

Precaution and Protectionism: GM Food and the WTO

Dan Rigby, Mike Burton and Trevor Young

Rigby and Young: Economic Studies, University of Manchester.

Burton: Agricultural and Resource Economics, University of Western Australia.

**Corresponding Author: Dr Dan Rigby, Economic Studies, School of Social Sciences,
Manchester University, Manchester UK, M13 9PL**

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

Email: dan.rigby@man.ac.uk



***Paper prepared for presentation at the 11th Congress of the EAAE
(European Association of Agricultural Economists),
Copenhagen, Denmark, August 24-27, 2005***

Copyright 2005 [Rigby, Burton & Young]. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Precaution and Protectionism: GM Food and the WTO

Dan Rigby, Mike Burton and Trevor Young^o

Please do not quote without the authors' permission

Abstract

The dispute between the US and EU over GM foods at the WTO is examined in terms of the issues it raises about protectionism and environmental protection and precaution. The issue of whether GM, GM Derived and Non-GM foods are equivalent to each other is examined using data from a national choice modelling study in the UK. These categories of food are critical since they underpin the EU's new food labelling regime which it hoped would defuse the WTO dispute. The results are analysed using a Bayesian mixed logit model which allows greater flexibility in the modelling of preference distributions. This is particularly crucial where, as in this case, bi-modal distributions are identified with some indifferent or mildly averse to GM foodtypes while others are strongly averse. A strong finding of the analysis is that people treat ingredients derived from GM crops (but free from altered DNA) as equivalent to GM ingredients. This supports a labelling regime based on *process* rather than simply *product* and suggests considerable consumer benefits from the EU's new GM labelling regime.

Keywords: GM food, mixed logit, WTP, Bayesian, WTO;
JEL classification: C11, C24, C25, D12, Q18

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. Differences over the authorisation of commercial growing of GM crops and the conditions under which genetically modified (GM) food can be traded have continued for many years, 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) after the failure of initial consultations following the matter first being taken to the WTO. Whereas the EU maintains it is dealing with the concerns raised by the US via new regulations regarding labelling and traceability of GM organisms (GMOs) in food, the US is adamant that the new legislative regime is unscientific, 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. Given that uncertainty and precaution are key motives for those opposed to GM imports a consideration of how such concepts fit in the WTO is appropriate.

The EU's new labelling and traceability regulations, discussed in the paper, were partly an attempt to resolve the dispute with the US and evidence is presented here regarding the extent to which the UK public value the changes in the GM labelling regime.

As well as being the first nationally representative, economic analysis of preferences for (non) GM food, the study throws light on the issue of process rather than product based labelling: whether

^o This paper draws on work commissioned by UK Department of Environment Food and Rural Affairs (DEFRA). The views presented in this paper are those of the authors alone and should not be regarded as those of DEFRA or of individuals within DEFRA.

consumers evaluate GM products on the basis of the process by which it was produced or the characteristics of the final product which, as we discuss, is crucial in the area of genetic modification.

The results are based on survey data generated within a choice modelling framework, which 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

Discontent and opposition regarding GMOs in the EU has developed, albeit unevenly, from 1996. In 1997 Austria and Luxembourg banned a series of GM varieties despite their having been authorised under Directive 90/220. Additional bans on approved crops followed in Austria as well as Greece, Italy and Germany. A number of states made it clear in 1998 that they would block further authorisations in the absence of a new labelling regime for GM crops. This block accounted for sufficient votes to prevent a qualified majority at the Council of Ministers from approving new GM products. Hence the *de facto* moratorium came into effect in 1998.

The continued EU moratorium on growing and importing of GM crops led, eventually, to the US filing a complaint at the WTO in May 2003. The complaint, backed by Canada and Argentina and other nations, instigated a consultation period, of up to 60 days. However it was quickly apparent that no resolution was in sight and hence the U.S., Canada and Argentina formally requested a WTO Dispute Settlement Body in August 2003. The ruling of the DSB was expected in June 2005.

The submissions of the parties to the DSB and those *Amicus Curiae* submitted by interested parties (see Busch *et al*, 2004) have referred to many treaties and agreements concerning trade, the environment, or both. These have included Multilateral Environmental Agreements (MEAs) in addition to past rulings by the DSB and the Appellate Body. 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 themselves have informed, to varying degrees, past rulings by the DSB and the AB, crucially in disputes such as *EC-Hormones*, *Japan-Alcoholic Beverages*, *US Shrimps*.

While there have been many past relevant rulings which may have provided a clue as to how the DSB would rule in this dispute, Boisson de Chazournes and Mbengue (2002, cited in Petitpierre *et al*, 2004) reject Carreau and Julliar's (1998) metaphor of a mosaic to describe various WTO rules combining to form a coherent totality. Instead they regard the situation as more akin to a puzzle where trade and environment pieces are ill fitting and in need of better integration. The ruling in the *EC-Biotech* case will be significant in terms of the overall picture the WTO provides concerning environmentally based trade restrictions.

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*.”

