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Capturing Preference Heterogeneity in Stated Choice Models: A Random Parameter Logit Model of the Demand for GM Food

by

Dan Rigby and Mike Burton

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Dan Rigby and Michael Burton[Ψ]

Abstract:

Analyses of data from random utility models of choice data have typically used fixed parameter representations, with consumer heterogeneity introduced by including factors such as the age, gender etc of the respondent. However, there is a class of models that assume that the underlying parameters of the estimated model (and hence preferences) are different for each individual within the sample, and that choices can be explained by identifying the parameters of the distribution from which they are drawn. Such a random parameter model is applied to stated choice data from the UK, and the results compared with standard fixed parameter models. The results provide new evidence of preferences for various aspects of the UK food system, particularly in relation to different forms of GM food but other environmental and technical aspects also. The results are also discussed in terms of their implications for further development and refinement of random parameter models.

Keywords: random parameter; mixed logit; choice modelling; GMOs; food safety;

JEL classification: C25, D12, Q18

Address for Correspondence:

Dr Dan Rigby
School of Economics
Manchester University
Manchester UK
M13 9PL

Tel: +44 (0)161 275 4808
Fax: +44 (0)161 275 4812

Email: dan.rigby@man.ac.uk

[Ψ] Burton is Associate Professor in the School of Agricultural and Resource Economics, University of Western Australia, Rigby is a Senior Lecturer in the School of Economic Studies, University of Manchester. An Australian Research Council award and Rigby's Henry Schapper Fellowship are gratefully acknowledged. The advice given by Kenneth Train and Simon Peters during the course of this research is also acknowledged.

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Analyses of data from random utility models of choice data have typically used fixed parameter representations, with consumer heterogeneity introduced by including factors such as the age, gender etc of the respondent. However, there is a class of models that assume that the underlying parameters of the estimated model (and hence preferences) are different for each individual within the sample, and that choices can be explained by identifying the parameters of the distribution from which they are drawn. Such a random parameter model is applied to stated choice data from the UK, and the results compared with standard fixed parameter models. The results provide new evidence of preferences for various aspects of the UK food system, particularly in relation to different forms of GM food but other environmental and technical aspects also. The results are also discussed in terms of their implications for further development and refinement of random parameter models.

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1. Introduction.

The assumption that preferences are homogenous has been a cornerstone of empirical analysis within demand and valuation studies. 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 considered, it is usually through the inclusion of individual specific variables such as age, gender, etc which act to modify the values of the parameters of the utility function. For example, household characteristics are employed in studies of demand (Deaton, 1997); individual experience is used to modify recreational choice (McConnell *et al*. 1995); gender is used to modify preference functions over the environment (Bennett and Blamey, 2001).

In the random utility model (RUM) commonly used to explain agents' choices across discrete outcomes, the random error term takes on an increased significance. It is the presence of this individual heterogeneity which accounts for different individuals making different choices when faced with the same choice sets.

Applications of the RUM have a widespread application in the analysis of revealed preference data (e.g. recreational demand choices over locations; travellers' choices over transport types) and also contingent data derived from survey (e.g. on environmental values, potential product purchasing etc). Similarly, within this structure, heterogeneity of preferences can be explicitly modelled by using individual characteristics as determinants of marginal values for attributes of the choices.

However, there are alternative specifications of the RUM that approach individual heterogeneity from a different perspective. The development of simulated maximum likelihood estimation methods has stimulated the use and refinement of random parameter models in which it is assumed that the functional form and arguments of utility are common across individuals within the sample, but that the parameters vary across individuals. This approach is regarded by many as the most promising discrete choice analytical model available and represents a fundamentally different approach to modelling heterogeneity than that employed in more traditional fixed parameter logit models where the approach is to segment the sample, the attributes or both (Hensher and Greene, 2003)[1].

The use of the random parameter model approach brings with it a number of advantages, but also some issues of interpretation and application. The intent of this paper is to present an application of a random parameter model to a choice modelling data set that has been used elsewhere to explore the preferences for food characteristics and compare it with the results obtained from the fixed parameter approach. The results are analysed in terms of the relative merits of the two approaches with the data supporting the use of the random parameter approach. Some of the limitations of current implementations of the random parameter approach, particularly in relation to the distributional assumptions used, and areas for further development of the technique are then discussed.

2. RUM and conditional logit models

Assume that the utility gained by individual n from some option j is given by a linear function of the attributes of j:

$$U_{nj} = \sum_{k=1}^{K} \beta_k X_{kj} + \varepsilon \qquad (1)$$

where there are k attributes. Formally, if presented with 2 options (such as the simple version in Table 1) the respondent will choose Option 1 if $U_1 > U_2$. The task of the statistical analysis is then to identify estimates of the parameters (β) so that the predicted choices, made on the basis of a comparison of the utilities predicted for each option using equation (1), match as closely as possible the actual choices revealed in the survey.

