"Are Preferences for Food Quality Attributes Really Normally Distributed? An Analysis using Flexible Mixing Distributions"

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Highlights

- We empirically question the commonly employed distributional assumption of normality of taste distribution in mixed logit models with continuous random parameters.
- We use a WTP-space random utility discrete choice model with flexible distributions
- We provide a specific exploration of estimates' sensitivity to the definition of the random coefficients' range of variation.
- We explore the sensitivity of different distributional features across cue and independent attributes when extending the attribute space.
- Results from this study indicate that non-normal distributional features prevail.
- Our findings suggest that researchers using mixed logit models should check the robustness of their findings by also using flexible distributions.

Are Preferences for Food Quality Attributes Really Normally Distributed? An Analysis using Flexible Mixing Distributions

Abstract:

We empirically question the commonly invoked assumption of normality of taste distribution in mixed logit models with continuous random parameters. We use a WTP-space random utility discrete choice model with flexible distributions on data from two choice experiments regarding beef with nested set of quality attributes. We specifically focus on distributional features such as asymmetry, multi-modality and range of variation, and find little support for normality. Our results are robust to attribute dimensionality in experimental design. Implications of our results for practitioners in the field are discussed.

Key words: Flexible taste distributions, mixed logit, logit mixed logit, food preferences, preference heterogneity

The authors would like to thank the editor, Jürgen Meyerhoff, and three anonymous journal reviewers for their helpful comments and suggestions.

Product differentiation is a strategic tool for food market operators. Success in this area is heavily reliant on market information derived from reliable methods to analyse differentiated consumer preference. As a consequence, the mixed logit models choice data analysis introduced by Revelt and Train in 1998 were enthusiastically embraced by empirical researchers in food choice (Bonnet and Simioni 2001; Cicia, Del Giudice and Scarpa 2002; Lusk and Schroeder 2004; Alfnes et al. 2006; Rigby and Burton 2006) and are still widely used (Ortega et al. 2011; Caputo, Nayga and Scarpa 2013; Scarpa et al. 2013; van Wezemael et al. 2014; De Marchi et al. 2016; Bazzani et al. 2017). Operationalizing mixed logit models, however, requires assumptions on mixing preference distributions for the sampled population.

The question of what statistical distribution should be selected to model random taste coefficients to avoid unwarrented (and sometimes unintended) impacts in terms of data fit and welfare estimates, still poses serious empirical challenges to analysts. Like others before us, we start by observing that the assumptions on which these models are predicated, despite being often strong and crucial to the conclusions, are most often left unpersuasively justified. The contribution of this article is to explore the effectiveness of recently introduced tools for a robust investigation of common assumptions. Specifically, we offer some significant results on range, asymmetry and multimodality of taste distributions, which we deem as substantive for the future practice of food choice analyses. Our results also have significant implications for conceptual models of consumer demand whose results may be questionable given their reliance on the assumption of uniform preferences (e.g., Crespi and Marette 2003; Lapan and Moschini 2007; Giannakas and Yiannaka, 2008).

The use of various types of preference mixing—finite, continuous or a combination thereof—is by now the presumptive approach in the field of food choice, and it has been in many other areas of application (e.g., environmental, health and transport economics). Yet, most published studies fail to explicitly report investigations on the sensitivity of their results to the sometimes crucial distributional assumptions under which they are derived. Futhermore, such assumptions are often predicated on weak arguments and motivation including operational convenience (e.g., such as mathematical tractability), and comparisons of fit with alternative distributional assumptions. In this context, it is worth highlighting that consistency of maximum likelihood estimates holds only under the correct specification, and applies only probabilistically to the “comparatively” best specification, especially when all the elements in the set of comparison share some shortcomings (e.g., all imply symmetry to the mean).

Almost universally in our review of food choice applications, when the selected model allows for continuous mixing of preferences, it relies on parametric distributions (normal, log-normal, triangular, uniform, etc.). This approach is attractive because it reduces the space of parameters needed for model fit (e.g. from quantiles to only first and second central moments), but it overly simplifies matters, thereby ruling out several behaviourally plausible features of taste distributions, such as limited range, asymmetry, strong skewness and multimodality. This leads to inadequate conclusions, that often fit oddly in the face of common sense or even of mere introspection. Such discomfort has been expressed several times before and traces of it can be found in the concluding remarks of several previous papers approaching the issue from various persectives (Train and Sonnier 2005, Cherchi and Pollak 2005, Burton, Balcombe and Rigby 2009). Warnings of significant biases due to erroneous distributional assumptions have been issued since the adoption of the mixed logit methodology. Yet, the issue has continued to receive little, if any, attention in empirical analyses of food choice.

To move the field forward, we explore the use of more robust approaches that can enable analysts to openly explore behaviourally realistic distributional structures of food taste. In practice, this requires the adoption of flexible distributional forms, such as mixture of parametric, semi-parametric or non-parametric approaches. There is some obvious resistance to adopting these approaches, as they are bound to be somewhat more complex to implement and tend to deliver the additional features at relatively large sample sizes (Franeschinis et al. 2017). Thus, a successful solution needs to be sufficiently practical to have wide applicability. In moving from a standard parametric description of preference variation to a more flexible one, the analyst faces several unfamiliar challenges linked to taste distributions. In this article, we focus on three important distribution features: the definition of the range of variation, symmetry and multi-modality. These features have obvious and important repercussions for the computation of statistical expectations and quantiles, which are crucial statistics in policy decisions. An example is the well-known so-called “fat-tail” problem (for a recent review see Parsons and Myers 2016).

Throughout the article, we use a recently proposed semi-parametric choice model: the Logit-Mixed Logit (LML) developed by Train (2016) to explore the sensitivity of our results to the three distributional features mentioned above. This model allows for extremely flexible mixing distributions, that can accommodate asymmetry and multimodality, but it requires setting the range of variation. Hence, we also explore the stability of results in distributional outcomes by varying the range (the empirical support of the distribution). In addition, in response to recent works on the effect of context in food choice (Gao and Schroeder 2009; and Caputo, Scarpa and Nayga 2017), we also explore the sensitivity of our distributional results across food attribute types (e.g., cue and independent) when increasing the number of attributes (from three to five) in the discrete choice experiment design and associated utility functions. Finally, to make the article more salient to recent tendencies in food choice, we specify random utility models specified in WTP-space, so as to avoid scale issues and focus on value distributions.

This study contributes to the existing literature of consumer food preference analysis in two important ways. First, we observe that by mostly invoking normality, the great majority of food choice studies[1] using continuous mixing tend to systematically fail to explore the plausibility of distributional assumptions to multimodality, asymmetry and range of variation. All of these features are of potential relevance to policy. Two of these issues (multimodality and asymmetry) were addressed in Scarpa, Thiene and Marangon (2008), but they only applied a flexible semi-parametric distribution to one of the various random coefficients in their specification and they specify a model in preference space. The present food choice study is the first to simultaneously address all three of these issues for all random coefficients, using utility in WTP-space by means of a flexible semi-parametric distribution. Our approach moves away from the standard assumptions of normality without excluding them.

Second, to the best of our knowledge, this is the first food choice study exploring the sensitivity of different distributional features across cue and independent attributes when extending the attribute space. As argued by Gao and Schroeder (2009) and Caputo, Scarpa and Nayga (2017), the way consumers value a 'cue' attribute (described as one whose levels

[1] The food choice literature accounts for over 200 studies using choice experiments on food choice selection. By limiting ourselves to the top 5 journals in the field of agricultural economics, which were selected according to their article influence score (http://www.eigenfactor.org/about.php) and the ISI Web of Knowledge Journal Citations Report, table A1 in the appendix reports the food choice experiment papers published since 2013 in the following peer-reviewed journals: *Food Policy, American Journal of Agricultural Economics, European Review of Agricultural Economics, Journal of Agricultural Economics, and Australian Journal of Agricultural and Resource Economics*. Results clearly demonstrate that most of the published studies on food choice experiments are based on MXL models that assume normal distribution for the non-monetary random taste parameters, and that none of these studies have explored the plausibility of distributional assumptions to multimodality, asymmetry, and range of variation.

correlate with the levels of other potentially absent attributes) and an independent attribute (relates to the physical aspects of the product whose information stands alone) can depend on the attribute space. Hence, this study adds to this stream of literature by showing that consumers would not only value these attributes differently across design dimensions, but also by suggesting that cue and independent attributes might be systematically characterized by different distributional features and context dependency.

More notably, this study adds to the emerging choice modeling literature by providing a specific exploration of estimates' sensitivity to the definition of the random coefficients' range of variation. To date, applications of the LML model can be found in the field of transportation and environmental economics. To illustrate, in the field of transportation, Bansal, Daziano, and Achtnicht (2017) extended the LM model, where all the utility parameters are assumed random, to a combination of fixed and random parameters (LML-FR) using data from a Monte Carlo study and a discrete choice experiment on vehicle preferences in Germany. Similarly, in the field of environmental economics, Franceschinis, Scarpa, and Thiene (2017) employed data from Monte Carlo experiments and an applied choice experiment survey on people's preferences for tap water quality to evaluate the accuracy of random parameters estimates from LML models. In addition, a recent application by Bazzani, Palma, and Nayga (2018) employed the LML model to test for differences in welfare estimates obtained from different assumptions on taste distributions using data from an induced real choice experiment study. Hence, together with these existing studies, this research contributes to a deeper understanding of distributional features of individual preferences in discrete choice analysis.