Furthermore:

“The status of the precautionary principle in international law continues to be the subject of debate among academics, law practitioners, regulators and judges. The precautionary principle is regarded by some as having crystallized into a general principle of customary international *environmental* law. Whether it has been widely accepted by Members as a principle of *general* or *customary international law* appears less than clear.”

However Petitpierre *et al* (2004) point out that the SPS is probably a relatively unfavourable agreement within which to defend the precautionary principle, contending that the TBT Agreement or even GATT '94 constitute a more favourable environment since the opening paragraph of the SPS preamble refers to

“Reaffirming that no Member should be prevented from adopting or enforcing measures necessary to protect human, animal or plant life or health”

whereas the 6th paragraph of the preamble to the TBT Agreement refers to a broader remit:

“the protection of human, animal or plant life or health, of the *environment*” (italics added)

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, and also that 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. This is central because the EU regards US GM crops and EU GM crops as like, and since the moratorium has concerned trade in as well as production of GM crops within the EU, the EU's position is that the moratorium has been GATT consistent. However the US regards GM crops and non-GM crops as like, hence its position that the moratorium violates GATT and WTO requirements. As will become clearer in Section 3, this issue of product and process is also central to the EU's new labelling regime.

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 are 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."

Taking the 4 criteria identified by Petitpierre *et al*, there is considerable evidence that the attitudes of many to GM foods are different to those for non-GM food and that there are significant differences in the price they are prepared to for such goods (even if these results are from stated preference and experimental studies). The physical characteristics issue is one which people can interpret in different ways. GM crops can be distinguished in laboratory conditions but have been regarded as 'substantially equivalent' even within the EU regulatory regime. The final use of the product might be seen as a more solid basis for likeness in the case of GM foods, however if consumers are not prepared to use the GM and non-GM products for the same end use then even this criteria looks more challenging.

The EU repeatedly stated it would be dealing with the issues raised by the US in negotiations and at the WTO via new regulations regarding labelling and traceability of GMOs in food, on the basis that the market development could only occur where a reasonable basis for consumer choice had been established.

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: i) Regulation on GM food and feed (Regulation 1829/2003), and ii) Regulation on traceability and labelling of GMOs and the traceability of food and feed products produced from GMOs (Regulation 1830/2003). Table 1 summarises the main implications of the new regulations on labelling food and feed.

Under the rules of the new Regulation on traceability, business operators must transmit and retain information about products that *contain* or are *produced from* GMOs at each stage of the placing on the market. In this system records must be created and maintained throughout the food chain. In practice a company selling GM seed must inform purchasers that it is genetically modified (including information allowing the specific GMO to be identified) and the cultivating farmer would have to inform purchasers of the crop that it is genetically modified and keep a register of those to whom he/she has sold. These traceability requirements apply to all GMOs that have received EU authorisation for placement in the market.

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 derived from GM material will now need to be labelled. These include common products such as soya oil, vegetable oil, lecithin and hydrolysed vegetable protein, modified starch, cornflour, maize starch, and maize oil. Genetically modified feed will also need to be labelled along the same principles to give livestock farmers accurate information on the composition and properties of feed.

However there are some notable continued exceptions from these labelling requirements. Products that are not food ingredients such as processing aids and enzymes (for example chymosin, used in the production of cheese) are exempt. Also exempt are products such as meat, milk or eggs obtained from animals fed with genetically modified feed or treated with genetically modified medicinal products.

Table 1. Labelling of GM-Food and GM-Feed – Examples*

<u>GMO-type</u>	<u>Example</u>	<u>Presence of Genetically Modified DNA or protein?</u>	<u>Labelling Required Before April 2004?</u>	<u>Labelling Required April 2004?</u>
GM plant	Chicory**	Yes	Yes	Yes
GM seed	Maize seeds	Yes	Yes	Yes
GM food	Maize, Soybean sprouts, Tomato	Yes	Yes	Yes
Food Produced From GMOs	Maize flour	Yes	Yes	Yes
	Highly refined maize oil, soybean oil, rape seed oil	No	No	Yes
	Glucose syrup produced from maize starch	No	No	Yes
Food from animals fed on GM feed	Eggs, meat, milk	No	No	No
Food produced with the help of a GM enzyme	Cheese produced with the help of chymosin	No	No	No
Food additive/flavouring produced from GMOs	Highly filtered lecithin extracted from soybean oil used in chocolate	No	No	Yes
GM Feed	Maize	Yes	Yes	Yes
Feed produced from a GMO	Corn gluten feed, Soybean meal	No	No	Yes
Feed additive produced from a GMO	Vitamin B2 (riboflavin)	No	No	Yes

* This table is derived from IIEL (2003) and EU Commission Briefing IP/01/1095.

** Once chicory has been approved for breeding purposes under Directive 90/220/EC, but not for food use.

The US Response to the new EU Regulations

The responses in the US to the new EU labelling and traceability 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. Indeed, significant actors in the US regard the regulations as a new, illegal, barrier to trade. David Hegwood, Trade Advisor to the U.S. Department of Agriculture Secretary, said that the new regulations would "disrupt international trade without serving any legitimate food safety or environmental safety objectives." 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."

