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Modeling Indifference and Dislike: A Bounded Bayesian Mixed Logit Model of the UK Market for GM Food

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Keywords: bounded mixed logit; choice modeling; GMOs; food safety; Bayesian

JEL classification: C11, C24, C25, D12, Q18

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The use of random utility model models has a relatively long history in the area of environmental valuation (see [17]). One of the central tenets of this analysis has been homogeneity in the utility function of agents which drive the valuations and choices made. For the analysis to be tractable one has typically had to assume that, at some level, agents have the same utility function, that the parameters of that function are common across individuals, and typically any heterogeneity is reduced to the residual, rationalized as the individual components that are not represented by the specified function.

Where heterogeneity is explicitly considered, it is usually through the inclusion of individual specific variables such as age and gender which act to modify the values of the parameters of the utility function. For example, household characteristics are employed in studies of demand [10]; individual experience is used to modify recreational choice [24]; gender is used to modify preference functions over the environment [2].

Alternative specifications of the random utility model which approach individual heterogeneity from a different perspective have developed in recent years, stimulated by the development of simulated maximum likelihood estimation methods. In these mixed logit or random parameter logit models [25, 35] it is assumed that the functional form and arguments of utility are common across individuals, but that the parameters vary across individuals. The analysis in this case aims to identify the parameters of the distribution from which the individual-specific parameters are drawn.

This approach represents a fundamentally different approach to modeling heterogeneity than that employed in more traditional fixed parameter logit models where the approach is to segment the sample, the attributes, or both and it is regarded by many as the most promising discrete choice analytical model available [16][1].

The use of a mixed logit model brings with it a number of advantages, but also some issues of interpretation and application. One of the key problems in moving away from the estimation of a single

[1] An additional approach is the use of latent class models (see [6] for an application and [13] for a comparison with a mixed logit model).

(or number of) point estimates of the parameter value and instead analyzing the distribution of parameters has been specifying the functional form for that distribution. The most commonly used has been the normal distribution, but as the following discussion indicates there are a number of circumstances in which this may be regarded as inappropriate and hence alternatives, such as the triangular or log-normal distribution have been implemented, again with a series of associated drawbacks which are also discussed in the paper. In the context of these developments regarding functional form and the remaining associated drawbacks, recent efforts have focused on the further development of mixed logit models using bounded distributions.

This paper discusses developments regarding the distributions implementable in mixed logit models and presents an application of Train and Sonnier's bounded mixed logit model [33] which is estimated using Bayesian techniques. The model is applied to data regarding consumer preferences for food attributes, including genetic modification, from the UK.

1. Modeling Heterogeneous Preferences

The relaxation of the assumption that all agents in the economic setting under analysis have the same underlying utility function poses new challenges. Among these is the issue of how preferences or tastes are distributed over the population in question. Consider the situation where person n chooses among J options in T periods. Person n's utility from alternative j in the t^{th} period is given by

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \qquad (1)$$

where vector x_{njt} contains variables of interest that drive choices made including choice attributes, respondent attributes etc. β_n and ε_{njt} are not observed and the logit model assumes that ε_{njt} is distributed IID extreme value. The β_n are assumed to vary across the population, and are drawn from some distribution: $\beta_n \sim F(b,\Omega)$. Thus the unobserved parameters can be considered to have two elements: the mean of the distribution and the stochastic distribution around the mean.

In the mixed logit approach the stochastic elements are separated, hence utility from option j for person *n* (suppressing the t subscript) is:

$$U_{nj} = \beta_n' x_{nj} + [\eta_{nj} + \varepsilon_{nj}] \tag{2}$$

This model assumes that ε_{njt} is IID extreme over alternatives with a mean of zero while η_{nj} can take on a number of functional forms. Estimation involves identifying the distribution parameters for the assumed functional form (e.g. the mean and variance for a two parameter distribution). A key issue therefore becomes the choice of functional form to employ. Most commonly normal and log-normal distributions [3, 4, 31, 28, 20] have been used, although triangular and uniform distributions have also been employed [28, 16, 34]. Clearly the choice of distribution is significant and the selection is neither simple nor, in many cases, amenable to testing. Hence Hensher and Greene note that "distributions are essentially arbitrary approximations to the real behavioral profile. We select specific distributions because we have a sense that the "empirical truth" is somewhere in their domain. All distributions in common practice unfortunately have at least one major deficiency – typically with respect to sign and length of the tail(s)" [16: 146].

The normal distribution might be seen as a natural choice for the distribution of preferences, but one implication of this assumption is that it implies that there will be some individuals who have, with some finite if small probability, extreme positive and extreme negative valuations of an attribute. In some cases this will be at variance with *a priori* reasoning. While there may be a distribution of marginal utilities of money, for example, it should in all cases be non-negative and, one could argue, positive. Assuming that the distribution is normal will violate this. This problem is one of the reasons for the popularity of the log-normal distribution since it can be restricted to either the positive or negative sign, but in practice this advantage has been compromised by some of its other characteristics. These include the long tail which often generates a large range of infeasible WTPs in the case of economic studies, and also the zero probability mass at zero which make it unsuitable for modeling a situation where a section of the population are indifferent to an attribute whilst the remainder are positively (or negatively) disposed towards it.

One resulting area of work has been development of estimatible forms of bounded distributions since, as Hensher and Greene observe, "truncated or constrained distributions appear to be the most promising direction in the future". In this paper the bounded mixed logit model developed by Train and Sonnier [33] is applied to stated choice data regarding food attributes in the UK.

The structure of the paper is as follow: the issues and data are first set out, the model is then formally presented and the results and their implications are then outlined and discussed.

2. An Application - Genetically Modified Food in the UK

Food containing GMOs first became available in the UK in 1997. Consumer unease and opposition to the use of GMOs in food grew in subsequent years and from 1998 the major UK food retailers began removing GM food and ingredients from their supply chain.

A 2002 UK survey [9] reported that only 32% of respondents found the idea of food produced from a GM plant acceptable, with the figures for the acceptability of fish and farm animals which had been genetically modified being 11% and 13 % respectively. Indeed, the survey reported that 35% of respondents would not accept any of the food uses put to them (food produced using a GM plant, bacteria, yeast, fish or animals), indicating the strength of general opposition to GM food among a significant section of the UK population.

This consumer concern in the UK is matched by widespread skepticism and concern in the rest of Europe, identified in a series of Eurobarometer attitudinal surveys. In 2001 [12] this pan-European survey reported 71% of respondents agreed with the statement "I do not want this type of food" and 95% agreeing that "I want to have the right to choose", whilst only 15% agreed that "this kind of food does not present any particular danger". Marris *et al*., report their qualitative work in the UK, Spain, France, Italy and Germany which found that:

> "Contrary to our expectations, there was an overwhelming similarity in the…results from the five countries studied, despite national differences in the amount of media coverage and the intensity of the public debate. There were some national differences in the emphasis placed on particular views, and in the examples used to support those views, *but underlying those differences, we found a broad similarity in the repertoire of arguments mobilised by focus group participants in all five countries.*" [22: 3].