The remainder of the article is organized as follows. In the next section, we provide a brief and essential literature review as a background to highlight the glaring knowledge gap that this study informs. The third section provides a description of the data used. The fourth section discusses the method we employ, and this is followed by a description of the estimation strategy and the discussion of the results. The final section presents our conclusions and some recommendations for changes in the practice.

Background

That the researcher's choice of taste distribution matters has been a central tenet of taste heterogeneity studies from its beginning. As early as 1999, Wedel et al. and later on in 2003 Hensher and Greene provided detailed guidance for its selection. A more recent review on the topic can be found in a working paper by Yuan, You, and Boyle (2015). Several early studies showed that parametric mixing distributions assumed ex-ante by researchers (e.g., normal, lognormal, among others) may be limiting and may introduce mis-specification problems (Train and Sonnier 2005, Cherchi and Pollak 2005, Burton, Balcombe and Rigby 2009). These papers focused on bounding ranges of variation and therefore signs, and suggested remedies on how to handle distributions for theoretically signed coefficients (e.g. for price) on the negative or positive orthants, and on asymmetry (e.g. log-normal, Johnson-S_B, etc.) and some forms of bi-modality (Johnson-S_B). The discussions in these papers, however, were confined to parametric distributions or transformations thereof which required further parameter estimates in the transformation function, often, as in the Johnson-S_B, of complex empirical identification. The evidence provided emphasised the vulnerability of results to bias of different importance and size, in terms of post-estimation applications. Bias affects probability forecasts, marginal effects and welfare measures, all of which are of high relevance in food choice analysis and food policy design.

Later studies have gone further in the direction of adding flexibility, often in an attempt to uncover multi-modality when present and of practical relevance. These studies have proposed either mixtures of parametric distributions (e.g. mixtures of normals Train 2008, Wasi and Carson 2013), or the use of either semi- or non-parametric mixing distributions (Bajari, Fox, and Ryan 2007; Fosgerau and Bierlaire 2007; Scarpa, Thiene and Marangon 2008; Train 2008; Bastin, Cirillo and Toint 2010; Fox, Ryan and Bajari 2011; and Fosgerau and Mabit 2013). Such distributions are more flexible in retrieving preference heterogeneity, thereby accommodating multimodality as well as asymmetry, and hence skewness. They may even come with the added bonus of being computationally less expensive in estimation (Train, 2016; Bansal, Daziano, and Achtnicht 2017), and able to provide welfare estimates with lower hypothetical bias (Bazzani, Palma, and Nayga, 2018). However, because they are based on splines or polynomials, they are reliant on a larger parameter space than simply means and variances. Morevover, their sample-size requirements to achieve given degrees of accuracy are likely to be larger than those required by parametric distributions.

When the focus of taste heterogeneity is on economic values of food attributes, the typical subjects of investigation are distributions of marginal willingness to pay (mWTPS) or total welfare changes for selected food attributes. In linear utility specifications, these are non-linear functions of parameter estimates, such as ratios, and whenever price coefficients are random, the estimates of these functions are sensitive to distributional assumptions on the price coefficient. Early attempts to deal with this issue often resulted in studies in which the price coefficient was assumed to be fixed. This is, however, a scarsely defensible assumption, as it implies a fixed marginal utility of money. Other solutions rely on bounding its range of variation by, for example, using constrained triangular distributions (Alfnes et al 2006; Hensher and

Greene 2009; Scarpa et al. 2013; Hensher, Rose and Greene 2015) or the previously mentioned uniform or Johnson-S_B distributions.

A solution for this has been eloquently and persuasively discussed elsewhere (Train and Weeks 2005; Scarpa, Thiene, and Train 2008; Daly, Hess and Train 2012), and it suggests rescaling utility by the error scale. This solution was suggested earlier by Cameron and James (1987) in the context of referendum contingent valuation data analysis, and it provides a specification of random utility directly in WTP-space. Here, the random coefficients of attributes can be readily interpreted as marginal WTPs, and their distributions are derived in a manner less sensitive to the distributional assumptions for the price coefficient. However, up until now, they still have been reliant on parametric distributional assumptions (Balcombe, Burton, and Rigby 2011; Thiene, Scarpa and Marangon 2008).

Finally, Rose and Masiero (2010) argued that the assumptions implied by random utility models can be context dependent and affected by the nature of datasets and/or dimensions of experimental designs. In food choice studies, for example, a number of recent papers have shown a specific interest in the sensitivity of marginal WTPs estimates to both the expansion and hierarchy of food attributes (Gao and Schroeder 2009; Caputo, Scarpa and Nayga 2017). This literature explores the effects of progressively adding independent food attributes to choice contexts based on cue attributes in experimental choice. They found evidence of significant shifts in the means of the marginal WTPs, an issue also addressed here.

Empirical Data

In our investigation, we use choice data from two choice experiments (A and B) exploring the effect of an incrementally larger set of attributes on beef selection. The dataset we use is part of a larger project investigating the effects of adding independent food attributes to cue attributes in discrete choice experiments published elsewhere (Caputo, Scarpa, and Nayga 2017). In this study, two experiments are conducted: Experiment A, which included only three beef attributes (*Certified U.S*., *Guaranteed Tender*, and *Price*), and Experiment B, which added two more beef characteristics (*Guaranteed Lean*, *Sell-By Date*) for a total of five attributes. As in Caputo, Scarpa, and Nayga (2017), in this study we defined *Certified U.S*. as "cue attributes', and *Guaranteed Tender, Guaranteed Lean*, and *Sell-By Date* as "independent attributes". In both experiments the price attribute was specified with four levels: $4.64; $6.93; $9.22; $11.50. The other attributes were simply binary (either present or absent). Each respondent was assigned to undertake a panel of eight choice tasks. Each task involved the selection of their preferred alternative out of three: two beefsteak profiles and the "no-purchase" option. Sample statistics and further details about the experimental designs are reported in Caputo, Scarpa, and Nayga (2017). Table 1 shows the attributes and attribute levels included in this study and highlights the differences in use of the data between Caputo, Scarpa, and Nayga (2017) and the present study.

<<Insert Table 1>>

Econometric Models

Throughout we use a WTP-space utility specification (Weeks and Train 2005) with flexible distributional assumptions for marginal WTPs, which allows us to retrieve more realistic taste (value) distributions for food attributes because they allow for multimodality and asymmetry. We then contrast these flexible semi-parametric results with those from conventional parametric distributions based on normality.

The flexible distribution approach is to be implemented by using the logit mixed logit (LML) model recently proposed by Train (2016). If the data display evidence of multimodality and asymmetry for some attribute, the flexible approach will make it apparent, while the MXL with normal distributions will not. For example, in Scarpa, Thiene and Marangon (2008), a random coefficient attribute that when assumed to be distributed normal showed an insignificant mean estimate with value close to zero and a very large standard deviation, once its distribution was evaluated semi-parametrically, using the Legendre polynomial method proposed by Fosgerau and Bierlaire (2007), it showed a much more plausible bi-modal distribution. The two modes, one at each side of zero made it clear that taste distribtuion was bi-polar, with some consumer types desiring the attribute and others avoiding it. The normal interpretation, instead, implied indifference to the attribute, a difference with clear implications for marketing.

However, the investigation of the sensitivity of the results to the range, which needs to be defined a-priori for the LML, needs some decision rule. Train (2016) uses a range spanning two standard deviations (2SD) at both sides of the estimated mean. So, to start with, we adopt this approach too, which should work if the real range of variation is symmetric around the mean. Yet, in the presence of fat tails or multimodality, this may not be the case. In such instances, one can obtain guidance on how to extend the range to investigate by visual inspection of the histogram depicting mixing distributions resulting from the LML approach. More on this issue is reported in the estimation strategy section. We now proceed by briefly detailing the nature of both models, but we direct the readers interested in the details to the seminal papers.

Utility in WTP-space

Following Train and Weeks (2005), the utility that individual *n* derives from choosing alternative *j* within a choice set *J* in choice situation *t* can be expressed as follows:

(1) $$U_{njt} = V_{njt} + \varepsilon_{njt} = \tau_n(-Price_{jt} + \omega_n' \mathrm{x}_{\mathrm{jt}}) + \varepsilon_{njt}$$

where V_{njt} is the observed portion of the utility; ε_{nit} is the i.i.d Gumbel distributed error term; τ_n is a random positive scalar representing the price/scale parameter; here $Price_{jt}$ is the price level for 12 ounce of beef steak for alternative *j* and choice situation *t*; ω_n is a vector of estimated marginal WTPs; $\mathbf{x}_{\mathrm{jt}}$ is the vector of observed non-price attributes for alternative *j*. In our application, these attributes are: US (*Certified US product*) and Tender (*Guaranteed Tender*) in in both experiment A and B, while in experiment B two more are added: Lean (*Guaranteed Lean*), and Sell (*Sell-by Date*).

