in survey research, is reported in Fischhoff and Bruine de Bruin (1999) and Bruine de Bruin et al. (2002), while Giustinelli et al. (2020*b*) focus on central and tail probabilities.

So, one issue we study is the robustness of behavioural estimates—marginal effects and willingness to pay—to the removal of those observations potentially affected by (near)'epistemic' uncertainty. That is, those that assign (near)equi-probable outcomes across alternatives. Our subjective probability question followed a response to a binary choice and does not allow indifference between the two alternatives. So, we could not identify precise 50-50 subjective choice probabilities in the sense that is used to conceptualise epistemic (pure) uncertainty by Fischhoff and Bruine de Bruin (1999), Bruine de Bruin and Fischhoff (2017). Hence, we use the term near epistemic uncertainty for the immediate neighbourhood around fifty percent.

Another strain of the literature on subjective probability elicitation focusses on the frequency of rounding to multiples of five and ten percent (see for example Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*a*, for seminal contributions in this field) and the significance of different distributions of such roundings in central and tail probabilities (Giustinelli et al., 2020*b*). However, here we concern ourselves exclusively with the effect of what we call near epistemic probabilities, which are those elicited in the immediate neighborhood of equiprobability of choice. And we focus on the implications for the practice of food choice experiments.

Specifically, since we use repeated probability elicitations from the same respondent, we study the determinants explaining both the presence and (if present) the number of potentially epistemic scores expressed within each choice sequence by respondents. A further question is whether these covariates also play a similar role in determining the variance structure of conventional heteroskedastic choice models, the dominant category of models used to address uncertainty in stated choice analysis.

Moving from stated preference data based on repeated preferred choice elicitation to data based on repeated subjective probability elicitation poses some challenges in econometric modelling. Hence we extend the range of models proposed in the seminal papers (e.g. the LAD model as in Blass et al., 2010;

Shoyama et al., 2013; Herriges et al., 2011; Pedersen et al., 2019) by implementing a fractional logit model, which adopts a similar error structure to the conventional logit model, as well as zero-inflated count models to explain occurrance and count of near epistemic probability scores.

Theory, hypotheses and method

Theoretical background

As a starting point, we illustrate the difference between the theoretical model of random utility (RU) under actual choice and that under stated choice, with an emphasis on the differences in the information sets. The case of actual choice is well known. Consider subject n evaluating alternative i at choice opportunity t: s/he conceives the total (expected) utility U_{nit} as a function of the qualitative attributes describing the alternative $\mathbf{x}_{nit}$, utility weights $\boldsymbol{\theta}$ and a stochastic idiosyncratic component ϵ_{ni}. As a consequence, from the analyst's perspective, the selection probability is generically defined as:

$$\Pr(i_{nt}) = \Pr\left[U_{nit}(\mathbf{x}_{nit}, \boldsymbol{\theta}, \epsilon_{nit}) \geq U_{nj}(\mathbf{x}_{njt}, \boldsymbol{\theta}, \epsilon_{njt})\right], \qquad \forall i \neq j \tag{1}$$

Now, consider the standard operational conditions for stated choice, and let the vector of attributes relevant to the decision-maker be partitioned in two subsets, one collecting the set of attributes of interest in the experiment $\mathbf{x}^o_{nit}$ and one collecting the additional set that the respondents would contemplate having available to inform real choice, which we denote by $\mathbf{x}^u_{nit}$ along with the attendant partitions of the utility coefficient vectors $\boldsymbol{\theta} = \boldsymbol{\beta}; \boldsymbol{\gamma}$.

We can now rewrite (1) as:

$$\Pr(i_{nt}) = \Pr\left[U_{ni}(\mathbf{x}^o_{nit}, \mathbf{x}^u_{nit}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \epsilon_{nit}) \geq U_{njt}(\mathbf{x}^o_{njt}, \mathbf{x}^u_{njt}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \epsilon_{njt})\right] \quad \forall i \neq j. \tag{2}$$

Adding the common assumptions of additive linearity we can rewrite (2) as:

$$\Pr(i_{nt}) = \Pr\left[\boldsymbol{\beta}'\mathbf{x}^o_{nit} + \boldsymbol{\gamma}'\mathbf{x}^u_{nit} + \epsilon_{nit} \geq \boldsymbol{\beta}'\mathbf{x}^o_{njt} + \boldsymbol{\gamma}'\mathbf{x}^u_{njt} + \epsilon_{njt}\right] \tag{3}$$

$$= \Pr\left[\boldsymbol{\beta}'(\mathbf{x}^o_{nit} - \mathbf{x}^o_{njt}) + \boldsymbol{\gamma}'(\mathbf{x}^u_{nit} - \mathbf{x}^u_{njt}) \geq \Delta\epsilon\right] \tag{4}$$

$$= \Pr\left[\boldsymbol{\beta}'(\Delta\mathbf{x}^o_n) + \boldsymbol{\gamma}'(\Delta\mathbf{x}^u_n) \geq \Delta\epsilon\right], \qquad \forall i \neq j. \tag{5}$$

Suitable assumptions on the distribution of ϵ and hence on $\Delta\epsilon$ makes the model tractable to estimate the taste intensities $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\gamma}}$, but only if both $\Delta\mathbf{x}^u_n$ and $\Delta\mathbf{x}^o_n$ $were$ observable, or if $E\left[\boldsymbol{\gamma}'(\Delta\mathbf{x}^u_n)\right] = 0$, which has little credibility.

In stated choice, however, due to the practical constraints imposed by the need of experimentally designed scenarios, subjects cannot reasonably be expected to receive all the information they would need in an actual choice. Nor can one credibly assume that the subjective expectation on the utility contribution from missing attributes will be nil. So, in stated choice only $\boldsymbol{\beta}'\Delta\mathbf{x}_n^o$ is observable. From the perspective of the analyst both $\boldsymbol{\gamma}'\Delta\mathbf{x}_n^u$ and $\Delta\epsilon$ are stochastic, but from the perspective of the consumer only the former is stochastic, s/he holds a known subjective distribution over $\boldsymbol{\gamma}'\Delta\mathbf{x}_n^u$. By asking respondents to state their subjective probabilities at the moment of stated choice, the researcher can gather useful information on the latter. It therefore makes sense—in principle—for the analyst to ask subjects to reveal their subjective probability of selection of i at time t, rather than making low credibility assumptions about it. The key issue for choice experiment practitioners is whether this additional information is worth the collection effort.

Let the unobservable component of the utility linked to the information that is needed but not supplied in the stated choice be $\boldsymbol{\gamma}'\Delta\mathbf{x}_n^u = \Delta\tilde{\epsilon}_{nit}$. This was termed 'resolvable uncertainty' (Blass et al., 2010), because in actual choice it would dissipate, while in stated choice it may be important. Respondents asked to state a probability of choice will formulate a subjective probability distribution Q_n over $\tilde{\epsilon}_{nit}$, so as to develop an expectation on differences in utility states from the alternatives in the choice set under evaluation, $\Delta\tilde{\epsilon}_{nit}$.

As a consequence, the probability derivation in equation (1) needs to be modified. From the perspective of the analyst the unobservable component of utility must now account for the unobservable component already expected in actual choice ϵ_{ni}, plus the subjective expectation of the respondent $\Delta\tilde{\epsilon}_{nit}$, or $\varepsilon_{nit} = \Delta\tilde{\epsilon}_{nit} + \Delta\epsilon_{nit}$.

Dropping the superscript 'o', the subjective probability of choice can be written as:

$$\Pr(i_{nt}) = q_{nit} = Q_n\left[\Delta\boldsymbol{\beta}'\mathbf{x}_{ni} > \varepsilon_{nit}\right], \qquad \forall i \neq j \tag{6}$$

With incomplete information on choice scenarios, when subjects are asked to state a preferred choice rather than a probability over alternative choices, if the choice probability is defined according to equation (6), the reported selected alternative will be i. However, due to the uncertainty on missing information, what is intended is that $q_{nit} \geq q_{njt} \forall i, j$ and not necessarily that $U_{nit} \geq U_{njt}$, which is true only when the reported value is $q_{nit} = 1$, i.e. only in the case of an extreme subjective probability. In this case clarifying resolvable uncertainty is immaterial regardless of the value of ε. In most cases though, resolvable uncertainty may distribute choice outcomes probabilistically. Which generate a mixture of probabilities of selection across alternatives. In the context of extra-virgin olive oil choice, it would imply that given a certain number of choice occasions, a consumer who is provided with the scenario information will not always make the same selection if faced with the given set of olive oils to choose from. The practical upshot of this is that respondents should be asked to state probabilities of selection

$p_{nt}(i) \in [0,1] \forall i \in J$ rather than—or in addition to— being asked to state preferred choice $y_{nt}(i) = 1$; thereby providing additional information on the nature of ε.

For consistency with the previously elicited preferred choice, we constrain the subsequent statements of subjective probability to be at least as large as 51 percent for the previously selected preferred alternative, so that $q_{jnt}|y_{jnt} = i \geq 0.51$, with $i, j \in J$.

One shortcoming of binary choice is that we do not identify the probability of no-buy. However, we believe this is irrelevant here, since the main focus of our study is on resolvable and epistemic uncertainty. The main consequence of not having the no-buy option is failure to identify minimum price or minimum quality thresholds triggering purchase behaviour, but in this study we are not evaluating this type of behavioural inference across models. Instead, we focus on comparisons of estimates for marginal probabilities of selection and marginal WTPs, which are less dependent on opt-out probabilities.

Hypotheses rationale

Hypothesis 1: same preferences for extreme and intermediate elicited probabilities

A first research question is whether under the standard assumptions of RU maximization of the logit model the preference structure underlying *preferred choice responses*—consistent only with extreme subjective probabilities of 0 and 1—is the same as the preference structure underlying *fractional responses* derived from subjective probabilities. We are unaware of food choice studies having tested such an hypothesis before. Failing to reject the null of no difference would suggest that the additional effort of collecting subjective choice probabilities can be avoided, at least in low-cognitive effort food choice experiments.

Hypothesis 2: robustness of behavioural quantities to near-epistemic elicited probabilities

Findings from the psychology literature suggest a further question: they warn us that not all probability statements have their numerically intended meaning. Near equi-probabable statements might need to be taken with a 'pinch of salt'. Specifically, in a binary context, values of 50-50%, or thereabout, might express epistemic uncertainty, rather than the intended numerical evaluation of a subjective probability of selection. In our analysis we evaluate the sensitivity of our estimates of marginal willingness to pay for olive oil attributes and marginal effects on choice probabilities to the presence of these potentially highly uncertain probability statements. The hypothesis *implicitly* held by practitioners in standard models of preferred choice is that results are robust to the presence of such near equi-probable subjective probabilities. But this hypothesis is rarely tested *explicitly* in choice experiments. If it is rejected it would suggest that the practice of collecting subjective probabilities during survey is worthwhile.

Hypothesis 3: socio-economic determinants of presence and counts of near-epistemic probabilities and rounding behaviour

We focus on explaining the *presence* and *counts* of potentially near-epistemic observations within the panel of T probability statements elicited from each respondent. Our hypothesis is that specific consumer profiles are more prone than others to express near equi-probable subjective choice probabilities or to engage in rounding to multiple of five and ten percent points (Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*). We have also explored the determinants of systematic rounding behaviour along the entire sequence of responses, but we report these results in the on-line appendix.

Hypothesis 4: determinants of near-epistemic presence and counts as determinants of choice variance

A corollary to the previous question is whether the determinants of near-epistemic responses and their counts are also responsible for increased choice uncertainty (or degree of choice discretion, according to the terminology used by Swait and Erdem (2007)) in the RU model explaining choice. The underlying hypothesis is that the determinants of near-epistemic uncertainty may also affect scale (variance) of the residual RU component in choice analysis (see for example Scarpa et al., 2003, for an early application addressing variance directly, instead of scale). If a positive effect is found for both the number of epistemic probabilities and the increase in Gumbel error variance, then it might be surmised that the additional information provided by subjective probability is not worth persuing because it is not separate from Gumbel variance. Therefore the standard use in choice experiment practice of heteroskedastic models of choice should suffice.

Models and tests

Behavioural quantities

Under the assumptions of binary choice and a linear-in-the-parameters utility function the values of utility coefficients are uninformative. So, to be practical, in our models we focus on behavioural quantities. The first such quantity of our interest is the marginal effect on predicted probability of choice:

$$\frac{\partial \Pr(i)}{\partial x_k} = \beta_k \Lambda(\hat{\boldsymbol{\beta}}'\mathbf{x}_{nt})(1 - \Lambda(\hat{\boldsymbol{\beta}}'\mathbf{x}_{nt})), \tag{7}$$

note that these can be either evaluated at the sample means of attributes, or predicted for each choice observed in the sample, so as to have sample values. The latter should give a better representation of the sample variance of such quantities, by comparing the sample statistics of relevance, such as mean, median and standard deviation.