A key result of this work was the view that people were not ‘anti-science’ and did not demand risk-free technological development but that, in addition to uncertainty about long-term environmental and health effects of the use of GMOs, questions were repeatedly raised regarding the distribution of the benefits of the technology. This is reflected in the UK survey cited above [9] which found that in answer to a question regarding who would benefit most from the use of GM technology in food production, interviewees most frequently identified the companies developing the technology (24%), food manufacturers (18%) and farmers (13%). Developing countries were identified by 11%, with consumers named by only 5%, behind food retailers, the government, and scientists.

The issues are extremely current and contentious in the UK with a number of policy decisions imminent. The UK government has recently undertaken a national public consultation on the issues associated with GM food leading to a decision, due in late 2003, on whether or not to move from field-scale trials of GM crops to commercial growing. This is occurring in the context of the escalating trade dispute between the US and the EU with the US requesting the formation of a WTO dispute settlement panel to rule on the EU's refusal to allow the sale of 30 US biotechnology products on precautionary grounds. This is despite the decision by the EU in July 2003 to move away from a ban on GM food and instead introduce a system of food labeling with the thresholds at which ingredients must be labeled tightened and labeling required for food ‘derived’ from GM crops regardless of whether or not it contains genetic material.

Since there is no evidence of widespread enthusiasm among UK consumers for GM food, one might consider this an attribute of food that generates near indifference among a section of the population, while for others it generates disutility. This combination of ambivalence and opposition toward the use of GMOs in food therefore represents a suitable case for estimating Train and Sonnier’s bounded mixed logit model.

While there have been a large number of attitudinal studies of consumers’ responses to the use of GMOs in food, quantitative economic studies of preferences, in any country, are still relatively few. The techniques which have been employed to estimate WTPs to avoid and/or WTAs to consume GM food have been contingent valuation [5, 1, 23, 26, 15], experimental auctions [18, 21, 19, 29, 30] and choice modeling [8, 7, 11].

In this paper the data from the study by Burton *et al*, [8], which comprise choice modeling data regarding food choices in the UK, are reconsidered using a mixed logit model with bounded distributions used to model preferences for a number of food attributes. Since a full description of the data collection process and subsequent analyses are provided in Burton *et al* only a summary is provided here.

The data were derived from a choice modeling survey of respondents in the UK in 2000, who were presented with a series of alternative 'food futures' comprising a number of attributes and associated levels and asked to choose between them. These attributes and their levels are shown in Table 1. The attributes of the options were limited to the form of production technology used (conventional, *gm1* [plant to plant gene transfer], *gm2* (animal to plant gene transfer]); level of agrochemical use (*chem*); food related health risks (*risk*); structure of the food system (food miles, *fm*); and the weekly food bill (*pay*). Changes in the weekly food bill were specified as percentage changes.

Each choice set comprised 3 alternatives: the status quo and two alternatives. Each individual was presented with 9 choice sets to complete. In total 228 individuals returned questionnaires, generating 2030 completed choice sets. In their analysis Burton *et al*., employ a range of alternative specifications and investigate the stability of preferences across sub-groups, consistency of the variance of the error term across sub groups, and the role of individual specific heterogeneity in determining choices. This represents what has become the standard approach to capture preference heterogeneity within such models, that of data segmentation, where the difficulty is identifying the appropriate segments.

In that original analysis the data were split into 3 groups, based on the individuals' frequency of organic food purchasing, subsequently labeled as 'Infrequent', 'Occasional' and 'Committed' (Groups 0, 1 and 2 respectively). Preferences were found to be highly differentiated between these 3 groups. In addition, gender was used as an interaction term, affecting the value respondents placed on a number of attributes, notably the use of GM production technology. Finally, the alternative specific constant (asc) associated with the current food system (the 'status quo', *sq*), was found to be strongly positively significant, indicating that there was a tendency to select the status quo irrespective of the attribute levels..

3. The Bounded Logit Model

The bounded mixed model employed here is described below with the exposition drawing heavily on Train and Sonnier [33]. Consider a person, *n*, choosing among J options in T periods. Person *n*'s utility from alternative *j* in the t^{th} period is:

$$U_{njt} = \beta_n ' x_{njt} + \varepsilon_{njt} \tag{3}$$

with ε_{njt} ~ iid extreme value and $\beta_n \sim N(b, \Omega)$. Denoting a person's choice in period t as y_{nt}, the sequence of choices over the T periods is defined as $y_n = \langle y_{n1},\ldots,y_{nT}\rangle$ and the set of $y_n \forall n$ as *Y*. The probability of person *n*'s sequence of choices is the product of standard logit formulas:

$$L(y_n \mid \beta_n) = \prod_t \frac{e^{\beta'_n x_{ny_{nt}t}}}{\sum_j e^{\beta'_n x_{njt}}} \tag{4}$$

To obtain the unconditional probability the integral of this expression over all values of β_n, weighted by the density of β_n, is required:

$$P_n(y_n \mid b, \Omega) = \int L(y_n \mid \beta_n)\ g(\beta_n \mid b, \Omega)\ d\Omega \tag{5}$$

where g(.) is the multivariate normal density. Representing a product of logits mixed over a density of marginal utilities[2], this expression is referred to as the mixed logit choice probability. Priors on the model parameters *b* and Ω are required for Bayesian implementation. The prior on *b* is normal with a large variance to generate an almost flat distribution, while the prior on Ω is inverted Wishart with K degrees of freedom and parameter KI where I is the K-dimensional identity matrix. Defining this density as IW (Ω|K, KI), the joint posterior on $\beta_n \forall$n, *b* and Ω is given by:

$$\Lambda(\beta_n \forall, b, \Omega \mid Y) \propto \prod_n L(y_n \mid \beta_n)\ g(\beta \mid b, \Omega)\ IW(\Omega \mid K, KI) \tag{6}$$

[2] Train refers to the β as "partworths". However, within the valuation literature this term has an established definition as the monetary valuation for a marginal change in an attribute, defined as the ratio of the attribute parameter to the parameter on the payment vehicle. Given that later in this paper we wish to consider these monetary valuations, we reserve the term "partworth" for these, and instead refer to the β as "marginal utilities".

Gibbs draws are taken to obtain information about the posterior, with draws taken sequentially from the conditional posterior of each of the parameters given the previous draws of the other parameters (see Train and Sonnier for more details of this process). The sequence of draws from the conditional posteriors converges to draws from the joint posterior.

This process is implemented using 30 000 iterations prior to convergence followed by 20 000 iterations with one in ten iterations retained for inference. More specifically, the mean of these draws represents the mean of the parameters and the standard deviation of these draws represents the standard error of the estimates.

4. Results: Unbounded Estimation

The model was initially estimated with all parameters normally distributed to allow comparison with both the original model estimated by Burton *et al* [8] and with subsequent specifications of the bounded model[3]. The subsequent use of a bounded model and the desire for comparability meant that the negatives of the levels of payment, agrochemical use, food miles and both forms of genetic modification (*pay*, *chem*, *fm*, *gm1* and *gm2* respectively) were used. This does not alter the estimation of the model, but should be borne in mind when interpreting the parameters.