Panel mixed logit

Let $y_{njt} = 1$ if individual *n* chooses alternative *j* in choice situation *t*, and 0 otherwise. Conditional on the vector $<\tau_n, \omega_n>$, the probability of a sequence of *T* choices, assuming independence between choices is:

$$(2) \qquad L_{njt}(\tau_n, \omega_n) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\tau_n(-Price_{\mathrm{jt}} + \omega_{\mathrm{n}}' \mathrm{x}_{\mathrm{jt}}))}{\sum_{i \in J} \exp(\tau_n(-Price_{\mathrm{it}} + \omega_{\mathrm{n}}' \mathrm{x}_{\mathrm{it}}))} \right]^{y_{njt}}$$

To simplify notation, let us re-define $<\tau_n, \omega_n>$ as β_n. The unconditional probability requires integrating over the distribution of the random parameter across respondents so that the probability of sequence of alternatives chosen by individual *n* can be expressed as follows:

$$(3) \qquad \mathrm{P}_n\{\Theta\} = \int L_{njt}(\beta_n) f(\beta_n|\Theta) d\beta_n$$

where $f(\beta_n|\Theta)$ is the probability density function of the vector of random parameters, as defined by the hyper-parameters Θ.

Panel Mixed Logit with Normal Taste Distributions (MXL)

In what we take as the reference model, the mixture for the random parameters β_n is multivariate normal, so $\beta_n \sim N(\mu, \Omega)$ and $\Theta =< \mu, \Omega >$. In other words, the hyper-parameters are the mean vector μ and the variance and covariance matrix Ω. Note here that for each random WTP the mean, median and mode all coincide, and the range with meaningful symmetric density around the means is a function of Ω. All these are undesirable restrictions that are relaxed in the flexible model that we now describe.

Panel Logit Mixed Logit Models with Flexible Taste Distributions (LML)

Unlike the MXL, in the LML model the joint mixing distribution of the random parameters ω_n is assumed discrete over a finite support set *S*. Discretization is not a constraint because the support set is essentially a multidimensional grid that can be made larger and denser by considering a broader domain of parameters and a higher number of grid points. As shown in Train (2016), the joint probability mass function of random parameters $\beta_r \in S$ in the LML is represented by a logit formula:

(4) $$\Pr(\beta_n = \beta_r) \equiv W(\beta_r|\alpha) = \frac{\exp(\alpha' z(\beta_r))}{\sum_{s \in S} \exp(\alpha' z(\beta_s))}$$

where α is a vector of probability mass parameters and $z(\beta_r)$ defines the shape of the mixing distribution. Substituting in equation (3), the unconditional probability $P_n(\alpha)$ of the sequence of choices of individual *n* is then:

(5) $$P_n(\alpha) = \sum_{r \in S} L_{njt}(\beta_n) \left[\frac{\exp\left(\alpha' z(\beta_r)\right)}{\sum_{s \in S} \exp\left(\alpha' z(\beta_s)\right)}\right].$$

Note that the hyper-parameter is now the vector α and that the flexibility depends on the nature of the logit transformation of the *z* functions, to which we now turn.

The z functions in the LML

Following Train (2016), three types of *z* functions are adopted here: orthogonal polynomials (for model LML-poly), grids (step-functions) (for model LML-step), and splines (for model LML-spline).

In his 2016 seminal article, Train starts by showing how normality can be approximated by specifying *z* as a second order polynomial in $\boldsymbol{\beta}_r$. More flexibility in the shape of the distribution, allowing for asymmetry and multimodality, can be achieved by higher order polynomials (in our LML-poly we use two, four, six, and eight orders), bearing in mind that the number of inflection points is equal to the polynomial order minus one. Of the various categories of polynomials available, orthogonal polynomials, such as Legendre polynomials (but also Hermite, Jacobi, Chebyshev, Bernstein polynomials), have the advantage of having uncorrelated terms. Correlation across $\boldsymbol{\beta}_r$ can be achieved by using cross-products of only first order terms, which greatly reduces the number of necessary parameters.

A second alternative for the $z(\boldsymbol{\beta}_r)$ used in LML-step is represented by a step function based on a grid over the parameter ranges (i.e. the support). Partitioning the set *S* into *G* possibly overlapping subsets H_g, consider the probability mass $W(\boldsymbol{\beta}_r|\alpha)$ being the same for all points in a given subset, but different across subsets. In this case we have the following probability mass function:

(6) $$\Pr(\boldsymbol{\beta}_n = \boldsymbol{\beta}_r) \equiv \mathrm{W}(\boldsymbol{\beta}_\mathrm{r}|\alpha) = \frac{\exp(\sum_{m=1}^{M} \alpha_m (\boldsymbol{\beta}_r \in T_m))}{\sum_{s \in S} \exp(\sum_{m=1}^{M} \alpha_m (\boldsymbol{\beta}_s \in T_m))}$$

This set up generates a type of latent class at each point, except that the parameter values of each class are predefined, instead of being the outcome of an estimation, as in the case of a standard latent class model. In practice, a computational limitation of this approach is that with many attributes in the utility function the number of evaluations becomes quickly infeasible, even with rather largely spaced grids. In this study we use LML-step with four, six, eight and ten mass points.

Splines can also be used (in LML-spline) as they conform to the $\alpha' z(\boldsymbol{\beta}_r)$ format required in (5). To illustrate, take an interval for a single parameter β that goes from start point β_1 and end point β_4, and consider the two intermediate points (knots) β_2 and β_3, with $\beta_1 < \beta_2 < \beta_3 < \beta_4$. Using $I(.)$ as an adequate indicator function, this gives rise to the following four elements of the vector $z(\beta)$:

$$z_1(\beta) = \left(1 - \frac{\beta - \beta_1}{\beta_2 - \beta_1}\right) I(\beta \le \beta_2),$$

$$z_2(\beta) = \left(\frac{\beta - \beta_1}{\beta_2 - \beta_1}\right) I(\beta \le \beta_2) + \left(1 - \frac{\beta - \beta_2}{\beta_3 - \beta_2}\right) I(\beta_2 < \beta \le \beta_3),$$

$$z_3(\beta) = \left(\frac{\beta - \beta_2}{\beta_3 - \beta_2}\right) I(\beta_2 < \beta \le \beta_3) + \left(1 - \frac{\beta - \beta_3}{\beta_4 - \beta_3}\right) I(\beta_3 < \beta),$$

$$z_4(\beta) = \left(\frac{\beta - \beta_3}{\beta_4 - \beta_3}\right) I(\beta_3 < \beta),$$

The elements of the vector α requiring estimation in this case are only three, since the height of the spline is standardized to one (only relative height matters). Note that in (5) it is $\exp(\alpha' z(\boldsymbol{\beta}_r))$ that defines the probability mass, and hence this non-linear transformation changes the spline shape, allowing flexibility. In this study, we use LML-spline with two, four, six and eight knots.

Model Estimation Strategy and Results

As a baseline, the data from Experiment A with two food attributes and price and Experiment B with the additional two food attributes are used to estimate separate MXL models. Normal mixing distributions are assumed for all mWTPs, i.e., $\omega_n \sim N(\mu, \Omega)$ and lognormal distribution for the scale/price coefficient factor. We termed these conventional specifications as MXL-N and we use the results as reference points for comparisons with the flexible distribution model. In our specification search, we estimate a range of flexible distribution models, with different *z* functions and increasing number of parameters to explore the sensitivity to increased flexibility. Specifically, four LML-polynomial (of order four, six, and eight), four LML-step (with four, six, eight, and ten "steps" or mass points), and four LML-spline (with two, four, six, and eight knots) models[2] are estimated from data from each experiment. These flexible distribution models were estimated by using [0, 2] as the range of variation for the price/scale coefficient. To explore the sensitivity to range, we investigate three different ranges for the mWTPs for food attributes. The endpoints of these ranges define the highest and the lowest marginal WTP values in the parameter space *S* and are constructed using the following three approaches:

1) two standard deviations above and below the mean marginal WTPs obtained from the MXL-N model (this is the approach used in the seminal paper by Train 2016);
2) three standard deviations above and below the mean of marginal WTPs obtained from the MXL-N model, to explore behavior in the tails; and
3) we then extended the upper or lower range limits any time a sufficiently high probability mass was observed at the lowest and/or highest bin of the histogram. That is, whenever the tails of the distribution derived from 1) and 2) above had large mass. This assessment was made by visual inspection, but formal tests can be used.

The rationale for extending the range in these cases rests on our desire to investigate whether the high mass probability is due to an accumulation of consumers predicted to have mWTPs values

[2] For all models, during estimation the probability integral in equation (3) was approximated by using 2000 random draws for each person in the sample.

at the upper end of the range, but who in reality have higher values and should hence have probability mass located outside the investigated range. Alternatively, these mass points at high/low mWTP values could be confirmed to be accurate representations of preference densities. Some degree of asymmetry is to be expected in these distributions because of the very nature of the attributes; however, the MXL-N model forces symmetry around the mean/median/mode. After ascertaining the robustness of distributional findings in terms of range, asymmetry and multimodality, we assess their repercussion comparatively to the MXL-N results and across the two experiments with varying number of attributes.

Data from each of the two experiments are used to estimate 24 models: four grid densities times three different ranges of variation times two experiments (A and B). This is repeated for each of the three types of *z* function (poly, step and spline), for a total of 52 flexible distribution models, respectively (26 per experiment).