A representative of the Biotechnology Industry Organization (BIO) reported that:

"...our customers among the farming and food producing communities tell us the new traceability and labeling standards are impractical. Impartial observers can see they are not scientifically defensible...It seems more likely that the new regulations will drive food manufacturers to re-formulate to shun biotech derived ingredients altogether as their only effective means of avoiding the impractical burdens the new regulations would impose. If this happens, as we fear, the result would be to replace an overt moratorium with a technical barrier to trade that would be no less indefensible"

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 barrierEuropean 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)

The new labelling and traceability regime is, it is argued, unscientific, an illegal restraint on trade and as bad as the *de facto* moratorium. Extending the basis of labelling from product to process is described as unscientific and of no value to consumers. While it is a precursor to the lifting of the ban on US imports of GM crops and their derivatives, the conditions under which this trade will take place has been changed.

4. Assessing the Benefits of Process-Based Labelling

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, such as maize and soy oil, 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).

The core issue was how people's preferences for Non-GM food and GM Food differed, if at all, from GM Derived Food (food derived from GM crops but free from altered DNA/protein). One of the issues to be decided when analysing consumer responses to the presence of GM or GM-derived ingredients, is how this food is to be described. In particular, is one to consider food in general ("the weekly food shop") or a specific food item?

Given the nature of the GM attributes dealt with it would have been difficult to convey the issue meaningfully to respondents in terms of the "average" food product or basket of goods. It was thought that the distinctions between GM, GM-derived ingredients and non-GM food was more amenable to explanation in the context of a specific good.

Bread was chosen as a good which should be familiar to everyone and for which the notion of GM crop ingredients, as well as ingredients derived from GM crops but free of altered DNA, was meaningful. Specifically, it was possible to explain GM and GM-derived ingredients using bread since it may contain grain from GM crops and/or refined oil processed from GM crops.

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 2 and an example choice set is given in Table 3.

Table 2. 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 3. An Example Choice Set

	Bread 1	Bread 2	Bread 3
	Usual brand	Usual brand - alternative option 2	Usual brand - alternative option 3
Price	100%	100%	-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 ? (tick one ➡)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

The survey was conducted in England, Wales and Scotland between July and September 2003. The sample was defined as men and women, aged 16 and over who were the main shopper for their household. Main shopper is defined as those who personally select half or more of the items bought for their household from supermarkets and food shops. The survey was conducted using Random Location Sampling. A sample comprising 608 respondents was achieved. Personal interviews were conducted in the home using CAPI (computer aided personal interviews).

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.

The use of a mixed logit model brings with it a number of advantages, but also some issues of interpretation and application. One of the key problems in moving away from the estimation of a single point estimates of the parameter associated with an attribute within the utility function, and instead estimating the parameters that describe a distribution, is in the ex ante selection of the distributions functional form.

Clearly the choice of distribution is significant and the selection is neither simple nor, in many cases, amenable to testing. Hence Hensher and Greene (p.146) note that “distributions are essentially arbitrary approximations to the real behavioral profile. We select specific distributions because we have a sense that the “empirical truth” is somewhere in their domain. All distributions in common practice unfortunately have at least one major deficiency – typically with respect to sign and length of the tail(s)”. One resulting area of work has been development of estimatable forms of bounded distributions since, as Hensher and Greene observe, “truncated or constrained distributions appear to be the most promising direction in the future”.

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). Given the frequency with which classical mixed logits are now used (McFadden and Train, 2000; Train, 2003) we will confine our explanation of the model to the Bayesian approach to its implementation.

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:

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

with $\varepsilon_{njt} \sim \text{iid extreme value}$ and $\beta_n \sim N(b, \varphi)$. Denoting person n ’s choice in period t as y_{nt} , the sequence of choices over the T periods is defined as $y_n = \langle y_{n1}, \dots, y_{nT} \rangle$ 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 :

$$L(y_n | \beta) = \prod_t \frac{e^{\beta' x_{ny_{nt}}}}{e^{\beta' x_{ny_{nt}}} + \sum_{j \neq y_{nt}} e^{\beta' x_{njt}}} \quad (2)$$

where $x_{ny_{nt}}$ 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 :

$$L(y_n | b, \varphi) = \int L(y_n | \beta) \psi(\beta | b, \varphi) d\beta \quad (3)$$

where $\psi(\beta | b, \varphi)$ is the normal density with mean b and variance φ .

Priors on both b and φ 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: $k(b) \sim N(b_0, r_0)$. The prior on φ is inverted Wishart: $k(\varphi) \sim IW(K, I)$ where I is the K -dimensional identity matrix. This is a conjugate prior. This assumption regarding the prior on φ 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 φ is:

$$K(\beta_n \forall n, b, \varphi | Y) \propto \prod_n L(y_n | \beta_n) \psi(\beta_n | b, \varphi) k(b, \varphi) \quad (4)$$

where $k(b, \varphi)$ is the prior on b and φ .