A second behavioural quantity of interest is the marginal willingness to pay for each attribute:

$$\widehat{WTP}_k = -\frac{\frac{\partial U}{\partial x_k}}{\frac{\partial U}{\partial x_{cost}}} = -\frac{\hat{\beta}_k}{\hat{\beta}_{cost}} \tag{8}$$

We use fixed coefficient RU models, so these quantities are population estimates.

Testing hypothesis 1

Consider a standard binary choice set with two olive oil bottles differing qualitatively as described by a vector of attributes $\mathbf{x}_i, i = 1,2$ and with preferred choice data $y_{nit} = 1$ or 0. Such discrete response data can be analysed by means of a standard binary logit model (BLGT) and interpreted under the conventional RU maximization theory assumptions. However, in our case we also elicit subjective choice probabilities $q_{nit} \in [0,1]$, and we observe $q_{nit} \in (0,1)$ as well as $q_{nit} = 0$ or 1. We know that only when the latter occur y_{nit} and q_{nit} coincide. So, one can test hypothesis 1, i.e. whether preference are the same for respondents reporting extreme subjective probabilities of 1 or 0, as for respondents expressing intermediate probabilities $q_{nit} \in (0,1)$ because of subjective unresolved uncertainty. Under these assumptions the utility component is i.i.d. Gumbel, and refers to the respondent's subjective distribution over the idiosyncratic utility component, which is now unknown to the respondent as well as to the econometrician.

This would test the formal hypotheses of:

$$\begin{cases} H_0^a : \boldsymbol{\beta}|y, 1\left(q = 0 \text{ or } 1\right) = \boldsymbol{\beta}|y, q \in [0,1] \\ H_A^a : \boldsymbol{\beta}|y, 1\left(q = 0 \text{ or } 1\right) \neq \boldsymbol{\beta}|y, q \in [0,1], \end{cases} \tag{9}$$

$$\begin{cases} H_0^b : \boldsymbol{\beta}|y, 1\left(q \in (0,1)\right) = \boldsymbol{\beta}|y, q \in [0,1] \\ H_A^b : \boldsymbol{\beta}|y, 1\left(q \in (0,1)\right) \neq \boldsymbol{\beta}|y, q \in [0,1], \end{cases} \tag{10}$$

both of which can be tested in two ways using the maximum likelihood estimator.

A straightforward test can be conducted using the method discussed by Swait and Louviere (1993) and based on two independent binary logit model estimates, one with the other without restrictions on the utility coefficients. This approach allows for difference in taste and Gumbel variance across the two sub-samples: one with corner and the other with interior subjective probabilities. Each of these will be an unbalanced panel because, in general, a respondent might have answered with an interior probability to some questions and with a corner probability to others.

The sum of the two log-likelihood values at convergence gives the unrestricted sample log-likelihood $\mathscr{L}^U_{q\in[1,0]} = \mathscr{L}_{q=(1 \text{ or } 0)} + \mathscr{L}_{q\in(1,0)}$, while the restricted $\mathscr{L}^R$ can be obtained by a heteroskedastic logit in which $\lambda = \exp(\alpha \times 1(y_{nit} = 1 \text{ or } 0))$ to account for scale differences across sub-samples while constraining $\boldsymbol{\beta}$ to be the same. The test has a statistic of $2(\mathscr{L}^R - \mathscr{L}^U)$ which is distributed χ^2_k, where k is the number of elements in $\boldsymbol{\beta}$.

Given the different informational interpretation of the idiosyncratic utility components across corner versus interior respondents, a significant difference between the two sets of respondents would suggest a difference in estimated preferences and their behavioural effects. Practitioners of choice experiments should therefore be alerted to this potential discrepancy, and investigate it further in other studies.

This test can be extended to models estimated on the basis of other splits in the values of q. For instance, the near-epistemic (e.g. $1(q \in (0.42, 0.58))$) or central probability scores (e.g. $1(q \in [0.25, 0.75])$) and their respective complements.

Testing hypothesis 2 under various assumptions

If one is willing to assume identical scale parameters (and hence error variance) in both near-epistemic and other probabilities an alternative test can be performed. This is based on a BLGT model on the entire sample which includes interaction terms between near-epistemic responses and attributes. We call this the BLGT_inter model. The advantage of this approach is that for each attribute one can evaluate the significance of marginal effects and difference in mWTPs from interactions with different ranges of near-epistemic probabilities.

Yet another approach can be used, by focussing on odd-ratios from fractional responses q_{nit}, as reported in the subjective probability of selection of olive oil i by consumer n at choice task t. Without loss of generality we use $q_{njt} = 1 - q_{nit}$ as a baseline for the odd-ratios. In our binary context, linear probability specifications can be used to consistently estimate $\boldsymbol{\beta}$ by OLS if $\boldsymbol{\beta}'\mathbf{x}_i \in [0,1] \forall i$. But this estimator suffers from error heteroskedasticity and inadmissible probability value forecast, as it admits $\hat{y}_{nit} \notin [0,1]$.

On the other hand, linear mean models of logs of the odd-ratios, such as:

$$\ln\left[\frac{q_{nit}}{1 - q_{nit}}\right] = \boldsymbol{\beta}'\Delta\mathbf{x}_{nit} + \varepsilon_{nit} \tag{11}$$

are also problematic for extreme probability values of $q_{nit} = 0$ or $q_{nit} = 1$. These are often focal rounding values for high or low q_{nit}. Such values fail the OLS estimator conditions as division by zero is infeasible.

Assuming a symmetric distribution of preferences around the true value of $\boldsymbol{\beta}$ only implies an error distribution with zero median regardless of the shape of the distribution at either side of zero. Then one can use the linear *median* regression (conditional on $\mathbf{x}$):

$$M\left[\ln\left(\frac{q_{nit}}{1 - q_{nit}}|\mathbf{x}\right)\right] = M\left(\boldsymbol{\beta}'\mathbf{x}_{ni}\right) + M(\varepsilon_{nit}) = \boldsymbol{\beta}'\mathbf{x}_{nit}. \tag{12}$$

Unlike the linear *mean* regression, the above provides a consistent estimator of $\boldsymbol{\beta}$ even in the presence of extreme values of 1 and 0, when these are substituted for by values close to zero or one (e.g. 0.001 and 0.999). This model can be estimated by quantile regression accounting for the panel nature of the data (Powell, 2014) using a Least Absolute Deviation regression (LADR). The estimates of $\hat{\boldsymbol{\beta}}$ in this case are the centre of symmetry of the preference distribution, rather than the means; a difference that is important to consider when distributions are skewed (Balcombe et al., 2009).

Another useful approach starts from the assumptions of

$$E(q_{nit}|\mathbf{x}_{nit},\boldsymbol{\beta}) = \Lambda(\boldsymbol{\beta}'\mathbf{x}_{nit}) = \left[1+\exp(-\boldsymbol{\beta}'\mathbf{x}_{nit})\right]^{-1} \tag{13}$$

$$Var(q_{nit}|\mathbf{x},\boldsymbol{\beta},\sigma^2) = \sigma^2\Lambda(\boldsymbol{\beta}'\mathbf{x}_{nit}) = \sigma^2\left[1+\exp(-\boldsymbol{\beta}'\mathbf{x}_{nit})\right]^{-1}, \tag{14}$$

which underlie the fractional response binary logit (FLGT) model (Papke and Wooldridge, 1996). This is interesting as it is an immediate extension of the standard logit model with likelihood:

$$\mathscr{L}_n = \sum_n \ln\left[\prod_t \left[\Lambda(\boldsymbol{\beta}'\mathbf{x}_{nit})^{q_{nit}} \times (1-\Lambda(\boldsymbol{\beta}'\mathbf{x}_{nit}))^{(1-q_{nit})}\right]\right], \tag{15}$$

with the only difference that the response variable is $q_{nit} \in [0,1]$, rather than being $y_{nit} = 0$ or 1 (i.e. fractional rather than discrete).

To explore the effect of fractional responses displaying near-epistemic uncertainty on the quantities in eq.(7) and (8), we contrast these quantities across models estimated on the full sample $\mathscr{M}$, and on samples in which these responses have been removed in gradually larger numbers $\mathscr{M}'$ (e.g. by first removing probability responses $q_{int} \in [48,52]$, then $q_{int} \in [46,54]$ and finally $q_{int} \in [42,58]$). We do not advocate dropping these observations in routine analyses. We do so here to test the effects of dropping uncertain choice observations and evaluate these effects under different specifications (e.g. binary logit, LADR and fractional logit) and in terms of fit of the models to the data and stability of significant coefficients.

Our choice data analysis is conducted by invoking different assumptions and using different response formats. The BLGT uses discrete $y_{int} = 0$ or 1 responses and invokes i.i.d. Gumbel errors, while the LADR and fractional logit use $q_{int} \in [0,1]$. The LADR assumes median independence, while the FLGT assumes a logit expected subjective probability as well as a logit variance, but all share the linear in the coefficient utility assumption. So, comparing the same model across specifications we can explore whether the effect of these assumptions matters.

In general the formal hypothesis under investigation in this case is that:

$$\begin{cases} H_0^c : f(\boldsymbol{\beta}|\mathscr{M}) = f(\boldsymbol{\beta}|\mathscr{M}') \\ H_A^c : f(\boldsymbol{\beta}|\mathscr{M}) \neq f(\boldsymbol{\beta}|\mathscr{M}'), \end{cases} \tag{16}$$

where $\mathscr{M}' \in \mathscr{M}$, as $\mathscr{M}'$ defines the adequately reduced sample from which epistemic observations have been removed and $\mathscr{M}$ the full sample; while $f(\boldsymbol{\beta})$ is the behavioural function of reference in eq.(7) or eq.(8). These hypotheses can be tested using various approaches. For example, formal tests on the significance of the difference across distributions of eq.(7) can be conducted using the Kolmogorov-Smirnov (Kolmogorov, 1933; Smirnov, 1948) and the Cramér-von Mises non-parametric tests (Cramér, 1928; von Mises, 1928). The specific hypothesis to test is that the sample distributions of the quantities in equation (7) with reference to alternative 1 differ significantly when fitted using $\hat{\boldsymbol{\beta}}$ estimated by dropping epistemic probabilities. Similarly, for differences between $\Delta\widehat{WTP}_k|\mathscr{M},\mathscr{M}'$, one can use various tests (e.g. Krinsky and Robb, 1986, 1990; Poe et al., 1994; Dorfman, 1938).

Testing hypothesis 3

To explain the count of near-epistemic subjective probabilities in the sequence of $T = 10$ choice statements collected from each respondent we tested several zero-inflated count models. The inflation factor is necessary because count models do not otherwise accommodate the large frequency of observed zeros (see figure 3). Letting $f(\cdot)$ be a count distribution (Poisson or Negative Binomial) with expectation:

$$\mu = \exp(\boldsymbol{\delta}'\mathbf{s}), \tag{17}$$

and zero inflation factor:

$$\pi = \Lambda(\boldsymbol{\theta}'\mathbf{z}) = \left[1 + \exp(\boldsymbol{\theta}'\mathbf{z})\right]^{-1}. \tag{18}$$

Note that the zero inflation is shared by both processes, while the positive count is only a count process $f(y|\mu,\cdot)$:

$$\Pr(Y = y) = \begin{cases} \pi + (1-\pi) f(y = 0|\mu,\cdot), & y = 0 \\ (1-\pi) f(y > 0|\mu,\cdot), & y = 1,2,3,\ldots \end{cases} \tag{19}$$

Our specification search over several count processes finds that the Negative Binomial provides the best fit, so in our case:

$$f(y_{nt}|\mu,\cdot) = \Pr(Y = y_{nt}|\mu,\alpha) = \frac{\Gamma(y_{nt} + \alpha^{-1})\left(1+\alpha\mu\right)^{-1/\alpha}}{\Gamma(\alpha^{-1})\Gamma(y_{nt}+1)} \left(\frac{\alpha\mu}{1+\alpha\mu}\right)^{y_{nt}} \tag{20}$$

The hypothesis under investigation here is that high counts of epistemic responses in the sequence can be plausibly explained by standard socio-economic observables. Although better predictors can obviously be collected from attitudinal questions and other consumer experience self-reports, we are keen to explore the effects of demographics commonly used in consumer surveys.