The results of the estimation of this fixed parameter model are presented in Table 2 where the mean value of the draws of b are shown which represent the estimated mean of the β_n's, while the variances of the β_n's displayed are the diagonal elements of Ω. The results in Table 2 are largely as expected. The insignificant *pay* parameter for Group 2 (the 'Committed' Organic group) is something found in Burton *et al*., indicating that on average these respondents were not considering changes in the payment vehicle as significant in their choices. The *gm1* and *fm* variables are insignificant at the 5% level for the Infrequent and Committed groups. Also the variances associated with status quo option and both GM attributes are very large across all 3 consumer groups.

It appears highly unlikely that individuals in the UK prefer, *ceteris paribus*, increases in the price of their food, higher levels of agrochemical use, food being moved longer distances, either type of GM

[3] All estimation employs GAUSS using code by Train (http://elsa.berkeley.edu/~train/software.html).

technology, or increases in the likelihood of food poisoning. Hence while indifference by many towards these attributes is likely, the negative portions of the distributions of the parameters on these variables seems questionable[4].

Table 3 shows the proportion of the population in each of the 3 groups predicted as having parameter values that conflict with *a priori* expectations. For example, the results imply that 21%, 32% and 39% of the sample for each consumer group prefer increases in price, whilst 56%, 7% and 10% respectively gain utility from the use of GM technology involving plant genes only. The values for food involving the transfer of genes from animals to plants are 3%, 4% and 5% respectively.

These variables were therefore identified as appropriate for estimation assuming a bounded distribution for the parameter. There was no prior view of the distribution of the status quo parameter and hence this was assumed to be normally distributed. The bounded distributions available using Train and Sonniers's implementation are the log-normal, a normal censored from below at zero and Johnson's S_B distribution. Given the problems already noted regarding the zero probability mass at zero and the long tail of the log-normal distribution, only censored normal and S_B distributions were employed in this study.

The bounded distributions all assume that the parameter of the utility function β_n is replaced by c_n, which is some transformation of a normal distribution. With the normal distribution censored from below at zero there is a mass point at zero so that with β normally distributed with mean b and variance σ, the transformation is $c = \max(0, \beta)$, with the density above zero identical to the normal density of β. Estimation involves identifying b and σ, and hence c, and thus the proportion of the population massed at zero and the proportion above zero.

In the case of the S_B distribution an upper and lower bound is specified for the distribution, so that the transformation $c = l + (u - l) \cdot (\exp(\beta)/(1+\exp(\beta)))$ produces a distribution between l and u, with the shape, mean and variance determined by the normally distributed β's mean and variance. As Train and Sonnier note, this distribution has the potential to resemble a log-normal distribution but with a specifiable upper bound, a plateau with sharp slopes on each side or be bi-modal.

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[4] Note that the negative of the value of all of these variables, except *risk*, is used. For *risk* a decrease in the value of the parameter represents an increase in the chance of food poisoning (i.e. from 1/10000 to 1/5000).

Both the censored normal and S_B distributions are transformations of a normally distributed β and, following Train and Sonnier, the expressions for a person's utility and the probability of their sequence of choices can be specified as:

$$U_{njt} = T(\beta_n)' x_{njt} + \varepsilon_{njt} \tag{7}$$

where $T(\beta_n) = c_n$ is a transformation depending only on β, with the distribution of c_n depending on the transformation implemented.

The probability of person n's sequence of choices is:

$$L(y_n \mid \beta_n) = \prod_t \frac{e^{T(\beta_n)' x_{ny_{nt}t}}}{\sum_j e^{T(\beta_n)' x_{njt}}} \tag{8}$$

Hence β_n may be considered a latent variable distributed ~N(b, Ω), which determines the utility function coefficients for an individual. For values of β_n, coefficients c_n are calculated with the distribution of β_n mapping on to a distribution of c_n.

5. Results: Bounded Estimation

Censored normal distributions were employed for the variables *chem*, *fm*, and *risk* while a normal distribution was used for the status quo asc (*sq*). Initial exploration of the data led to censored normal distributions of the GM parameters with exceptionally large variances, and hence S_B distributions, with specified upper and lower bounds were used for both forms of GM technology (*gm1, gm2*). An S_B distribution was also used for the payment vehicle. The S_B distributions for the payment vehicle and both GM parameters were implemented using a lower bound of zero and an upper bound that was reduced in an iterative process. The final S_B distribution implemented for *pay* used a lower bound of 0 and an upper bound at 0.3 while for both GM variables lower bounds of 0 were used with upper bounds at 10.

The results of this estimation procedure are shown in Tables 4, 5, 6 and 7 and in Figures 1 to 4. The results in Table 4 show the mean of the draws of b and the diagonal elements of Ω, again representing the estimated mean and variance of the β_n's respectively. In addition, the mean and variance of the transformed variables (c_n) which represent the marginal utilities associated with the various attributes are shown. These distributions of marginal utilities are generated by making repeated draws from the distribution of β_n implied by the estimates of b and Ω. Each of these draws is transformed to represent a draw of c_n, the marginal utilities, and hence their distributions are identified. It is immediately apparent when comparing the results of this bounded model with the unbounded model reported in Table 2 that the log-likelihoods of the models for all three groups are considerably higher than those for the bounded models.

An additional advantage of this Bayesian implementation of the bounded mixed logit model is that it is possible to estimate the correlations between the estimated marginal utilities. Train and Sonnier note that this is a significant development since classical procedures do not accommodate fully correlated marginal utilities well because of the proliferation of parameters, while Bayesian procedures handle them without difficulty. However, they point out, generating marginal utilities that are bounded *and* correlated via either procedure had previously been problematic.

Table 5 displays these correlations between the marginal utilities generated from the bounded model. As one might expect, the *gm1* and *gm2* terms are very strongly correlated across Groups 0, 1 and 2 indicating that those who are concerned about *gm1* tended to be concerned about *gm2*. The correlations between *pay* and *gm1* and *gm2* are markedly different across the 3 groups although in all 3 cases it is a negative correlation. There is a small correlation between the payment level and the GM terms in Group 0, these are greater in Group 1 and there is a very strong negative correlation evident in Group 2.

Figure 1 shows the distributions of the S_B distributed price parameters. Regarding this plot, note that the upper limit of 0.3 appears to accommodate the full range of this parameter's values (results with a higher upper limit did not change the distribution in any significant way). The flexibility of the S_B distribution is revealed in these plots, where the distribution for Group 0 in Figure 1a resembles a truncated normal or possibly a log-normal distribution, while for Groups 1 and 2 the plots in Figures 1b and 1c resemble more a censored normal distribution with a mass point close to zero.

Figures 2a-2c show the S_B distributions of the parameters for the two GM variables, *gm1* and *gm2*, for each of the 3 consumer groups. The distribution of *gm1* for Group 0 resembles a censored normal with a large probability mass close to zero, that is, near indifference to GM food involving only plant to plant gene transfer. For Groups 1 and 2 the distribution of *gm1* is bi-modal, although as one moves from Group 1 to Group 2 the portion of the sample in the lower end of the distribution reduces sharply with an increase in the number whose utility is strongly negatively affected by the presence of this attribute in a food choice.

