Precaution and Protectionism: ‘Likeness’ and GM Food at the WTO

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1. Introduction

Few trade issues have caused such bitter divisions between the governments of the USA and EU states as that of genetic modification in agriculture notably since the EU's '*de facto* moratorium' on GM crops came into effect in 1998. In August 2003 the US took the issue to a WTO Dispute Settlement Body (DSB). Whereas the EU maintains it is dealing with the concerns raised by the US via *inter alia* new regulations regarding labelling and traceability of GM organisms (GMOs) in food, the US is adamant the new legislative regime is an illegal restraint to trade and of no benefit to consumers. These issues go to the heart of the debate about the circumstances to which nation states may restrict trade on the grounds of environmental protection and public concern if adhering to WTO rules.

In this paper the role of uncertainty and precaution within the WTO are discussed as is the EU's new labelling and traceability regulations which were partly an attempt to resolve the dispute with the US. Findings are presented here regarding the extent to which the UK public values the changes in the new GM labelling regime. These findings from a nationally representative, choice modelling study throws light on the issue of process- as opposed rather than product-based labelling: whether consumers evaluate GM products on the basis of the process by which it was produced or the characteristics of the final product. The data are analysed using Bayesian as well as classical statistical mixed logit models. As the results show, Bayesian methods allow more flexibility in the representation of preferences, and are particularly well suited to modelling the situation where many in the population are indifferent to a food type whilst others dislike it intensely.

2. GM Food and the US-EU Trade Dispute

The EU *de facto* moratorium came into effect in 1998 leading to the US filing a complaint at the WTO in May 2003. The complaint, backed by Canada and Argentina led to the formation of a WTO Dispute Settlement Body in August 2003 with its ruling repeatedly postponed, and now due in January 2006.

Those trying to predict the DSB's ruling have referred to many treaties and agreements concerning trade, the environment, or both and past rulings by the DSB and the Appellate Body

(AB). Hence GATT Articles, GATT & WTO Agreements (such as SPS and TBT) the Convention on Biological Diversity and the Cartagena (biosafety) Protocol as well as the Codex Alimentarius have all been scoured for precedents. These have informed, to varying degrees, past rulings by the DSB and the AB, in disputes such as *EC-Hormones*, *Japan-Alcoholic Beverages* and *US Shrimps*.

One central difference in the US and EU positions in the dispute (which reflect past differences also) concerns the nature of risk and its assessment and the role, if any, of the precautionary principle in the management of uncertainty. A crucial ruling in this regard, particularly concerning the precautionary principle, concerns the EU's ban of beef produced with growth promoting hormones (*EC-Hormones*). This was the first dispute settled under the Sanitary and Phytosanitary Measures Agreement. The AB, following the EU's appeal against the DSB ruling, ruled that:

> "First, the [precautionary] principle has not been written into the *SPS Agreement* as a ground for justifying SPS measures that are otherwise inconsistent with the obligations of Members…the precautionary principle does not…relieve a panel from the duty of applying the normal (i.e. customary international law) principles of treaty interpretation in reading the provisions of the *SPS Agreement*….We accordingly agree with the finding of the Panel that the precautionary principle does not override the provisions of Articles 5.1 and 5.2 of the *SPS Agreement*…The status of the precautionary principle in international law continues to be the subject of debate among academics, law practitioners, regulators and judges…Whether it has been widely accepted by Members as a principle of *general* or *customary international law* appears less than clear."

In terms of MEAs the Cartagena Protocol does allow trade restrictions related to risk, and in its preamble refers to itself as:

> "a Protocol on biosafety, specifically focusing on transboundary movement of any living modified organism resulting from modern biotechnology that may have adverse effect on the conservation and sustainable use of biological diversity, setting out for consideration, in particular, appropriate procedures for advance informed agreement"

However it is important to note that the Cartagena Protocol is explicit that other international obligations, such as WTO requirements, are unaltered by the Protocol. Also the US has not signed up to the Protocol. As such defence of the moratorium at the WTO via the Cartagena Protocol is deeply problematic.