Testing hypothesis 4

Finally, to test whether the effects of determinants of epistemic responses **s** in eq. (17) also play a significant role in explaining heteroskedasticity in choice, as suggested by other studies dealing with uncertainty in choice (Scarpa et al., 2003; Lundhede et al., 2009, 2015; Kassahun et al., 2016), we use a heteroskedastic conditional logit model:

$$\Pr(j) = \frac{\exp(\lambda \boldsymbol{\beta}' \mathbf{x})}{\sum_j \exp(\lambda \boldsymbol{\beta}' \mathbf{x})}, \tag{21}$$

with exponential scale factor $\lambda = \exp(\boldsymbol{\delta}' \mathbf{s})$.

All estimations are conducted by maximizing the sample likelihoods or quasi-likelihoods using Stata. The final hypothesis under investigation is that the determinants in **z** or **s** related to high or zero epistemic scores from the count model in eq.(19) are also significant as determinants of error scale variation in eq.(21).

Survey and data

Italy has traditionally been amongst the most world-renown suppliers of quality extra virgin olive oil. In 2017 it held about 60% of the German olive oil market share. In 2014 Germany was the second importer of extra virgin olive oil from Italy, ranking below the United States. Subjective probabilities for selection of bottles of Italian olive oil were elicited from a sample of German olive oil consumers after recording their preferred choices. A questionnaire was administered online to a sample provided by a reputable market research firm in September 2015.[2] The firm rewarded respondent participation with reward points convertible into prizes or money.

A screening question was used to select only consumers of olive oil to be part of the sample. A quota target of 1,000 respondents was set, and a final sample of 1,008 respondents was obtained. Although representativeness is not a key factor in this behavioural study, the sample is representative of the German population in terms of gender and age quotas (DESTATIS, 2016). The descriptive statistics of the socio-demographic characteristics of the sample are reported in Table A1 (online).

Figure 1 (online) shows an example of choice task. Ten choice tasks were answered by each respondent,

[2] The data was released only recently after a period of embargo for use in academic research.

each choice task presented two 500 ml bottles of Italian extra virgin olive oil. Respondents were asked to first choose which of the two bottles they preferred to buy and then to state their subjective choice probability for the selected bottle by expressing a probability equal to or larger than 51%. Specifically, the preference elicitation was introduced as follows:

> *"Imagine being in a supermarket and intending to buy a 500 ml bottle of Italian extra virgin olive oil to be used to prepare your meals. We will show you ten scenarios, each including two bottles of extra virgin olive oil. In each group, please choose the bottle you prefer. Then, please evaluate what is your effective probability of choosing the bottle you indicated as your preferred one. Probability should be expressed as a number from 51 to 100. For example: if you give a score of 51, it means that if you were to make the same choice for 100 times, you would prefer your selected bottle 51 times, and that means that your preference is not strong. If you give a score of 100, it means that your preference is strong and you would always choose that bottle."*

Olive oil attributes and their levels, profiling different types of olive oil, were derived from previous stated preference studies for olive oil (Ward et al., 2003; Scarpa and Del Giudice, 2004; Krystallis and Ness, 2005; Dekhili and d'Hauteville, 2009; Chan-Halbrendt et al., 2010; Dekhili et al., 2011; Menapace et al., 2011; Aprile et al., 2012). Attributes and levels are listed in Table 1.

The ten choice tasks allocated to each respondent were constructed by allocating attribute levels by means of an unlabelled experimental design optimal orthogonal in the differences (OOD) (Street et al., 2005). It produced 100 choice tasks, which were blocked in ten orthogonal blocks. To avoid ordering effects related to fatigue or learning, choice tasks were randomly presented to respondents.

Results and discussion

A histogram of the distribution of the 10,080 statements of subjective choice probability for alternative 1 is plotted in Figure 2 (online). We observe that the elicited probabilities data cluster around 'focal' values, i.e. 0, 100, or 50 percent. The tendency of respondents to report subjective probabilities in rounded form of multiples of 10 percent and, to a lower extent, of 5 percent manifests clearly in our sample. Such results are consistent with the findings reported in seminal studies (Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*).

Results for hypothesis 1: same preferences for extreme and intermediate elicited probabilities

The BLGT fitted to extreme choice probabilities gives $\mathscr{L}_{y=1\mathrm{or}0} = -801$, while fitting it to the sub-sample with interior probabilities gives $\mathscr{L}_{y\in(1,0)} = -4534$, giving an unrestricted fit of -5335. The restricted model fitted to the pooled sample gives a value of $\mathscr{L}^R = -5346$. So, the $2(\mathscr{L}^R - \mathscr{L}^U) = 19$, which is distributed χ^2_{13} with p-value = 0.123. The data reject the null hypothesis of same coefficients across extreme and fractional probability responses only if we hold a confidence on the test higher than 88 percent, but not at lower confidence. The marginality of this result cautions us against a complete dismissal of the potential difference in utility structure from the two categories of responses.

Results for hypothesis 2: robustness of behavioural quantities to near-epistemic elicited probabilities

In tables 2, 3, 4 and 5 we report the estimates for various model specifications suitable to evaluate hypothesis 2.

The first is the binomial logit (BLGT) from discrete responses. The following two are from fractional responses: the least absolute deviation regression (LADR) and fractional logit models (FLGT), respectively. The last is also a binomial logit model from discrete response (BLGT_inter), but it focusses on interaction effects from pooled samples, rather than on their gradual removal. The first three models are estimated by gradually removing a wider interval of central probabilities and exploring what such removals imply for behavioural estimates. To ease comparison, rather than reporting coefficient estimates (available in the online Appendix) we report the sample statistics of the behavioural effects implied by each model: the marginal probabilities and the marginal WTP estimates. This because these quantities are comparable across models, while coefficients are confounded by scale. To address the issue of dependence of choice probabilities by the same respondent, all z-values are derived from standard errors corrected clustered by respondent.

In tables 2, 3 and 4 the number of observations varies from the left to the right model, as increasingly larger sets of observations with near epistemic subjective probabilities are dropped, making the panel unbalanced, and reducing the number of respondents in the sample. The leftmost pair of columns describe results of a model with all responses, while the second pair of columns include results from a model estimated on a reduced sample, having dropped 1,311 responses (13.0% of the total) whose subjective probabilities are within a the range 0.48–0.52 inclusive. The third and fourth models increased the exclusion range to wider intervals: to 0.46–0.54 and 0.42–0.58, dropping 1,421 (14.1%) and 1,988 (19.7%) responses, respectively. If epistemic responses are uncorrelated with marginal selection probabilities and marginal WTPs, then these should not be affected and the fit of the model should remain stable. Conversely, if they are correlated with attribute differences, then behavioural estimates should change as more epistemic observations are dropped.

Signs, relative magnitudes and statistical significance of the investigated attributes are mostly stable across model specifications, type of response variables and to the exclusion of epistemic responses. The only exception being that the mWTP for Chianti Classico is always significant only in the FLGT model, but in the BLGT model it is significant only when the broadest set of epistemic responses have been removed. In this model the mWTP for Veneto Valpolicella is also significant and is insignificant elsewhere. We note that the LADR model is completely stable across all levels of removal of near epistemic responses.

The price coefficient (unreported) was highly significant and negative across all models. German buyers significantly like the display of the Italian flag on the label, and significantly dislike the traditional bottle shape in favour of the modern shape. Yet, these attributes have moderate effects on marginal probabilities and marginal WTPs. Stronger positive and significant effects emerge for the four types of production processes, with organic production and cold-press extraction being particularly high, and not too far behind CO_2 reduction and hand-picking of olives. Confidence intervals for all the significant marginal WTPs for attributes largely overlap, across models and specifications. We know this to be a restrictive test of equality, so other approaches based on bootstrapping (parametrically or empirically) to approximate the asymptotic sampling distribution (e.g. Krinsky and Robb, 1986, 1990; Poe et al., 1994) or on the delta method (Dorfman, 1938) would also fail to reject the null of no difference across WTPs.

It is noteworthy that as the dependent variable turns from a discrete outcome (BLGT) to a fractional response (LADR and FLGT) the point estimates of mWTP decrease. The LADR models provide lowest point estimates, possibly because of their emphasis on the median rather than expectation, which should attenuate the common fat tail effects. Finally, table 5 reports the marginal effects at the averages from the RU model with interactions between attributes and central probability scores. As can be seen from the values in the upper part of the table, the main effects are quite stable across ranges of central probabilities. The only interaction effect of significance across all ranges of the central probabilities are the positive constant and the positive interaction for the Chianti classico origin. This latter interaction effect has a magnitude that changes the net sign of the total effect in this set of central probabilities. Both imply higher utility. In the rightmost column, for the interactions with the wider range of $(0.42-0.58)$, we also observe a significant and positive effect for price (implying a very slightly higher marginal utility of income) and for the traditional bottle. Altogether, in the wider central probability range, the results suggest that scores are associated with a rather minor difference in preferences for money, Chianti origin and traditional bottle shape, and with lower significance for the Valpolicella origin. Overall we cannot reject the null of no difference across behavioural quantities, models and ranges of exclusion of observations with near-epistemic probabilities.

Results for hypothesis 3: determinants of counts and presence of near epistemic responses

Figure 3 (online) illustrates the predictions $\hat{y}^c$ of several count data models for the count of central probabilities in the sequence of T choice probabilities by respondent n. There is a slight mis-match between predicted and observed at $y_n = 10$, which is due to a small degree of systematic near epistemic reporting, an aspect we chose not to explore further in this instance, but might be worth investigating in future studies. In terms of squared departure of predictions to the observed values, the zero-inflated Negative Binomial (ZINB) performs best, so we only report its estimates in model ziNB 1 of table 6. We note that using a truncated distribution at maximum value of ten did not change the results. In this exploratory regression we use demographic variables that are most likely to be available to market research firms, since we lack a specific explanatory theory justifying the use of other variables.

The count is significantly and positively affected by respondents self-reporting as 'never' having visited any of the areas of olive oil production (as suggested by Alamanos et al., 2016) and by a square function of age. The age effect is positive overall and peaks at age 53. Being a man (52 percent of the sample), instead, has an insignificant effect on the count equation, yet it is positive and significant in the zero inflation factor, and this manifests itself in a very significant and negative marginal effect on $\hat{y}^c$. This suggests that men report systematically fewer subjective probabilities in the near epistemic range than women: men report their preferences as more certain.

To better understand the effects of determinants on the number of near epistemic responses, we illustrate the predictions for responses of $y \in [0.46, 0.54]$ from model ziNB1 for two ages (30 and 60 year old) and for the extreme points of the scale used for frequency of consumption (in a scale from 1 to 7). These are reported in table 7, inclusive of the inflation factor and of all variables, independently of their significance. Rows alternate man and woman predictions to ease comparison across genders. For all profiles the median probability is always zero (see the column $\widehat{\Pr}(y_n = 0)$, which combines the predicted zero inflation probability with the one predicted by the count model), except for 60 year old women who reported low frequency of consumption. Particularly high probabilities of zero epistemic counts are predicted for 30 year old men, especially when they self-report high frequency of purchase, and regardless of whether they visited the production of origin sites (over 70%). This would suggest that more experienced consumers of olive oil tend to be less inclined to produce epistemic probability responses: a plausible result, but the coefficient estimate was insignificant in both equations in the model.

Because rounding behaviour is so prevalent, the last two models in table 6 focus on explaining counts of *un*rounded probabilities in the individual sequence of responses (see figure 4 online). Model ziNB2 explains the total count of *un*rounded probability statements (y_n). Had the fifty-fifty option been made available, statements of 49 and 51% might have been fifty-fifty and hence could count as rounded statements. Model ziNB3 explains the count of *un*rounded probability statements with 49 and 51% statements removed, to check the sensitivity of ziNB2 results to these very central probabilities. In terms of marginal effects only being a man significantly affects this count, while once the 49 and 51% counts are removed, age and education are found to be significant in increasing rounded responses. This is in keeping with previous results (Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*).

Results for hypothesis 4: determinants of near-epistemic counts and presence as determinants of choice variance

The middle part of table 8, under the heading of 'scale variables' reports the estimates for the parameter vector $\hat{\boldsymbol{\delta}}$ as estimated from the discrete choice responses. Scale is inversely proportional to Gumbel error variance.