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 φ and $\beta_n \forall n$ as if they were known, then takes a draw of φ conditional on b and $\beta_n \forall n$ and finally a draw of $\beta_n \forall n$ conditional on b and φ . The resulting three conditional posteriors are:

$$K(\beta_n | b, \varphi, y_n) \quad (5a)$$

$$K(b | \varphi, \beta_n \forall n) \quad (5b)$$

$$K(\varphi | \beta_n \forall n, b) \quad (5c)$$

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 4 present 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 5 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 4. 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 5. 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 σ , 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 σ , 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. As Train and Sonnier note, 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: the empirical outcome depends upon the estimated moments of the underlying normal distribution.

All these distributions are transformations of a normally distributed β . A person's utility and the probability of their sequence of choices can be specified as:

$$U_{njt} = Z(\beta_n)'x_{njt} + \varepsilon_{njt} \quad (6)$$

where $Z(\beta_n) = t_n$ is a transformation depending on β , with the distribution of t_n depending on the transformation implemented. Hence the probability of person n 's sequence of choices is now:

$$L(y_n | \beta_n) = \prod_t \frac{e^{Z(\beta_n)'x_{nynt}}}{e^{Z(\beta_n)'x_{njt}}} \quad (7)$$

The estimation process can accommodate such changes to functional form of the parameters easily as long as it is a transformation of a normal distribution.

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. Regarding 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 former handles a range of like and dislike (perhaps associated with perceived taste effects of added fibre or the 'un-naturalness' of longer shelflife), whereas the censored normal distribution would accommodate better the situation if some preferred more fibre or longer shelflife whereas others were indifferent.

The initial Preferred model was Model 7, which employs a Log Normal Price, Censored Normal Shelf and Fibre and S_B distributed GM terms. In Models 8-12 the bounds on the S_B distributions were adjusted: reducing the upper bounds on the GM and GM Derived parameters to 8 reduced the log likelihood while increasing it improved the fit, although this stabilised at bounds of 14. Allowing the lower bound to be below zero (allowing positive preferences for GM) in Model 13 worsened the fit. The preferred model is therefore Model 10.

Table 6. Alternative specifications of the Bayesian Mixed Logit Model

Model	price	shelf	fibre	GM	GM Derived	log likelihood
1	norm	norm	norm	norm	norm	-1369.4849
2	norm	norm	norm	$S_B(0, 10)$	$S_B(0, 10)$	-1393.2056
3	Log norm	norm	norm	$S_B(0, 10)$	$S_B(0, 10)$	-1294.3588
4	Log norm	norm	Cens norm	$S_B(0, 10)$	$S_B(0, 10)$	-1297.5457
5	norm	Cens norm	Cens norm	$S_B(0, 10)$	$S_B(0, 10)$	-1312.1241
6	Cens norm	Cens norm	Cens norm	$S_B(0, 10)$	$S_B(0, 10)$	-1195.1103
7	Log norm	Cens norm	Cens norm	$S_B(0, 10)$	$S_B(0, 10)$	-1170.7256
8	Log norm	Cens norm	Cens norm	$S_B(0, 8)$	$S_B(0, 8)$	-1171.3592
9	Log norm	Cens norm	Cens norm	$S_B(0, 12)$	$S_B(0, 12)$	-1168.0297
10	Log norm	Cens norm	Cens norm	$S_B(0, 14)$	$S_B(0, 14)$	-1166.9633
11	Log norm	Cens norm	Cens norm	$S_B(0, 16)$	$S_B(0, 16)$	-1166.4847
12	Log norm	Cens norm	Cens norm	$S_B(0, 20)$	$S_B(0, 20)$	-1166.5758
13	Log norm	Cens norm	Cens norm	$S_B(-2, 14)$	$S_B(-2, 14)$	-1174.1462

Table 7 presents for the results for this preferred Bayesian 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 7 the estimated β s 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 7. Preferred Specification Bayesian Bounded Model

(Price Log normal, Shelf and Fibre Censored normal, GM $S_B(0, 14)$, GM Derived $S_B(0, 14)$)

	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

Note that the price term is assumed to follow a log normal distribution rather than be a fixed term, this is because no coding exists to include a fixed term although in principle the Bayesian approach can accommodate such terms (although they would significantly increase time to convergence). As will be

seen, this assumption of log normality has implications for the WTPs for attributes which the model provides.

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.

Distributions of the marginal utilities are shown in Figures 1-4. Both GM terms (Figures 1, 2) are found to be bi-modal with mass points at either end of the range. This suggests a mass who are indifferent or mildly averse to the use of these technologies in bread production, and a mass point fiercely averse to it, about 20% of the sample are distributed between these mass points for both GM and GM derived. Note that the S_B distribution does not impose bi-modality, it can resemble a censored normal, a log-normal distribution but with a specifiable upper bound, a plateau with sharp slopes on each side as well as being bi-modal: the empirical outcome depends upon the estimated moments of the underlying normal distribution.

In the case of the censored normal distributions of shelflife and fibre marginal utilities (Figures 1, 2) there are very significant mass points at or close to zero in both cases, with 46% and 96% of the sample estimated to be strictly indifferent to shelflife and fibre attributes respectively.