Interpreting and analysing the *EC-Biotech* WTO Dispute on the basis of past rulings and agreements raises the issue of restrictions on trade on the basis of *product* and of *process*. Article 1 of GATT requires that like products are treated equally. Exactly what is 'like' in the context of GM foods is analysed in this paper. The issue of process based trade restriction has featured in previous disputes, most notably in the *US Shrimps* GATT dispute over the US ban on shrimp (products) not certified as having being harvested using methods not causing incidental deaths of turtles. In discussing the tension between legitimate environmental protection and illegitimate protectionism the Appellate Body talked of

> "…locating and marking out a line of equilibrium between the right of a Member to invoke an exception under Article XX and the rights of the other Members under varying substantive provisions (e.g., Article XI) of the GATT 1994, so that neither of the competing rights will cancel out the other…*The location of the line of equilibrium, as expressed in the chapeau, is not fixed and unchanging; the line moves as the kind and the shape of the measures at stake vary and as the facts making up specific cases differ*." (italics added)

This evolving and changing line between the right to restrict and right to trade will be affected by the DSB ruling (and any subsequent AB ruling) on the current *EC-Biotech* case. Regarding issues of product, process and likeness in past DSB rulings, Petitpierre *et al* (2004) identify 4 criteria which the DSB/AB have used to determine whether products are indeed like: the price consumers are willing to pay; consumers' perception; physical characteristics; the final use of a product. Presenting multiple criteria may initially appear odd, but this multi faceted approach is reflected in one of the most revealing passages from an AB ruling on 'likeness', in the *Japan-Alcoholic Beverages* case:

> "…there can be no one precise and absolute definition of what is 'like'. The concept of 'likeness' is a relative one that evokes the image of an accordion. The accordion of 'likeness' stretches and squeezes in different places as different provisions of the WTO Agreement are applied."

These 4 criteria will be revisited. First we consider the regulations regarding labelling and traceability of GMOs in food which the EU repeatedly stated would bring the moratorium and the dispute to an end.

3. The New EU Regulations on GM Food and Feed and Traceability and Labelling

The new legislation on traceability and labelling, briefly outlined below, was seen as potentially defusing the US-EU dispute. Two new Regulations came into effect from April 2004 (Regulations 1829/2003, 1830/2003). A crucial change to the regulatory framework is the extension of the current labelling provisions to genetically modified food or feed, *regardless of whether it contains detectable modified DNA or protein*. Any food or feed which consist of, contain or are produced from GMOs will require a label. For example, this includes tomato paste and ketchup produced from a GM tomato or starch, as well as oil or flour produced from GM maize.

This represents a significant change from the requirement before April 2004 which was based on the detectability of genetically modified DNA or protein in the final food product. A range of highly processed foodstuffs using ingredients derived from GM material will now need to be labelled. These include common products such as soya oil, vegetable oil, hydrolysed vegetable protein, modified starch, cornflour, maize starch, and maize oil.

The responses in the US to the new EU labelling and traceabiliy regime have been far from positive. This is reflected in the fact that the US decided to proceed to the Dispute Panel even when it was known that the EU regulations were imminent.

The response from US agro-industry was that the new labelling and traceability regime was unscientific, an illegal restraint on trade and as bad as the *de facto* moratorium. Extending the basis of labelling from product to process was described as unscientific and of no value to consumers. Hence Ron Gaskill, from the American Farm Bureau Federation, said that the labelling and traceability rules are "just as inconsistent with the WTO agreement on technical barriers to trade and sanitary and phytosanitary measures as the moratorium itself is." The US National Food Processors Association responded to the new regime with:

> "By finalizing these new requirements.... the EU has turned away from food science and food safety, and has established a serious trade barrier ....European consumers will see such labels on food products as 'warning labels.....Mandatory labeling should be based on the composition, intended use, and health and safety characteristics of a food product, not on the 'genetic process' from which it was derived. Moreover, the traceability requirements are a classic case of regulatory overkill, putting complex and detailed new requirements on food companies, *with no benefit for consumers*." [italics added] (NFPA Press Release 20/10/03)

4. **Consumer responses to GM Foodtypes**

The statistical analysis presented here draws partly on work, funded by DEFRA, investigating the existence and magnitude of consumer benefits from the extension of the labelling regime to include those foods with ingredients produced from GMOs despite the absence of modified DNA or protein. The technique employed for the statistical analysis was choice modelling (see Rigby *et al.*, 2004 for more details of the study).