The proper selection method for best performing models in the context of choice models with flexible semi-parametric distributions is still a subject of debate. In our case, we use standard information criteria that promote parsimony in the number of parameters: Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), and modified Akaike Information Criteria (3AIC). The lower the information criterion value, the better the fit. Table 2 reports the model fit statistics for all models estimated across experiments A and B for each range approach utilized to define the highest and the lowest marginal WTP values in the parameter space *S*.

<< Insert Table 2>>

It can be noted that increasing the number of parameters improves the log-likelihood value, but does not necessary improve the information criteria values as these penalize for over-parameterization. This finding is consistent with Bansal, Daziano, and Achtnicht (2017), who employed the LML-polynomial, LML-step, and LML-spline models in both a Monte Carlo and empirical studies in the field of transportation. For ranges selected using the method of 2SD around the means estimated from the MXL-N, the best performing (accounting for all criteria) LML-polynomial models are of fourth order in both experiments. In the LML-step models, it is with 6 steps and 4 for Experiment A and B, respectively, although for Experiment B the one with 8 steps has lowest AIC. For the LML-spline model, those with two knots outperform the rest in both experiments. More importantly, all flexible models outperform the MXL-N, except for the data in Experiment B, but only when used in an extended asymmetric range. Intuitively, exploring asymmetry seems to be more costly with over-parameterized models. For models with ranges established as 3SD around the MXL-N means, the best performing models are those with the fewest parameters. This is true across all three *z* functions, although in Experiment B, the LML-step with 4 steps has better performance.

We now turn our attention to asymmetry. To explore it, we extend the range of variation for selected mWTPs based on visual inspection of the histogram representations of the mWTPs distributions from the 2SD and 3SD. These are reported in figure 1 for the two steak attributes of Experiment A (*Certified US product* and guaranteed tender).

<< Figure 1>>

Both attributes show evidence of bi-modality in both 2SD and 3SD taste distributions, with high mass around small positive dollar values (0-6 for *Certified US product* and 0-3 for guaranteed tender, both with highest mass at around 2 dollars), but also some high mass at the upper end of the dollar range. These upper tail values on the mWTP range are worth investigating further by extending the range. As a consequence, the upper limit in the third set of models for the *Guaranteed tender* attribute was extended from 6 and 8 dollars to 16, with the results of shifting and spreading the probability mass previously cumulated at 6 and 8 dollars over the range 8-12 dollars. A similar re-estimation for the attribute *Certified US product*, with range increased to a highly unlikely 50 dollars, shows that significant mass is still present at values over 20 dollars, with a third mode with mass at 40! This is brought about by a shift in the polynomial from the 4^{th} to the 6^{th} order. In fact, asymmetry in the range increases the number of parameters of the best fitting models across all *z* functions, for both experiments, except for Experiment B with LML-polynomial.

We finally turn our attention to the stability of the distributional features to the addition of other food attributes in choice, by comparing the histograms for *Certified US product* and *Guaranteed tender* attributes of Experiment B (the two top rows of Figure 2) with 4 non-price attributes with the results obtained in Experiment A with only two (in Figure 1).

<< Figure 2>>

Unexplained context-dependency of results is generally regarded as a negative feature in all methods, and this has been a criticism recently leveled to discrete choice models from experimental food data (Gao and Schroeder 2009; Caputo, Scarpa, and Nayga 2017). This evidence, however, was obtained under normal distributional assumptions. We explore whether this is still evident with flexible functional forms. Comparing figures 1 and 2, we note that the bimodality of the taste distribution for the *Certified US product* (cue attribute) is still supported by the results obtained with the symmetric ranges used (2SD, 3SD, and visual inspection). The fact that only the cue attribute (*Certified US product*) remains bimodal across the experiments is an intriguing finding that may be explained by how consumers process cue attribute information. These are described as indicators (proxies) of other unobservable quality attributes. A number of market research and consumer psychology studies found that consumers use cues to develop beliefs (Dewar and Parker 1994; Aqueveque 2006; Aqueveque 2008; Akdeniz, Calantone and Voorhees 2014), and how they evaluate products might be a direct function of these mediating beliefs (Garrido-Morgado, González-Benito and Martos-Partal 2016). Since these tend to be clustered (e.g. Verdurme and Viaene 2003) they would be consistent with multimodality in cue attributes, as we find here.

Moreover, we note that the taste distribution for the independent attribute (*Guaranteed tender*) is bimodal in Experiment A, while in Experiment B the bimodality of the taste distribution for the independent attributes (*Guaranteed tender*, *Guaranteed lean*, and *Sell-by date*) are only supported by the results obtained with the symmetric ranges 2SD and 3SD. In fact, once the asymmetric range is used, the distributions appear unimodal and strongly skewed to the left—much more so than what a normal distribution would correctly capture—and with well-behaved upper tails that taper out. Balcombe, Burton and Rigby (2009) already focussed on skewness and reported this to be a major empirical regularity in preference distributions. The different distributional features characterizing the cue and independent attributes may partly be explained by the degree to which consumers use food attributes (both independent and cue) as quality cues, which has been shown to depend on the design dimensions (e.g., number of attributes, Caputo, Scarpa, and Nayga 2017). Hence, we speculate that in Experiment A, where fewer attributes were used, consumers perceive both cue (*Certified US product*) and independent (guaranteed tender) attributes as quality cues. On the other hand, in Experiment B, where three additional independent attributes were used, the cue role of the independent attributes in Experiment A dissipated because in Experiment B the alternative profiles became more explicit.

Further, we note that the value range is less extended for these attributes in Experiment B than in Experiment A. This is consistent with what we expect in a choice context in which some cue attributes lose value in the presence of properly specified independent attributes, which would otherwise embed some value in the cue attributes when they are unspecified (Caputo, Scarpa, and Nayga 2017). This is confirmed also by the mean and standard deviation values for the mWTPs reported in Table 3.

<< Table 3>>

This evidence corroborates the hypothesis that results are somewhat senstive to the choice context, even when using flexible distributions. Yet, the main non-normal features of the distributions of tastes for cue attributes seem relatively stable to context. Interestingly, extending the range to the right, which allows for asymmetry, in the mWTP for the sell-by date attribute produces an upper tail that tapers out, rather than the binomial distribution portrayed in the symmetric 2SD and 3SD results. Once again, behavior in the tails matters, and it is best captured by the asymmetric range, as the 2SD and 3SD representation still indicate bimodality for taste of this attribute. Altogether, these results suggest significant departures from the standard normality assumptions commonly invoked by food choice analysts in existing preference heterogeneity studies.

Robustness check of observable vs. unobservable sources of heterogeneity

Differences in consumer preferences for food attributes can be explained by observable and/or unobservable sources of preference heterogeneity. Observable sources of preference heterogeneity such as demographics are those known by the researcher. They are commonly incorporated into discrete choice models through interactions with the experimentally designed levels of the attributes. The basic assumption of this modeling approach is that consumer preferences are heterogeneous due, at least in part, to differences in preferences across diverse socio-demographic groups. However, unobservable sources of preference heterogeneity may still remain even after such interactions are accounted for. These are unknown to the researcher and often modeled by assuming random taste variation in MXL models, where the distribution of random coefficients is intended to approximate unobserved sources of preference heterogeneity.

A natural question to ask in our study is whether the distributional features identified by the LML for each attribute of interest are due to observed and/or unobserved sources of preference heterogeneity. To profile our respondents, we collected socio-demographic data during the CE surveys. So, the samples from both experiments (A and B) were used to estimate models that account for observed sources of preference heterogeneity by interacting the experimentally designed attribute levels with the individual characteristics of our respondents. If interactions coefficients yield statistically insignificant estimates, then we can conclude that observed individual characteristics fail to explain preference heterogeneity around the mean (Hensher, Rose, and Greene 2015). This does not imply absence of preference heterogeneity around the mean, but simply that the socio-demographic characteristics of respondents fail to account for it. Results are presented in table 4 for both experiment A and B.

<< Table 4>>

As can be seen from Table 4, with the exception of gender in Experiment A, none of such interaction terms yield statistically significant estimates in our experiments. Hence, our findings generally confirm results from a number of applications of discrete choice models analyzing consumer food preferences, which have shown that demographic characteristics of respondents often fail to explain preference heterogeneity (Nilsson, Foster and Lusk 2006; Gracia, Loureiro and Nayga Jr. 2009; Caputo, Nayga and Scarpa 2013). Nilsson, Foster and Lusk (2006) suggest that the observable consumer characteristics might be poor indicators of food preference heterogeneity when analyzing consumer preferences for credence attributes of food products (e.g. country of origin, brands, etc.) due to the strong separability assumption between food attributes and demographic information.

Given the significance of the interaction term between gender and the *US Certified label* in Experiment A, we estimated a LML[3] for each sub-sample based on gender (male and female) to further explore if there is heterogeneity in the estimates. As before, for each sub-sample, extreme marginal WTP values in the parameter space *S* are set to two and three standard deviations above and below estimated means of marginal WTPs from the MXL-N model with covariates. Any time a sufficiently high probability mass was observed at the lowest and/or highest bin of the histogram we extended the upper or lower range limits. Figures 3 (female sub-sample) and 4 (male sub-sample) report the estimated WTP distributions for *Certified US product* and for *guaranteed tender*.

