Accounting for Consumer Heterogeneity in Preferences over GM Foods: An Application of the Latent Market Segmentation Model

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Fourth BIOECON Workshop on The Economics and Biodiversity Conservation
28th -29th August, 2003
Venice, Italy

Abstract
Understanding consumer heterogeneity in preferences over GM foods is one of the most vital components of the policy discussions over labelling and market segmentation. The paper presents an application of the latent segmentation (LS) model as an alternative approach to accounting for preference heterogeneity in the demand for GM foods. The model is applied to a data set obtained from a stated preference choice experiment study on the value of reducing the genetically modified content in the production of one commonly consumed food, namely eggs. The LS is based on the behavioural framework of McFadden (1986a) that allows for constructing an econometric model that simultaneously estimates segment membership and product choice. The model also utilises latent constructs as direct determinants of segment membership and indirect determinants of product choice as prescribed by Ben-Akiva *et al.* (1997). The analysis shows that the latent market segmentation model not only accounts for preference heterogeneity across individuals, but at the same time identifies segments of consumers that are characterised by common demographic and psychographic traits. This modelling approach is then compared to other more commonly used means of accounting for preference heterogeneity, the interaction effects, covariance heterogeneity and random parameters models, and is shown to outperform all alternative specifications on both econometric and policy relevance grounds.

Key Words: choice experiment, preference heterogeneity, GM foods

1. Introduction

The use of biotechnology for the production of genetically modified (GM) foods has been under increasing public scrutiny and debate. Several surveys and polls conducted in the EU and the US during the last few years have shown that the application of biotechnology to food production is received differently be different segments of the public. For example different segments have been shown to have different attitudes, perceptions and ultimately preferences over the presence of GM content in foods. Both the GM industry and policy makers have thus come to realise that the viability of any labelling or market segmentation scheme can only be sustained if sufficient public support is documented. Hence, understanding the source and nature of preference heterogeneity across individual consumers or segments of consumers is perhaps the most vital component of the policy discussions over labelling systems, market segmentation, and niche market creation schemes.

This paper provides an application of the latent segmentation (LS) model as an *alternative approach* to accounting for preference heterogeneity in the demand for GM foods. The model is applied to a data set obtained from a stated preference choice experiment study on the value of reducing the genetically modified content in the production of one commonly consumed food, namely eggs. Such a data set is characterised by discrete choice data that can be sought as being generated *via* a random utility process. The usefulness of data sets obtained from choice experiment of conjoint analysis studies is becoming increasingly apparent to the GM literature as attested by the upsurge of such studies on both sides of the Atlantic. Yet, accounting for preference heterogeneity in discrete choice revealed and stated preference data motivated from random utility models has been highly incomplete.

Most analysis of such data use the standard multinomial logistic model (McFadden, 1974). Though the simplicity in constructing and analysing such a model has proven very useful, the behavioural restrictions it imposes on the data have increasingly troubled applied econometricians. One of the limiting implications of the standard model is that it imposes homogeneity with respect to individual preferences. Failing to account for preference heterogeneity, when it is warranted, leads to biased utility parameter estimates (Green 1997). Such biased estimates have been shown to produce misleading predictions of the main variables of interest such as participation probabilities, market shares as well as marginal and total welfare measures (Breffle and Morey, 2000). Moreover, accounting for preference heterogeneity provides a broader picture of the distributional and other impacts of policy decisions. Hence, the unwarranted imposition of preference homogeneity ultimately undermines the policy usefulness of the results. Commonly used approaches to account for preference heterogeneity in a random utility framework have focused on variants of random and fixed effects heteroscedastic extreme value models (e.g. Swait and Adamowicz, 1996) as well as random parameter models (e.g. Train, 1998). This paper provides a contribution to this series of econometric developments by presenting an application of the latent segmentation model as an alternative model for accounting for preference heterogeneity in data derived from stated preference choice experiment studies. The exploration of this particular type of modelling approach was motivated by recent assessments of the analysis of choice experiment data that have acknowledged the policy usefulness of accounting for preference heterogeneity at the segment level and have thus highlighted this as an area for fruitful novel research (e.g. Adamowicz and Boxall, 2001; Louviere *et al.* 2000).

