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

Dan Rigby and Michael Burton[Ψ]

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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 lecturer in the School of Economic Studies, University of Manchester. An Australian Research Council award and Rigby's Henry Schapper Fellowship are gratefully acknowledged.

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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 GM food but other environmental and technical aspects also. Indications of how random parameter models might be developed further are discussed on the basis of these results.

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

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 random parameter framework assumes that the functional form and arguments of utility are common across individuals within the sample, but the parameters vary across individuals. 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. It also gives some indications of the limitations of some of the distributional assumptions used, and areas for further development of the technique.

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.

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 Gumbal 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 the 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 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

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 analysis are provided in Burton *et al*., (2001) 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 below 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.

In the original analysis (Burton *et al*., 2001) a range of alternative specifications were explored, including investigations of 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. 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’)[1].

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 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

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

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, as already noted, is small and only statistically significant at the 15% level for the 'Committed' consumer group. The implication is that Committed and, to some extent, Occasional groups are not placing a great weight on the food bill component of choices.

As estimated, these standard fixed parameter logit models exhibit three technical traits which may be of concern. First, the model imposes IIA. The implications 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 irrelevance, and this leads to imprecise estimates of the population average '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 implications for all three of these concerns. The models do not exhibit IIA, they can explicitly account for the repeated nature of the choices made, 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:

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

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 are feasible for the distribution of β_n: Here the results of models estimated using a normal distribution is reported.

5. RPL estimation

As a starting point, the conditional logit models specified in Table 3 are re-estimated as random parameter models for direct comparison purposes[2]. 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 has an estimated 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 the 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.

[2] All estimation employs GAUSS, and the software developed by Train (http://elsa.berkeley.edu/~train/software.html). We particularly acknowledge the advice and encouragement given by Prof Train during the course of this research.

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 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 presented here was the preferred specification in Burton *et al*., (2001) to enable a comparison, and as such they have not been based on any extensive exploration of the underlying specification of the model using the RPL framework. However, an extensive range of tests of structure have been 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;
c) if the gender interaction effects should be maintained;

The results of these tests (results available on request) indicate that the 3 group structure should be maintained and that in only one case 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. The results of these models are reported in Table 5 and Table 6 showing parameter estimates and associated partworths respectively.

Note that these partworths again only rely open the mean of the attributes preference parameter, and the food bill parameter. Of more interest is the implied distribution of the partworths. These are plotted in Figure 1 for the willingness to pay to avoid food produced involving the transfer of genes from other plants, and in Figure 2 for food involving the transfer of genes 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.

What is of more interest is the extent to which the model implies positive values: i.e. a *preference* for GM. In Figure 1 half the distribution for 2 of the 3 groups falls in the positive WTP range, and for the third group it is still a substantial proportion of the distribution. Regarding WTP for **GM(P+A)** food in Figure 2, in all three cases there is a reasonable portion of the distribution that that lies in this positive WTP range, implying people with a preference for GM 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. This leads to a consideration of whether a different distribution should be used for the parameter distribution. For example, it seem reasonable to suggest that, in the case of GM technology, preferences may be truncated or censored at indifference towards the attribute, with some elements being indifferent and the rest of the population averse to the attribute (for example, one might want to restrict the coefficient on the payment vehicle to be always negative).

Alternative distributions are available that can achieve this outcome. For example the lognormal distribution will impose a single sign on preferences. However, features of this function include the fact (i) the density function equals zero at zero i.e. the model implies that no-one in the population is indifferent to the attribute, and (ii) there is a very long negative tail, implying a huge negative mean WTP. In this context, censored or truncated distributions (as illustrated in Figure 3) would be more attractive. The software capable of estimating such distributions is becoming available, and this appears to be a promising area for exploration.

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 imply that, for the data set under consideration, a random parameter representation is appropriate rather than the conventional fixed parameter model. Indeed despite the robust and statistically significant parameter estimates presented in Burton et al., 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 development of RPL models like those presented here may change the view of what is the best way to accommodate heterogeneity. 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 opens up the possibility of 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 2 parameter models exist (e.g. lognormal, or restricted triangular distributions) but these distributions may be too restrictive. Truncated or censored distributions, which are becoming available, may represent an alternative, but no doubt will raise issues for themselves: in particular the feasibility or otherwise of statistically testing for the 'best' distribution. 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
bill	-0.031	0.004	-9.09
chem	-0.040	0.005	-8.33
fm	-0.016	0.005	-3.28
risk	0.147	0.022	6.69
sq	1.766	0.189	9.37
GM(P) -M	0.041	0.295	0.14
GM(P)-F	0.105	0.232	0.45
GM(P+A)-M	-1.389	0.345	-4.03
GM(P+A)-F	-1.249	0.242	-5.15