Insert Table 1 Here

The model is implemented by choosing a particular distribution of disturbances. If it is assumed that the disturbances are independent and identically distributed, with a Weibull distribution (Greene, 1997):

$$F(\varepsilon) = \exp(-\exp(u)) \qquad (2)$$

(where u is normally distributed) then one has a conditional logit model. The probability of choosing option i from J options is expressed as:

$$\text{Prob}(Y = i) = \frac{\exp\left[\sum_{k=1}^{K} \beta_k X_{ki}\right]}{\sum_{j=1}^{J} \exp\left[\sum_{k=1}^{K} \beta_k X_{kj}\right]} \qquad (3)$$

It is important to note that individual heterogeneity can be incorporated in such a model to explain choices, but it has to be done in a particular way. Since personal characteristics are constant over all choices made by an individual they have no impact on the choices made if they enter the utility function linearly. However, personal characteristics can be included in the analysis, if they affect the way that attributes contribute to utility, hence such characteristics are introduced as modifiers to the parameter on attribute levels so that the β's become a function of individual characteristics.

In the context of the application presented below, an important aspect of the interpretation of the outcomes from choice modelling results is the notion of a 'partworth'. As is more fully explained in Section 3, the choice modelling approach presents respondents with a series (usually 3) options, each of which is defined by common attributes but with differing levels. It is usual to have as one of the attributes a payment vehicle, for example the price of a recreation trip or the cost of the product. It is these attributes levels (interacting with personal characteristics) that determine the choices made. Estimates are therefore derived for the impact marginal changes in attribute levels has on the likelihood of an option being chosen. Although individual parameters generated by the model do not have a direct interpretation, other than in their signs or statistical significance they can be combined to identify monetary values associated

[1] An addional approach is the use of latent class models (see Boxall and Adamowicz 2002, for an application and Greene and Hensher 2003 for a comparison with an RPL model).

with changes in each attribute's level. The partworth of a marginal change in an attribute level is given by the (negative) ratio of the attribute parameter to the payment vehicle parameter.

3. Choices of food futures in the UK

Examples of surveys of consumer attitudes and preferences towards GM foods, across many countries, include: Kelley, 1995; Kuznesof, and Ritson, 1996; Hoban, 1998; Norton *et al.*, 1998; Smith and Riethmuller, 1999; Yann Campbell Hoare Wheeler, 1999; Wolf and Domegan, 2000; Mendenhall, 2000; Wirthlin Group, 2000; Boccaletti and Moro, 2000; Baker and Burnham, 2001; Lusk *et al*., 2001; Marris *et al*., 2001; Huffman, *et al*., 2001; Moon and Balasubramanian, 2001; Burton and Pearse, 2002; House *et al*., 2002; Huffman and Tegene, 2002; Rousu *et al*., 2002a, 2002b. Most quantitative econometric analyses of such preferences are based on either contingent valuation studies or experimental auctions.

Choice modelling applications are less common, with Burton *et al*., (2001) being an exception. Burton *et al*., (2001) report the data collection process for a choice modelling application they conducted in the UK in 2000. The authors analyse these data using a fixed parameter conditional logit model. Since a full description of the data collection and subsequent analysis are provided in their paper only a summary is provided here.

The data were derived from a survey of respondents in the UK, who were presented with a number of alternative 'food futures' and asked to choose between them. The attributes of the options were limited to the form of production technology used (conventional, GM based on plants, GM based on plants and animals); level of on-farm chemical use; food related health risks; structure of the food system; and weekly food bills. Each choice set comprised 3 alternatives: one being the status quo and then two alternatives that had some aspect of the food system changed. Each individual was presented with 9 choice sets to complete. In total 228 individuals returned questionnaires, generating 2030 completed choice sets. Table 2 reports the attribute levels employed in the choice set design. By presenting respondents with a wide range of alternative choice sets with varying attribute levels the utility function can be empirically identified.

Insert Table 2 Here

In their original analysis Burton *et al*. employed a range of alternative specifications testing the stability of preferences across sub-groups, the consistency of the variance of the error term across sub groups, and the role of individual specific heterogeneity in determining choices. For current purposes a simplified modelling structure is presented. The data was split into 3 groups, based on the individuals self declared purchasing habits for organic food, identified as 'Infrequent', 'Occasional' and 'Committed'. Preferences for the food futures presented to the respondents was found to be highly differentiated between these 3 groups. Individual conditional logit models were then estimated for each group. In line with the original paper, the gender of the respondent was used as a determinant of the value placed on GM technology.