In previous models being a man decreased the probability of near-epistemic central probabilities in the zero-inflated count models, and increased the probability of rounding. In this model it does not show a significant effect on scale. On the other hand, higher frequency of purchase, which is insignificant in the zero-inflated count models, is found to consistently increase error variance. This implies that respondents reporting frequent olive oil consumption have lower choice determinacy, perhaps because they have higher scope for resolvable uncertainty due to their comparatively broader experience.

Gumbel error variance significantly decreases with age, showing highest determinacy at age 44, despite being older increasing the number of epistemic subjective probabilities in the zero-inflated count models. This effect is robust to the removal of epistemic observations. The contrasting directions of these effects between count models and heteroschedastic logit suggest that choice variance and epistemic probabilities are quite separate phenomena.

Having never visited the sites of origin of extra-virgin olive oils also decreases choice variance, but it has only a marginal statistical significance and only in the sample with central probabilities. Nevertheless, it is consistent with lower resolvable uncertainty, and a higher reliance on information provided in the choice experiment scenario, rather than on externally sourced information.

Moving the attention to the point estimates of marginal WTPs we note how these are lower than those derived from the standard BLGT in table (2), and more aligned with those from the LADR and FLGT. However, the confidence intervals widely overlap, suggesting that the differences are statistically insignificant.

Overall these results suggest that near-epistemic uncertainty does not share the same determinants with choice uncertainty, and support the hypotheses of the two types of uncertainty being distinct and therefore worthwhile exloring in their own rights.

Conclusions and further research

We elicited preferred choices of bottles of extra virgin olive oil in a stated preference experiment. Respondents first stated their preferred alternative and then were asked for the subjective probabilites of their choice. This allowed us to focus on modelling the effects of unresolvable and near-epistemic (close to %50) uncertainty, as well as rounding behaviour. Resolvable uncertainty is due to the mismatch of information made available at the moment in which subjects are asked their preferred choice in the survey and the information subjects expect to have when making real purchases. Such a mismatch is quite pervasive in stated preference studies of hypothetical purchase decisions (Manski, 2004; Manski and Molinari, 2010; Blass et al., 2010). Our focus on near-epistemic uncertainty, instead, was inspired by the recent and authoritative call to research action made by Bruine de Bruin and Fischhoff (2017) and Manski (2017). Finally, rounding behaviour in subjective probabilities has been highlighted by previous seminal studies by (Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*).

Apart from the substantive policy conclusions regarding what drives German consumers in their choice of extra-virgin olive oil produced in Italy, we can draw three main methodological conclusions in relation to epistemic and resolvable uncertainty.

Firstly, the hypothesis that there exist differences in the underlying preference structure between subjective probabilities of choice with extreme values of zero and one and those derived from intermediate probabilities, cannot be rejected with high confidence, but only at relatively low confidence (< 88%). This suggests that resolvable uncertainty, in as much as it is captured by subjective probabilities and ignored by preferred choice, may matter. So, further research should be undertaken to clarify its role. Choice experiment practitioners intending to explore this further should consider asking additional follow-up questions after asking the preferred choice alternative.

Secondly, we move the focus to whether the preference differences are such that they can impact behavioural quantities, such as marginal effects and WTPs. Using various specifications, identification and gradual removal of fractional responses potentially linked to near-epistemic uncertainty (i.e. those around 42-58% interval are about 19.7% of the total) does not seem to affect the robustness of significant utility coefficient attributes, nor the fit of standard choice models. No significant differences are detected in terms of marginal probability effects at the sample statistics level, nor for the average marginal willingness to pay estimates. It would therefore appear that identifying and excluding these observations does not significanly affect commonly used behavioural quantities. Choice experiment practitioners should hence feel reassured of the robustness of the conventional approach based on preferred choice and random utility maximization.

Our results on behavioural inference are similar to those obtained in other stated preference experiments based on subjective probabilities. For example, Pedersen et al. (2019) study choice of first employment by senior medical students. For these subjects the consequences of a wrong decisions are more serious than buying the wrong bottle of olive oil, and they presumably have better average numeracy skills than in our sample. However, the scope for the amount of information asymmetry between stated and real choice is comparatively larger and hence the scope for resolvable uncertainty stronger.

Moreover, our results might differ slightly from those in Pedersen et al. (2019) since the authors used a slider to elicit subjective probabilities, while we implemented an open-ended question. de Bruin and Carman (2018) observed that fifty percent (epistemic) responses were significantly reduced when a slider (especially a clickable slider) was used relative to the traditional open-ended mode, and this might have affected our data. Nevertheless, the joint empirical evidence of the present study and that by Pedersen et al. (2019) suggests that if the goal is forecasting marginal effects or mWTP then ignoring resolvable and epistemic uncertainty may well not be a problem.

Thirdly, we use standard socio-economic covariates for consumers as determinants of presence and counts of epistemic uncertainty statements. Apart from age, the explored determinants while behaviourally plausible in their signs—especially for frequency of consumption—do not always induce effects in a similar direction on choice uncertainty as measured by Gumbel error scale in a heteroskedastic binary logit model. Hence, epistemic uncertainty does not seem to share the same determinants with choice uncertainty. This suggests that a more sophisticated investigation of the causes of uncertainty in food choice might well benefit from the collection of subjective probability statements, and by addressing the two issues separately.

Finally, we find rounding behaviour and tendency to express central probabilities to be prevalent and explained by gender, age and to a certain extent education level. This confirms the results of seminal works on this issue.

In conclusion, eliciting subjective probabilities, along with preferred choices of olive oils might well have a low informational value at conventional sample sizes. This might plausibly extend to decisions requiring low cognitive burdens, such as stated food choices. Confirmation from future studies of this initial finding of robustness will increase the validity of stated choice experiments. In essence, the issue of near-epistemic uncertainty might be less of a concern to economists using choice experiments to derive behavioural quantities than it is to psychologists. However, this finding might also be due to a limitation of our study as we could not elicit proper fifty-fifty responses, but only responses in that proximity. Thus, future studies may consider using survey methods to reveal specifically the 'fifty-fifty' responses, so as to be correctly interpreted as 'pure' rather than 'near'-epistemic uncertainty as conceptualized in Fischhoff and Bruine de Bruin (1999) and Bruine de Bruin et al. (2002). While our results support the current state of practice, they also provide practitioners with methods to identify whether resolvable and epistemic uncertainty might be a problem in their stated preference data. The methods used here will increase the range of available tools to evaluate the validity of stated preference data in a manner that aligns our discipline with issues that currently concern psychologists, paving the way for better interdisciplinary efforts and broader validity of analytical results.

We obviously need to acknowledge the several limitations of our study. For example, our neglect of modelling unobserved preference variation across respondents, and the administration of the survey on-line to a panel of respondents, rather than in-person and to a sample extracted from a better sampling frame than the panel of the on-line data provider. Both of these have well-known shortcomings in terms of external validity of results. We nevertheless think we have provided a detailed and novel econometric approach to conceptually important behavioural issues that have hitherto received scant attention in food choice. This despite their being pervasive in the practice of stated preference experiments and central to much empirical research in psychology. These conclusions can only be strengthened and extended by research bringing these questions to the realm of revealed preference under adequate experimental conditions.

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Tables

Table 1: Attributes and levels of the experimental design

Attributes	Levels
Protected Designation of Origin	None (100 % Italian)
	Chianti Classico PDO
	Veneto Valpolicella PDO
	Garda PDO
	Riviera Ligure PDO
Bottle shape	Traditional / Modern
Production process	No information
	Organic production
	Reduction of CO_2 emissions
	Cold pressing
	Hand-picked olives
Sensorial profile	Delicate taste/Strong taste
Italian flag	Present/ Absent
Price in €	9.99, 12.49, 14.99, 17.49, 19.99

Table 2: Behavioural estimates from BLGT models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
	$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$	
Utility Attribute	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.
Italian flag	1.184	0.196	1.188	0.210	1.188	0.211	1.178	0.215
Chianti Classico	−1.161	0.192	−1.165	0.206	−1.165	0.207	−1.155	0.211
Garda	−0.348	0.058	−0.349	0.062	−0.349	0.062	−0.346	0.063
Ligurian coast	−0.230	0.038	−0.231	0.041	−0.231	0.041	−0.229	0.042
Veneto Valpolicella	0.244	0.040	0.244	0.043	0.244	0.043	0.242	0.044
Trad. Bottle	−0.954	0.158	−0.957	0.169	−0.957	0.170	−0.949	0.173
Organic logo	6.990	1.157	7.012	1.238	7.013	1.244	6.954	1.269
CO_2 reduction	3.115	0.516	3.125	0.552	3.125	0.554	3.099	0.565
Cold-pressed	6.967	1.153	6.989	1.234	6.989	1.240	6.931	1.264
Hand-picked	5.782	0.957	5.800	1.024	5.800	1.029	5.752	1.049
Delicate	0.414	0.069	0.415	0.073	0.415	0.074	0.412	0.075
Price	−1.899	0.314	−1.905	0.336	−1.905	0.338	−1.889	0.345
Constant	3.457	0.572	3.468	0.612	3.468	0.615	3.439	0.627
$m\widehat{WTP}$	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean.	95% Conf. Int.
Italian flag	0.816***	0.53, 1.11	0.766***	0.47, 1.06	0.766***	0.47, 1.07	0.710***	0.40, 1.02
Chianti Classico	−0.313	−0.88, 0.25	−0.558	−1.15, 0.03	−0.542	−1.13, 0.05	−0.611*	−1.21, −0.01
Garda	0.345	−0.31, 1.00	0.134	−0.54, 0.81	0.112	−0.56, 0.79	0.254	−0.45, 0.95
Ligurian coast	0.251	−0.46, 0.96	0.003	−0.73, 0.74	0.036	−0.70, 0.78	0.164	−0.60, 0.92
Veneto Valpolicella	0.449	−0.10, 1.00	0.523	−0.05, 1.10	0.567	−0.01, 1.15	0.655**	0.06, 1.25
Trad. Bottle	−0.483**	−0.83, −0.14	−0.459*	−0.81, −0.10	−0.494**	−0.85, −0.14	−0.599**	−0.96, −0.24
Organic logo	3.911***	3.21, 4.61	3.962***	3.24, 4.69	3.945***	3.22, 4.67	3.915***	3.17, 4.66
CO_2 reduction	2.049***	1.50, 2.60	2.136***	1.57, 2.70	2.141***	1.57, 2.71	2.107***	1.52, 2.69
Cold-pressed	4.625***	3.81, 5.44	4.553***	3.70, 5.41	4.505***	3.64, 5.37	4.340***	3.47, 5.21
Hand-picked	3.838***	3.09, 4.59	3.845***	3.06, 4.63	3.837***	3.05, 4.63	3.782***	2.98, 4.58
Delicate	0.182	−0.13, 0.49	0.208	−0.11, 0.53	0.191	−0.13, 0.51	0.242	−0.08, 0.57
N. of choices	10080		8769		8659		8092	
N. of respondents	1008		964		964		959	
$\mathscr{L}(\hat{\beta})$	−5887.5		−5132.5		−5066.9		−4701.7	
average $\mathscr{L}(\hat{\beta}) \times 100$	−58.4		−58.5		−58.5		−58.1	