Random parameter

		coeff	st.error	t
bill		-0.052	0.006	-8.41
chem		-0.058	0.011	-5.28
	var	-0.063	0.014	-4.42
Fm		-0.024	0.009	-2.56
	var	-0.045	0.012	-3.62
Risk		0.227	0.050	4.52
	var	0.320	0.060	5.38
Sq		2.948	0.348	8.47
	var	-0.434	0.448	-0.97
GM(P) -M		0.278	0.582	0.48
	var	1.432	0.611	2.34
GM(P)-F		0.131	0.435	0.30
	var	1.659	0.369	4.50
GM(P+A)-M		-2.331	0.725	-3.22
	var	1.138	0.675	1.69
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
bill	-0.012	0.003	-4.05
chem	-0.049	0.004	-10.97
fm	-0.014	0.005	-3.05
risk	0.050	0.020	2.51
sq	1.173	0.179	6.57
GM(P) -M	0.359	0.268	1.34
GM(P)-F	-0.378	0.220	-1.72
GM(P+A)-M	-0.542	0.269	-2.02
GM(P+A)-F	-1.697	0.249	-6.81

Random parameter

		coeff	st.error	t
bill		-0.028	0.006	-4.96
chem		-0.100	0.012	-8.10
	var	-0.031	0.011	-2.91
Fm		-0.019	0.010	-1.83
	var	-0.048	0.014	-3.52
Risk		0.123	0.054	2.30
	var	0.369	0.068	5.44
Sq		2.108	0.320	6.59
	var	-1.080	0.307	-3.52
GM(P) -M		0.509	0.668	0.76
	var	3.047	1.095	2.78
GM(P)-F		-1.155	0.569	-2.03
	var	3.215	0.828	3.88
GM(P+A)-M		-5.085	1.609	-3.16
	var	4.408	0.918	4.80
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 Female	-1.25 -3.30	-0.80	-31.42 33.54*	13.64	88.64 192.81	106.33***
GM (P+A) free Male Female	44.17*** 39.68***	48.60***	46.19 148.56***	211.09***	268.75 483.08*	322.76***
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)