Tables 3 and 4 provide a summary of the results generated via the fixed parameter conditional logit model used by Burton *et al*.. In Table 3 parameter estimates are provided for each of the 3 groups identified in the sample (headed 'conditional logit'). Table 4 contains the associated estimated partworths (headed 'CL')[2].

Insert Tables 3 and 4 here

As one might expect, the model reveals a preference for cheaper food (**bill**), lower chemical use (**chem**), lower risk of health impacts (**risk**) and a desire for more locally sourced food (**fm**). An additional variable appearing in Table 3 is identified as **sq**, representing 'status quo', a term which merits a little attention before the GM results are discussed. A common aspect of choice modelling applications is determining whether there are impacts on utility which are associated with an option as a whole, rather than the individual attribute levels which comprise the option. This is only relevant when there is an obvious interpretation of the option in question. There is such an interpretation to the *status quo* option included in every choice set in the survey. It is therefore possible to test whether respondents may have a tendency to simply select the current position, irrespective of the attribute levels of the other options used. The other two food futures which, along with the status quo, comprise each choice set, have no equivalent interpretation. Hence a dummy variable, **sq**, was defined, taking a value of 1 if the option is the *status quo*, and zero otherwise. Table 3 indicates a strong positive preference for this option,

The results in Table 3 indicate that the response to agricultural technologies is complex. There are few statistically significant parameters relating to GM foods developed using plant genes (**GM P**) across any of the 3 groups (the exception is females in the 'Committed' organic group) and no significant partworths. There is concern and significant partworths regarding the use of GM food that involves the introduction of genes from animals and plants (**GM P+A**) in those groups which more frequently purchase organic produce. However, the estimated partworths are large, and in places unreasonably so. The statistical insignificance of the willingness to pay estimates for these more frequent organic purchasers do not imply that the attribute is unimportant in respondents' choices, on the contrary the results in Table 3 indicate the coefficients on the individual attributes are statistically significant. Rather they indicate the (im)precision with which a monetary valuation can be identified. The latter depends on the marginal utility of food bill changes, which is small and only statistically significant at the 15% level for the 'Committed' group. The

[2] Note these do not correspond exactly with those in Burton *et al* (2001) due to the slightly different specification, but are extremely similar.

implication is that those in the 'Committed' and, to some extent, the 'Occasional' group are not placing a great weight on the food bill component of choices.

As estimated, these standard fixed parameter conditional logit models exhibit three technical traits which may be of concern. First, the model imposes IIA. The implication of this is that the relative probability of two choices is independent of the attribute levels in the 3rd. Under some circumstances this may be unreasonable, and may be rejected statistically. This can be treated by appropriate nesting structures, but there may be issues about what is the appropriate configuration of choices. Second, the representation of heterogeneity of preferences over attributes (as opposed to the random component of utility) is restricted to those individual attributes that are measured and may be included. Given the widespread public concern about GM in the UK, it is perhaps surprising that the GM (plant) variable is not significant. However, this may reflect the fact that there is a diversity of opinion, ranging from deep concern to indifference, and this leads to imprecise estimates of the average population 'preference'. Finally, the data consists of repeated choices (in the this case, up to nine) which may well exhibit some degree of correlation. However, the conditional logit model as estimated assumes that all choices are independent, as if each choice is being made by a different person.

4. The random parameter model.

The random parameter model has characteristics that relate to these shortcomings of fixed parameter models such as that employed by Burton *et al*. The models do not exhibit IIA (a range of substitution patterns is implementable with such models), they can explicitly account for the repeated nature of the choices made by respondents, and they explicitly allow for a distribution of preferences within the population. In this section the form of the random parameter logit models estimated in this study are outlined (the exposition draws heavily on Train, 1998; Revelt and Train, 1998; Train, 1999).

A person faces a choice among the alternatives in choice set j on each of the occasions they make a choice. The number of choice situations can vary over people, and the choice set can vary over people and choice situations. The utility that respondent n obtains from alternative j in choice situation t is:

$$U_{njt} = \beta_n ' x_{njt} + \varepsilon_{njt} \qquad (4)$$

where x_{njt} is a vector of observed variables and coefficient vector β_n, representing peoples' tastes, is unobserved for each person and varies in the population with density $f(\beta_n|\theta^*)$ where θ^* are the (true) parameters of this distribution. ε_{njt} is an unobserved random term that is distributed iid extreme value, independent of β_n and x_{njt}. This is a standard logit specification except that the coefficients β_n vary across the population rather than being fixed. Note there is no t subscript on the β_n term: tastes vary across those making choices in the survey, but not across the choices made by the same person.