Bread was chosen as a good via which to explore preferences as it was familiar. Choice modelling requires decomposing the description of the good into a number of component attributes. Following a series of semi-structured interviews undertaken by a food psychologist in different parts of the UK 'Shelflife' and 'Fibre Content' were chosen as the attributes of bread alongside price and the GM or otherwise nature of its ingredients. These attributes and their levels are described in Table 1 and an example choice set is given in Table 2.

Table 1. Attributes and Levels

Attribute	Levels
Price (%)	-67, -50, -33, -17, Usual, +17, +33
GM Type	Non-GM, GM-Derived, GM
Shelflife	Usual, Usual + 1 day, Usual + 2 days, Usual + 3 days
Fibre Content	Usual, Usual + 10%, Usual + 30%, Usual + 50%

Table 2. An Example Choice Set

	Bread 1	**Bread 2**	**Bread 3**
	Usual brand	**Usual brand - alternative option 2**	**Usual brand - alternative option 3**
Price	Usual	Usual	Usual -50%
GM Type	Non-GM	GM-Derived	GM
Shelflife	Usual shelflife	Usual shelflife	Usual +2 days
Fibre Content	Usual fibre content	Usual +30%	Usual +10%
Which bread do you prefer ?			

The survey was conducted in the home in England, Wales and Scotland between July and September 2003 using Random Location Sampling with a sample comprising 608 respondents.

5. Statistical Analysis: Mixed Logit

Results from the choice modelling have been analysed using a variety of methods (including conditional logit and latent class models) but here the focus is on mixed logits and specifically their implementation using Bayesian rather than classical means.

Conceptually, the mixed logit, or random parameter model considers each individual to be their own 'segment' of the sample, with unique parameters of the utility function. Without inordinate amounts of data, estimating such a model requires some restriction to be placed on the possible values of the parameters, which is achieved by assuming that within the population the utility function parameters are drawn from a distribution. The analysis in this case aims to identify the parameters of the distribution from which the individual-specific parameters are drawn.

Clearly the choice of distribution is significant and the selection is neither simple nor, in many cases, amenable to testing typically with respect to the sign and length of the tails. Hence the normal distribution implies that some individuals have extreme positive and negative valuations of an attribute. This may be unrealistic, for example with respect to changes in prices. One resulting area of work has been development of estimatible forms of bounded distributions such as the log normal and triangular. However these may not suitable if there is a probability mass point at zero (indifference) with the rest of the population (dis)liking the attribute.

The analysis here draws on Train and Sonnier's bounded mixed logit model (Train and Sonnier, 2003) estimated using Bayesian techniques which offers scope for a greater variety of bounded distributions from which the utility function parameters are drawn (discussed in more detail below). For reasons of brevity we confine our explanation of the model to the Bayesian approach.

6. The Bayesian Mixed Logit Model

Consider a person, n, choosing among J options in T periods. Person n's utility from alternative j in the t^{th} period is:

$$U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt} \tag{1}$$

where x_{njt} is a vector of observed variables, the coefficient vector β_n represents the consumer's tastes and is distributed in the population as N(b, j), and ε_{njt}, an unobserved random term, is independently and identically distributed with an extreme value distribution. Denoting person n'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 choices of all in the sample ($y_n \forall n$) as *Y*. The probability of person *n*'s sequence of choices occurring is the product of standard logit formulas, conditional on *β*:

$$L(y_n \mid \mathrm{b}) = \prod_t \frac{e^{\mathrm{b}' x_{ny_{nt}t}}}{e^{\mathrm{b}' x_{njt}}} \qquad (2)$$

where $x_{ny_{nt}t}$ is the value of *x* associated with the selected choice, y, in period t.

The unconditional probability is the integral of this expression over all values of β, weighted by the density of β:

$$L(y_n \mid b, \mathrm{j}) = \int L(y_n \mid \mathrm{b})\, \mathrm{y}(\mathrm{b} \mid b, \mathrm{j})\, d\mathrm{b} \qquad (3)$$

where ψ (β|b, j) is the normal density with mean *b* and variance j .