Regarding *gm2*, GM food involving animal to plant gene transfer, the parameter distributions in all three groups are again bi-modal. The proportion of the sample at the upper mass point increases across the three groups. For Groups 1 and 2 the plots indicate large increases in the proportion of the population strongly opposed to food choices containing this option. When the upper bounds on the *gm2* distribution were raised above 10, most of the upper mass points shifted to the new upper limit, while the overall shape of the distribution was unchanged. These results imply a section of the population seeming to be unwilling to consume this foodtype at all.

In the results presented so far, the focus has been on the estimated marginal utilities associated with each attribute. Although the distributions of these are of interest, their values have no absolute interpretation. However, one can obtain monetary equivalents by dividing the parameter of the attribute by *pay*, the parameter on the payment vehicle, to give a partworth, which gives the equivalent marginal value of a change in an attribute in monetary terms. One of the implications of having a lower bound at zero for the price parameter is the scope for a considerable density at values very close to zero and hence an associated upper range of WTPs for GM food which are infeasibly large.

Two options one could employ are to raise the lower bound on *pay* marginally above zero, or alternatively consider only the lower, feasible, range of WTPs inferring that those above, say, a 100% discount are never likely to consume GM food knowingly. The latter option is employed here. In Figures 3a-3c the simulated distribution of partworths for *gm1* and *gm2* are shown with the upper tail of the distribution above 100% reported as a single mass, accumulated at a partworth equivalent to 100% of the weekly food bill. Similarly, in Figures 4a-4c the simulated distribution of partworths for *chem* are shown again with the upper tail of the distribution above 100% reported as a single mass, accumulated at a partworth equivalent to 100% of the weekly food bill. Table 6 provides additional details about the distribution of these *chem*, *gm1* and *gm2* partworths. The median figures identified in Table 6 give an additional indication of discounts required to induce purchase of the good with such attributes. For example, while the mean discount required to induce purchase of *gm1* food in Group 0 is 55%, the median figure is only 0.1%, a figure reflecting the mass point close to zero in the distribution of partworths. The equivalent figures for Group 1 are a mean of 830% for the purchase of *gm1* food, with a median figure of only 7.7% However in all three consumer groups the median partworths for *gm2* food are infeasibly large.

The bi-modal nature of the partworth distributions for GM food mean that while mean or indeed median partworths are high, sections of the market may be willing to purchase GM food at more reasonable discounts. The distributions of partworths for GM food are therefore re-considered in Table 7 which displays the simulated shares of the market in the three consumer groups willing to buy GM food at discounts of 10% and 20%. The results for Group 0 indicate that 78% of people in this group are estimated as willing to consume *gm1* food with discounts of up to 10% of current food costs. For *gm2*, GM food involving the transfer from animals to plants, the market outlook is considerably less promising with the share of Group 0 willing to consume at discounts up to 10% reduced to about one quarter of the market. The additional market share generated by a discount of 20% is not large for Group O, with only an additional 3% and 4% induced to purchase *gm1* and *gm2* food respectively. For Groups 1 and 2 the shares at 10% discounts are lower, but the pattern of small additional market share gains when discounts are increased to 20% is repeated.

6. Conclusions

The development of computational techniques enabling the estimation of mixed logit models has stimulated the development of a number of advances in the way that preference heterogeneity can be modeled. Mixed logits are a powerful analytical tool for accommodating diverse preferences in studies of consumer choice which may be regarded as attractive because the distribution in question may be more revealing than segmented point estimates.

The approach has intuitive appeal in so far as it allows explicitly for a range of attitudes towards attributes within the population. This is likely to be important in circumstances where one is interested in potential market penetration, or levels of consumer resistance to the introduction of a new product: it is not the average attitude that is important to identify, but the size of the group who will or will not be prepared to accept a product.

One of the key areas of research that has been prompted by the development of mixed logit models is the choice of functional form of the mixing distribution of the parameters. As yet, there are no clear answers on this issue; the researcher needs to identify distributions that are, overall, best suited to the reality approximated in the model. For some distributions (e.g. normal and log-normal) the inherent properties of the distribution may make them unattractive for modeling the preference distribution for some attributes. In particular, the lack of a probability density at zero is particularly problematic in modeling a situation where one expects none or only trivial numbers in the population to be positively (negatively) disposed towards a choice attribute while there may be a significant proportion who are indifferent to it.

The censored normal and S_B bounded distributions made operational by Train and Sonnier therefore represent a significant development in this area. While the use of such distributions brings with it its own issues of application and interpretation, such as the specification of the bounds to be used in the S_B distribution, they appear to offer an attractive method of dealing with the issue. In particular, the use of the S_B distribution seems to offer a flexible approach to modeling preferences within a two parameter distribution. In particular, its potential to generate bi-modal distributions which can mimic situations where the population is broadly divided into those who are largely indifferent and those who are strongly averse to an attribute is useful in a situation such as that of GM foods in the UK, where casual observation of community expression indicates that preferences are likely to follow such a pattern.

The bi-modal distributions of *gm1* and *gm2* parameters and the associated partworths reported here indicate significant proportions of the population are indifferent to the GM technologies, while others strongly oppose them. The size of these proportions changes as one moves from technology involving only plant to plant gene transfer to GM technology that has an animal component, a result which is consistent with other studies.

The results indicate also that while segments of the UK market (ranging between about a quarter and three quarters for *gm1*) may be prepared to buy GM food with discounts of up to 10%, the additional market share gained by further discounting is small. This price inelastic demand, in the range of 10% to 20% discounts, supports the view that a significant section of the UK market is unwilling to trade-off the GM nature of food against price, certainly not over any range likely to occur in practice.

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Table 1. Attributes and their levels

Attribute		Levels
Level of weekly food bill (% change from current)	***pay***	-50, -40, -30, -20, -10, 0, +10, +20, +30, +40
Form of production technology used		Current,
	gm1	GM(plants),
	gm2	GM(plants and animals)
Level of on-farm chemical use	***chem***	-30%, No change, +10%
Structure of food system (food miles)	***fm***	-30%, No change, +10%
Food health risk	***risk***	1/15000, 1/10000, 1/5000

Table 2. Unbounded mixed logit model: all coefficients normally distributed

Group 0	β_n mean	β_n var	t
pay (-)	0.4172	0.2995	5.14
s.e.	0.0812	0.0683	4.39
chem (-)	0.5118	0.5874	4.37
s.e.	0.1172	0.1643	3.58
fm (-)	0.1358	0.4635	1.16
s.e.	0.1168	0.1190	3.89
risk	1.8451	6.2191	3.66
s.e.	0.5047	2.0271	3.07
sq	24.4519	184.6317	8.32
s.e.	2.9392	71.0255	2.60
gm1 (-)	-1.4039	144.7591	-0.50
s.e.	2.8342	48.6312	2.98
gm2 (-)	17.4203	85.2059	8.39
s.e.	2.0770	33.3245	2.56
	log-likelihood= -546.3		