Confidence intervals from st. errors clustered by respondent

$^{*}p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$

Table 3: Behavioural estimates from LADR models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
	$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$	
Utility Attribute	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.
Italian flag	1.458	0.033	1.431	0.048	1.429	0.048	1.415	0.053
Chianti Classico	−1.430	0.032	−1.403	0.047	−1.401	0.047	−1.388	0.052
Garda	−0.428	0.010	−0.420	0.014	−0.420	0.014	−0.416	0.016
Ligurian coast	−0.284	0.006	−0.279	0.009	−0.278	0.009	−0.275	0.010
Veneto Valpolicella	0.300	0.007	0.295	0.010	0.294	0.010	0.291	0.011
Trad. Bottle	−1.174	0.027	−1.152	0.038	−1.151	0.039	−1.140	0.043
Organic logo	8.608	0.195	8.448	0.281	8.437	0.284	8.354	0.315
CO_2 reduction	3.836	0.087	3.764	0.125	3.759	0.126	3.723	0.140
Cold-pressed	8.579	0.194	8.420	0.280	8.408	0.283	8.326	0.314
Hand-picked	7.120	0.161	6.988	0.233	6.978	0.235	6.910	0.260
Delicate	0.510	0.012	0.500	0.017	0.499	0.017	0.495	0.019
Price	−2.339	0.053	−2.295	0.076	−2.292	0.077	−2.270	0.085
Constant	4.257	0.096	4.178	0.139	4.172	0.140	4.131	0.156
$m\widehat{WTP}$	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean.	95% Conf. Int.
Italian flag	0.742^{***}	0.41, 1.07	0.544^{***}	0.27, 0.82	0.466^{***}	0.21, 0.73	0.387^{***}	0.15, 0.62
Chianti Classico	−0.428	−0.98, 0.12	−0.041	−0.57, 0.49	−0.056	−0.56, 0.45	−0.199	−0.62, 0.22
Garda	−0.272	−0.99, 0.44	0.118	−0.51, 0.75	0.103	−0.48, 0.69	0.249	−0.29, 0.79
Ligurian coast	−0.193	−0.91, 0.53	0.456	−0.23, 1.14	0.422	−0.23, 1.07	0.298	−0.29, 0.88
Veneto Valpolicella	0.275	−0.38, 0.93	0.217	−0.30, 0.73	0.319	−0.20, 0.84	0.229	−0.21, 0.67
Trad. Bottle	-0.586^{***}	−0.92, −0.25	-0.456^{**}	−0.76, −0.15	-0.466^{**}	−0.75, −0.18	-0.363^{**}	−0.63, −0.10
Organic logo	3.378^{***}	2.70, 4.05	3.196^{***}	2.27, 4.12	3.180^{***}	2.32, 4.04	2.995^{***}	2.06, 3.93
CO_2 reduction	1.332^{***}	0.75, 1.91	1.456^{***}	0.94, 1.97	1.526^{***}	1.04, 2.01	1.294^{***}	0.83, 1.76
Cold-pressed	3.020^{***}	2.13, 3.91	2.828^{***}	1.94, 3.72	2.849^{***}	2.02, 3.68	2.316^{***}	1.48, 3.15
Hand-picked	2.350^{***}	1.52, 3.18	2.660^{***}	1.91, 3.41	2.654^{***}	1.94, 3.37	2.153^{***}	1.47, 2.84
Delicate	0.255	−0.06, 0.57	0.287^{*}	0.01, 0.56	0.267^{*}	0.001, 0.53	0.015	−0.22, 0.25
N. of choices	10080		8769		8659		8092	
N. of respondents	1008		964		964		959	
Objective Function ×100	43.5		47.6		48.0		50.1	

Confidence intervals from st. errors clustered by respondent

$^{*}p \le 0.05$, $^{**}p \le 0.01$, $^{***}p \le 0.001$

Table 4: Behavioural estimates from FLGT Model

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
	$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$		$\partial\hat{P}_n/\partial x_k \times 100$	
Utility Attribute	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.
Italian flag	1.389	0.083	1.357	0.106	1.355	0.108	1.339	0.119
Chianti Classico	−1.362	0.081	−1.331	0.104	−1.328	0.106	−1.312	0.116
Garda	−0.408	0.024	−0.399	0.031	−0.398	0.032	−0.393	0.035
Ligurian coast	−0.270	0.016	−0.264	0.021	−0.264	0.021	−0.260	0.023
Veneto Valpolicella	0.286	0.017	0.279	0.022	0.279	0.022	0.275	0.024
Trad. Bottle	−1.119	0.067	−1.093	0.086	−1.091	0.087	−1.078	0.096
Organic logo	8.200	0.488	8.012	0.629	7.996	0.638	7.900	0.701
CO_2 reduction	3.654	0.218	3.570	0.280	3.563	0.284	3.520	0.312
Cold-pressed	8.173	0.487	7.985	0.626	7.969	0.636	7.874	0.698
Hand-picked	6.782	0.404	6.626	0.520	6.613	0.528	6.534	0.580
Delicate	0.485	0.029	0.474	0.037	0.473	0.038	0.468	0.041
Price	−2.228	0.133	−2.177	0.171	−2.172	0.173	−2.147	0.190
Constant	4.055	0.241	3.962	0.311	3.954	0.315	3.907	0.347
$m\widehat{WTP}$	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.
Italian flag	0.624***	0.35, 0.90	0.626***	0.35, 0.90	0.623***	0.35, 0.90	0.601**	0.32, 0.89
Chianti Classico	−0.611*	−1.16, −0.07	−0.683*	−1.23, −0.14	−0.678*	−1.22, −0.13	−0.703*	−1.25, −0.15
Garda	−0.183	−0.81, 0.44	−0.162	−0.79, 0.46	−0.160	−0.79, 0.47	−0.103	−0.74, 0.53
Ligurian coast	−0.121	−0.81, 0.56	−0.144	−0.83, 0.54	−0.140	−0.83, 0.55	−0.102	−0.80, 0.60
Veneto Valpolicella	0.128	−0.40, 0.66	0.127	−0.41, 0.66	0.133	−0.40, 0.67	0.157	−0.386, 0.70
Trad. Bottle	−0.502**	−0.83, −0.17	−0.510**	−0.84, −0.18	−0.518**	−0.85, −0.19	−0.523**	−0.86, −0.19
Organic logo	3.680***	2.93, 4.43	3.729***	2.98, 4.48	3.723***	2.98, 4.47	3.725***	2.92, 4.60
CO_2 reduction	1.640***	1.12, 2.16	1.723***	1.20, 2.24	1.728***	1.21, 2.25	1.730***	1.20, 2.26
Cold-pressed	3.668***	2.83, 4.51	3.761***	2.93, 4.59	3.755***	2.92, 4.59	3.758***	2.92, 4.60
Hand-picked	3.044***	2.30, 3.78	3.194***	2.46, 3.93	3.192***	2.45, 3.93	3.214***	2.47, 3.96
Delicate	0.218*	−0.08, 0.52	0.193	−0.10, 0.49	0.200	−0.10, 0.50	0.201	−0.10, 0.50
N. of choices	10080		8769		8659		8092	
N. of respondents	1008		964		964		959	
log pseudo-likelihood	−6631.91		−5671.37		−5591.31		−5176.97	
average log pseudo-lik. ×100	−65.8		−64.7		−64.6		−64.0	

Confidence intervals from st. errors clustered by respondent

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 5: Estimates of marginal effects from conditional logit with interactions (BLGT_inter)

	Interval (0.48 – 0.52)			Interval (0.46 – 0.54)			Interval (0.42 – 0.58)		
	$\partial\hat{P}_n/\partial x_k \times 100$		z-value	$\partial\hat{P}_n/\partial x_k \times 100$		z-value	$\partial\hat{P}_n/\partial x_k \times 100$		z-value
Italian flag	1.742	***	4.66	1.747	***	4.65	1.658	***	4.27
Chianti Classico	−1.293		−1.92	−1.262		−1.86	−1.451		−2.07
Garda	0.311		0.39	0.257		0.32	0.606		0.71
Ligurian Coast	−0.009		−0.01	0.065		0.07	0.377		0.41
Veneto Valpolicella	1.182		1.71	1.282		1.83	1.524	*	2.08
Trad. Bottle	−1.072	**	−2.60	−1.152	**	−2.78	−1.419	***	−3.30
Organic Logo	9.073	***	8.31	9.059	***	8.28	9.190	***	8.23
CO_2 reduction	4.890	***	6.32	4.914	***	6.28	4.945	***	6.14
Cold-pressed	10.445	***	8.14	10.362	***	8.05	10.207	***	7.85
Hand-picked	8.854	***	7.80	8.859	***	7.75	8.922	***	7.63
Delicate	0.504		1.33	0.470		1.23	0.595		1.51
Price	−2.261	***	−24.57	−2.265	***	−24.41	−2.318	***	−24.09
Marginal effects (×100) of interactions with central probabilities									
Italian flag	0.454		0.55	0.414		0.50	0.657		0.88
Chianti Classico	4.386	*	2.33	3.801	*	2.12	3.420	*	2.20
Garda	3.452		1.74	3.610		1.88	0.898		0.51
Ligurian Coast	4.110		1.96	3.278		1.61	0.855		0.47
Veneto Valpolicella	−1.330		−0.81	−1.809		−1.14	−2.464		−1.68
Trad. Bottle	−0.124		−0.13	0.437		0.47	1.664	*	2.03
Organic Logo	−2.817		−1.50	−2.600		−1.45	−2.450		−1.59
CO_2 reduction	−2.164		−1.36	−2.130		−1.38	−1.364		−0.97
Cold-pressed	−1.463		−0.66	−0.678		−0.31	0.594		0.31
Hand-picked	−2.248		−1.03	−2.011		−0.95	−1.149		−0.60
Delicate	−0.702		−0.72	−0.336		−0.37	−0.920		−1.20
Price	0.354		1.39	0.351		1.40	0.481	*	2.24
Constant	5.659	***	12.32	5.665	***	12.32	5.680	***	12.36
$\mathscr{L}(\hat{\beta})$	−5876.96			−5875.78			−5868.12		

Asymptotic z-statistics from st. errors clustered by respondent — * $p \le 0.05$, ** $p \le 0.01$, *** $p \le 0.001$

Table 6: ZI-NegBin estimates: counts of central and *un*rounded prob. in the sequence

	Counts of central probabilities		Count of unrounded probabilities			
	ziNB 1		ziNB 2		ziNB 3	
	y_n^c $\in [46, 54]$	$\frac{\partial y}{\partial x}$ Marg. Eff.	y_n All unrounded	$\frac{\partial y}{\partial x}$ Marg. Eff.	y_n^* 49,51 excluded	$\frac{\partial y}{\partial x}$ Marg. Eff.
Frequency of purchase (ord. 1-7)	−0.046	−0.066	−0.033	−0.099	−0.028	−0.053
	(−1.25)	(−1.25)	(−1.64)	(−1.64)	(−1.05)	(−1.04)
Never Visited	0.340**	0.489*	0.065	0.195	−0.157	−0.297
	(2.66)	(2.56)	(0.90)	(0.90)	(−1.64)	(−1.62)
Male (man=1)	−0.165	−0.504**	−0.092	−0.829***	-0.098	−0.336
	(−1.18)	(−2.76)	(−1.33)	(−3.61)	(−1.07)	(−1.73)
Age (in years)	0.073*	0.118**	0.006	0.014	−0.011	−0.084*
	(2.34)	(2.89)	(0.40)	(0.30)	(−0.62)	(−2.19)
Age^2 (years^2/10000)	−7.012*	−11.550**	−0.499	−2.489	1.014	7.062
	(−2.06)	(−2.62)	(−0.33)	(−0.48)	(0.55)	(1.70)*
Education	−0.057	−0.082	−0.049	−0.148	−0.108*	−0.205*
	(−0.89)	(−0.88)	(−1.36)	(−1.35)	(−2.16)	(−2.14)
Constant	−0.613		1.667***		2.148***	
	(−0.83)		(4.89)		(4.97)	
Zero Inflation Logit						
Male (man=1)	0.502*		0.612***		0.175	
	(1.96)		(3.58)		(1.09)	
Age (years)	−0.024		0.003		0.074*	
	(−0.45)		(0.08)		(2.20)	
Age^2 (years^2/10000)	2.772		1.095		−5.966	
	(0.50)		(0.30)		(−1.68)	
Constant	−0.207		−1.531		−2.256**	
	(−0.24)		(−1.94)		(−2.92)	
ln(α)	0.328		-0.882***		-0.612***	
	(1.25)		(−6.37)		(−3.42)	
Observations			935			
Zero counts	569		345		508	
$\mathscr{L}(\hat{\beta})$	−1394.37		−2029.71		−1605.99	

Asymptotic z-statistics in parentheses

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table 7: Predictions of counts of subjective probabilities in the range [0.46 – 0.54] from ZINB regression