The paper presents the latent segmentation model that consists of *simultaneous* estimation of segment membership and choice. The model is applied to data obtained from a stated preference choice experiment study on the value of reducing the genetically modified content in the production of one commonly consumed food, namely eggs. The analysis shows that the latent market segmentation model accounts for preference heterogeneity across individuals by identifying segments of consumers that are characterised by common demographic and psychographic traits. This modelling approach is then compared to other more commonly used means of accounting for preference heterogeneity, mainly the interaction effects, random parameter logit and covariance heterogeneity models, and is shown to outperform all alternative specifications on statistical grounds. Finally, the specific application of the latent market segmentation model shows that it provides added and unique policy relevant information, and hence it outperforms rival specifications on economic and policy relevant grounds.

2. Accounting for preference heterogeneity in random utility models

Identifying sources of preference heterogeneity in discrete choice models as opposed to standard demand analysis is complicated by the fact that variables on individual characteristics (i.e. the sources of heterogeneity) do not vary across alternatives. To clarify this point, let us examine the basic discrete choice model framed in terms of a random utility model. The random utility model (RUM) is base on postulating the composite utility function:

$$U_{ni} = V_{ni}(X_{ni}) + \varepsilon_{ni} \qquad \text{Eq. 1}$$

Where U_{ni} is the total utility that individual n obtains from choosing the alternative i from a finite set *C*. It is decomposed into a systematic (deterministic) part, V_{ni}, which is a function of a vector, X_{ni}, consisting choice-specific attributes as well as individual specific characteristics, and a random part ε_{ni} which is assumed to be independent of X_{ni} and follows some predetermined distribution. Alternative i will be chosen over j if $V_{ni}(X_{ni}) + \varepsilon_{ni} > V_{nj}(X_{nj}) + \varepsilon_{nj}; \forall\ i \neq j, \forall\ \mathrm{j} \in C$ and the probability that this is the case will be given by

$$\pi_{in} = \Pr ob\{V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}; \forall\ i \neq j, \forall\ j \in C\ \} \qquad \text{Eq. 2}$$

By assuming a specific distribution for the error components in Eq. 2 we can construct an operational discrete choice model. Assuming a linear functional form for $V_{ni}(X_{ni})$ and that the ε_{ni} disturbances are independently and identically distributed (iid) following a Weibull distribution we can derive the basic multinomial logit model (McFadden, 1974):

$$\pi_{in} = \frac{e^{\mu(\beta X_i)}}{\sum_{j \in C} e^{\mu(\beta X_j)}} \qquad \text{Eq. 3}$$

Where β is a vector of parameters to be estimated and μ is a scale parameter that is usually assumed to equal 1 so that the $\beta's$ can be identified. The vector β also includes a series of alternative specific constant term (ASC_i) that capture the effects in utility from any attributes not included in X_{ni}. The choice model in Eq. 3 assumes homogeneity of preferences which follows from the assumption that the deterministic component of the utility function is invariant across individuals (i.e. $\beta_n X_i = \beta X_i$). This further implies that the variance of the error term is assumed to be the same for all individuals and that there is no correlation across occasions for a given respondent (this implication follows from the *iid* assumption). In practical econometric terms this translates into the inability of identifying and estimating the coefficients of individual characteristics in the indirect utility function since terms that do not vary across alternatives fall out of the probability (Green, 1997, p.914). Hence, even if we directly included such individual characteristics in the vector X_{ni} their effect on the probability of choosing a particular option $\pi_n(i)$ cannot be assessed. The sub-sections that follow discuss alternative approaches to account for and identify the sources of preference heterogeneity. These are conditional logit models with interacted individual characteristics, the random parameter logit models, covariance heterogeneity models and latent class models.

2.1 Multinomial Logit with interacted individual characteristics

The most common strategy around this problem has been to interact individual-specific characteristics with attributes of the choices or with the alternative specific constant(s) of the indirect utility functions. (Greene, 1997). Commonly chosen individual characteristics include income, age and education. This approach allows the $\beta's$ to vary across individuals in a systematic way as a function of individual characteristics. The analyst can thus assess the distributional impacts of a particular policy change. Yet, the results from such models are very sensitive to the way in which the parameters and individual characteristics are interacted. Moreover, multicollinearity is often a problem with too many interactions (see Breffle and Morey, 2000). Also, the majority of the applied discrete choice literature has avoided exploring the effects of individual variables other than demographics, such as attitudinal, motivational and perceptual variables, as sources of heterogeneity. This is partly due to the inability of obtaining such data but also reflects a hesitancy to utilise such variables in economic analysis. Yet, the importance of incorporating psychographic variables in the analysis of choice has been long acknowledged and argued for (e.g. McFadden 1986, Ben-Akiva *et al.,* 1997). There use is, thus, worthy of further investigation.