The variation in β_n introduces correlation in utility across choices. The vector of coefficients β_n can be expressed as the population mean (b) and the individual specific deviation from that mean η_n. Hence the utility that respondent n obtains from alternative j in choice situation t (equation 4) can be re-written as:

$$U_{njt} = b_n' x_{njt} + \eta_n' x_{njt} + \varepsilon_{njt} \qquad (5)$$

The estimation process described below estimates b but η_n is not observed and hence there is correlation in unobserved utility ($\eta'_n x_{njt} + \varepsilon_{njt}$) across options and choice situations via the presence of the η_n term.

Conditional on β_n, the probability that person n chooses alternative i in choice situation t is:

$$L_{nit}(\beta_n) = \frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}} \qquad (6)$$

If β_n were known to take the value β, the probability of a particular option being chosen would be given by a standard logit. Given that the values of β_n are not known, the probability of choosing option i in choice t is the integral of the conditional probability in (6) over all possible values of β_n which depend on the parameters of the distribution of β_n. This integral takes the form:

$$Q_{nit}(\theta^*) = \int L_{nit}(\beta_n) f(\beta_n \mid \theta^*) d\beta_n \qquad (7)$$

For maximum likelihood estimation the probability of each respondent's sequence of observed choices is required. Denoting the alternative that person n chose in period t as i(n,t) and assuming that $\beta_n = \beta$, the probability of person n's observed sequence of choices is given by:

$$S_n(\beta_n) = \prod_t L_{ni(n,t)t}(\beta_n) \qquad (8)$$

Given that β_n is unobserved, the unconditional probability for the sequence of choices is the integral of (8) over all possible values of β:

$$P_n(\theta^*)=\int S_n(\beta_n) f(\beta_n \mid \theta^*) d\beta_n \qquad (9)$$

The coefficient vector β_n is the parameters associated with person n, representing that person's tastes. These tastes vary over people; the density of this distribution has parameters θ^*. The aim of the estimation procedure is to estimate θ^*, that is, the population parameters that describe the distribution of individual parameters.

The log-likelihood function is $LL(\theta)= \Sigma_n \ln P_n(\theta)$.

This log-likelihood function is maximized via simulation. Specifically, $P(\theta)$ is approximated by a summation over values of β_n generated by Halton draws (Train, 1999). For a given value of the parameters θ, a value of β_n is drawn from its distribution and on the basis of this draw of β_n, $S_n(\beta_n)$, the product of standard logits is calculated. This process is repeated for many draws, and the mean of the resulting values of $S_n(\beta_n)$ is taken as the estimated choice probability:

$$SP_n(\theta)= (1/R) \sum_{r=1,\ldots,R} S_n(\beta_n^{r|\theta}) \qquad (10)$$

where R is the number of draws of β_n, $\beta_n^{r|\theta}$ is the r-th draw from $f(\beta_n|\theta)$, and $SP_n(\theta)$ is the simulated probability of person n's sequence of choices. $SP_n(\theta)$ is an unbiased estimator of $P_n(\theta)$ whose variance decreases as the number of draws increases and is strictly positive for any realization of the finite R draws, such that the log of the simulated probability is always defined.

The simulated log-likelihood function is constructed as $SLL(\theta) = \Sigma_n \ln(SP_n(\theta))$ and the estimated parameters are those that maximize SLL.

A number of alternative distributions, including log-normal, triangular and uniform are feasible for the distribution of β_n. In this paper estimation of the models assuming a normal distribution is reported and the implications of additional distributional shapes discussed toward the end of the paper.

5. Comparative Results and Discussion

As a starting point, the conditional logit models specified in Table 3 are re-estimated as random parameter models for direct comparison purposes[3]. These are reported in the right hand section of Table 3 (headed 'random parameter'). As outlined above, for each preference parameter (apart from the food bill variable) one estimates a coefficient for the mean of the distribution, and one for the variance of the distribution. Associated with each of these is an estimate of the standard error, so one can draw standard inferences about the significance of each coefficient. If the estimate of the variance is not different from zero, then one can infer that the preference parameter is constant across the population. If the mean coefficient is zero, but the variance estimate is significant one cannot infer that the attribute does not affect choice: but rather that there is a diversity of preferences, both positive and negative. For an attribute to be declared as having no impact on choices, both the estimate of the mean and the variance have to be insignificantly different from zero.

Table 4 compares the partworths from the conditional logit and random parameter logit models. Note that the estimates of the partworths from the RPL models are derived from the estimate of the mean of the distribution for each attribute and do not reflect the whole distribution. The CL and RPL results are largely similar, but with some noteworthy differences. For example, the GM Male partworths (for both GM types) are different in some cases. For the 'Occasional' organic group, the conditional logit has very large values for the partworths, but the significance of the partworths is very low (insignificant or only at 15%). The RPL model produces (smaller) estimates which are far more statistically accurate, in most cases significant at the 5% level.