Freq. of consumption	Never visited	Man	Age	Zero inflation	$\widehat{\Pr}(y=0)$	$\widehat{\Pr}(y=1)$	$\widehat{\Pr}(y=2)$	$\widehat{\Pr}(y=3)$	$\widehat{\Pr}(y=4)$	$\widehat{\Pr}(y=5)$	$\widehat{\Pr}(y=6)$	$\widehat{\Pr}(y=7)$	$\widehat{\Pr}(y=8)$	$\widehat{\Pr}(y=9)$	$\widehat{\Pr}(y=10)$
1	1	1	30	0.372	0.596	0.125	0.082	0.056	0.039	0.028	0.020	0.015	0.011	0.008	0.006
1	1	0	30	0.265	0.502	0.137	0.094	0.067	0.049	0.036	0.027	0.021	0.016	0.012	0.009
1	0	1	30	0.352	0.636	0.141	0.083	0.051	0.032	0.020	0.013	0.008	0.005	0.004	0.002
1	0	0	30	0.249	0.549	0.158	0.098	0.063	0.042	0.028	0.019	0.013	0.009	0.006	0.004
7	1	1	30	0.529	0.707	0.096	0.061	0.041	0.028	0.019	0.014	0.010	0.007	0.005	0.003
7	1	0	30	0.407	0.609	0.115	0.077	0.054	0.038	0.028	0.020	0.015	0.011	0.008	0.006
7	0	1	30	0.508	0.735	0.109	0.062	0.036	0.022	0.014	0.008	0.005	0.003	0.002	0.001
7	0	0	30	0.387	0.645	0.132	0.079	0.050	0.032	0.021	0.014	0.009	0.006	0.004	0.003
1	1	1	60	0.370	0.556	0.111	0.078	0.058	0.044	0.033	0.026	0.020	0.016	0.012	0.010
1	1	0	60	0.264	0.458	0.120	0.087	0.066	0.052	0.041	0.033	0.026	0.021	0.017	0.014
1	0	1	60	0.351	0.590	0.131	0.085	0.057	0.040	0.028	0.020	0.014	0.010	0.007	0.005
1	0	0	60	0.248	0.498	0.144	0.097	0.068	0.049	0.036	0.027	0.020	0.015	0.011	0.008
7	1	1	60	0.528	0.675	0.087	0.060	0.043	0.032	0.024	0.018	0.014	0.011	0.008	0.006
7	1	0	60	0.406	0.572	0.101	0.072	0.054	0.042	0.032	0.025	0.020	0.016	0.013	0.010
7	0	1	60	0.507	0.699	0.103	0.064	0.042	0.028	0.019	0.013	0.009	0.006	0.005	0.003
7	0	0	60	0.385	0.602	0.121	0.080	0.055	0.039	0.028	0.020	0.015	0.011	0.008	0.006

Table 8: Estimates from Heteroskedastic Logit Model

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
	$\partial \hat{P}_n / \partial x_k \times 100$		$\partial \hat{P}_n / \partial x_k \times 100$		$\partial \hat{P}_n / \partial x_k \times 100$		$\partial \hat{P}_n / \partial x_k \times 100$	
Utility Attribute	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.	Means	St. Dev.
Italian flag	1.042	0.391	1.295	0.145	1.291	0.148	1.231	0.184
Chianti Classico	−1.021	0.383	−1.269	0.142	−1.265	0.145	−1.207	0.180
Garda	−0.306	0.115	−0.380	0.043	−0.379	0.044	−0.361	0.054
Ligurian coast	−0.203	0.076	−0.252	0.028	−0.251	0.029	−0.240	0.036
Veneto Valpolicella	0.214	0.080	0.266	0.030	0.266	0.031	0.253	0.038
Trad. Bottle	−0.839	0.314	−1.042	0.117	−1.039	0.119	−0.991	0.148
Organic logo	6.148	2.305	7.641	0.855	7.617	0.876	7.265	1.085
CO_2 reduction	2.739	1.027	3.405	0.381	3.394	0.390	3.237	0.483
Cold-pressed	6.127	2.297	7.615	0.853	7.592	0.873	7.241	1.081
Hand-picked	5.085	1.907	6.320	0.708	6.300	0.724	6.009	0.897
Delicate	0.364	0.136	0.452	0.051	0.451	0.052	0.430	0.064
Price	−1.670	0.626	−2.076	0.232	−2.070	0.238	−1.974	0.295
Constant	3.040	1.140	3.779	0.423	3.767	0.433	3.593	0.537
Scale Variables	Coeff.	$\lvert z$-value$\rvert$	Coeff.	$\lvert z$-value$\rvert$	Coeff.	$\lvert z$-value$\rvert$	Coeff.	$\lvert z$-value$\rvert$
Frequency of Purchase	-0.117^{***}	5.59	-0.118^{***}	5.20	-0.119^{***}	5.22	-0.125^{***}	5.51
Never Visited	0.135	1.82	0.106	1.34	0.103	1.29	0.092	1.14
Man	0.008	0.10	0.023	0.29	0.028	0.36	0.032	0.40
Age	0.041^{**}	2.58	0.043^{*}	2.50	0.042^{*}	2.47	0.038^{**}	2.21
Age^2 ($years^2/100$)	-0.046^{**}	2.58	-0.051^{**}	2.64	-0.051^{**}	2.63	-0.046^{**}	2.39
$m\widehat{WTP}$	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.	Mean	95% Conf. Int.
Italian flag	0.735^{***}	0.46, 1.01	0.691^{**}	0.41, 0.97	0.696^{***}	0.42, 0.97	0.622^{***}	0.34, 0.90
Chianti Classico	−0.258	−0.81, 0.29	-0.583^{*}	−1.15, 0.02	-0.571^{*}	−1.14, −0.00	-0.626^{*}	−1.20, −0.05
Garda	0.151	−0.48, 0.78	−0.112	−0.75, 0.53	−0.128	−0.77, 0.52	−0.012	−0.69, 0.66
Ligurian coast	0.201	−0.48, 0.88	−0.052	−0.75, 0.64	−0.024	−0.72, 0.68	0.062	−0.66, 0.78
Veneto Valpolicella	0.185	−0.34, 0.71	0.212	−0.33, 0.75	0.251	−0.30, 0.80	0.355	−0.20, 0.91
Trad. Bottle	-0.393^{*}	−0.73, −0.06	-0.356^{*}	−0.70, −0.01	-0.389^{*}	−0.73, −0.04	-0.478^{***}	−0.82, −0.13
Organic logo	3.270^{***}	2.61, 3.93	3.295^{***}	2.62, 3.97	3.276^{**}	2.60, 3.95	3.213^{***}	2.53, 3.90
CO_2 reduction	1.739^{***}	1.21, 2.27	1.812^{***}	1.27, 2.36	1.710^{**}	1.25, 2.35	1.792^{***}	1.24, 2.34
Cold-pressed	3.867^{***}	3.10, 4.63	3.764^{***}	2.96, 4.56	3.708^{**}	2.91, 4.51	3.489^{***}	2.69, 4.29
Hand-picked	3.330^{***}	2.64, 4.02	3.329^{***}	2.60, 4.06	3.296^{**}	2.56, 4.03	3.211^{***}	2.47, 3.95
Delicate	0.175	−0.14, 0.48	0.199	−0.12, 0.52	0.179	−0.14, 0.50	0.218	−0.10, 0.54
N. of choices	9350		8107		8008		7474	
N. of respondents	935		894		894		889	
$\mathscr{L}(\hat{\beta})$	−5305.9		−4606.5		−4546.6		−4198.2	
Average $\mathscr{L}(\hat{\beta})$	−56.7		−56.8		−56.8		−56.2	

Asymptotic z-statistics from st. errors clustered by respondent

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Online Appendix

This appendix reports the summary statistics for the socio-demographic variables (A1) and the coefficient estimates for the various models used to derive the behavioural estimates reported in the main paper, such as the BLGT model in table A2, the LADR model in table A3, the FLGT model in table A.vi, and the heteroskedastic model in table A5. It also includes additional analysis to respond to issues raised by a reviewer and following the findings in the seminal literature on rounding behaviour (see for example, Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*). We expand on this in what follows.

A.i Models for sequential rounding behaviour

Rounding of subjective probabilities of purchase is defined as a respondent expressing a probability value in the scale 0-100 that is divisible by 5 without decimal residual. In our data collection methods there are 19 such values since the 50% option is not allowed for consistency with the previously elicited preferred choice. So, we created a dummy variable ($y_n = 1$) for each respondent indicating a full sequence of $T = 10$ rounded responses, and used binary logit modelling to try and identify the determinants of this systematic pattern of response in rounding behaviour; we call y_n an indicator of 'sequential' or 'systematic' rounding. The sample frequency of this behaviour was 36.9% (372/1,008) respondents, and 39.78 % of the active sample ($N = 935$) used in model estimation (missing obervations are due to incomplete demographics).

It seems plausible to assume that respondents who wanted to express a rounding at 50% would have chosen the closest possible amounts of either 49 or 51%. So, a second 'sequential rounding' variable was created (y^*_n) where responses of 51 and 49% were also treated as legitimate rounde responses. The sample frequency of this behaviour was 54% (545/1,008) respondents, and 58.29 % of the active sample ($N = 935$) for model estimation, the difference being due to missing socio-economic data. So, about 37-40 percent engaged in 'sequential rounding' when 49 and 51% responses were treated this way.

Table A6 reports the binary logit estimates for coefficients and their respective marginal effects. The latter are computed at the sample averages of the covariates. We used selected socio-economic covariates, some of which were found to be of significance in previous studies, to explain the probability of observing sequential rounding. In the binary logit results we observe significance of being a **male** respondent with a marginal effect of 12.5% in **Model A1** for y_n, where responses for 51 and 49% were excluded. In **Model A2** for y^*_n, the only significant and positive variable is **age**, with a small marginal effect of 1.5%.

We conclude that sequential rounding is a prevalent behaviour, significantly more so in men and older respondents.

A.ii Models for the count of *un*rounded subjective probabilities

We also explored the intensive margin of *un*rounding behaviour by means of count models (see discussion in the paper).

Given the large fraction of observed 51 and 49% statements, which could be seen as potential roundings to 50%, we also proceeded to estimate a count model for *un*rounded probabilities in the whole sequence of responses without 51 and 49% statements. We denote the count variable y^*_{1n} when 51 and 49% statements are treated as unrounded probabilities (in **Model A3**) and denote the count variable y_{1n} when 51 and 49% statements are removed from the unrounded count and counted as rounded (Model A4).

We repeat this count analysis for responses in the central range of $[25, 75]$ interval, to see if central unrounding has different determinants from those in the whole sequence. A separate model is warranted under the assumption that in this interval there is more uncertainty, possibly of the resolvable type.

We also estimated count models for explaining the number of central probability statements, but these produced no significant effects of socio-economic covariates.

Summary statistics of these counts are in Table A7, histograms of the count distributions are in figures 4 in the main text of the paper and Figure 5 in this appendix, while figure 6 compares the in-sample forecasts from various count models, such as poisson (POI), negative binomial 2 (NB2), and their zero-inflated (using logit as a link-function) zi-Poisson (ziP) and zi-Neg.Bin.2 (ziNB). The latter provides the forecasts that best approximate the observations, we will hence use this model in the analysis.

The estimates for the zi-NB models for y_1^* and y_1 are in Table 6, along with the implied marginal effects. Being a **male respondent** is the only variable that significantly **diminishes** the count of *un*rounded probability scores for y_1^*, with a negative marginal effect on the expected count of nearly one (0.83).

Excluding the statements in the [25,75] interval (Model A2) is equivalent to treating these as rounded and modifies the significance: in this case it is lower and it is found for the variables age and education, suggesting that **younger and more educated respondents** are more inclined to round. This effect is reinforced by the positive and significant effect of age also in the zero inflation equation.

We conclude that the count of rounded probability responses is positively affected only by gender when extended to 49 and 51% responses, and positively by age and education when these are excluded.

A.iii Unrounding in the central interval

Given the relevance of central probability responses in expressing uncertainty, a further investigation was conducted. Analogue estimates for counts of unrounded responses along the central interval [25,75] are reported in Table A8. For the more inclusive count of unrounded responses (y_2^*) mild significance is found in the marginal effects for four out of five socio-economic variables considered. The only insignificant marginal effect is found for having visited the locations of origin of the extra virgin olive oil (origin_nvr).

Respondents increased the number of unrounded probability statements with age, but at a decreasing rate as age increases. In this case the net marginal effect of age is always positive and peaks at age 48, with a value of 2.2, and then it declines. This is consistent with younger respondents rounding more than older ones, and when rounding doing so with probabilities outside the central range (i.e. having more certainty). For the model for the less inclusive count (y_2) only frequency of purchase is significant and negative. So, the higher the frequency of purchase the higher is the number of central rounding scores, for both these variables.

Zero count of rounded probabilities are significantly and positively impacted only by being a male for y_2^* and only by age in the y_2 estimates. Once again, treating 49 and 51 % as rounding removes the gender effect.

We conclude that the count of central and rounded probability responses is positively affected by frequency of purchase, gender and age when extended to 49 and 51% responses, and only by by frequency of purchase when these are excluded, while age has its effect on the zero inflation of unrounded responses.

A.iv Models explaining fractions of roundings and of central probabilities

From a sequence of 10 choice probability statements per respondent one can compute the fraction of rounded probability statements in the whole sequence. These fractions can be computed in two ways, either treating 49 and 51% statements as unrounded probabilities, or as rounded. We denote with π_n (mean 0.6974, st.dev.0.3374) the former (Model A7), and π_n^* (mean 0.8069 and st.dev. 0.2864) the latter (Model A8).