Group 1	β_n mean	β_n var	t
pay (-)	0.3311	0.5512	3.16
s.e.	0.1047	0.1371	4.02
chem (-)	1.0167	1.0749	5.62
s.e.	0.1810	0.3052	3.52
fm (-)	0.3144	0.5581	2.32
s.e.	0.1353	0.1338	4.17
risk	0.8802	9.5371	1.64
s.e.	0.5358	3.4068	2.80
sq	23.8852	1004.2546	4.78
s.e.	4.9935	278.8018	3.60
gm1 (-)	4.1021	7.4406	6.09
s.e.	0.6738	3.0714	2.42
gm2 (-)	37.4534	445.3675	10.42
s.e.	3.5946	123.6501	3.60
	log-likelihood=-609.6		

Group 2	β_n mean	β_n var	t
pay (-)	0.1944	0.4747	1.41
s.e.	0.1382	0.1421	3.34
chem (-)	1.2973	1.0759	4.50
s.e.	0.2885	0.4739	2.27
fm (-)	0.3278	0.7950	1.01
s.e.	0.3259	0.3064	2.59
risk	-0.0627	17.7059	-0.06
s.e.	0.9971	9.3280	1.90
sq	25.3743	374.5147	3.57
s.e.	7.1007	199.1519	1.88
gm1 (-)	20.7198	269.5058	3.84
s.e.	5.3894	218.3582	1.23
gm2 (-)	65.7504	1548.9652	5.69
s.e.	11.5507	853.8783	1.81
	log-likelihood=-270.4		

Table 3. Shares of parameter distributions above and below zero

	Group 0		Group 1		Group 2	
	Share<0	**Share>0**	**Share<0**	**Share>0**	**Share<0**	**Share>0**
pay (-)	0.21	0.79	0.32	0.68	0.39	0.61
chem (-)	0.24	0.76	0.16	0.84	0.11	0.89
fm (-)	0.43	0.57	0.36	0.64	0.37	0.63
risk	0.22	0.78	0.39	0.61	0.50	0.50
sq	0.04	0.96	0.23	0.77	0.10	0.90
gm1 (-)	0.56	0.44	0.07	0.93	0.10	0.90
gm2 (-)	0.03	0.97	0.04	0.96	0.05	0.95

Table 4. Bounded mixed logit model results

Group 0	β_n		marginal utilities	
	mean	var	mean	var
pay (-)	-1.53	2.3119	0.0763	0.0045
s.e.	0.3141	0.9722		
chem (-)	-0.3822	0.5717	0.1560	0.1081
s.e.	0.2047	0.2367		
fm (-)	-2.1291	2.2096	0.0503	0.0581
s.e.	0.5557	1.1085		
risk	0.0859	1.1749	0.4808	0.4272
s.e.	0.2408	0.5901		
sq	3.5372	6.3976	3.5798	6.4559
s.e.	0.6426	2.5002		
gm1 (-)	-7.9878	39.7839	1.1573	7.1983
s.e.	1.677	25.9933		
gm2 (-)	0.2306	24.505	5.2081	17.1447
s.e.	0.9063	15.8493		
	log-likelihood= -413.3053			

Group 1	β_n		marginal utilities	
	mean	var	mean	var
pay (-)	-2.7708	2.8441	0.0383	0.0024
s.e.	0.6207	2.099		
chem (-)	-0.0506	0.3198	0.2076	0.1056
s.e.	0.1111	0.0927		
fm (-)	-5.2242	4.9789	0.0081	0.0098
s.e.	1.4995	3.4212		
risk	-1.4435	4.7891	0.3307	0.5735
s.e.	0.9662	3.1608		
sq	2.3967	13.408	2.4454	13.6450
s.e.	0.7978	6.8225		
gm1 (-)	-4.2416	43.191	2.7106	15.1125
s.e.	1.3848	22.0661		
gm2 (-)	3.9936	83.5188	6.6183	18.5157
s.e.	1.6855	38.7554		
	log-likelihood= -411.2133			

Group 2	β_n		marginal utilities	
	mean	var	mean	var
pay (-)	-8.3252	27.1321	0.0195	0.0034
s.e.	4.0454	24.5823		
chem (-)	0.0284	0.3375	0.2502	0.1286
s.e.	0.1196	0.1095		
fm (-)	-13.2222	50.887	0.0944	0.4272
s.e.	2.7543	29.4601		
risk	-2.2223	6.9941	0.2984	0.6472
s.e.	1.4596	5.47		
sq	1.9749	4.0599	1.9904	4.1185
s.e.	0.7948	2.644		
gm1 (-)	-0.5	47.9577	4.6872	19.1307
s.e.	1.4212	30.2863		
gm2 (-)	5.3083	38.7418	7.9848	11.8089
s.e.	2.2532	35.3042		
	log-likelihood= -236.6731			

Table 5. Correlations of marginal utilities

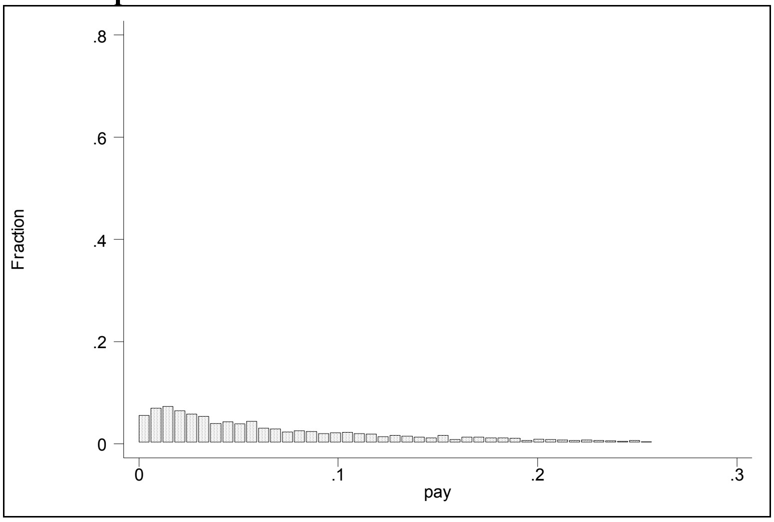
Group 0	pay(-)	chem(-)	fm(-)	risk	sq	gm1(-)	gm2(-)
pay(-)	1.0000						
chem(-)	0.0533	1.0000					
fm(-)	-0.1539	0.2932	1.0000				
risk	0.5126	0.1030	-0.1322	1.0000			
sq	0.5612	0.3807	0.1005	0.5556	1.0000		
gm1(-)	-0.1042	0.4133	0.5726	-0.0464	0.2721	1.0000	
gm2(-)	-0.1222	0.4050	0.5472	-0.0626	0.2362	0.8940	1.0000

Group 1	pay(-)	chem(-)	fm(-)	risk	sq	gm1(-)	gm2(-)
pay(-)	1.0000						
chem(-)	0.0182	1.0000					
fm(-)	-0.2127	0.0610	1.0000				
risk	0.3537	0.1307	-0.3734	1.0000			
sq	0.2923	0.4131	-0.0242	0.4266	1.0000		
gm1(-)	-0.2696	0.2605	0.4042	-0.3479	0.3489	1.0000	
gm2(-)	-0.2984	0.2494	0.4854	-0.4006	0.2920	0.9091	1.0000