2.2 Random Parameter Logit

The random parameter logit models (RPL) allow all choice-specific parameters to vary randomly across individuals. That is, β in Eq. 3 becomes β_n. This is accomplished by assuming that β_n is drawn from a joint density function, the parameters of which (mean and standard deviation) are recovered by simulation (see Train 1998). Recent applications of RP logit models have shown that they outperform conditional logit approaches both in terms of overall fit as well as in the accuracy of their welfare measure estimates. (e.g. Cicia, Del Giudice and Scarpa, 2001; Breffle and Morey, 2000

Some have cautioned that while the RP logit model explicitly account for preference heterogeneity, they are not well-suited to explaining the *sources* of heterogeneity (e.g. Boxall and Adamowicz, 1999). This can be somewhat rectified by including individual characteristics in the utility function. By doing so the RPL logit model will pick up two types of variation in preferences. A systematic type (i.e. preference vary with respect to individual characteristics) and a random type (i.e. unconditional taste heterogeneity). The caveats mentioned above of multicolinearity among individual characteristics and of the absence of psychometric characteristics in most applied work carry over. Moreover, the selection of a particular multivariate distributional function describing the random parameters (e.g. multivariate normal) may be hard to justify (Bateman *et al.,* 2003).

2.3 Covariance Heterogeneity Models

CovHet models belong to the family of heteroscedastic extreme value (HEV) models that attempt to parameterise the scale factor, μ, in Eq. 3 with individual socio-demographic variables. Recent examples include Muller *et al.* (2001) and Johnson, Banzhaf and Desvousges (2000), Louviere *et al.* (2000). These studies have shown that models with a parameterised scale parameter are statistically superior to models that impose the restriction of μ being equal to one. Yet, applied econometricians have questioned whether this approach by which individual characteristics enter the model as affecting the scale parameter, is more appropriate than an alternative approach in which these variables influence tastes (i.e. utility parameter differences) (Boxall and Adamowicz, 1999). In essence, scale heterogeneity models are examining a different aspect of survey responses. Models of scale heterogeneity target capturing differences in respondent coherence, decision-making ability or interest in the activity (Breffle and Morey 2000). Preference heterogeneity models on the other hand examine how choice attributes differ across individuals with different types of individual characteristics. It is an empirical issue which form of heterogeneity is most suitable for each particular data set.

2.4 Latent class models

Latent class models provide another approach that has tried to identify sources of heterogeneity in tastes using individual characteristics. These models use some form of multivariate cluster analysis of socio-demographic characteristics to reveal and determine relatively homogeneous latent segments of the sampled population. Once these homogeneous segments have been identified separate multinomial (logit) choice models can be estimated.

Applications of this approach include Salomon and Ben-Akiva (1983) and Gross (1995). These studies have revealed that models that separately estimated coefficients for each segment were statistically superior to the models that assumed that the sample was drawn from a single homogeneous segment. In contrast to the RP logit model, latent class approaches are quite successful at identifying sources of heterogeneity. Also, note that whereas the RP logit model allows choice parameters to vary across each individual, the latent class approach assumes that these parameters vary across segments of individuals. In many cases, this property makes the latent class model more policy relevant than the RP logit model. For example, the policy debate over GM foods is highly pre-occupied with discussions over the feasibility of segregating food into GM and GM-free markets. In such cases, models that account for heterogeneity at the segment and not individual level would provide more actionable, operationally meaningful and policy relevant information.

Despite their appeal, a troubling aspect of the latent class models is that they assume that cluster membership depends solely on ones individual characteristics and is *independent* from one's choice decisions. It seems reasonable, however, to expect that these two decisions are not separate but somehow related. Moreover, the use of these models has been based on statistical grounds and has lacked sufficient behavioural foundations motivating their use. Most latent class models mentioned above classify individuals into clusters purely on statistical grounds and provide no behavioural foundations on which they can postulate an explicit behavioural mechanism through which the latent classes emerge. In addition, past applications of latent class models have mainly relied on socio-demographic and not attitudinal variables in determining the number and nature of latent classes. It is likely, however, that psychographic variables are equally (if not more) important determinants of segment membership and should be considered.