<<Insert Figures 3 and 4>>>

Even after fitting LML models to data by gender sub-samples, clear evidence of asymmetry—and to some extent of bimodality—remains, thereby rejecting normality.

Conclusions and Recommendations for Practice

Food choice studies that addressed taste heterogeneity have used parametric mixing distributions (i.e., largely normal distributions) that fail to simultaneously address the three issues we focus on in this study in relation to distribution features: the definition of the range of variation, symmetry

[3] Results of the LML by segmented samples (female and male) are reported in Appendix, table A5.

and multi-modality. This is an important topic since these distribution issues could significantly affect marginal WTP estimates that are used for important marketing and policy decisions. This study is the first to simultaneously focus on all of these issues for all random coefficients of food attributes by using a flexible semi-parametric distribution estimated in WTP space.

Should future investigations of preference heterogeneity in food choice studies move beyond the pervasive assumptions of normality implicitly assuming symmetry and unimodality? Our findings suggest that the answer to this question is a resounding "yes". Researchers using mixed logit models should check the robustness of their findings by also using flexible distributions over ranges that go beyond the one implied by the rule of mean plus or minus two standard deviations. In our investigation on beef preferences, we use a flexible semi-parametric approach, the logit mixed logit estimator proposed by Train (2016) and discover that non-normal distributional features prevail. These features are sensitive to the setting of the range of variation and include acute skewness, asymmetry and bimodality. All of these features would affect policy and marketing implications because they are likely to lead to different consumer stratifications from those derived using normality assumptions. We also note that flexible distributions imply over-parameterization. Over-parameterization is always a risk, but the consequences of misspecification are difficult to generalize: they depend on the loss function of the decision maker. So, what is the cost of getting it wrong? Is it higher than the benefit of searching for a better fit? These are empirical questions requiring an empirical answer. In our case, believing that there is only one mode, rather two or more, will imply losing some market shares in substantive segments.

The approach used in this study is very flexible and not computationally burdensome, at least in our application. Our results suggest that the marginal WTP values show lower means in our experiments with a larger set of attributes, in accordance with previous findings in these contexts. Some significant probability mass extends over ranges of values that might appear very unlikely in reality, because they are excessively high. To limit this problem, and retain flexibility, we suggest that upper ranges for marginal WTP distributions from flexible distributions might need to be informed by responses to specific questions that can be included in survey questionnaires. In this way, the delimitation of the range could be grounded to some empirical data based, for example, on self-reported maximum willingness to pay statements for specific attributes. To sum up, given our findings, future food choice analysts should consider systematic testing of the sensitivity of their results to the use of different parameter distributional features. Our hope is that this study will start a serious discussion about and consideration for this issue, given the increasing popularity of the use of discrete choice models in food choice studies. These studies are typically used not just for business applications but also for welfare and policy analysis.

Our results also have significant implications for research in other fields of inquiry where uniform type distributions between two extremes are commonly used (e.g., studies investigating the market and welfare effects of novel food products and labels) since failure to capture deviations from normality could have serious economic consequences. Most notably, although this study focuses on food choices, our findings may also have a bearing in other fields (e.g., environmental economics, transportation, development economics, and market research, among others) where discrete choice models are widely employed. This study adds to the emerging choice modeling literature (Train 2017; Bansal, Daziano, and Achtnicht 2017; Franceschinis, Scarpa, and Thiene 2017; and Bazzani, Palma, and Nayga 2018) by providing further evidence corroborating for asymmetry and multi-modality in preference distribution, and for the first time evidencing their sensitivity to ranges of variation.

Acknowledgment

This work was partially supported by the USDA National Institute of Food and Agriculture, [Hatch] project [1013332].

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Tables

Table 1. Attributes and Experiments

	Caputo, Scarpa, and Nayga 2017						Present Study	
	Experiment A		Experiment B		Experiment C		Experiment A	Experiment B
Attributes (attribute levels)	A1	A2	B1	B2	C1	C2	From A1	From C1
Price ($4.64;$6.93; $9.22; $11.50)	√	√	√	√	√	√	√	√
Certified U.S. Product (absent/not absent)	√	√	√	√	√	√	√	√
Guaranteed Tender (absent/not absent)	√	√	√	√	√	√	√	√
Guaranteed Lean (absent/not absent)		√	√	√	√	√		√
Days before Sell-by Data (2 days; 8 days)				√	√	√		
Enhanced Omega-3 fatty acids (absent/not absent)						√		
N. of respondents	201		183		208		201	208

Table 2. Model Information Criteria of MXL-N and LML models, Experiments A and B

Model	LL	Par	BIC	AIC	3AIC	LL	Par	BIC	AIC	3AIC
	Experiment A (1,608 choices, N=201)					Experiment B (1,664 choices, N= 208)				
					Normal Distribution					
MXL-N	-1125	10	2324	2270	2280	-1294	21	2744	2630	2651
					2SD above and below the mean					
LML Polynomial										
4	-995	19	2129	2027	2046	-1239	34	2730	2546	2580
6	-986	27	2172	2027	2054	-1233	46	2807	2558	2604
8	-974	35	2206	2018	2053	-1225	58	2881	2566	2624
10	-974	43	2266	2035	2078	-1209	70	2937	2558	2628
LML Step										
4	-993	21	2142	2029	2050	-1248	38	2778	2573	2611
6	-979	29	2173	2016	2045	-1233	50	2836	2565	2615
8	-982	37	2237	2038	2075	-1220	62	2900	2564	2626
10	-968	45	2269	2026	2071	-1216	74	2981	2580	2654
LML Spline										
2	-987	21	2130	2017	2038	-1243	38	2768	2562	2600
4	-979	29	2173	2017	2046	-1230	50	2831	2560	2610
6	-974	37	2221	2022	2059	-1221	62	2902	2566	2628
8	-957	45	2247	2005	2050	-1210	74	2969	2568	2642
					3SD above and below the mean					
LML Polynomial										
4	-982	19	2104	2001	2020	-1265	34	2782	2598	2632
6	-977	27	2153	2007	2034	-1259	46	2859	2610	2656

8	-975	35	2209	2021	2056	-1245	58	2920	2606	2664
10	-972	43	2261	2029	2072	-1240	70	3000	2620	2690
LML Step										
4	-987	21	2130	2017	2038	-1261	38	2805	2599	2637
6	-990	29	2194	2038	2067	-1261	50	2892	2622	2672
8	-981	37	2236	2037	2074	-1238	62	2936	2600	2662
10	-977	45	2286	2044	2089	-1236	74	3021	2620	2694
LML Spline										
2	-984	21	2122	2009	2030	-1270	38	2821	2615	2653
4	-978	29	2170	2014	2043	-1255	50	2882	2611	2661
6	-976	37	2225	2026	2063	-1245	62	2951	2615	2677
8	-969	45	2271	2028	2073	-1235	74	3019	2619	2693
					Visual Inspection					
LML Polynomial										
4	-1021	19	2182	2080	2099	-1353	34	2959	2775	2809
6	-1000	27	2200	2054	2081	-1349	46	3038	2789	2835
8	-994	35	2247	2059	2094	-1345	58	3121	2807	2865
10	-994	43	2306	2074	2117	-1341	70	3202	2822	2892
LML Step										
4	-1015	21	2186	2073	2094	-1367	38	3016	2810	2848
6	-990	29	2194	2038	2067	-1343	50	3056	2785	2835
8	-997	37	2268	2068	2105	-1331	62	3121	2786	2848
10	-993	45	2319	2077	2122	-1326	74	3200	2799	2873
LML Spline										
2	-1016	21	2187	2074	2095	-1365	38	3011	2806	2844
4	-993	29	2200	2044	2073	-1341	50	3053	2782	2832
6	-994	37	2261	2062	2099	-1331	62	3121	2786	2848
8	-981	45	2294	2052	2097	-1324	74	3197	2796	2870

Table 3. Statistics of Marginal WTP Estimates from MXL-N and LML (Bootstrapped Standard Errors) models, Experiments A and B

Models		Experiment A				Experiment B			
		MXL-N	**LML-Polynomial**			**MXL-N**	**LML-Polynomial**		
Variables	Par		*2SD*	*3SD*	*Vis. Insp.*		*2SD*	*3SD*	*Vis. Insp.*
US	μ	5.56*	5.13*	6.14*	7.92*	3.53*	3.75*	4.29*	5.87*
		(0.47)[1]	(0.54)	(0.73)	(1.20)	(0.30)	(0.30)	(0.39)	(0.77)
	σ	4.39*	4.32*	5.76*	9.42*	3.17*	3.36*	3.94*	6.46*
		(0.64)	(0.44)	(0.62)	(1.85)	(0.33)	(0.22)	(0.33)	(0.82)
Tender	μ	2.35*	1.89*	2.18*	2.43**	1.26*	1.82*	1.51*	1.89**
		(0.37)	(0.31)	(0.38)	(2.43)	(0.34)	(0.22)	(0.26)	(0.58)
	σ	1.79*	1.29*	2.11*	2.98*	1.99*	1.71*	2.70*	4.40*
		(0.47)	(0.28)	(0.33)	(0.76)	(0.34)	(0.21)	(0.28)	(0.77)
Lean	μ					1.26*	1.62*	1.22*	1.85*
						(0.31)	(0.27)	(0.29)	(0.58)
	σ					2.07*	1.36*	2.19*	4.85*
						(0.29)	(0.21)	(0.30)	(0.97)
Sell	μ					1.13*	1.02*	1.00*	1.61**
						(0.24)	(0.26)	(0.30)	(0.57)
	σ					1.88*	1.49*	2.26*	4.31*
						(0.31)	(0.20)	(0.23)	(0.67)

Note: Asterisk (*) and double asterisk (**) denote coefficients significant at 1% and 5%, respectively.