Figures 1-4. Estimated Distributions of Marginal Utilities

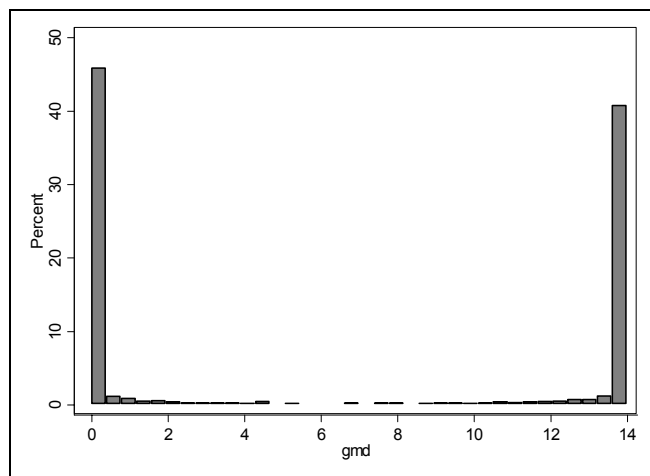


Figure 1. GM Derived

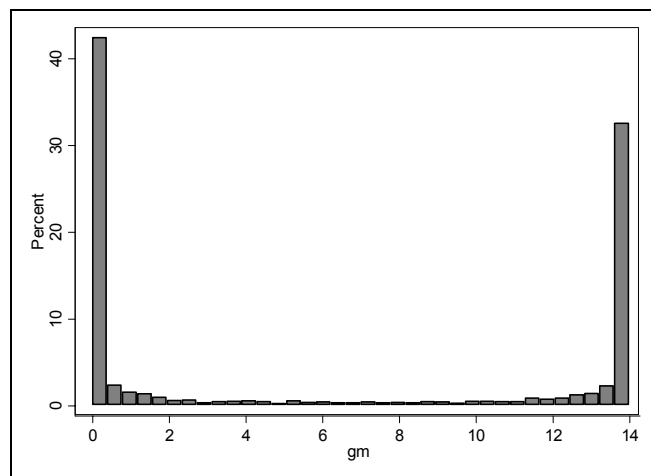


Figure 2. GM

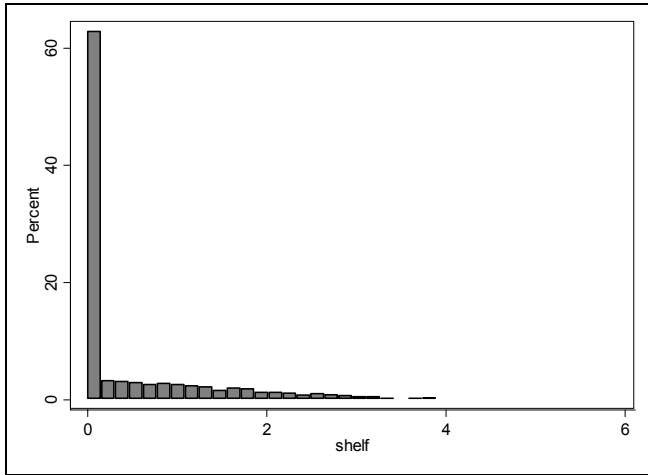


Figure 3. Shelflife

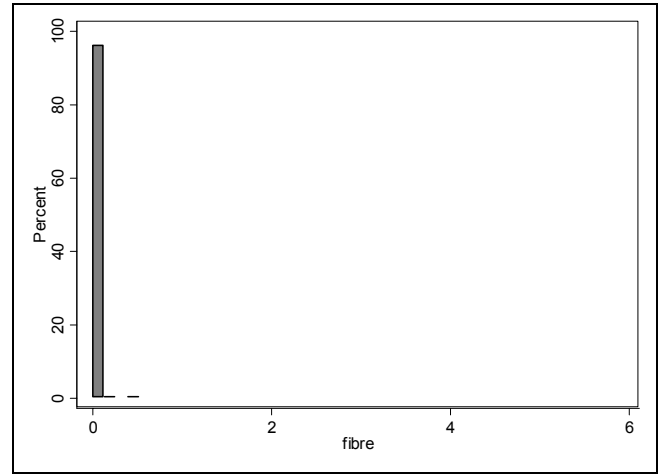


Figure 4. Fibre

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 8 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 of over 100%, i.e. more than a doubling of their bread price.

The median values however, at 40% and 63% (of 1€) are far lower and more feasible and the mass points at and near indifference for the GM attributes leads to significant proportions of consumers willing to buy at zero or small discounts. Table 8 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.

Table 8. 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

This analysis of the distribution of partworths in Table 8 shows that there is little to be gained from an analysis of the mean of a bimodal distribution. The upper limit can be changed by altering the upper limit on the S_B distribution, but this has little effect statistically, for the reasons noted above. 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 5 and 6. Note that in these figures values >100% have been stacked at the 100% value (this only relates to the graphs, it is not involved in the estimation or the results presented in Table 8). An alternative would be to graph the distribution for those with partworths up to 100%, but this would give a misleading picture as one would not be able to assess visually the proportion with WTPs over 100%. The nature of the market shares discussed above become clearer after consideration of Figures 5 and 6 and the bimodal preferences in the population.