Note however that one is just using the mean of the parameters from the RPL model for these partworth estimates in order to make some rather crude comparisons across the models; one is ignoring the other information generated by the RPL model regarding the distribution of the parameters.

The starting point for the random parameter logit results reported above are the preferred specification in Burton *et al*., (2001) to enable a comparison. An extensive range of tests of structure were then conducted to evaluate:

a) whether the 3 RPL models can be collapsed into a single model, with common preference parameters across all three;
b) if any parameters can be treated as fixed, rather than random;

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

c) if the gender interaction effects should be maintained;

The results of these likelihood ratio tests (results available on request) indicate that the 3 group structure should be maintained and that in only a few cases can any of the parameters be treated as fixed. In addition the results do not support the inclusion of gender as a determinant of preferences towards GM technology: that is, the use of a random parameter specification to capture heterogeneity obviates the need for an explicit measure of heterogeneity based on gender. The results of these models are reported in Table 5 and Table 6 showing parameter estimates and associated partworths respectively, with the partworths for the random parameter model again compared with those generated by Burton *et al.,* (2001).

Insert Tables 5 and 6 here

The parameter estimates in Table 5 reveal a very high number of significant parameters, both for the coefficient estimate, and also the estimate of the variance of the distribution. Only food miles in the 'Occasional' and 'Committed' groups, and chemicals in the 'Committed' group suggest that a fixed parameter is required: in all other cases the variance of the distribution is significant.

Note that the partworths in Table 6 again rely only on the mean of the attributes preference parameter, and the food bill parameter. Again, the results of the RPL and the conventional approach are broadly similar if one considers the mean of the RPL values although, again, the GM values show some variation. However, of more interest is the implied distribution of the partworths. These are plotted in Figure 1 for the value associated with food produced involving the transfer of genes from plants to other plants, and in Figure 2 for food involving the transfer of genes to plants from other plants and animals. Imposing a normal distribution on the preference parameter implies that, with small levels of probability, there will be extreme levels of WTP.

Insert Figures 1 and 2 here

For the 'Infrequent' and 'Occasional' groups, the distributions show that the means of the distribution are not just statistically insignificant from zero, but also, in absolute terms, close to zero: the distribution of partworths is centred around zero. This should not be taken to imply that for these groups, the attribute is not important. The significance of the variance term implies that the model is making use of an implied heterogeneity in preferences. However, the implication of this is the extent to which the model implies positive values: i.e. a *preference* for GM. In Figure 1 half the distribution for these 2 consumer groups falls in the positive range. For the 'Committed' group, the mean of the distribution is different to zero, but there is still a substantial proportion of the distribution in the positive range.

Given the consistent result that preferences are much more clearly negative for **GM(P+A)** food, it is not surprising to note that the distributions for all 3 groups are shifted to the left, and in all 3 cases, the mean of the distribution is significantly different from zero. However, as Figure 2 shows, in all three cases there is a reasonable portion of the distribution that lies in the positive range, implying people with a preference for GM food produced with the defined "plant and animal' technology. Given the use of the traditional technology as the status quo, this implies a willingness to pay a higher price in order to purchase this food.

One can reasonably ask the question whether this implied set of preferences in the population is genuine, or whether it is an artefact of the use of the normal distribution. It seems reasonable to assume, indeed the evidence bears it out, that there is heterogeneity of preferences in the population. Hence the random parameter approach seems superior, indeed the likelihood ratio tests indicated very strongly that fixed parameters models were not supported by the data. However given these preferences are better represented by a distribution rather than a fixed point, the question then becomes whether the use of the normal distribution simply generates positive values for these attributes as a second best solution i.e. that the positive values are artefacts of the normal distribution used.

This leads to a consideration of whether a different distribution should be used for the parameter distribution. For example, it seems reasonable in certain circumstances to employ distributions which restrict preferences to be positive (or negative). The log-normal is an option here that has been employed in several studies (Bhat, 1998, 2000; Train, 1998; Revelt and Train, 1998; Johnson, 2000) but while non-negativity (for example with respect to the food bill) is a useful property, the long tail generated in practice when estimating models of this form generates infeasible ranges of parameter values and, therefore, WTPs. In the case of GM technology, in the UK at least (the position is likely to be different in the USA), it may be the case that a distribution is required which not only makes positive preferences for GM food impossible, but also offers the option of indifference for a (potentially large) portion of the population. The log-normal distribution can not provide this since there is zero probability mass at zero for this distribution.

Hence in the case of GM technology models which allow the preferences to be truncated or censored at zero, with some elements being indifferent and the rest of the population averse to the attribute, would be a considerable advance. Additionally, models in which the long tail of the log-normal distribution is avoided whilst non-negativity for the attribute is retained, for example on the payment vehicle, would also offer considerable value.