Table 4. Statistics of Marginal WTP Estimates from MXL-N model including socio-demographics, Experiments A and B

		Experiment A	Experiment B
Models		MXL-N	MXL-N
Variables	Par		
Main effects			
	μ	5.22*	3.05*
US		(0.75)	(0.75)
	σ	4.02*	3.13*
		(0.57)	(0.38)
	μ	1.92*	1.30*
Tender		(0.67)	(0.58)
	σ	1.80*	1.96*
		(0.44)	(0.40)
	μ		1.34*
Lean			(0.62)
	σ		2.06*
			(0.45)
	μ		0.19*
Sell			(0.51)
	σ		1.82*
			(0.29)
	σ		
Interaction terms			
*US * Female*	μ	0.61**	0.47
		(0.31)	(0.29)
*US * Education*	μ	0.07	0.16
		(0.32)	(0.34)
*US * Age*	μ	0.29	0.04
		(0.33)	(0.30)
*US * Income*	μ	0.28	0.23
		(0.32)	(0.30)
*Tender * Female*	μ	0.08	0.31
		(0.20)	(0.29)
*Tender * Education*	μ	0.34	0.10
		(0.23)	(0.28)
*Tender * Age*	μ	0.08	0.27
		(0.23)	(0.26)
*Tender * Income*	μ	0.08	0.19
		(0.23)	(0.28)
*Lean * Female*	μ		0.29
			(0.26)
*Lean * Education*	μ		0.04

			(0.26)
*Lean * Age*	μ		0.29
			(0.25)
*Lean * Income*	μ		0.05
			(0.26)
*Sell * Female*	μ		0.21
			(0.23)
*Sell * Education*	μ		0.28
			(0.23)
*Sell * Age*	μ		0.04
			(0.22)
*Sell * Income*	μ		0.37
			(0.24)
Statistics			
Choices		1608	1664
LL		-1119.67	-1280.62
Par		18	37
N of. Respondents		201	208

Note: Asterisk (*) and double asterisk (**) denote coefficients significant at 1% and 5%, respectively.

Figure 1: Estimated distributions of food attribute coefficients, Experiment A

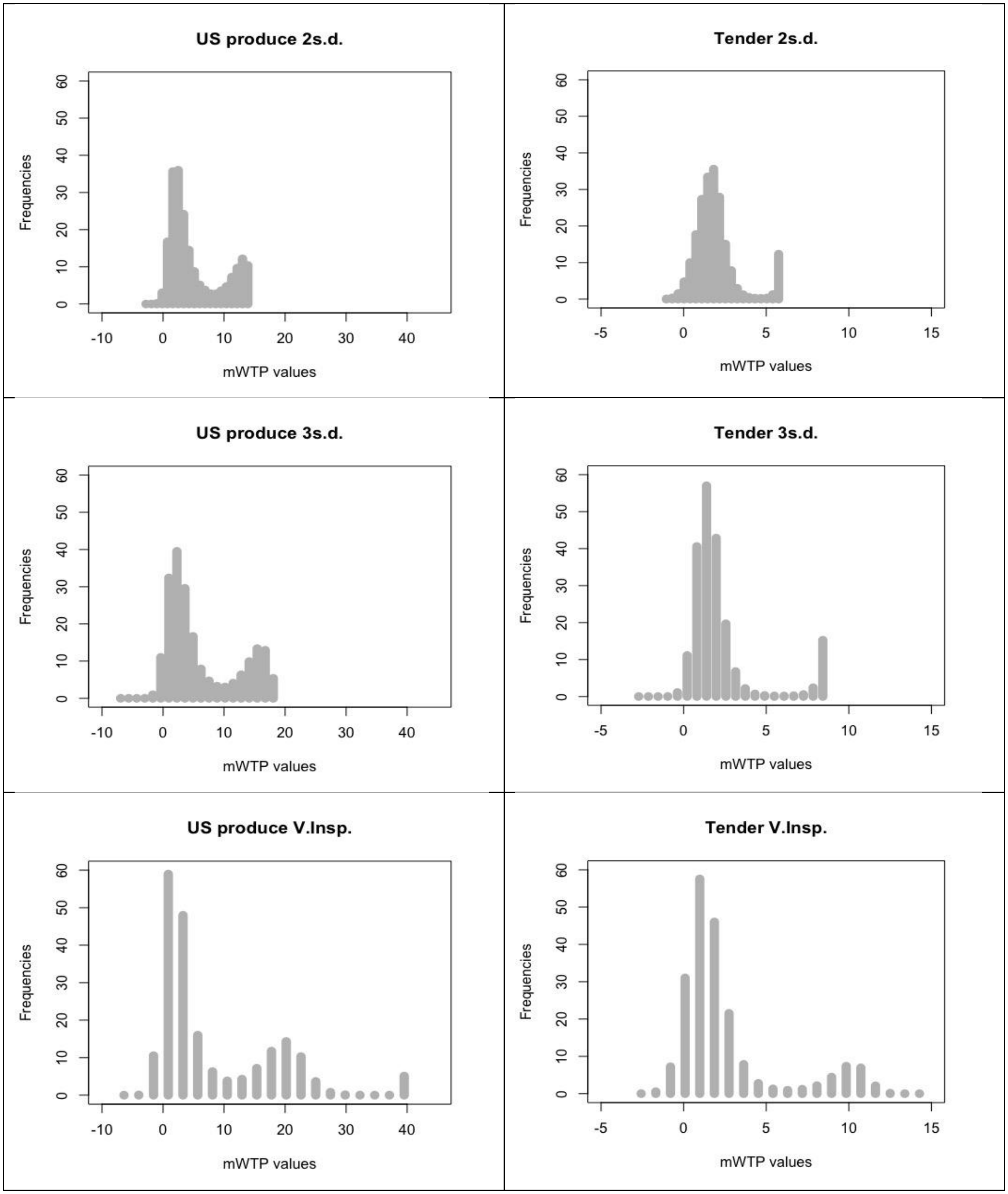


Figure 2: Estimated distributions of food attribute coefficients, Experiment B

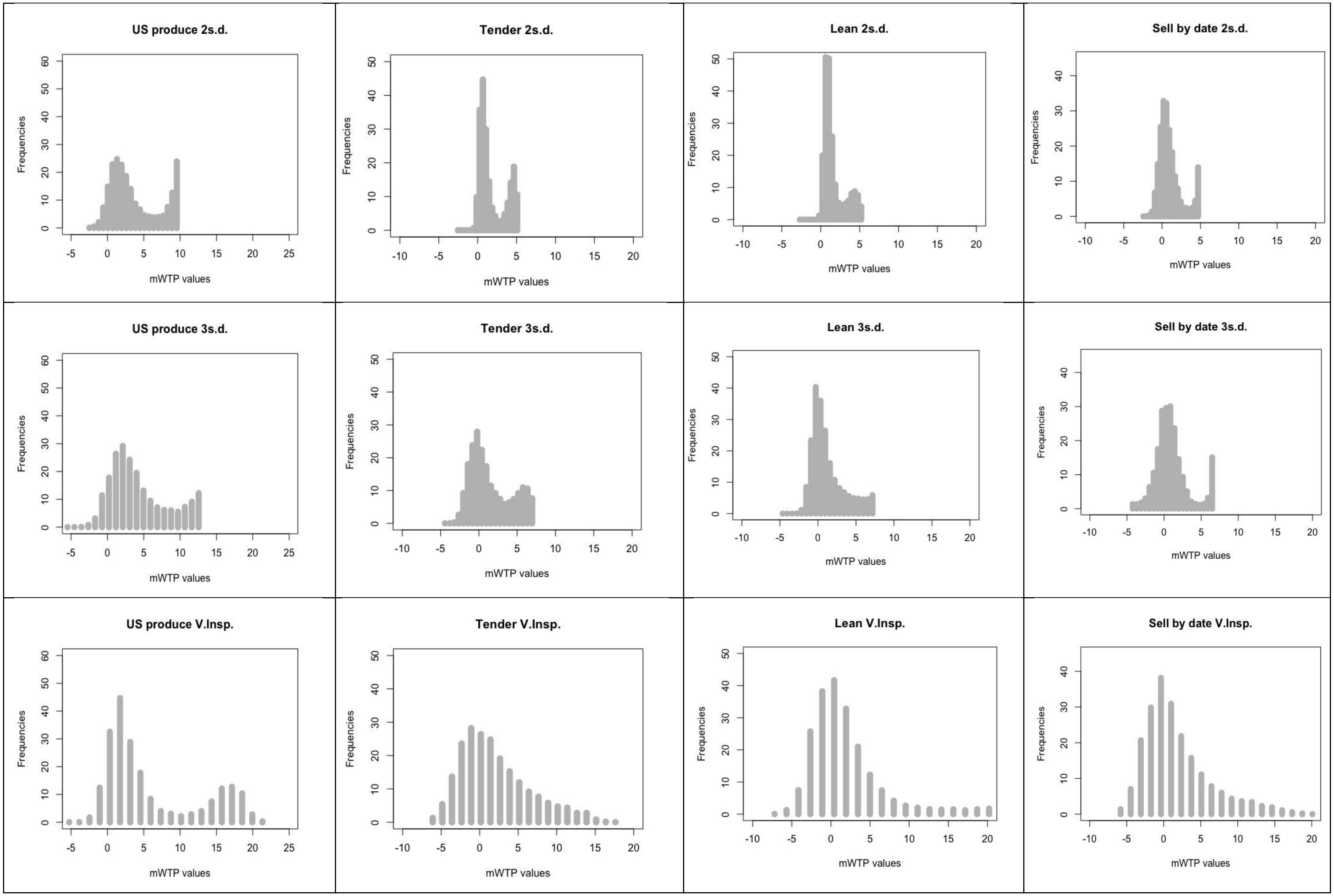


Figure 3: Estimated distributions of food attribute coefficients for Female, Experiment A