This paper uses the analysis of Swait (1994) and Boxall and Adamowicz (1999) and presents another avenue for accounting for preference heterogeneity in RUM's, the latent segmentation model (LS). The LS model has several affinities to the latent class approach yet differs in many important ways. Like the latent class models mentioned above, the LS model identifies sources of preference heterogeneity by revealing a finite number of latent segments of consumers that are characterized by relatively common tastes. Yet, unlike previous latent class models the LS model presented here *simultaneously* performs market segmentation and explains choice for a given segment of the population. In addition, the framework presented in this paper for determining the sources of preference heterogeneity does not rely merely on information from socio-demographic data but also utilises the information from psychographic data. By using psychographic variables it is argued that the model attempts to satisfy the, often neglected, plea for including latent taste, attitudinal and perceptual variables in micro-econometric analysis. Most notably McFadden (1986) has argued that:

> "… the critical constructs in modelling the cognitive decision process are *perceptions* or beliefs regarding the products, generalized *attitudes* or values, *preferences* among products, decision protocols that map preferences into choices, and *behavioural intentions* for choice" (McFadden 1986, p.276).

Hence the work presented in this paper is related to the emerging literature in the analysis of discrete choice data that emphasized the importance of the explicit treatment of latent individual characteristics in the decision-making processes (see Kontoleon 2003 for references). The main outcome from this research is that the incorporation of latent attitudinal, perceptual and motivational constructs leads to a more behaviourally realistic representation of the choice process, and consequently, better explanatory power. Moreover, the same body of work has shown that psychometric data captures taste heterogeneity more adequately than demographic characteristics. This development has been followed by the stated preference literature. For example the NOOA panel have recommended the use of such variables in models of stated values in order to assess the construct validity of the results (Arrow *et al.* 1993, p.4609), while Langford *et al.* (2000) have shown that that attitudinal indexes, as opposed to socio-economic or demographic indicators, can in many cases be the primary driver of stated values. Bateman *et al.* (2002) point out that despite such findings the emphasis in many stated preference studies has been upon the latter at the expense of the former, an approach which seems unbalanced given the paucity of clear and definite expectations afforded by economic theory.

Finally, the main advantage of the LS approach presented here is that the market segments are derived not just on the basis of attitudinal and socio-economic data, but also on the basis of observed choice behaviour and the attributes of the various alternatives. This is achieved by virtue of the simultaneous nature of the estimation procedure. Such 'behaviour-based' segments are much more actionable and operationally useful to policy makers than segments obtained from other statistical or 'demographic-based' methods mentioned above.

3. The Latent Segment Membership Model

The LS model is related to the so-called finite-mixture models (see Titterington *et al.* 1985) frequently encountered in the marketing literature. Although other approaches for accounting for preference heterogeneity have received considerable attention (see previous Section), the LS model has not been widely utilized in the micro-econometric literature (neither for the analysis of revealed nor stated discrete choice data. The LS model presented here utilizes the theoretical framework developed by McFadden (1986) that allows the researcher to postulate a behavioural mechanism for simultaneously determining segment membership and product choice as well as providing a theoretically consistent justification for incorporating latent variables into the analysis.

3.1 Conceptual framework of the LS model.

The underlying behavioural model of the choice process is depicted in Figure 1 of Appendix 1 that has been adapted from McFadden (1986), Ben Akiva *et al.* (1997) and Swait (1994).

This path diagram includes both observed and unobserved (latent) variables that affect both segment membership and the realisation of choice. The shaded area of the diagram incorporates all latent variables. These include the subjective perceptions the individual has for the product attributes, the individual's preference function as well as the mental processes governing individual decisions. Moreover, the unobservable section of the diagram also includes the likelihood that a particular individual n (where $n = 1....N$) belongs to a particular class or segment s (where $s = 1...S$), the selection mechanism process by which individuals are classified into segments and the actual number of segments that characterize a particular population. In theory there can exist as many segments as individuals (i.e. N=S). The boxes outside the shade area refer to observable variables. These include the objective attributes of each choice alternative, the socio-demographical characteristics of the individual, the indicators of the individual's general attitudes and perceptions, the exogenous market constrains and institutional conditions that an individual faces when undertaking his/her choice and the final outcome of choice.

Following McFadden (1986) the mechanism that leads to the realization of choice is as follows:

a) Individual latent attitudes, perception and motives (approximated by observed attitudinal indexes) together with the individual's socio-demographic traits determine his/her segment membership likelihood function.
b) Through a latent segment classification mechanism, the membership likelihood function determines the latent segment to which an individual belongs.
c) The individual's preferences over a set of choices are influenced by the latent class one belongs to as well as by one's socio-demographic traits and his/her subjective perceptions of the choice objective attributes.
d) These preferences are then processed according to a decision protocol which leads to the observance of the final choice. In random utility models this protocol is governed by some form of constrained utility maximization.