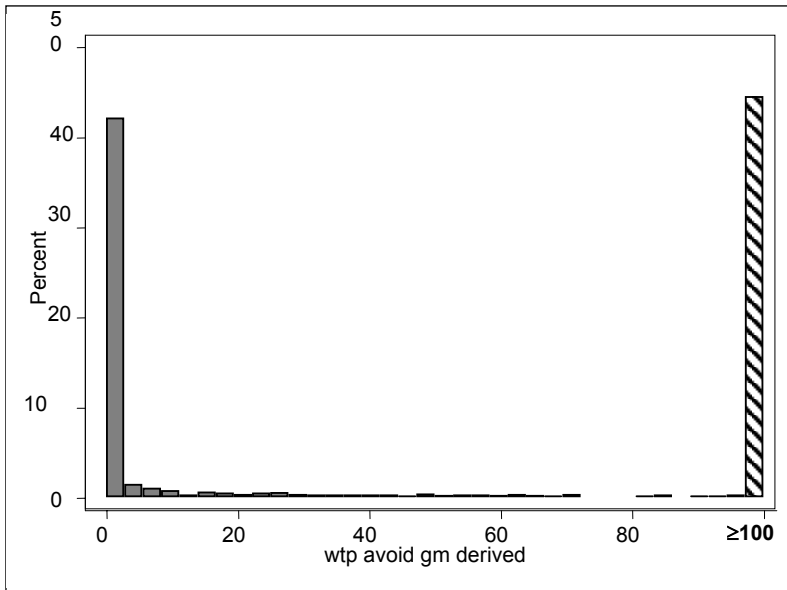


Figure 5. Distribution of WTPs to Avoid GM Derived Food (values>100 stacked at 100)

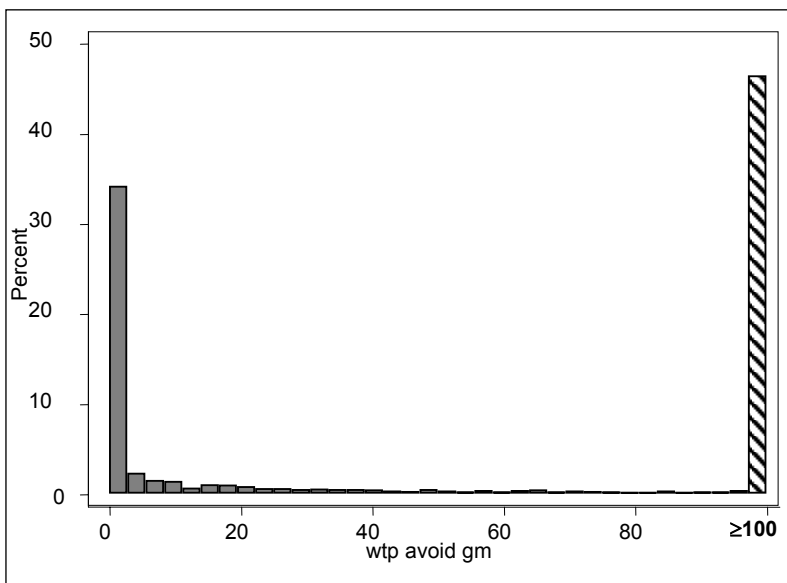


Figure 6. Distribution of WTPs to Avoid GM Food (values>100 stacked at 100)

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. In practice classical mixed logit estimation typically involves setting the off-diagonal elements of the variance-covariance matrix to zero. This is usually to restrict the number of parameters to be estimated to make estimation more manageable rather than any *a priori* reasoning that the parameters really are uncorrelated. Given the practical difficulties of convergence often associated with the use of log normal distributions in mixed logit models, then the problems for classical estimation techniques are compounded if one wished to use a bounded distribution and estimate the full covariance structure. The use of Bayesian methods means that the computational costs of estimating the off-diagonal elements of the variance-covariance matrix, even in the presence of bounded distributions, are modest.

Table 9 shows the correlations between the marginal utilities generated from the full variance-covariance matrix estimated with the Bayesian bounded model. These correlations reveal that, for

example, those for whom price is important are less likely to be concerned about fibre levels and more likely to value additional shelflife of their bread. The correlation structure across preferences also reveals 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.

Table 9. Correlation Structure

	Price	Shelf	Fibre	GM Derived	GM
Price	1.0000				
Shelf	-0.5256	1.0000			
Fibre	0.4312	-0.1807	1.0000		
GM Derived	0.2277	-0.0497	0.5636	1.0000	
GM	0.1542	0.0406	0.5418	0.9670	1.0000

Although the correlations in Table 9 provide information on the relationships between preferences for attributes, they do not reveal the full picture. Figure 7 shows a bivariate kernel estimate of the joint density of the GM and GM Derived parameters which reveals a starkly divided population with the a cluster at indifference or *relatively* low aversion to both GM ingredient types. The second cluster comprises those strongly averse to both types of GM ingredients.