Priors on both *b* and j are required for Bayesian implementation. The prior on *b* is normal with mean zero and an extremely large variance to generate an almost flat distribution: k(b) ~N(b_0, r_0). The prior on j is inverted Wishart: k(j) ~ IW(K,I) where I is the K-dimensional identity matrix. This is a conjugate prior. This assumption regarding the prior on j has the advantage of providing a distribution which is easy to draw from whilst not affecting the results at convergence. The joint posterior on $\beta_n \forall$n, *b* and j is:

$$K(\mathrm{b}_n \forall n, b, \mathrm{j} \mid Y) \propto \prod_n L(y_n \mid \mathrm{b}_n)\, \mathrm{y}(\mathrm{b}_n \mid b, \mathrm{j})\, k(b, \mathrm{j}) \qquad (4)$$

where k (*b*, j) is the prior on *b* and j .

One could draw from this joint posterior but in practice it is faster to use Gibbs sampling, with draws taken sequentially from the conditional posterior of each of the parameters given the previous draws of the other parameters (see Train, 2003 for more details). Hence one takes a draw of the mean of the parameters *b* conditional on j and $\beta_n \forall$n as if they were known, then takes a draw of j conditional on b and $\beta_n \forall$n and finally a draw of $\beta_n \forall$n conditional on *b* and j . The resulting three conditional posteriors are:

$$K(\beta_n \mid b, \mathrm{j}, y_n); \qquad K(b \mid \mathrm{j}, \beta_n \forall n); \qquad K(\mathrm{j} \mid \beta_n \forall n, b) \qquad (5)$$

The sequence of these draws from the conditional posteriors converges to a draw from the joint posterior. Since the procedure does not involve maximization of a function, the process is implemented using a high number (30 000 in this case) of iterations prior to convergence as *burn*-in followed by 20 000 iterations with one in ten iterations retained for inference. The retention of only one tenth of the draws after burn-in is to reduce or eliminate the correlation amongst the draws that the Gibbs sampling creates. The mean of the retained draws is the simulated mean of the posterior which, in classical terms, gives the parameter estimates whilst the standard deviation of the draws provides the standard errors of the parameter estimates.

7. Results: Unbounded Classical Estimation

The model was initially estimated, using 'classical' rather than Bayesian methods, with all parameters normally distributed except the fixed price term. This allowed comparison with subsequent Bayesian specifications of the bounded model. The imposition of a fixed price for the payment vehicle is common: in part it aids identification of partworths (the distribution of the ratio of two normal variables is strictly indeterminate), but also Ruud (1996) suggests that having all random coefficients leads to a near unidentified model.

Table 3 presents results from a classical estimation of this mixed logit model. As one might expect, the mean of both GM terms as well as the fixed price coefficient are negative. All terms, means and standard deviations, are significant at the 5% level. The assumption of normally distributed terms means inevitably that shares of the population are modelled as having positive and negative marginal utilities of the attributes. This is shown in Table 4 where 40% of people prefer bread with shorter shelflife, 31% prefer bread with less fibre, 23% prefer bread containing GM Derived ingredients and 8% prefer it made with GM ingredients.

Table 3. Results: Classical Model: random parameters normally distributed

Parameters	beta	std.err	beta/st.error
Price	-0.0178	0.0025	-7.006
GM Derived	-2.5264	0.3308	-7.636
sd	3.4389	0.4829	7.121
GM	-2.2950	0.2548	-9.006
sd	1.6475	0.3358	4.906
Shelf	0.1619	0.0593	2.730
sd	0.6062	0.0811	7.474
Fibre	0.0134	0.0034	3.947
sd	-0.0263	0.0048	-5.423
Log-likelihood	-1224.85		

Table 4. Shares of marginal utilities above and below zero

	Share<0	Share>0
Shelf	39.6	60.4
Fibre	30.7	69.3
GM Derived	76.6	23.4
GM	91.8	8.2

Some of these preferences might be regarded as unconvincing. One might expect some people to be indifferent to some or all of the attributes but, *ceteris paribus*, preferring (and being prepared to pay more for) bread made with GM ingredients or which goes stale quicker seems unlikely.