This framework allows for the inclusion of both 'objective' and 'subjective' (or perceptual) data in the analysis of individual choice. Moreover, this model of choice implies that preferences are *indirectly* affected by attitudes, perception and motives through membership in a particular latent segment. This comes into contrast with other preference heterogeneity models that imply that attitudes and perceptions directly influence preferences. More importantly, the model acknowledges that it is possible to simultaneously explain individual choices and infer latent segment membership.

3.2 Building the econometric model

This section attempts to operationalise the choice process described above within the random utility framework. The utility function of Eq. 1 now becomes

$$U_{ni/s} = V_{ni/s}(X_{ni/s}) + \varepsilon_{ni/s} \qquad \text{Eq. 4}$$

which gives the utility generated from the i^{th} alternative of the n^{th} individual that belongs to a particular segment s. By assuming a linear functional form for $V_{ni/s}(X_{ni/s})$ Eq. 1 becomes:

$$U_{ni/s} = \beta_s X_{in} + \varepsilon_{ni/s} \qquad \text{Eq. 5}$$

where β_s is the utility parameter vector for segment *s*. Within this framework preference heterogeneity implies that that each segment has its own utility vector (i.e. $\beta_s \neq \beta_k; \forall s \neq k, \forall k \in S$). In other words, through β_s the model captures the idea that preferences and choices are affected by latent segment membership (Swait 1994). The decision protocol for a utility maximizing individual *n* that belongs to a segment *s* will be to chose alternative i if $V_{ni/s}(X_{ni/s})+\varepsilon_{ni/s} > V_{nj/s}(X_{nj/s})+\varepsilon_{nj/s}; \forall\ i \neq j, \forall\ j \in C$ and the probability that this is the case will be given by:

$$\pi_{in} = \Pr ob\{V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}; \forall\ i \neq j, \forall\ j \in C\} \qquad \text{Eq. 6}$$

And by assuming that the disturbances ε_{ni} are iid and follow a Type I (or Gumbel) distribution we can derive the probabilistic response function:

$$\pi_{n/s}(i) = \frac{e^{\mu_s(\beta_s X_{in})}}{\sum_{j \in C} e^{\mu_s(\beta_s X_{jn})}} \qquad \text{Eq. 7}$$

This function represents the choice decision and provides the probabilities that an individual n belonging to a particular segment s will choose an option i. In essence it is a conditional logit model (e.g. McFadden, 1974) in which segment specific utility parameters are a function of choice attributes. Clearly if $s = 1$ then Eq. 7 collapses to the standard multinomial logit model of Eq. 3. Also the scale parameter μ_s may vary cross segments although in practice it is usually assumed that $\mu_1 = \mu_2 = ... = \mu_s = 1$.

In order to construct a segment membership function it is assumed that there exist a finite number of segments S $(S \leq N)$ in which each individual can be classified with some probability W_{ns}. The actual number of segments is itself a latent variable and will have to recovered from the estimation processes. Let Y_{ns}^* represent a latent variable that determines segment classification of all N individuals into one of the segments in S. According to the behavioural framework presented in Figure 1, Y_{ns}^* was described as being a function of both observable and unobservable (latent) individual characteristics. Following Ben-Akiva *et al.* (1997) and Swait (1994) this relationship can be formulated *via* the structural equations:

$$Y_{ns}^* = \Gamma_{ps} G_{np}^* + \Gamma_{as} G_{na}^* + \Gamma_s X_n + \zeta_{ns} \qquad \text{Eq. 8}$$

$$G_{np} = \delta_p G_{np}^* + \zeta_{np} \qquad \text{Eq. 9}$$

$$G_{na} = \delta_a G_{na}^* + \zeta_{na} \qquad \text{Eq. 10}$$

where, G^*_{np} and G^*_{na} are vectors of individual latent perceptual and attitudinal variables, G_{np} and G_{na} the vectors of observable indicators of these variables, X_n the vector of observable individual socio-demographic characteristics, $\Gamma_{ps}, \Gamma_{as}, \delta_p, \delta_a$ and Γ_s are the corresponding parameter vectors to be estimated and ζ_{np}, ζ_{na} and ζ_{ns} the residual terms. For brevity we can express Eq. 8 in the more succinct form:

$$Y^*_{ns} = \alpha_s Z_n + \zeta_{ns} \qquad \text{Eq. 11}$$

Where Z_n contains both the psychographic and demographic characteristics of the individual and a_s is the corresponding parameter vector. That is:

$$Z_n = \begin{bmatrix} G_{np} \\ G_{na} \\ X_n \end{bmatrix} \quad \text{and} \quad \alpha_s = (\Gamma_{ps}, \Gamma_{as}, \Gamma_s) \qquad \text{Eq. 12}$$