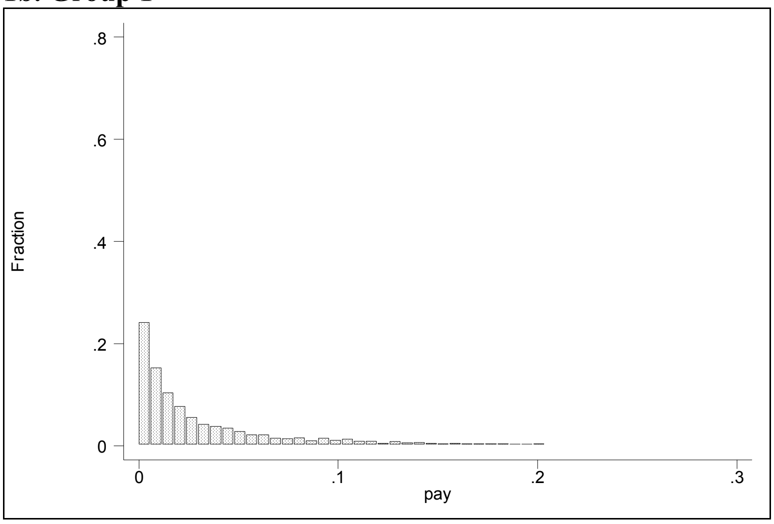
Group 2	pay(-)	chem(-)	fm(-)	risk	sq	gm1(-)	gm2(-)
pay(-)	1.0000						
chem(-)	-0.1713	1.0000					
fm(-)	0.7638	-0.2131	1.0000				
risk	0.6659	-0.0519	0.6255	1.0000			
sq	0.0286	0.2911	-0.1263	0.2639	1.0000		
gm1(-)	-0.8085	0.2149	-0.8921	-0.6844	0.1087	1.0000	
gm2(-)	-0.6573	0.2471	-0.8350	-0.4378	0.2844	0.7748	1.0000