8. Bounded Distributions in the Bayesian Mixed Logit Model

Several variables (*gm*, *gm derived*, *shelf* and *fibre*) were therefore identified as appropriate for estimation assuming a bounded distribution for the parameter. The bounded distributions available using Train and Sonnier's implementation are the log-normal, a censored normal and Johnson's S_B distribution. The bounded distributions all assume that the appropriate parameters of the utility function β_n are replaced by t_n, which is a transformation of a normal distribution.

With the normal distribution censored from above at zero there is a mass point at zero so that with β normally distributed with mean b and variance s, the transformation is $t_n = \min(0, \beta)$, with the density below zero identical to the normal density of β. Estimation involves identifying b and s, and hence t, and thus the proportion of the population massed at zero and the proportion below zero.

For the log-normal the transformation is $c = exp(\beta)$ with the distribution bounded below at zero with a zero probability mass at zero. The distribution is also employed on the negative of undesirable attributes. In the case of the S_B distribution an upper and lower bound is specified for the distribution, so that the transformation $t_n = l + (u - l) \cdot (\exp(\beta)/(1+\exp(\beta)))$ produces a distribution between l and u, with the shape, mean and variance determined by the normally distributed β's mean and variance. This distribution has the potential to resemble a censored normal, a log-normal distribution but with a specifiable upper bound, a plateau with sharp slopes on each side or be bi-modal with the mass points at the bounds. Note that bimodality is *not* imposed.

9. Results: Bounded Bayesian Estimation

Initially a model (Model 1) with all terms normally distributed was estimated and then a range of alternative specifications tried. Note that in this model and subsequent specifications, the coefficient on the price variable is no longer held fixed. This is because no GAUSS coding exists to include a fixed term, although in principle the Bayesian approach can accommodate such terms (but they would significantly increase time to convergence). For the price term, the censored normal and lognormal specifications were employed: people are unlikely to prefer more expensive food, but some people may be allocating a zero weight to the price attribute in their survey choices. The possibility of either normal or censored normal distributions were employed for the shelf and fibre terms. The preferred model with price distributed log normally, fibre and shelflife distributed as censored normals and GM and GM Derived terms assumed to follow a Johnson's S_B distribution with bounds at 0 and 14. In Table 5 the estimated βs and their standard errors are shown, as well as the mean and variance of the transformed variables, representing the marginal utilities. Note that the price and GM terms have been multiplied by (-1) for estimation purposes, hence the positive mean of the marginal utility distribution for these 3 terms.

Table 5. Preferred Specification Bayesian Bounded Model

		β_n		marginal utilities	
		mean	**var**	**mean**	**var**
price (-)		-4.3129	3.9914	0.1058	0.485
	s.e.	0.2691	1.3004		
shelf		-0.467	3.1239	0.5163	0.7825
	s.e.	0.5307	1.6262		
fibre		-3.8177	5.186	0.0415	0.0667
	s.e.	1.2384	3.3352		
GM Derived (-)		-0.8726	465.0687	6.6599	45.2124
	s.e.	2.0346	534.1769		
GM (-)		-1.1138	126.2812	6.3039	41.6009
	s.e.	1.1055	185.7616		
log likelihood = -1166.9633					

It may seem surprising that in the Bayesian model the GM variables appear to be statistically insignificant (i.e. both means and variances have very high standard errors). However, this does not indicate that these variables are not significantly affecting the fit of the model. Removing them from the model significantly reduces the log likelihood (from -1166 to -1403). This is an example of a common paradox in models where there is a strong relationship between variables, but imprecision in the estimate of that effect. Thus, in this case, it is possible to change the estimates of the means and variances considerably, but there is little change in the simulated distribution for the marginal utilities.

In mixed logit models partworths or WTPs are obtained from the ratio of an attribute's marginal utility to the marginal utility of the payment vehicle, i.e. the ratio of coefficients. Details of the distributions of WTPs and associated shares of the market buying at various discounts are shown in Table 6 for both the Classical and Bayesian models. All monetary values are expressed as % of base price of bread which was respondent specific and averaged approximately 1€. Hence a WTP of 10 represents approximately 0.1€. In comparing the results across Classical and Bayesian models one should note that there are 2 causes of difference: the different distributional assumptions in the models and the presence of a (log normally) distributed rather than fixed price term in the Bayesian model.