An individual will be classified in a particular segment s as opposed to any other segment $k \in S$ according to the classification mechanism:

$$Y^*_{ns} = \max\{Y^*_{nk}\}, k \neq s, k = 1,.., S \qquad \text{Eq. 13}$$

Since, Y^*_{ns} is a random variable, we can assess the probability that a particular individual belongs to a specific segment by specifying the distribution and nature of the residual terms in Eq. 11. By assuming that the $\zeta_{ns}'s$ are independent across individuals and segments as well as independent of ζ_{np} and ζ_{na}, and that they follow a Gumbel distribution with scale parameter λ we can derive the probability function for segment membership:

$$W_{ns} = \frac{e^{\lambda(a_s Z_n)}}{\sum_{k=1}^{S} e^{\lambda(a_k Z_n)}} \qquad \text{Eq. 14}$$

Note that Eq. 14 is simply the multinomial logit model that determines the probability of a an event occurring only on the basis of individual specific and not choice-specific variables (Green, 1997).

In order to derive a model that simultaneously accounts for choice and segment membership we bring together the two logit models of Eq. 7 and Eq. 14 to construct a mixed-logit model that consists of the joint probability that individual n belongs to segment s *and* chooses alternative i:

$$P_{isn} = \left(\pi_{in/s}\right)\cdot\left(W_{ns}\right) = \left[\frac{e^{\mu_s(\beta_s X_{in})}}{\sum_{j\in C} e^{\mu_s(\beta_s X_{jn})}}\right]\cdot\left[\frac{e^{\lambda(a_s Z_n)}}{\sum_{k=1}^{S} e^{\lambda(a_k Z_n)}}\right] \qquad \text{Eq. 15}$$

While the formulation of the marginal probability of an individual n in segment s choosing option i is given by:

$$P_{isn} = \sum_{s=1}^{S}\left[\frac{e^{\mu_s(\beta_s X_{in})}}{\sum_{j\in C} e^{\mu_s(\beta_s X_{jn})}}\right]\cdot\left[\frac{e^{\lambda(a_s Z_n)}}{\sum_{k=1}^{S} e^{\lambda(a_k Z_n)}}\right] \qquad \text{Eq. 16}$$

This expression contains the two types of logit formulations described above. The first corresponds to conditional logit model that contains segment specific utility parameters. The second is the multinomial logit model that consists of segment membership parameters. It can be interpretd as a mixture model since it allows the use of both choice attribute data and individual characteristics to simultaneously explain choice behaviour and segment membership (Titterington *et al.,* 1985).

Note that if we impose the restrictions $\alpha_s = 0, \beta_s = \beta, \mu_s = \mu, \forall s$ we are in essence assuming homogeneity in tastes (i.e. the population is characterized by a single segment) and the model in Eq. 14 collapses to the standard MN logit model of Eq. 3. Alternatively, Swait (1994) points out that as $S \rightarrow N$ (i.e. the number of segments approaches the number of individuals in the sample or population) the model of Eq. 16 becomes more and more akin to the random parameter logit model discussed above. Finally, it is worth noting that we need not assume the restrictive IIA assumption for mixture models such as the type of Eq. 16 (Shownkwiler and Shaw 1997).

3.3 Estimation process.

To estimate the LS model we utilize the sequential estimation approach of McFadden (1986). **First**, we estimate the parameter vectors δ_p and δ_a using psychometric techniques. **Secondly**, we obtained scores for the vector of observable attitudinal indexes G_{np} and G_{na}. **Third**, we specify the variables that determine segment membership (i.e. the variables in z_n which includes the vectors G_{np} and G_{na} as well as demographic variables) and the variables that determine choice (i.e. the variables in x_{in} which include attributes but also socio-economic characteristics). **Fourth**, we construct the log-likelihood function of Eq. 16 and use full information maximum likelihood to estimate the model for a specified value of *S*. The likelihood function is maximized with respect to utility (choice) parameters β and segment membership parameters α. The log-likelihood function for *N* individuals that provide data for *m* choice sets over a set of alternatives *C*, is given by:

$$\hat{L}(\beta,\alpha/S)=\sum_{n=1}^{N}\sum_{\forall m} f_{in}\ln\left(\sum_{s=1}^{S}\pi_{in/s}\cdot\hat{W}_{ns}\right) \qquad \text{Eq. 17}$$

$$=\sum_{n=1}^{N}\sum_{\forall m} f_{in}\ln\left\{\sum_{s=1}^{S}\left[\frac{e^{\mu_s(\beta_s X_{in})}}{\sum_{j\in C} e^{\mu_s(\beta_s X_{jn})}}\right]\cdot\left[\frac{e^{\lambda(\hat{a}_s Z_n)}}{\sum_{k=1}^{S} e^{\lambda(\hat{a}_k Z_n)}}\right]\right\}$$

We then repeatedly estimate the model for several segments up until a reasonable number of segments (roughly more than 3 and less than 10). **Lastly**, we use statistical criteria to decide which model fits the data best which amounts to deciding on the optimal or most appropriate number of segments that the specific sample or population can be divided into.

Determining the optimal number of segments *S* is a subjective process that requires that use of a combination of multiple statistical criteria as well as personal subjective judgment dictated by the objectives of the study. The aim is to determine whether the 'benefit' obtained from an extra segment is worth the 'cost' of the extra segment. The optimal number of segments is reached when additional segments provide little extra information or simply are superfluous. Hence the aim is to attain 'segment parsimony', i.e. the avoidance of choosing superfluous number of segments that would lead to spurious results that do not add to our understanding of the underlying behavioural process but merely bring in undesirable noise into the model (Swait 1994). Various criteria for deciding on the optimal number of latent segments, S^*, have been suggested (see Kontoleon 2003 for multiple references). These criteria attempt to optimise a certain objective function that involves the log likelihood ratio statistic defined with respect to the null hypothesis that all parameters are equal to zero. The shared rationale behind these criteria is to penalize log-likelihood improvements due to larger number of parameters that are estimated with each additional segment (Louviere *et al.* 2000). Such criteria include the Akaike's Information Criterion (AIC):

$$AIC = -2(L(\hat{\beta},\hat{\alpha}/s) + (S \cdot K_\beta + (S-1) \cdot K_\alpha)) \qquad \text{Eq. 18}$$

Where $L(\hat{\beta},\hat{\alpha}/s)$ is the estimated log-likelihood, K_β the number of parameters in β and K_α the total number or parameters in α. The selection criterion is to choose the number of segments, *s*, which minimizes the AIC. Equivalently, one can use the Bayesian Information Criterion (BIC) which is a function of both dimensionality (i.e. number of parameters) as well as sample size (*N*):

$$BIC = -L(\hat{\beta},\hat{\alpha}/s) + \left[\left(\frac{(S \cdot K_\beta + (S-1) \cdot K_\alpha)}{2}\right)(\ln(N))\right] \qquad \text{Eq. 19}$$

The value of *S* that minimizes each of these measures suggests the preferred model. Alternatively, applied econometricians have modified McFadden's ρ^2 to construct the Akaike Likelihood Ratio Index for deciding S^*:

$$\bar{\rho}^2(s,\beta,\alpha) = 1 - \frac{AIC}{2\hat{L}(0,0/1)} \qquad \text{Eq. 20}$$

The segment membership model that maximizes this criterion is chosen (e.g. Ben-Akiva and Swait, 1986).

4. Accounting for preference heterogeneity in RUMs: an application of the LS model

The LS model presented in Section 3 was explored in the choice experiment study on the demand for GM food. The main policy aim of this study was to assess the marginal willingness to pay for avoiding GM content in one commonly consumed food, namely eggs. The experimental design constructed a series of egg profiles characterised by different levels of five attributes:

1) Hen living condition: free range Vs battery cage
2) Pesticide in chicken feed: organic Vs non-organic
3) Quality information on box: included Vs not included
4) GM content in chicken feed: 0%, 1%, 5%, 30%
5) Price of box of six medium-sized eggs: 0.38GBP, 0.68GBP, 0.98GBP, and 1.28GBP