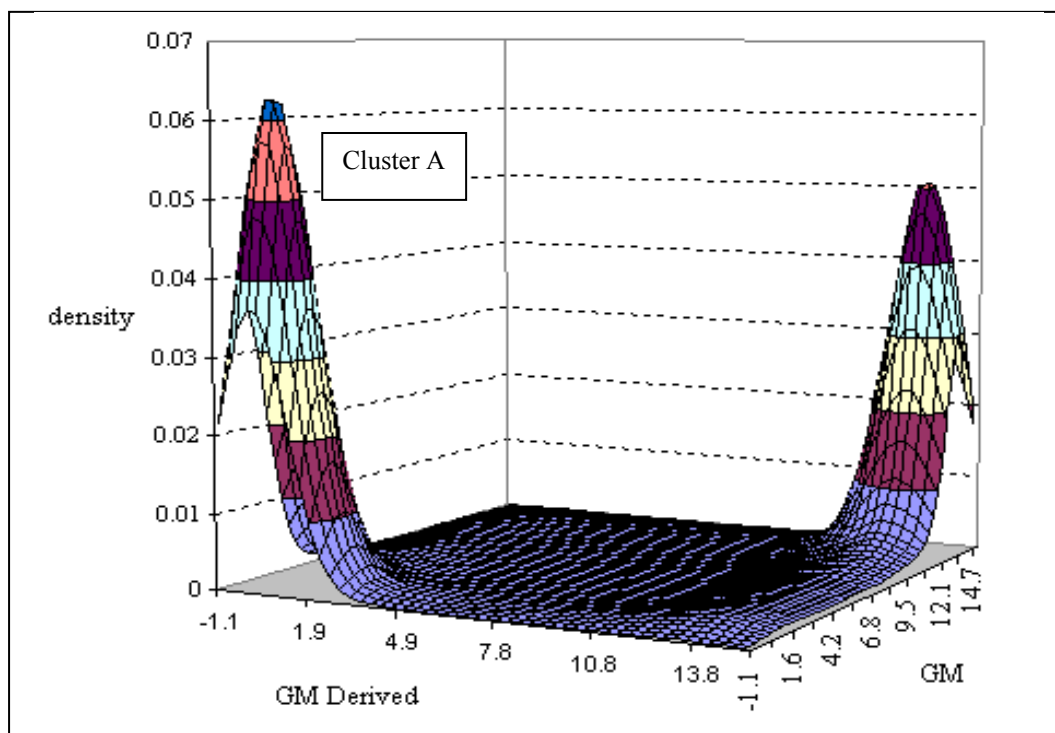


Figure 7. Joint density of GM and GM Derived Marginal Utilities

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 7.

The possibility of such a distribution is shown by previous work (Rigby and Burton, 2004) which considered 2 forms of genetic modification, that involving plant gene transfer (*gm1*) and that involving animal gene transfer (*gm2*). Figure 8 shows a kernel density estimate from that work identifying 3 main concentrations or classifications of consumers: those who are indifferent to both forms of GM food ('cluster 1'), those who are indifferent to *gm1* but are strongly averse to *gm2* forms ('cluster 2') and those who are strongly averse to both ('cluster 3'). It reveals, perhaps unsurprisingly, that there is no group who are averse to plant modification but indifferent to animal modification. This past finding suggests significant numbers not simply responding to the GM 'headline' instead having a more nuanced response, in that case depending on the type of gene transfer involved.

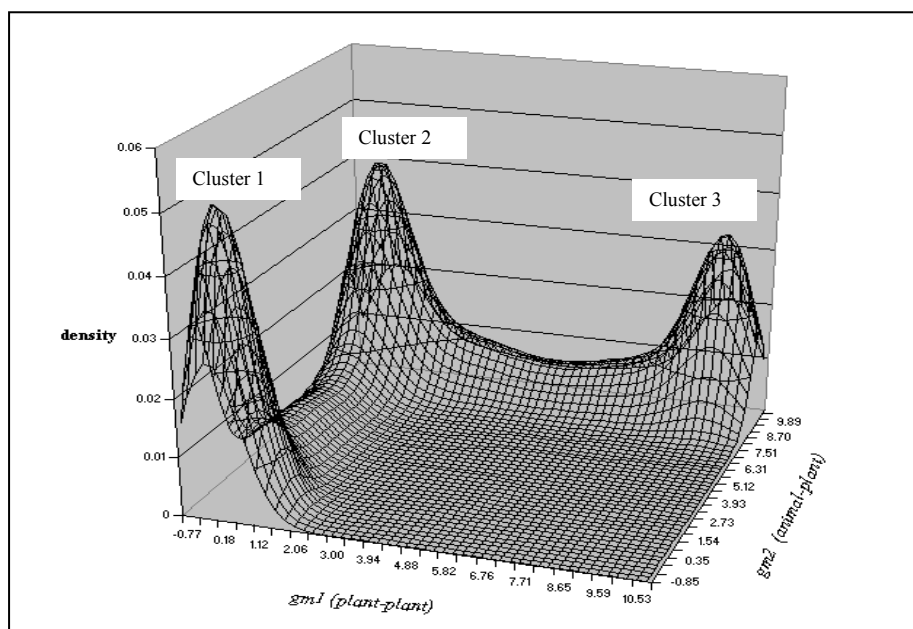


Figure 8. Joint density of the preferences for 2 GM foodtypes: plant and animal gene transfer (from Rigby and Burton, 2004)

The results from Figure 7 suggest that in this case, there is no significant third cluster, that is no sizeable group who are indifferent or mildly averse to GM Derived food, but strongly averse to GM food. Preferences for the 2 types of genetically modified ingredients are largely the same.