The mean WTPs to avoid GM food in the Bayesian model are unfeasibly large, a result of the tail of the log normal price distribution and the strong aversion to GM technology among some in the sample. Hence 44% and 46% of the sample have WTPs to avoid GM-Derived and GM bread respectively of over 100%, i.e. more than a doubling of their bread price.

The median values, however, at 40% for GM-Derived and 63% (of 1€) for GM bread are far lower and more feasible, and the mass points at and near indifference for the GM attributes lead to significant proportions of consumers willing to buy at zero or small discounts. Table 6 shows that in the Bayesian model, 45% will buy bread produced from GM Derived ingredients, and 39% with GM ingredients, at discounts up to 10%. The equivalent figures for the Classical model are 25% and 10% respectively.

This analysis of the distribution of partworths in Table 6 shows that there is little to be gained from an analysis of the mean of a bimodal distribution. Of more interest is the median of the Bayesian distribution, which is determined by the lower tail of the distribution. The medians of the GM variables for the classical model are substantially higher, as the estimated normal distribution is pulled upwards by the need to accommodate that portion of the sample that is strongly averse to the use of GM. More information about the distributions of WTPs to avoid GM ingredients are provided in Figures 1 and 2 Note that in these figures values >100% have been stacked

Table 6. Partworth Distributions and Market Shares

	Fibre	Shelflife	GM Derived	GM
Bayesian				
Mean	13.5	60.7	2241.1	2283.1
std.dev	197.6	563.5	9955.4	9966.2
Median	0.0	0.0	40.0	63.1
% values >100			44	46
% buying: 10% discount			45	39
% buying: 20% discount			47	43
Classical				
Mean	0.75	9.10	128.93	141.9
std.dev	1.48	34.06	92.56	192.7
Median	0.75	9.10	128.93	141.9
% values >100			59	62
% buying: 10% discount			25	10
% buying: 20% discount			26	12

at the 100% value (this only relates to the graphs, it is not involved in the estimation or the results presented in Table 6).

Figure 1. Distribution of WTPs to Avoid GM Derived Food (values>100 stacked at 100)