Figures 1a-1c. S_B distribution of the price parameter

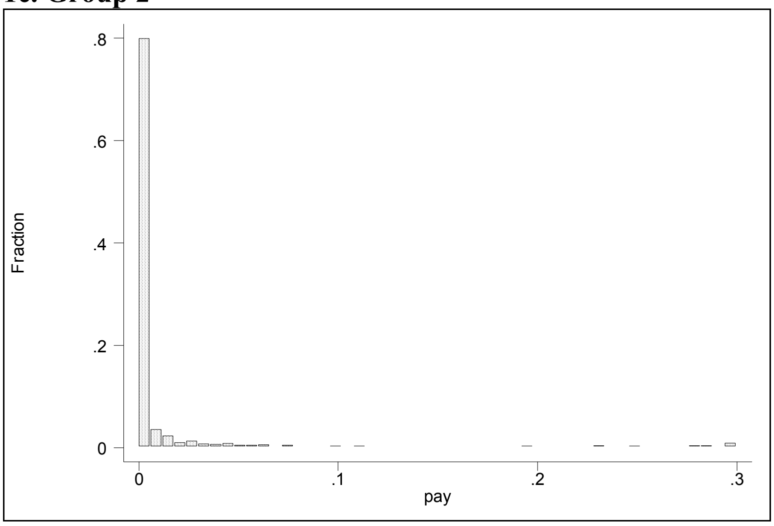
1a. Group 0



1b. Group 1

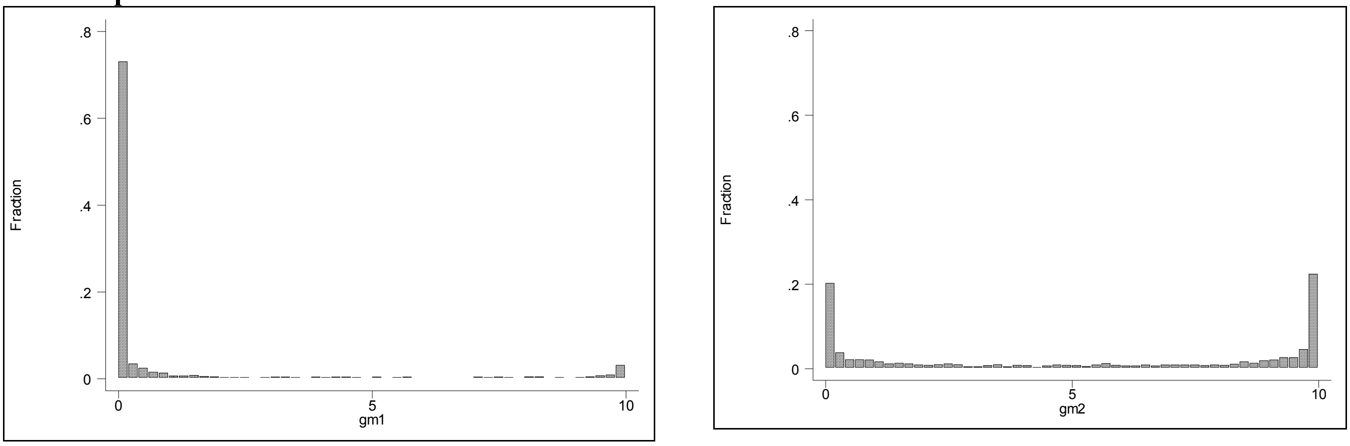


1c. Group 2

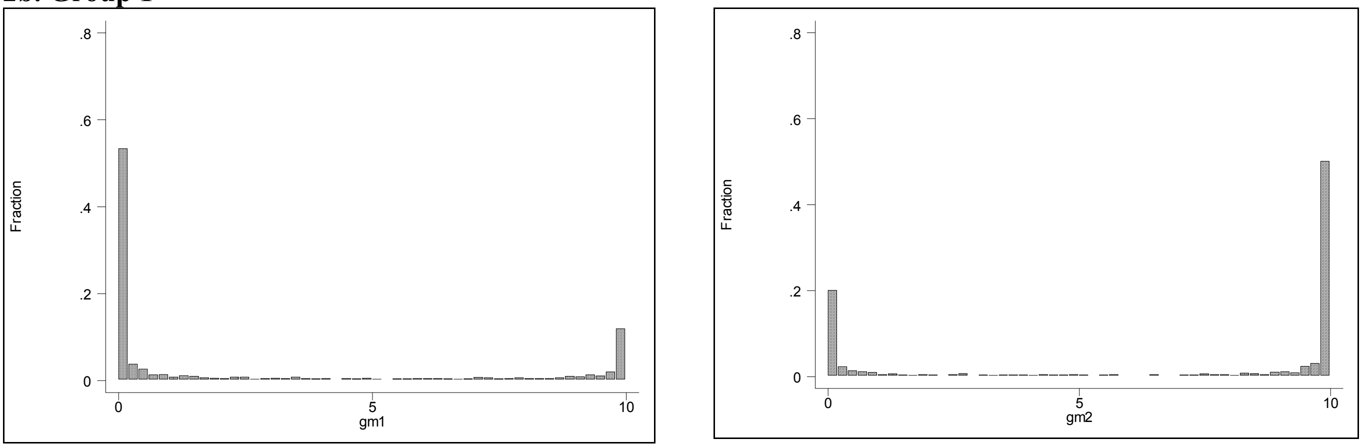


Figures 2a-2c. Bounded S_B distributions of *gm1* and *gm2* parameters

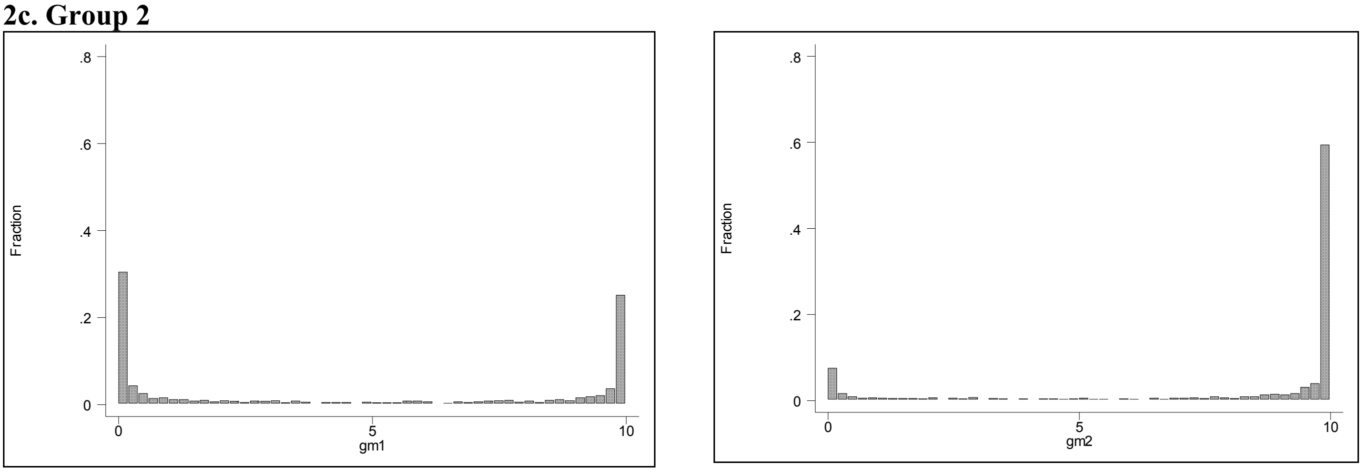
2a. Group 0



2b. Group 1

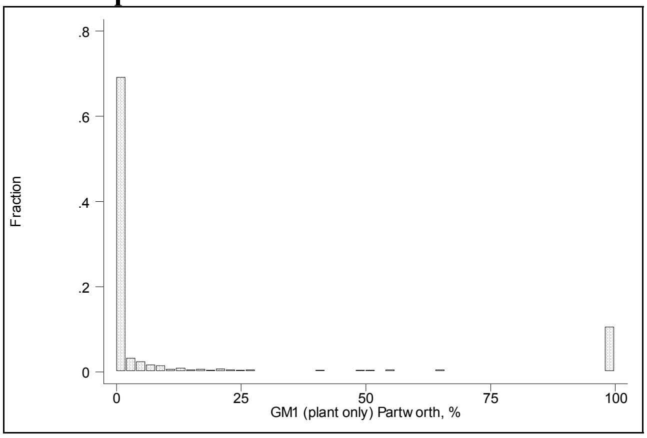


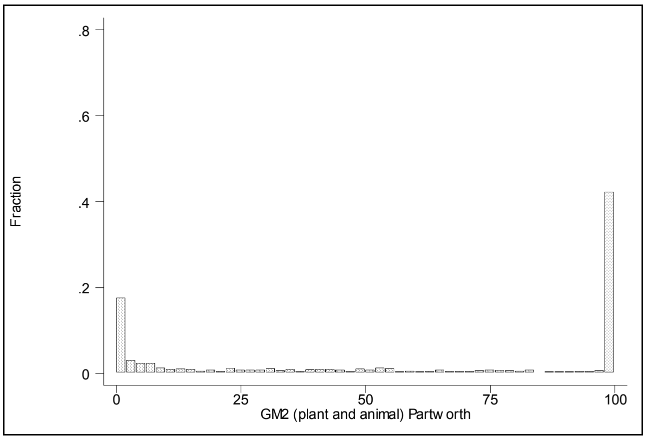
2c. Group 2



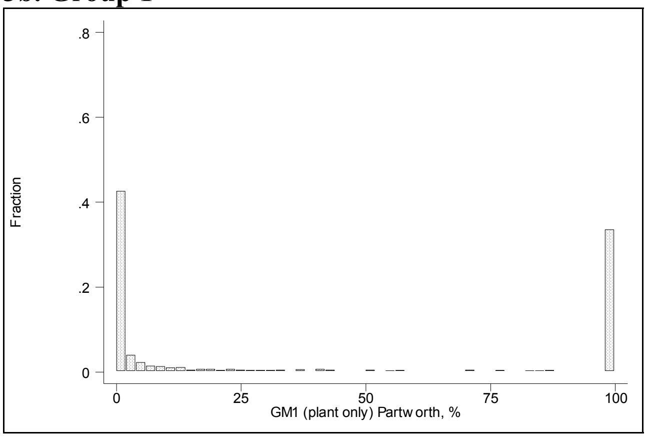
Figures 3a-3c. Distributions of *gm1* and *gm2* partworths