In this context, implementable censored and truncated distributions would be very attractive. Such models are not available using classical estimation methods but Train and Sonnier (2003) offer an example of such a model using Bayesian methods which appears to offer new opportunities to researchers in this area.

6. Conclusions

In this paper we have explored the implications of using a random parameter specification to estimate a conditional logit model for food demand. The approach has some intuitive attraction 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: it is not the average attitude that is important to identify, but the size of the group who will/will not be prepared to accept the product.

The results we have estimated indicate that, for the dataset under consideration, a random parameter representation is superior to the conventional fixed parameter model. Likelihood ratio tests indicated that the imposition of fixed rather than distributed parameters was strongly rejected. Indeed despite the robust and statistically significant parameter estimates presented in Burton *et al*., (2001) the work reported here has revealed the very large distribution of 'tastes' around those point estimates which the standard conditional logit model are unable to capture or convey.

The results indicate considerable heterogeneity of preferences regarding different types of GM food technology both between and within the 3 organic purchasing groups identified in Burton *et al*. Preferences regarding GM technology involving plant to plant gene transfer are markedly different from those regarding animal to plant gene transfer.

The development of RPL models like those presented here may change the view of what is the best way to accommodate heterogeneity in such analyses. The use of gender was no longer supported once a random parameter specification was employed. However, the results also raise a number of technical issues. A simple normal distribution for preference parameters guarantees both positive and negative attitudes towards an attribute. In some cases one may hold strong priors that they should be mono-valued. In that case one requires some restriction on the distribution. Simple two parameter models exist (e.g. lognormal, or restricted triangular distributions) but these distributions may be too restrictive. Development of truncated and censored distributions represent an extremely promising alternative, but no doubt will raise issues themselves. In particular the feasibility or otherwise of statistically testing for the 'best' distribution is a challenge that will become more pertinent as non-nested models of this sort become available. However, the random parameter structure appears to offer a rich seam of research for further exploration.

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Table 1 A Simple Choice Set

Attributes	Option1	Option 2
Technology	Traditional	GM
Weekly food bill	100% of current	80% of current

Table 2. Attributes and their Levels

Attribute	Level
Level of weekly food bill (% change from current) **(bill)**	-50, -40, -30, -20, -10, 0, +10, +20, +30, +40
Form of production technology used **GM(P)** **GM(P+A)**	Traditional, GM(plants), 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 3 Comparison of Conditional logit and random parameter estimates

Infrequent organic group

Conditional logit	coeff	st.error	t	Random parameter		coeff	st.error	t
bill	-0.031	0.004	-9.09	bill		-0.052	0.006	-8.41
chem	-0.040	0.005	-8.33	chem		-0.058	0.011	-5.28
					var	-0.063	0.014	-4.42
fm	-0.016	0.005	-3.28	fm		-0.024	0.009	-2.56
					var	-0.045	0.012	-3.62
risk	0.147	0.022	6.69	risk		0.227	0.050	4.52
					var	0.320	0.060	5.38
sq	1.766	0.189	9.37	sq		2.948	0.348	8.47
					var	-0.434	0.448	-0.97
GM(P)-M	0.041	0.295	0.14	GM(P)-M		0.278	0.582	0.48
					var	1.432	0.611	2.34
GM(P)-F	0.105	0.232	0.45	GM(P)-F		0.131	0.435	0.30
					var	1.659	0.369	4.50
GM(P+A)-M	-1.389	0.345	-4.03	GM(P+A)-M		-2.331	0.725	-3.22
					var	1.138	0.675	1.69
GM(P+A)-F	-1.249	0.242	-5.15	GM(P+A)-F		-2.393	0.547	-4.37
					var	1.637	0.415	3.95

Occasional organic group

Conditional logit	coeff	st.error	t	Random parameter		coeff	st.error	t
bill	-0.012	0.003	-4.05	bill		-0.028	0.006	-4.96
chem	-0.049	0.004	-10.97	chem		-0.100	0.012	-8.10
					var	-0.031	0.011	-2.91
fm	-0.014	0.005	-3.05	fm		-0.019	0.010	-1.83
					var	-0.048	0.014	-3.52
risk	0.050	0.020	2.51	risk		0.123	0.054	2.30
					var	0.369	0.068	5.44
sq	1.173	0.179	6.57	sq		2.108	0.320	6.59
					var	-1.080	0.307	-3.52
GM(P)-M	0.359	0.268	1.34	GM(P)-M		0.509	0.668	0.76
					var	3.047	1.095	2.78
GM(P)-F	-0.378	0.220	-1.72	GM(P)-F		-1.155	0.569	-2.03
					var	3.215	0.828	3.88
GM(P+A)-M	-0.542	0.269	-2.02	GM(P+A)-M		-5.085	1.609	-3.16
					var	4.408	0.918	4.80
GM(P+A)-F	-1.697	0.249	-6.81	GM(P+A)-F		-4.641	1.369	-3.39
					var	6.286	1.773	3.55