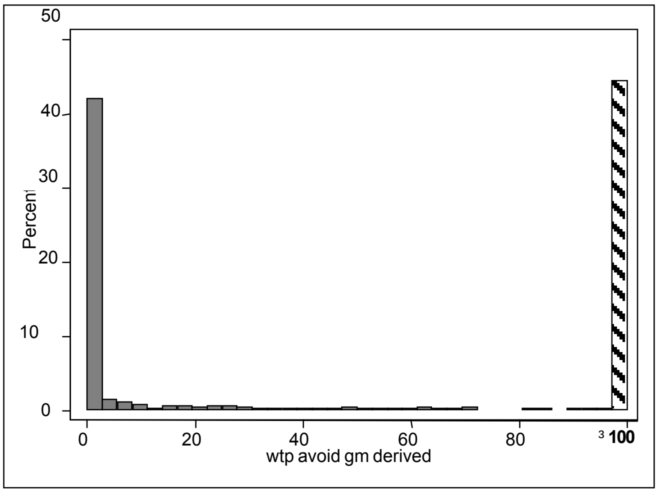
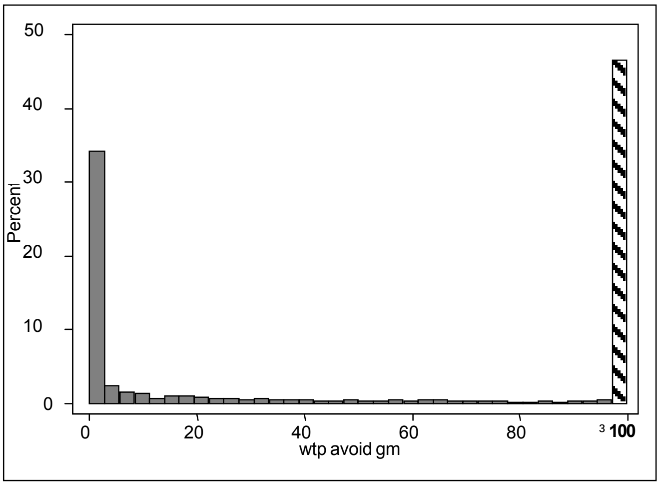
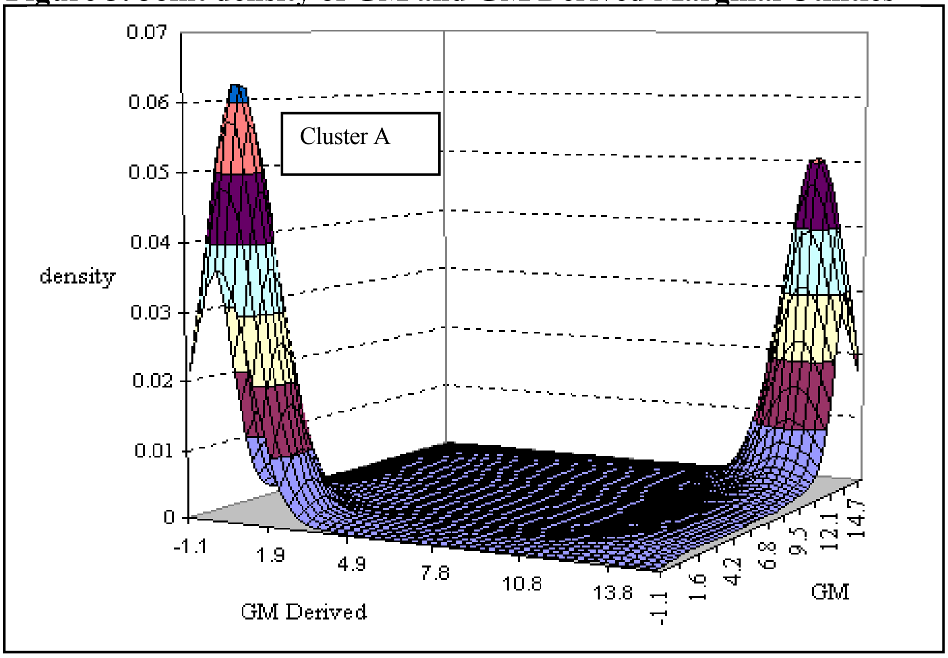


Figure 2. Distribution of WTPs to Avoid GM Food (values>100 stacked at 100)



The shapes and scales of the distributions of WTP to avoid the 2 GM types are very similar, and this raises the questions of how closely correlated are preferences for GM and GM Derived foods. An additional advantage of this Bayesian implementation of the mixed logit model is that it is possible to estimate the correlations between the estimated marginal utilities by deriving the full variance-covariance matrix with the Bayesian bounded model. The correlations reveal, for example, the strong similarity between the two forms of GM food. They have a very high level of correlation (implying that those averse to GM Derived products have a similar level of aversion to GM products) but also strong similarities in structure across the other attributes. This is shown clearly in Figure 3, a bivariate kernel estimate of the joint density of the GM and GM Derived parameters. It reveals a starkly divided population with a cluster (Cluster A) at indifference or *relatively* low aversion to both GM ingredient types. The second cluster comprises those strongly averse to both types of GM ingredients.

Figure 3. Joint density of GM and GM Derived Marginal Utilities



What the distribution of partworths indicates is that there are two distinct subpopulations within the sample: those indifferent or mildly averse and those who are extremely averse to both technologies. What is missing from this distribution (and which is technically possible) is the presence of a group who are indifferent to GM Derived products but strongly averse to GM food. This group would be revealed as a spike at the back left position in Figure 3 of people close to indifference regarding GM Derived food but strongly disliking GM food (a spike of a similar nature is reported by Rigby and Burton, 2005, using older data from the UK). The absence of this spike points to the absence of a mass point of people distinguishing GM foods on the basis of final product composition. People appear to be responding, whether that be disinterest or dislike, on a process basis to GM food, rather than on the basis of whether the final product contains GM material or not.

10. Conclusions

In this paper preferences for GM and GM Derived food in the UK have been examined using data from the first nationally representative economic study of preferences for GM foodtypes. The choice modelling data has been analysed using Classical and Bayesian implementations of the mixed logit model. The Bayesian model has strong advantages in terms of (i) ease of convergence with certain specifications (such as log normal distributions), (ii) ability to estimate a full variance-covariance matrix at little additional computational cost, (iii) the additional (bounded) functional forms it can accommodate.