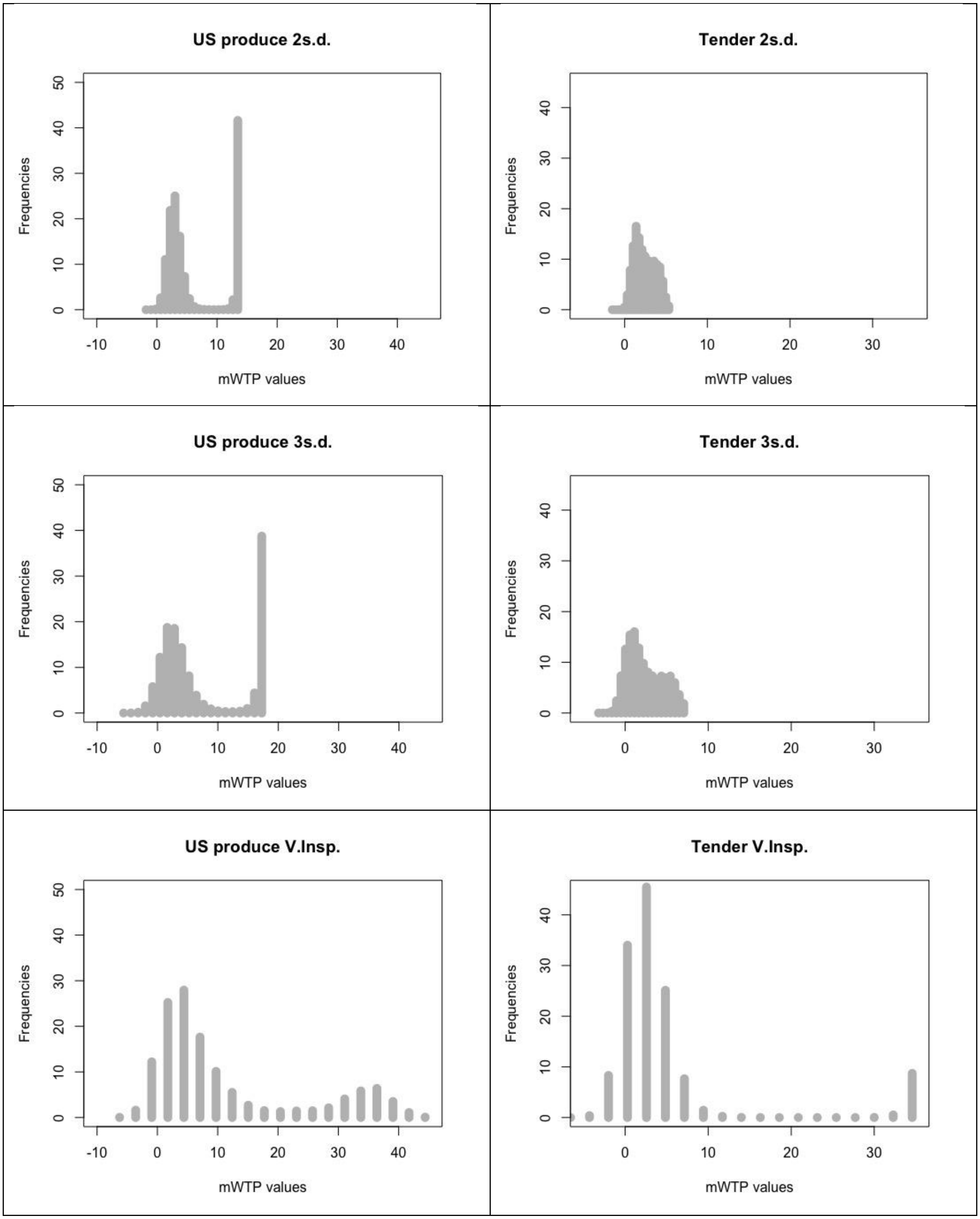
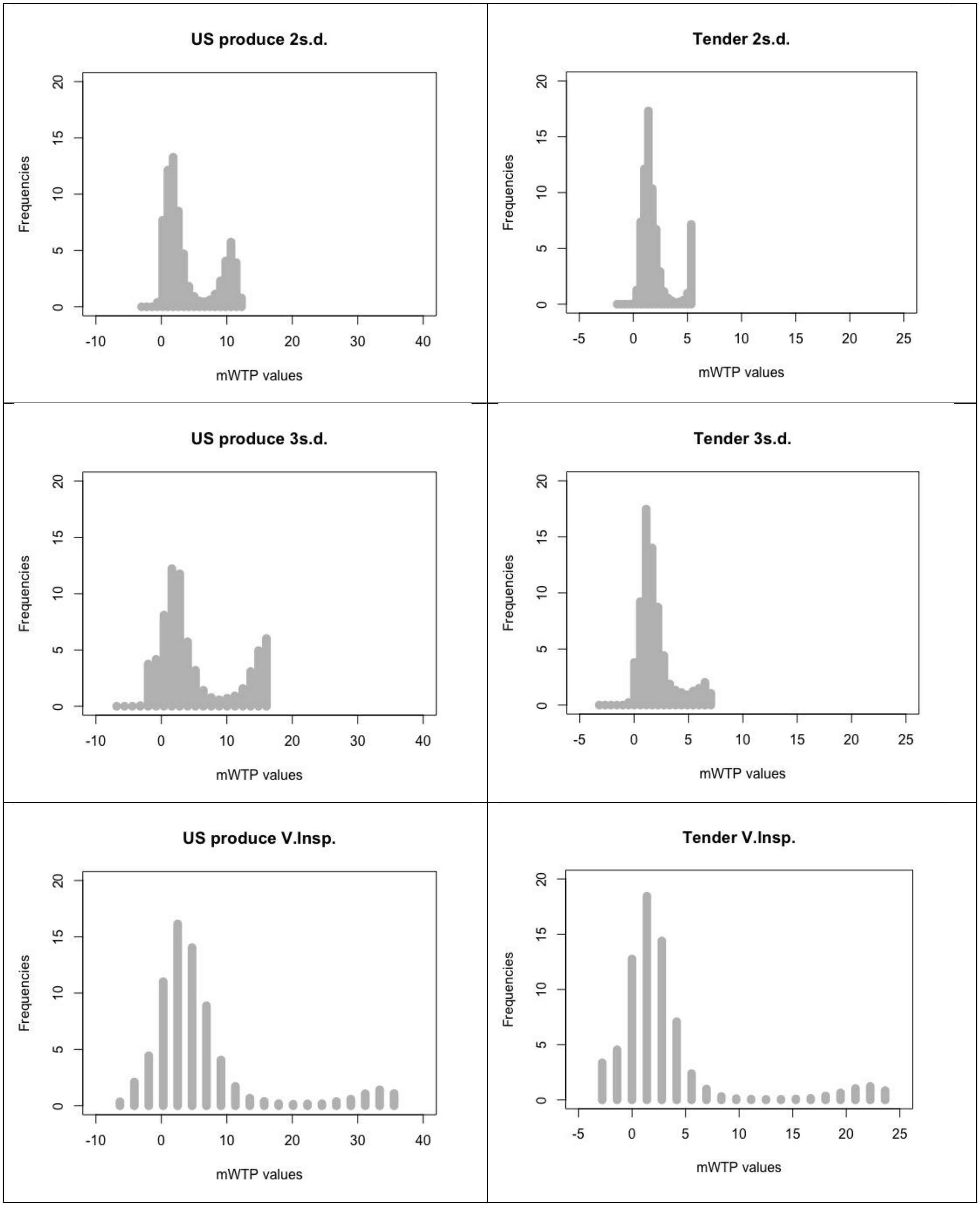


Figure 4: Estimated distributions of food attribute coefficients for Male, Experiment A


US produce 2s.d.
Tender 2s.d.
US produce 3s.d.
Tender 3s.d.
US produce V.Insp.
Tender V.Insp.
Frequencies
mWTP values
0
5
10
15
20
25
30
40
-5
-10

Appendix

Table A1. Summary of recent consumer studies on food choice experiments since 2013[1]

Authors/Paper Title	**Year**	**Model**	**Distribution of non-monetary random parameters**
FOOD POLICY			
Grebitus, C., Jensen, H. H., & Roosen, J.	2013	MXL	Normal
US and German consumer preferences for ground beef packaged under a modified atmosphere–Different regulations, different behaviour?			
Rousseau, S., & Vranken, L.	2013	CL, MXL	Normal
Green market expansion by reducing information asymmetries: Evidence for labeled organic food products.			
Bechtold, K. B., & Abdulai, A.	2014	CL, LC	None
Combining attitudinal statements with choice experiments to analyze preference heterogeneity for functional dairy products.			
Van Wezemael, L., Caputo, V., Nayga Jr, R. M., Chryssochoidis, G., & Verbeke, W.	2014	MXL-EC	Normal
European consumer preferences for beef with nutrition and health claims: A multi-country investigation using discrete choice experiments.			
Van Loo, E. J., Caputo, V., Nayga Jr, R. M., & Verbeke, W.	2014	MXL-EC	Normal
Consumers' valuation of sustainability labels on meat.			