While Figure 7 provides a powerful picture of the distribution of preferences across GM foodtypes, the units are simply the marginal utilities. As such, it is difficult to assess the degree of aversion of those at or near Cluster A. A similar plot but in terms of WTPs can provide that information. If the model included a fixed price term one would simply be rescaling the units on both axes, however here the price term is log normally distributed and so the plot is altered more substantially. Figure 9 presents such a bivariate kernel density plot for WTPs to avoid the GM foodtypes. As with Figures 5 and 6, WTPs to avoid over 100% have been set at 100%.

Figure 5, 6 and 9 provide a consistent picture regarding preferences for the 2 GM foodtypes. The population is bimodal regarding preferences for both GM and GM Derived Food, and typically treats

both foodtypes in a similar manner: those indifferent or mildly averse to GM Derived food tend to be indifferent or mildly averse to GM food, with a similar consistency regarding strong aversion. In Figures 5, 6 and 8 WTPs greater than 100% (1€) have been capped at 100%, this is purely for presentation purposes; those people with WTPs to avoid over this value are unlikely to consume such food in the current context.

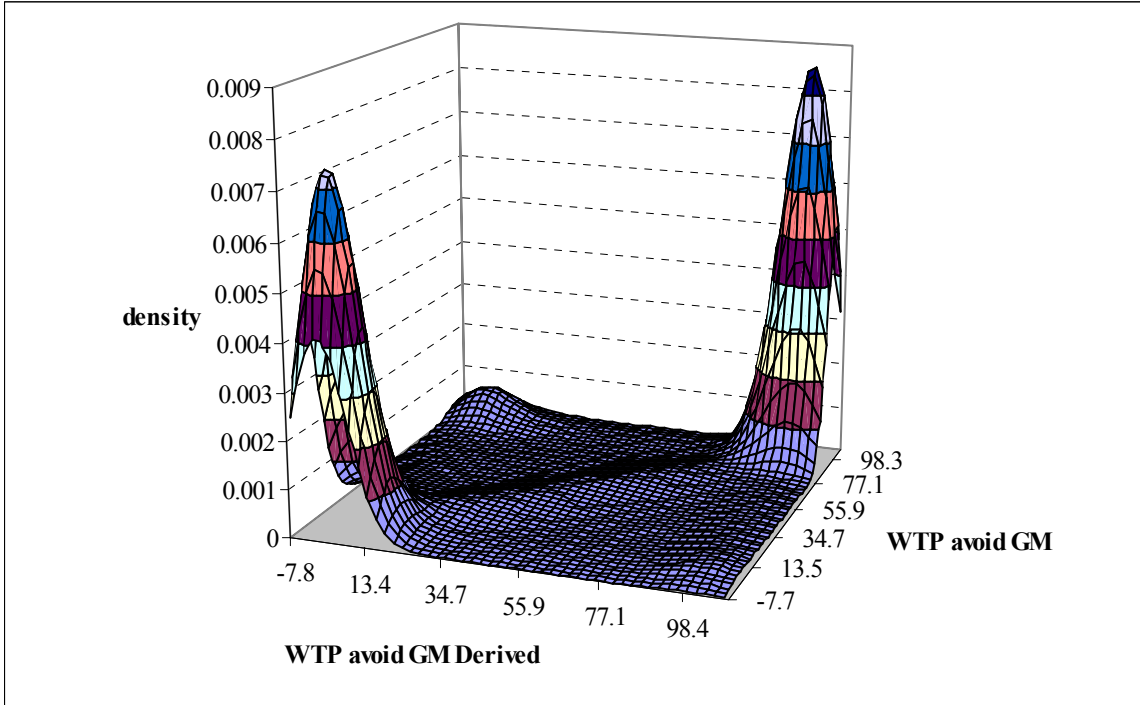


Figure 9. Joint density of WTPs to Avoid GM and GM Derived Food.

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 8 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 7 (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

Boisson de Chazournes, Laurence. (2002). A propos de la régulation juridique de stratégies économiques dans le domaine de l'environnement. In *L'outil économique en droit international et européen de l'environnement*, sous la direction de Sandrine Maljean-Dubois, 227-243. Paris : CERIC et La documentation française.

Busch, L, Grove-White, R, Jasanoff, S, Winickoff, D and B Wynne (2004) *Amicus Curiae* Brief. Submitted to the dispute settlement panel of the world trade organization in the case of EC: measures affecting the approval and marketing of biotech product.

Carreau, D. et P. Julliard (1998) *Droit international économique*, LGDJ, Paris.

Institute of International Economic Law (IIEL) (2003) "Proposed Regulation on genetically modified food and feed". November 8th 2003.

http://www.law.georgetown.edu/iiel/current/gmos/gmos_ec_gmoreg.html#publication

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 Economic 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. Paper under review with *Environmental and Resource Economic*.

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.