Table 3 continued

Committed organic group

Conditional logit

	coeff	st.error	t
bill	-0.007	0.004	-1.61
chem	-0.062	0.007	-9.19
fm	-0.024	0.008	-3.07
risk	0.066	0.033	2.01
sq	1.201	0.227	5.28
GM(P)-M	-0.568	0.377	-1.51
GM(P)-F	-1.237	0.313	-3.95
GM(P+A)-M	-1.736	0.414	-4.20
GM(P+A)-F	-3.108	0.433	-7.18

Random parameter

		coeff	st.error	t
bill		-0.019	0.007	-2.52
chem		-0.114	0.018	-6.28
	var	0.049	0.021	2.32
fm		-0.043	0.015	-2.95
	var	0.032	0.015	2.14
risk		0.137	0.079	1.73
	var	0.374	0.072	5.17
sq		2.053	0.404	5.08
	var	-0.497	0.472	-1.05
GM(P)-M		-2.434	1.200	-2.03
	var	3.063	0.834	3.67
GM(P)-F		-2.522	0.839	-3.01
	var	2.775	1.271	2.18
GM(P+A)-M		-2.525	0.971	-2.60
	var	3.152	1.059	2.98
GM(P+A)-F		-8.784	2.478	-3.54
	var	4.195	1.462	2.87

Table 4 Partworths for selected changes in attribute levels: Conditional logit (CL) and Random Parameter Logit (RPL) Models

	CL	RPL	CL	RPL	CL	RPL
	Infrequent		**Occasional**		**Committed**	
GM (P) free						
Male	-1.25	-5.31	-31.42	-18.24	88.64	130.87*
Female	-3.30	-2.50	33.54*	41.41***	192.81	135.59***
GM (P+A) free						
Male	44.17***	44.48***	46.19	182.25***	268.75	135.76***
Female	39.68***	45.67***	148.56***	166.33***	483.08*	472.27***
10% reduction chemical use	12.79***	11.09***	43.01***	35.88***	97.03*	61.13***
10% reduction in food miles	5.17***	4.561***	12.39***	6.85**	36.41*	23.07***
Food risk 1/10000 to 1/15000	23.42***	21.70***	21.02***	22.08**	50.00	36.72*

(*)(**) (***) partworth significant at the 15% (10%) (5%) level.

Table 5 Random parameter logit estimates: preferred specification

Infrequent organic group

	coeff	st.error	t
pay	-0.049	0.006	-8.61
chem	-0.068	0.011	-6.17
var	0.055	0.011	4.98
fm	-0.023	0.009	-2.60
var	0.038	0.011	3.49
risk	0.267	0.051	5.21
var	-0.253	0.044	-5.75
sq	2.817	0.316	8.92
var	0.609	0.358	1.70
GM(P)	0.040	0.391	0.10
var	1.407	0.357	3.94
GM(P+A)	-2.386	0.514	-4.65
var	-1.910	0.485	-3.94

Occasional organic group

	coeff	st.error	t
pay	-0.026	0.005	-4.901
chem	-0.096	0.012	-7.792
var	0.043	0.010	4.273
fm	-0.028	0.010	-2.871
var	0.014	0.015	0.882
risk	0.178	0.076	2.337
var	-0.368	0.062	-5.929
sq	2.069	0.312	6.641
var	-0.899	0.294	-3.06
GM(P)	-0.279	0.451	-0.618
var	3.051	0.601	5.078
GM(P+A)	-6.623	1.617	-4.097
var	-6.756	1.225	-5.513

Committed organic group

	coeff	st.error	t
pay	-0.022	0.008	-2.964
chem	-0.135	0.021	-6.444
var	-0.026	0.018	-1.482
fm	-0.060	0.016	-3.73
var	-0.007	0.013	-0.531
risk	0.103	0.070	1.48
var	-0.527	0.105	-5.041
sq	2.327	0.483	4.817
var	-2.294	0.515	-4.451
GM(P)	-2.382	0.711	-3.348
var	3.390	0.832	4.076
GM(P+A)	-7.230	1.633	-4.428
var	4.419	1.152	3.837

Table 6 Partworths for selected changes in attribute levels:
Conditional Logit (CL) and preferred specification of the Random Parameter Logit (RPL) Model

	CL	**RPL**	**CL**	**RPL**	**CL**	**RPL**
	Infrequent		**Occasional**		**Committed**	
GM (P) free						
Male	-1.25	-0.80	-31.42	13.64	88.64	106.33***
Female	-3.30		33.54*		192.81	
GM (P+A) free						
Male	44.17***	48.60***	46.19	211.09***	268.75	322.76***
Female	39.68***		148.56***		483.08*	
10% reduction chemical use	12.79***	13.83***	43.01***	32.41***	97.03*	60.40***
10% reduction in food miles	5.17***	4.66***	12.39***	9.15***	36.41*	26.74***
Food risk 1/10000 to 1/15000	23.42***	27.18***	21.02***	23.54***	50.00	23.06

(*)(**) (***) partworth significant at the 15% (10%) (5%) level.