Uchida, H., Onozaka, Y., Morita, T., & Managi, S. *Demand for ecolabeled seafood in the Japanese market: A conjoint analysis of the impact of information and interaction with other labels.*	2014	MXL	Normal
Grebitus, C., Steiner, B., & Veeman, M. *The roles of human values and generalized trust on stated preferences when food is labeled with environmental footprints: Insights from Germany*	2015	MNL, MXL	Normal
De Marchi, E., Caputo, V., Nayga Jr, R. M., & Banterle, A. *Time preferences and food choices: evidence from a choice experiment.*	2016	MXL-EC	Normal
Apostolidis, C., & McLeay, F. *Should we stop meating like this? Reducing meat consumption through substitution.*	2016	MNL, LC	None
Balcombe, K., Bradley, D., Fraser, I., & Hussein, M. *Consumer preferences regarding country of origin for multiple meat products.*	2016	MXL	Normal
Gao, Z., House, L., & Bi, X. *Impact of satisficing behavior in online surveys on consumer preference and welfare estimates.*	2016	CL, MXL	Normal
Balogh, P., Békési, D., Gorton, M., Popp, J., & Lengyel, P. *Consumer willingness to pay for traditional food products.*	2016	MXL, GMNL	Normal

Petrolia, D. R. *Risk preferences, risk perceptions, and risky food.*	2016	MXL	Normal
Wongprawmas, R., & Canavari, M. *Consumers' willingness-to-pay for food safety labels in an emerging market: The case of fresh produce in Thailand.*	2017	GMXL	Normal
Zhou, J., Liu, Q., Mao, R., & Yu, X. *Habit spillovers or induced awareness: Willingness to pay for eco-labels of rice in China*.	2017	MXL	Normal
Maples, J. G., Lusk, J. L., & Peel, D. S. *Unintended consequences of the quest for increased efficiency in beef cattle: When bigger isn't better.*	2018	CL, LC	None
AMERICAN JOURNAL OF AGRICULTURAL ECONOMICS			
Scarpa, R., Zanoli, R., Bruschi, V., & Naspetti, S. *Inferred and stated attribute non-attendance in food choice experiments.*	2013	MXL-EC	Normal
De-Magistris, T., Gracia, A., & Nayga Jr, R. M. *On the use of honesty priming tasks to mitigate hypothetical bias in choice experiments.*	2013	MXL	Normal
Meas, T., Hu, W., Batte, M. T., Woods, T. A., & Ernst, S. *Substitutes or complements? Consumer preference for local and organic food attributes.*	2014	CL, MXL	Normal (only in the MXL)

Balcombe, K., Fraser, I., Lowe, B., & Souza Monteiro, D.	2015	MXL	Normal, log-normal
Information customization and food choice.			
Lusk, J. L.	2017	MNL	None
Consumer research with big data: Applications from the food demand survey (FooDS).			
EUROPEAN REVIEW OF AGRICULTURAL ECONOMICS			
Moser, R., Raffaelli, R., & Notaro, S.	2013	MNL, MXL	Normal (MXL)
Testing hypothetical bias with a real choice experiment using respondents' own money			
Lusk, J. L., Schroeder, T. C., & Tonsor, G. T.	2014	MXL	Normal
Distinguishing beliefs from preferences in food choice.			
Chalak, A., Abiad, M., & Balcombe, K.	2016	MXL	Normal, Log-normal
Joint use of attribute importance rankings and non-attendance data in choice experiments.			
Caputo, V., Scarpa, R., & Nayga, R. M.	2017	MXL-EC	Normal
Cue versus independent food attributes: the effect of adding attributes in choice experiments			
Van Loo, E. J., Nayga, R. M., Campbell, D., Seo, H. S., & Verbeke, W.	2018	MXL-EC	Normal
Using eye tracking to account for attribute non-attendance in choice experiments.			
JOURNAL OF AGRICULTURAL ECONOMICS			

Kehlbacher, A., Balcombe, K., & Bennett, R. *Stated Attribute Non-attendance in Successive Choice Experiments.*	2013	MXL	Normal
Balcombe, K., Bitzios, M., Fraser, I., & Haddock-Fraser, J. *Using attribute importance rankings within discrete choice experiments: An application to valuing bread attributes.*	2014	MXL	Normal, Lognormal
Gracia, A., Barreiro- Hurlia, A., Barreirortance *Are local and organic claims complements or substitutes? A consumer preferences study for eggs.*	2014	LC	None
Viegas, I., Nunes, L. C., Madureira, L., Fontes, M. A., & Santos, J. L. *Beef credence attributes: Implications of substitution effects on consumers' WTP.*	2014	MXL	Normal
Yue, C., Zhao, S., & Kuzma, J. *Heterogeneous Consumer Preferences for Nanotechnology and Genetic-modification Technology in Food Products.*	2015	LC	None
Erdem, S. *Consumers' preferences for nanotechnology in food packaging: a discrete choice experiment.*	2015	MNL, MXL	Normal
Gerini, F., Alfnes, F., & Schjøll, A. *Organic-and Animal Welfare-labelled Eggs: Competing for the Same Consumers?*	2016	MXL	Normal

Lewis, K. E., Grebitus, C., Colson, G., & Hu, W.	2017	MXL	Normal
German and British consumer willingness to pay for beef labeled with food safety attributes.			
Alphonce, R., & Alfnes, F.	2017	MXL	Normal
Eliciting consumer WTP for food characteristics in a developing context: Application of four valuation methods in an African market.			
Edenbrandt, A. K., Gamborg, C., & Thorsen, B. J.	2018	MXL	Normal
Consumers' Preferences for Bread: Transgenic, Cisgenic, Organic or Pesticide-free?			
Caputo, V., Van Loo, E. J., Scarpa, R., Nayga, R. M., & Verbeke, W.	2018	MXL, LC	Normal
Comparing Serial, and Choice Task Stated and Inferred Attribute Non-Attendance Methods in Food Choice Experiments.			
AUSTRALIAN JOURNAL OF AGRICULTURAL AND RESOURCE ECONOMICS			
Caputo, V., Nayga, R. M., & Scarpa, R.	2013	MNL, MXL, MXL-EC, LC	Normal
Food miles or carbon emissions? Exploring labelling preference for food transport footprint with a stated choice study.			

[1] Selected Peer-Reviewed Journals: *Food Policy, American Journal of Agricultural Economics, European Review of Agricultural Economics, Journal of Agricultural Economics, and Australian Journal of Agricultural and Resource Economics* (see footnote 1).

Note: **MXL** = mixed logit model or Random Parameter Logit model; **CL**=Conditional logit model; **MNL**= Multinomial Logit Model; **LC**= Latent Class Logit Model; **GXML**=Generalized Mixed Logit Model.

Table A2. Statistics of Marginal WTP Estimates from the LML model across demographics (Bootstrapped Standard Errors), Experiment A

Models		Female			Male		
		Polynomial			Polynomial		
		2SD	*3SD*	*Vis. Insp.*	*2SD*	*3SD*	*Vis. Insp.*
Variables	Par						
US	μ	6.49*	7.64*	10.69*	4.13*	5.15*	5.55*
		(0.63)	(0.78)	(1.76)	(0.59)	(0.79)	(1.45)
	σ	5.12*	7.16*	12.25*	3.91*	5.76*	8.16*
		(0.47)	(0.65)	(2.34)	(0.47)	(0.68)	(1.77)
Tender	μ	2.44*	2.37*	4.73*	1.94*	1.97*	2 87*
		(0.42)	(0.45)	(1.75)	(0.46)	(0.48)	(1.05)
	σ	1.26**	2.11*	8.65*	1.40*	1.62*	5. 22*
		(0.35)	(0.47)	(3.01)	(0.35)	(0.39)	(1.77)
Statistics							
Choices		1056	1056	1056	552	552	552
LL		672.44	672.50	678.62	312.74	308.84	321.14
Par		19	19	19	19	19	19
N of. Respondents		132	132	132	69	69	69

Note: Asterisk (*) and double asterisk (**) denote coefficients significant at 1% and 5%, respectively.