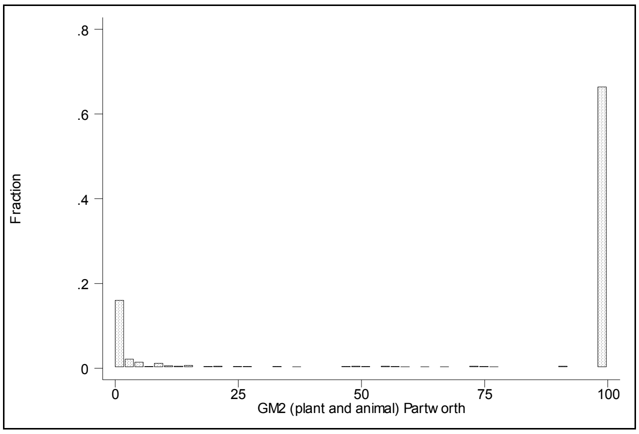
3a. Group 0



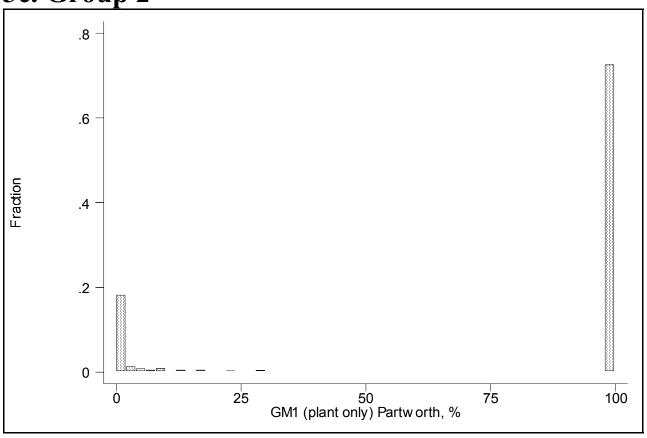


3b. Group 1





3c. Group 2



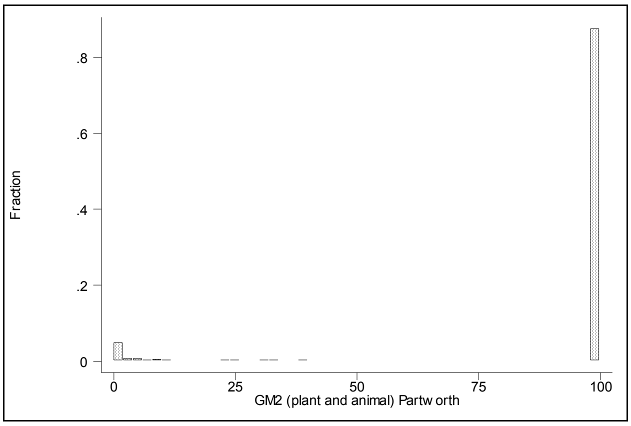
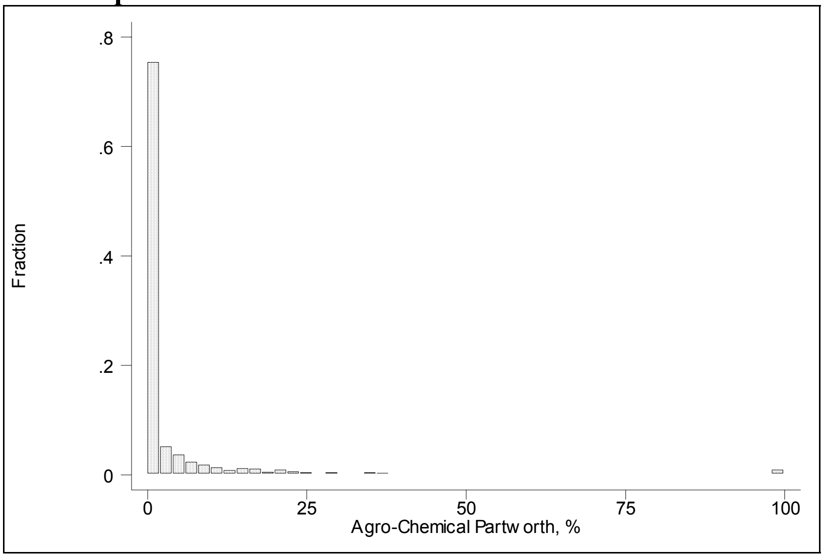
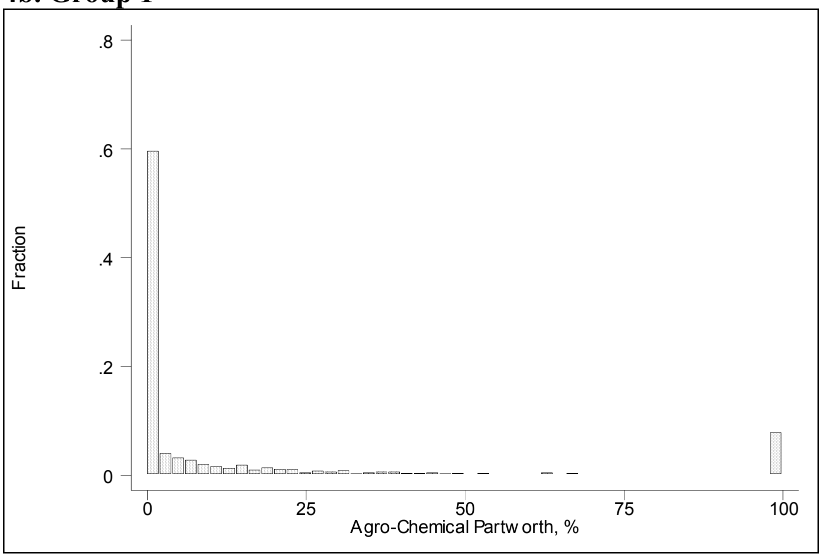


Figure 4. Censored normal distributions of chem partworths (%)

4a. Group 0



4b. Group 1



4c. Group 2

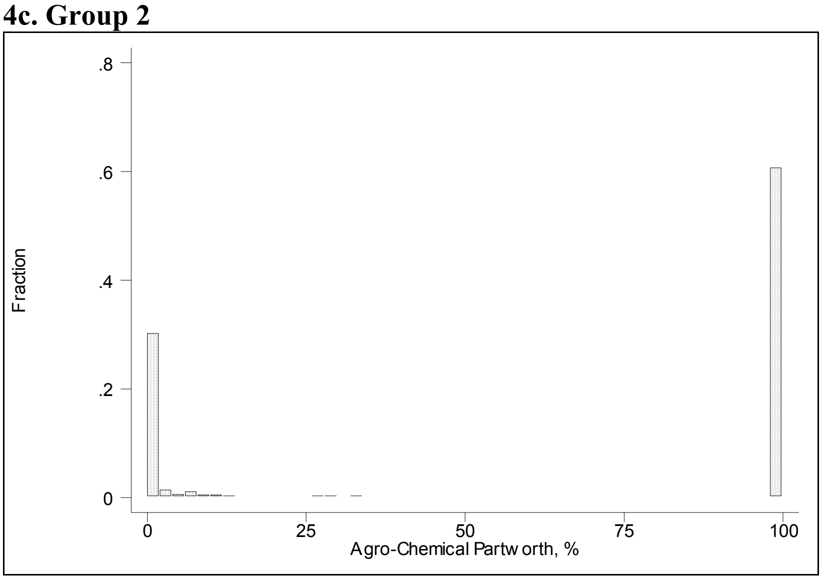


Table 6. Partworth distributions

Group 0	chem	gm1	gm2
n	2000	2000	2000
mean	6.4	55.1	278.7
std.dev	39.6	289.5	930.4
percentile – 25%	0.0	0.0	7.5
percentile – 50%	0.0	0.6	68.9
percentile – 75%	1.9	6.3	217.2
nos>100	17	208	835

Group 1	chem	gm1	gm2
n	2000	2000	2000
mean	39.2	830.0	1652.9
std.dev	220.3	3983.5	5526.3
percentile – 25%	0.0	0.1	32.3
percentile – 50%	0.0	7.7	291.9
percentile – 75%	14.4	257.8	1120.2
nos>100	150	668	1322

Group 2	chem	gm1	gm2
n	1079*	1079*	1079*
mean	698.1	10606.1	22060.2
std.dev	2069.1	24408.8	34902.8
percentile – 25%	0.0	0.2	128.0
percentile – 50%	0.0	82.0	2940.5
percentile – 75%	154.2	4387	24978.5
nos>100	289	527	827

* The presence of zero marginal utilities of money create missing partworth values in this group.

Table 7. Population shares willing to consume GM food at 10% and 20% discounts

	Discounts	
Group 0	**10%**	**20%**
gm1	78	81
gm2	27	31
Group 1	**10%**	**20%**
gm1	51	55
gm2	21	23
Group 2	**10%**	**20%**
gm1	22	23
gm2	7	8