Figure 1. Distributions of WTP for GM food (plant gene transfer only)

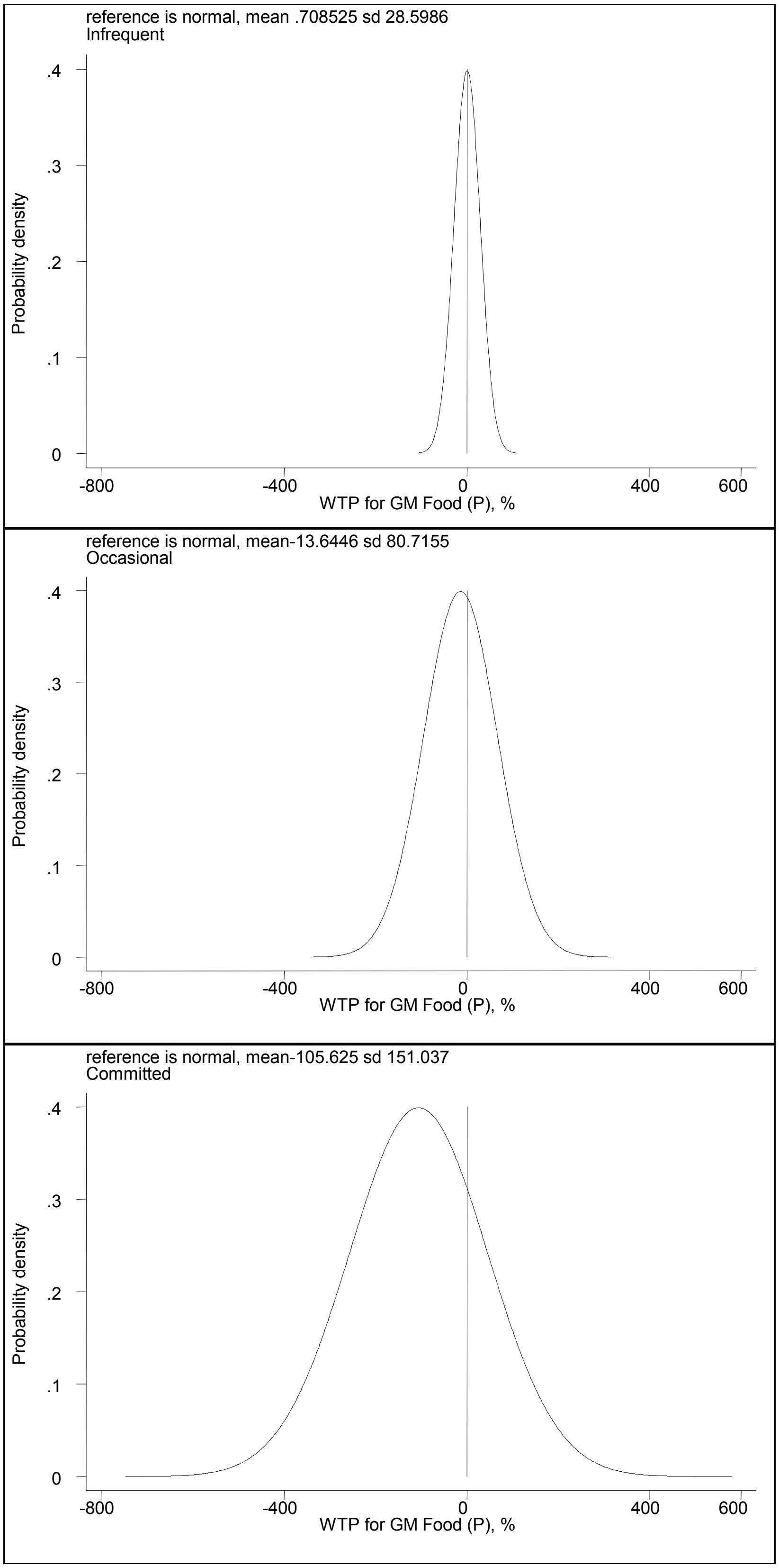

Figure 2. Distributions of WTP for GM food (plant and animal gene transfer)