Given their relevance for uncertainty, we are also interested in the determinants of the fraction of rounded responses that each respondent allocates to the central interval [25,75] out of the total. We denote these with π_n^c (mean 0.4967 st.dev. 0.3478, Model A9).

One can model these directly by estimating fractional regression models, such as fractional logit, Beta regressions or Dirichlet regressions. We use the first following Papke and Wooldridge (1996). The three models are reported in Table A9. The results in Model A7 show that men are significantly more associated with rounding when 49 and 51% statements are removed. However, in Model Model A8, when these are responses are classified as rounded and included in the computation of the fraction, the significance of the effect for the male variable disappears, while **age** and **education** appear to have a positive and significant effect. None of the variables are significant in Model A9 for the fraction of central probability statements in the sequence.

Unsurprisingly these result confirm the previous ones. We conclude that the count of central and rounded probability responses is positively affected by frequency of purchase and gender when near-epistemic rounding is excluded. When the latter is included, then age and education emerge as significant.

A.v Conclusions

Our results align, by and large, with those observed in previous seminal studies (see for example, Manski and Molinari, 2010; Kleinjans and Van Soest, 2014; Giustinelli et al., 2020*b*)

A.vi Tables of Online Appendix

Table A1: Socio-demographic characteristics of the sample, $N = 1,008$

Characteristics	Levels	Observations	Percentage
Gender	Women	486	48.2
Age class	18-20	28	2.8
	21-30	157	15.6
	31-40	166	16.5
	41-50	226	22.4
	51-60	242	24.0
	61-70	143	14.2
	71 and older	42	4.2
Education level	Primary School	3	0.3
	Technical Schools	95	9.4
	High School/Secondary School	684	67.9
	University/College	226	22.4
Occupation	Worker	74	7.3
	Employer	455	45.1
	Freelance	68	6.7
	Manager	45	4.5
	Housewife	64	6.3
	Retired	180	17.9
	Unemployed	35	3.5
	Student	61	6.1
	Other	26	2.6
Gross income in €	less than 10,000	69	6.8
	10,000-12,499	66	6.5
	12,500-14,999	30	3.0
	15,000-19,999	74	7.3
	20,000-24,999	69	6.8
	25,000-29,999	100	9.9
	30,000-34,999	100	9.9
	35,000-39,999	73	7.2
	40,000-44,999	60	6.0
	45,000-49,999	60	6.0
	50,000-59,999	88	8.7
	60,000-74,999	96	9.5
	75,000-99,999	79	7.8
	100,000-124,999	22	2.2
	125,000-149,999	6	0.6
	150,000 or more	14	1.4
Frequency of consumption	Never	99	9.8
	Once every other month	67	6.6
	Once a month	99	9.8
	Once every other week	174	17.3
	Once a week	200	19.8
	Several times a week	308	30.6
	Everyday	61	6.1
Visited PDO areas	Never visited any PDO areas	430	45.8
	Visited at least one of the areas	509	54.2

Table A2: Coefficient estimates from BLGT models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
N. of choices	10080		8769		8659		8092	
N. of respondents	1008		964		964		959	
$\mathscr{L}(\hat{\beta})$	−5887.51		−5132.54		−5066.95		−4701.73	
average $\mathscr{L}(\hat{\beta}) \times 100$	−58.4		−58.5		−58.5		−58.1	
Utility Variable	Coeff.	$\|z\text{-value}\|$	Coeff.	$\|z\text{-value}\|$	Coeff.	$\|z\text{-value}\|$	Coeff.	$\|z\text{-value}\|$
Italian flag	0.137***	5.63	0.132***	5.14	0.132***	5.14	0.125***	4.65
Chianti	−0.053	1.09	−0.096	1.85	−0.094	1.80	−0.108**	2.00
Garda Lake	0.058	1.04	0.023	0.39	0.019	0.33	0.045	0.73
Ligurian coast	0.042	0.69	0.001	0.01	0.006	0.11	0.029	0.42
Valpolicella	0.075	1.61	0.091	1.79	0.098	1.93	0.116*	2.18
Trad. Bottle	−0.081**	2.79	−0.079**	2.56	−0.085**	2.74	−0.106**	4.20
Organic logo	0.657***	12.41	0.684***	12.19	0.682***	12.11	0.691***	11.92
CO_2reduction	0.344***	7.55	0.369***	7.61	0.370***	7.56	0.372***	7.32
Cold-pressed	0.777***	12.40	0.786***	11.69	0.779***	11.49	0.765***	10.94
Hand-picked	0.645***	10.94	0.664***	10.61	0.663***	10.50	0.667***	10.20
Delicate	0.300	1.15	0.036	1.27	0.033	1.17	0.042*	1.46
Price	−0.168***	23.49	−0.173***	22.14	−0.173***	22.02	−0.176***	21.52
Constant	0.429***	14.93	0.371***	12.43	0.368***	12.29	0.374***	12.00

Asymptotic z-values from clustered standard errors. $^{*}p \le 0.05$, $^{**}p \le 0.01$, $^{***}p \le 0.001$

Table A3: Coefficient estimates from LADR models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
N. of choices	10080		8769		8659		8092	
N. of respondents	1008		964		964		959	
Objective Function ×100	43.5		47.6		48.0		50.1	
Variable	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$
Italian flag	0.041***	4.72	0.040***	4.03	0.035***	3.65	0.032**	3.38
Chianti Classico	−0.024	1.52	−0.003	0.15	−0.004	0.22	−0.016	0.92
Garda Lake	−0.015	0.74	0.009	0.37	0.008	0.35	0.021	0.91
Ligurian coast	−0.011	0.52	0.034	1.33	0.031	1.29	0.025	1.01
Valpolicella	0.015	0.83	0.016	0.83	0.024	1.20	0.019	1.02
Trad. Bottle	−0.032**	3.42	−0.034**	2.99	−0.035***	3.25	−0.030**	2.79
Organic logo	0.186***	10.45	0.235***	7.27	0.237***	7.74	0.247***	6.92
CO_2reduction	0.073***	4.58	0.107***	5.67	0.114***	6.45	0.107***	5.81
Cold-pressed	0.167***	7.19	0.208***	6.72	0.212***	7.22	0.191***	5.83
Hand-picked	0.130***	5.67	0.195***	7.42	0.197***	7.83	0.178***	6.71
Delicate	0.014	1.57	0.021*	2.05	0.020**	1.98	0.001	0.12
Price	−0.055***	19.05	−0.073***	25.33	−0.074***	25.86	−0.083***	28.41
Constant	0.076***	7.07	0.136***	11.37	0.142***	12.19	0.170***	13.52

t-values from clustered standard errors.

* $p \le 0.05$, ** $p \le 0.01$, *** $p \le 0.001$

Table A4: Coefficient estimates from FLGT Models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
N. of choices	10 080		8769		8659		8092	
N. of respondents	1008		964		964		959	
log pseudo-likelihood	−6631.91		−5671.37		−5591.31		−5176.97	
average log pseudo-lik. ×100	−65.8		−64.7		−64.6		−64.0	
Variable	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$	Coeff.	$\lvert z\text{-value}\rvert$
Italian flag	0.060***	4.55	0.069***	4.57	0.069***	4.54	0.072***	4.36
Chianti	−0.059*	2.18	−0.075*	2.44	−0.075*	2.42	−0.083*	2.49
Garda Lake	−0.017	0.57	−0.017	0.51	−0.018	0.50	−0.012	0.32
Ligurian coast	−0.011	0.35	−0.016	0.41	−0.016	0.40	−0.012	0.29
Valpolicella	0.012	0.48	0.014	0.47	0.015	0.49	0.019	0.57
Trad. Bottle	−0.048**	3.03	−0.056**	3.08	−0.058**	3.12	−0.062**	3.12
Organic logo	0.352***	12.02	0.413***	11.35	0.417***	11.32	0.443***	11.27
CO_2 reduction	0.160***	6.44	0.190***	6.78	0.193***	6.78	0.205***	6.71
Cold-pressed	0.351***	9.65	0.416***	10.02	0.420***	9.98	0.447***	9.92
Hand-picked	0.291***	8.89	0.353***	9.44	0.357***	9.41	0.382***	9.38
Delicate	0.021*	1.44	0.021	1.27	0.022	1.31	0.023	1.31
Price	−0.095***	23.31	−0.110***	23.40	−0.112***	23.39	−0.119***	23.18
Constant	0.174***	11.15	0.201***	11.19	0.204***	11.19	0.218***	11.12

t-values from clustered standard errors. * $p \le 0.05$, ** $p \le 0.01$, *** $p \le 0.001$

Table A5: Coefficient estimates from Heteroskedastic Logit Models

	All choices		Removed (0.48 – 0.52)		Removed (0.46 – 0.54)		Removed (0.42 – 0.58)	
N. of choices	9350		8107		8008		7474	
N. of respondents	935		894		894		889	
$\mathscr{L}(\hat{\beta})$	−5305.9		−4606.5		−4546.6		−4198.2	
Average $\mathscr{L}(\hat{\beta})$	−56.748		−56.821		−56.776		−56.171	
Utility Variables	Coeff.	$\|t\text{-value}\|$	Coeff.	$\|t\text{-value}\|$	Coeff.	$\|t\text{-value}\|$	Coeff.	$\|t\text{-value}\|$
Italian flag	0.092**	2.46	0.095*	2.33	0.097*	2.32	0.101*	2.24
Chianti	−0.032	0.88	−0.080	1.63	−0.080	1.60	−0.102	1.68
Garda Lake	0.019	0.46	−0.015	−0.34	−0.018	0.39	−0.002	0.04
Ligurian coast	0.025	0.57	−0.001	0.15	−0.004	0.08	0.010	0.17
Valpolicella	0.023	0.67	0.029	0.73	0.034	0.85	0.058	1.13
Trad. Bottle	−0.049	1.81	−0.049	1.66	−0.054	1.75	−0.078	1.94
Organic logo	0.407**	2.75	0.452**	2.66	0.456**	2.65	0.525	2.67
CO_2 reduction	0.217**	2.62	0.249*	2.57	0.250*	2.55	0.293**	2.65
Cold-pressed	0.482**	2.80	0.517**	2.70	0.516**	2.68	0.570**	2.67
Hand-picked	0.415**	2.78	0.457**	2.70	0.459**	2.68	0.524**	2.69
Delicate	0.022	1.02	0.027	1.12	0.025	1.02	0.036	1.21
Price	−0.125**	2.87	−0.137**	2.75	−0.140**	2.73	−0.163**	2.74
Constant	0.302**	2.81	0.270**	2.65	0.272**	2.65	0.313**	2.66
Frequency of Purchase	−0.117***	5.59	−0.118***	5.20	−0.119***	5.22	−0.125***	5.51
Never Visited	0.135	1.82	0.106	1.34	0.103	1.29	0.092	1.14
Man	0.008	0.10	0.023	0.29	0.028	0.36	0.032	0.40
Age	0.041**	2.58	0.043*	2.50	0.042*	2.47	0.038**	2.21
Age^2 ($years^2/100$)	−0.046**	2.58	−0.051**	2.64	−0.051**	2.63	−0.046**	2.39

Asymptotic z-values from clustered standard errors. $^{*}p \le 0.05$, $^{**}p \le 0.01$, $^{***}p \le 0.001$

Table A6: Logit model estimates for the probability of $y_n = 1$ for sequential rounding

	Model A1 ($y_n = 1$ is 39.78%)		Model A2 $y_n^* = 1$ is 58.28%	
	y_n 49,51 $excluded$	$\frac{\partial y}{\partial x}$ Marg. Eff.	y_n 49,51 $included$	$\frac{\partial y}{\partial x}$ Marg. Eff.
freq_purchase	0.0654	0.0148	0.0459	0.0111
	(1.59)	(1.60)	(1.17)	(1.18)
orig_nvr	0.0268	0.00606	0.120	0.0290
	(0.19)	(0.19)	(0.86)	(0.86)
male	0.553***	0.125***	0.193	0.0467
	(3.96)	(4.09)	(1.44)	(1.44)
age	−0.00568	−0.00128	0.0626*	0.0152*
	(−0.20)	(−0.20)	(2.26)	(2.28)
age_sq	1.743	0.394	−4.976	−1.206
	(0.57)	(0.57)	(−1.67)	(−1.68)
edu	0.0686	0.0155	0.0737	0.0179
	(0.95)	(0.96)	(1.05)	(1.05)
Constant	−1.537*		−2.174**	
	(−2.16)		(−3.16)	
Observations	$N = 935, \mathscr{L}(\hat{\beta}) = -602.445$		$N = 935, \mathscr{L}(\hat{\beta}) = -633.543$	

t statistics in parentheses $\quad$ * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Statistics of counts for unrounded probabilities