In this paper log normal, censored normal and S_B distributions have been employed, only the first of which can be accommodated in the classically estimated model, albeit often with great difficulty. A range of specifications of the Bayesian model were presented which indicated that model fit with bounded distributions of preferences was consistently better than with normally distributed preferences. Of particular interest was the S_B distribution given the flexible range of shapes it can take: a censored normal, a log-normal distribution with a specifiable upper bound, a plateau with sharp slopes or bi-modal.

The S_B distribution was employed for the preference distributions for both GM and GM Derived food and in all specifications a bi-modal distribution of preferences resulted. The population was found to be bi-modal in terms of both GM foodtypes with one group indifferent or mildly averse to both forms of modified food, the other group were strongly averse. In this context of 'disinterest and dislike' the S_B distribution is extremely powerful in its ability to represent but not impose bi-modality. The advantages of the Bayesian model presented highlight the merit in further developing it, in terms of adding the scope for fixed terms and endogenising the bounds employed for the S_B distribution.

Turning from methodology to the substantive issue, the findings presented cast light on the current dispute between the EU and the USA at the WTO and the validity or otherwise of the EU's new labelling regime which has itself provoked such fierce opposition from agroindustry in the USA. While it is not the case that everyone in the UK sample was strongly averse to GM food, for most in the population it was not treated the same as Non-GM food. While it was found that 45% and 39% might buy GM Derived and GM food with discounts of up to 10%, over half the population would not buy either foodtype at discounts of 20%.

A striking feature throughout the results has been the consistency with which the respondents viewed the 2 GM foodtypes. This was evident in estimates of the respective marginal utilities, the correlation structure across all attributes and in the nature of the WTPs to avoid the GM foods. Figure 3 is particularly striking in this respect: with the 2 clusters indicating that the vast majority of people regarded GM and GM Derived food as equivalent. Whether they were indifferent or averse, that equivalence was dominant.

This provides evidence of considerable consumer benefits associated with the new EU labelling regime: those consumers who want to know if their food contains GM ingredients want to know if it contains GM Derived ingredients. The pattern of preferences in Figure 8 (from a previous paper) has indicated that this is not always the case. In that sample of UK consumers, significant numbers of people treated different forms of genetically modified food differently. That was not the case here.

In terms of trade restrictions, the WTO and 'likeness', the results are significant also. The identified equivalence of preferences for GM and GM Derived food points to the majority of people responding to their food in terms of the *process* by which it is produced rather than simply the final *product* composition. Returning to the 4 criteria of likeness (Petitpierre *et al*, 2004) we find that that the perception of the majority of consumers and the price they are willing to pay are, in this case, driven by process and not simply the 'physical characteristics' of their food.

References

McFadden, D and K. Train (2000), "Mixed MNL models of discrete response." *Journal of Applied Econometrics* **15** 447–470.

Petitpierre, A, Boisson De Chazournes, L, Perrez, F, Pythoud, F, Mbengue, M and U. Thomas (2004) Trade, The Environment And The International Regulation Of Biotechnology. Special Issue of Ecolomic Policy And Law, Journal of Trade and Environment Studies, Geneva, Switzerland.

Rigby, D, Young, T and M.Burton (2004). Consumer willingness to pay to reduce GMOs in food & increase the robustness of GM labelling. Report to Department of the Environment, Food and Rural Affairs. School of Economic Studies, Manchester University.

Rigby, D and M.Burton (2004) Modeling Disinterest and Dislike: A Bounded Bayesian Mixed Logit Model of the UK Market for GM Food. Forthcoming in *Environmental and Resource Economics.*

Ruud,P. (1996) , "Simulation of the multinomial probit model: an analysis of covariance matrix estimation", Working paper, Department of Economics, University of California, Berkeley

Train, K, and G.Sonnier (2003), "Mixed Logit with bounded distributions of partworths." Working paper, University of California, Department of Economics.

Train, K (2003) *Discrete choice methods with simulation*. Cambridge University Press, New York.