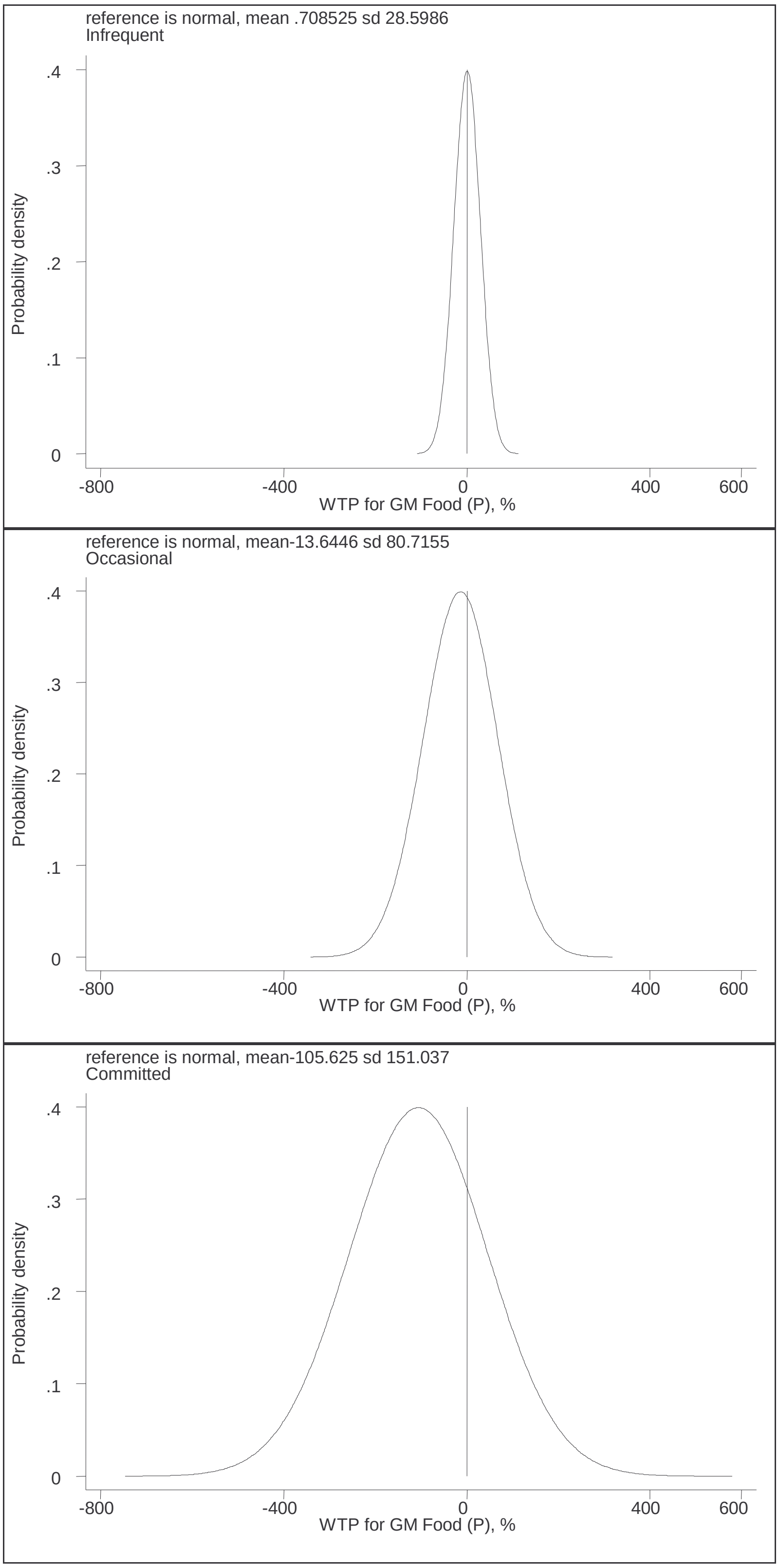

Figure 2. Distributions of WTP for GM food (plant and animal gene transfer)

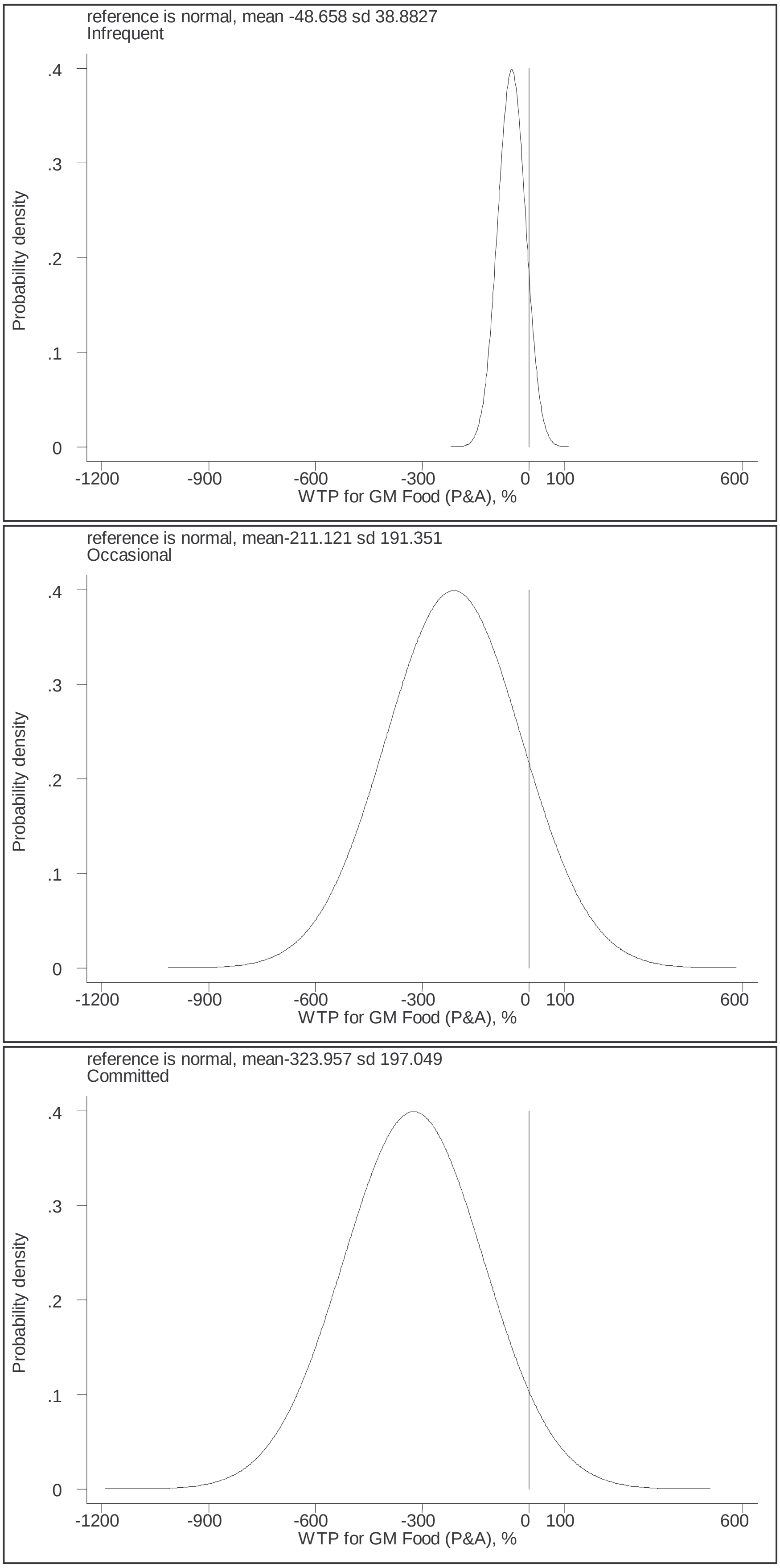

Figure 3. Alternative distributional assumptions