Variable	Mean	Std. Dev.	25%	50%	75%
	In the sequence				
y_1^*	3.026	3.374	0	2	3
y_1 (49 and 51 % excluded)	1.931	2.864	0	0	3
	In the central range $[0.25, 0.75]$				
y_2^*	2.012	2.843	0	1	3
y_2 (49 and 51 % excluded)	0.917	1.812	0	0	1

Table A8: ZI-NegBin estimates: counts of *un*rounded prob. in the range $[25, 75]$

	Model A5		Model A6	
	y_2^*	$\frac{\partial y}{\partial x}$	y_2	$\frac{\partial y}{\partial x}$
	All unrounded	Marg. Eff.	49,51 excluded	Marg. Eff.
Frequency of purchase (ord. 1-7)	−0.0557*	−0.112*	−0.0890*	−0.0797*
	(−2.05)	(−2.03)	(−2.23)	(−2.17)
Never Visited	0.174	0.349	−0.171	−0.154
	(1.86)	(1.85)	(−1.35)	(−1.33)
Male (man=1)	−0.0937	−0.459*	0.128	0.0344
	(−1.00)	(−2.36)	(0.97)	(0.29)
Age (in years)	0.0436*	0.0921*	0.0320	−0.0165
	(2.20)	(2.23)	(1.31)	(−0.71)
Age^2 (years^2/10000)	−4.160	−9.517*	−3.034	1.182
	(−1.93)	(−2.14)	(−1.17)	(0.47)
Education	−0.0268	−0.0539	−0.0654	−0.0586
	(−0.57)	(−0.57)	(−0.98)	(−0.97)
Constant	0.426		0.634	
	(0.89)		(1.01)	
Zero Inflation Logit				
Male (man=1)	0.363*		0.156	
	(1.99)		(0.83)	
Age (years)	−0.00598		0.0879*	
	(−0.16)		(2.17)	
Age^2 (years^2/10000)	1.559		−7.594	
	(0.39)		(−1.80)	
Constant	−0.785		−2.030*	
	(−0.89)		(−2.09)	
$\ln(\alpha)$	−0.440*		−0.428	
	(−2.52)		(−1.49)	
Observations	935		935	
Zero counts	345		508	
$\mathscr{L}(\hat{\beta})$	−2029.713		−1605.993	

Asymptotic z-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Fractional logit for rounded and central probability statements

	Model A7		Model A8		Model A9	
	π_n 49,51 *excluded*	$\frac{\partial \pi_n}{\partial x}$ Marg. Eff.	π_n^* 49,51 *included*	$\frac{\partial \pi_n^*}{\partial x}$ Marg. Eff.	π_n^c Central	$\frac{\partial \pi_n^c}{\partial x}$ Marg. Eff.
Frequency of purchase (ord. 1-7)	0.0672*	0.0139*	0.0495	0.00752	0.00681	0.00170
	(2.23)	(2.24)	(1.45)	(1.45)	(0.25)	(0.25)
Never Visited	−0.0826	−0.0171	0.189	0.0287	0.106	0.0264
	(−0.76)	(−0.76)	(1.52)	(1.52)	(1.11)	(1.11)
Male (man=1)	0.413***	0.0856***	0.230	0.0350	0.0348	0.00868
	(3.91)	(3.97)	(1.88)	(1.89)	(0.38)	(0.38)
Age (years)	−0.0102	−0.00212	0.0494*	0.00751*	0.0275	0.00686
	(−0.47)	(−0.47)	(2.01)	(2.01)	(1.53)	(1.53)
Age^2 (years^2/10000)	1.602	0.332	−4.053	−0.616	−2.735	−0.682
	(0.68)	(0.68)	(−1.50)	(−1.50)	(−1.38)	(−1.39)
Education	0.0948	0.0197	0.135*	0.0205*	−0.0181	−0.00451
	(1.65)	(1.66)	(2.04)	(2.04)	(−0.38)	(−0.38)
Constant	0.133		-0.772		-0.659	
	(0.25)		(−1.32)		(−1.53)	
Observations			935			
$\mathscr{L}(\hat{\beta})$	−564.95		−448.94		−647.04	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.vii Figures of Online Appendix

Figure 1: An example of choice task

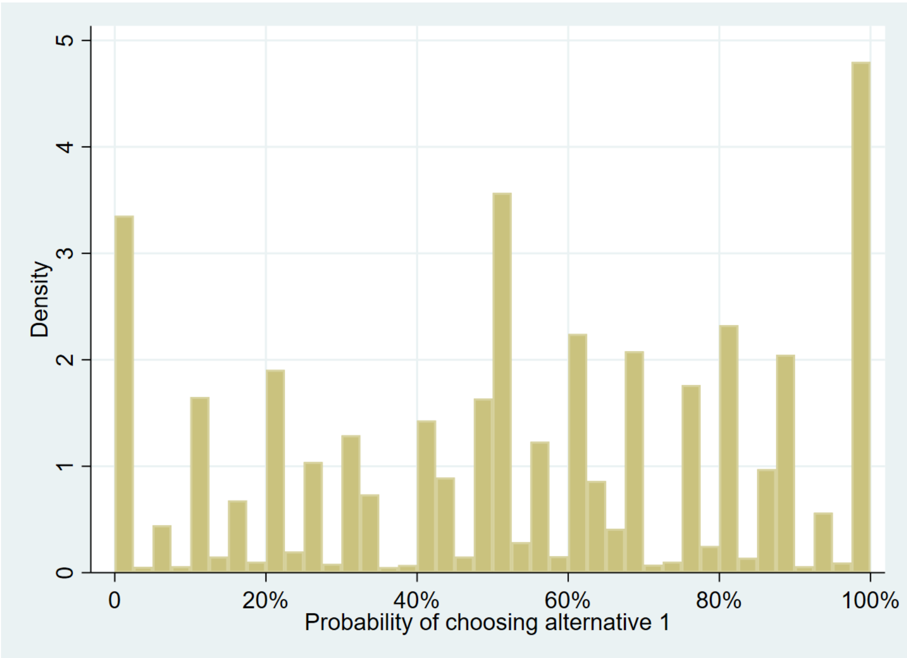

Figure 2: Histogram of elicited probabilities

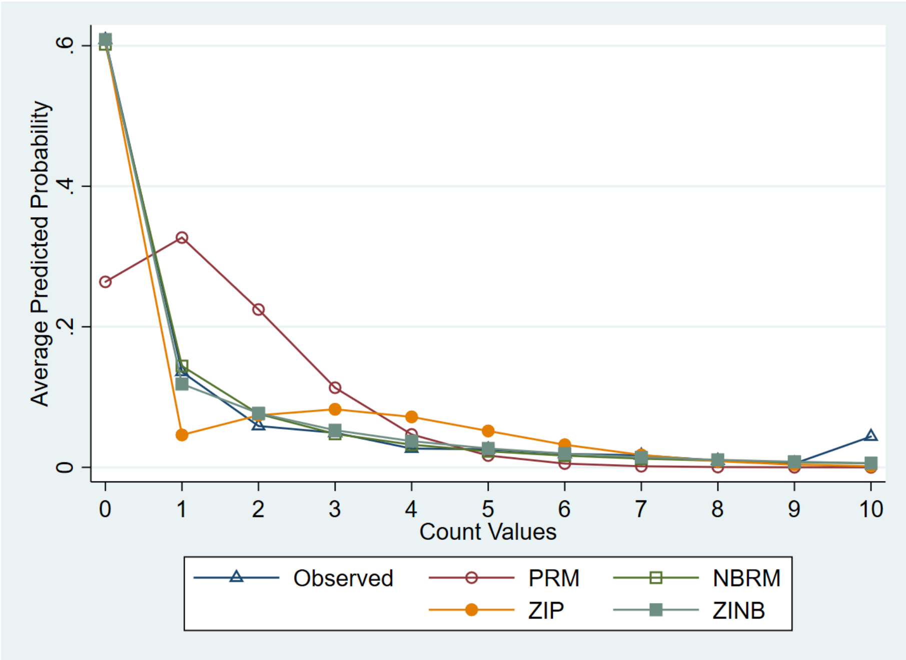

Figure 3: Predicted counts for subjective probabilities of selection 0.46 – 0.54

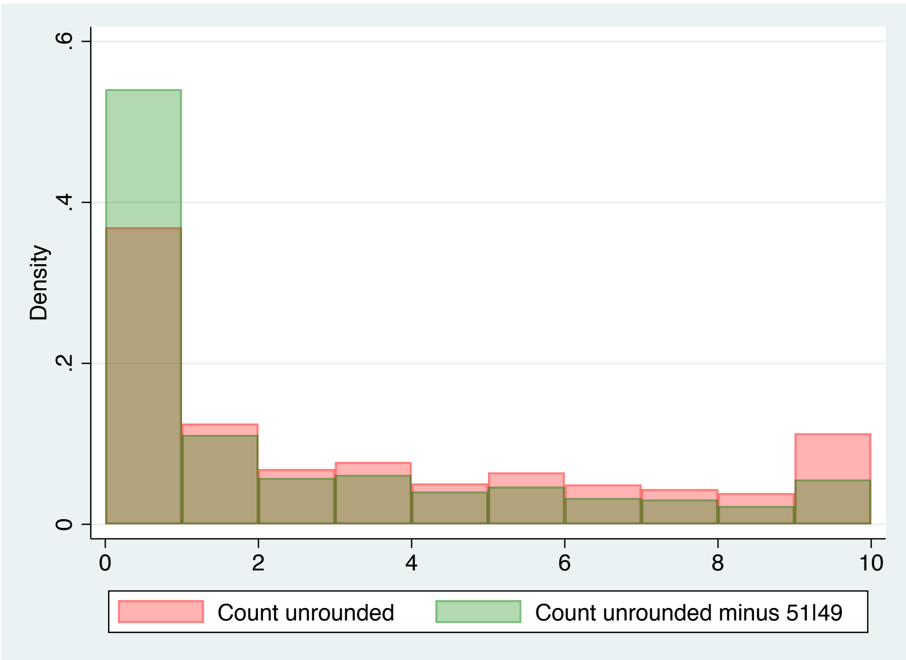

Figure 4: Histogram of unrounded probability statements (entire sequence)

Figure 5: Histogram of unrounded and central prob. statements (∈ [25, 75])

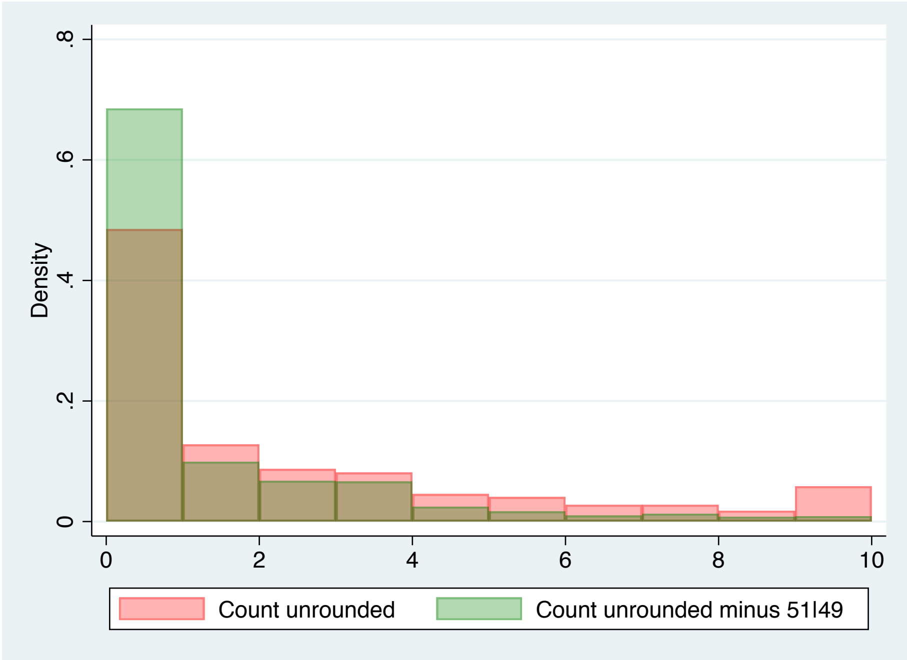

Figure 6: Comparisons of forecasts across count models for unrounded probabilities