The marginal WTP to avoid GM content in eggs would be given by the ratio of the coefficient of the GM content attribute over the coefficient of the price attribute. Using a random parameter logit model it was found that UK individuals do in fact have a negative WTP value for increasing percentages of GM content in this particular food (see Kontoleon 2003 for details). These preliminary results corroborate numerous attitudinal studies that have been undertaken in Europe that have found a negative consumer predisposition towards GM content in foods. Yet, these studies have also established that the welfare of consumers is not affected to the same degree and in the same manner from the introduction of GM foods into the food chain. These findings are compatible with the well-established fact that the overall food industry (which includes the market for GM foods) is characterised by a particularly high level of consumer heterogeneity and dominated by the presence of influential consumer segments. (e.g. Baker and Burnham, 2001) In light of this evidence, it is understandable that we observe a general consensus emerging in both policy and industry circles that the very future of the GM food industry itself is under serious doubt unless the distributional impacts on consumer welfare from the spreading of GM foods are understood (Lusk and Hudson forthcoming, 2003). This requires obtaining an enhanced understanding of the sources of heterogeneity as well as the nature and relative size of market segments with respect to GM foods. [1]

The current paper provides a direct contribution to this important policy issue by providing the first attempt to account for preference heterogeneity with respect decisions over GM foods. The aim is to obtain an enhanced understanding of how different types or segments of individuals are affected by the presence of GM contents in foods. To this end the latent segmentation model is used which is a relatively novel approach for accounting for preference heterogeneity in discrete choice data. The estimates from the LS model are compared and

[1] See Lusk and Hudson (2002) for arguments why the understanding of distributional impacts is more important for some issues (such as the introduction of GM foods) rather than others.

contrasted with those obtained from other, more commonly used, heterogeneity models. The following sections merely provide an exposition of how the LS model can be estimated as well as an insight to the policy usefulness of its results. For full details of the study and description of the CE study see Kontoleon (2003).

5. Latent variables and preference over food products

Implementation of the LS model requires the specification of the vectors of individual latent perceptual and attitudinal constructs (G^*_{np} and G^*_{na}) underpinning segment membership and choice behaviour. These vectors can conceivably include a very large number of variables. Hence, we first attempted to assess which latent concerns are the most relevant for the specific case study. This was achieved via an extensive literature review. Then we proceeded with determining survey questions that would be indicative of these key latent variables. This was accomplished via pilot studies. Finally, responses to these survey questions were factor analysed to obtain proxy variables to these latent constructs. This process produced data for five new variables that were then used to parameterise the vectors G_{np} and G_{na} in Eq. 9 and Eq. 10. (see Kontoleon 2003 for details).

> *Environment and animal welfare concerns*: these refer to concerns over the impact of GM foods on the state of the environmental as well as on welfare of live-stock animals.
>
> *Food Safety concerns:* this refers to a more specific type of latent variable that is more related to food safety consciousness than to overall health concerns.
>
> *Cost and bargain concerns:* these would characterise an individual who is has a generally high sense of 'bargains-proneness'. It is qualitatively different than price sensitivity since it may not be necessary associated with low-income groups.
>
> *Ethical concerns:* these refer to moral concerns against GM technology that may affect ones food-purchasing decisions. These concerns convey the idea that GM foods may be objectionable as a matter of principle (such as the objection to 'playing God' or 'intervene in nature'). These concerns should be distinguished from a more teleological or utilitarian reasoning against GM foods (e.g. 'GM foods should be rejected since their benefits do not exceed their risks. If this were not true they would not be objectionable')
>
> *Mistrust and Disbelief:* this factor captures the degree to which the individual trusts the authorities, scientists and the industry when handling/managing this new technology. It also includes the level of trust in the information on the risks and benefits of GM foods that the individual receives.

6. Basic Multinomial Logit model

Before running the LS model the data was explored using the standard multinomial logit (MN) logit model. This provided a first 'feel' of the data that was helpful in specifying the utility portion of the LS model (i.e. the functional form and specification of $\beta_s X_{in}$). Moreover, the MN logit model can also account for heterogeneity across individuals by including individual characteristics (interacted with choice specific attributes) directly in the indirect utility function. Hence, the results from this model can also be contrasted with those obtained from the LS model presented in the next section.

The choice sets of the model included three egg profiles A, B and C and an opt-out option D. The basic MN logit model assumes that the choice between these options is only a function of an alternative specific constant (ASC) and the attribute of the alternatives. The attributes that had two levels were effects coded, that is: 'Living conditions' (free range = 1, cage = -1), 'Use of agricultural chemicals and fertilizers' (non use = 1, use = -1), and 'Certification' (yes = 1, no = -1). After various exploratory estimates the levels used for the price attribute were entered in a cardinal-linear form (taking the values 0.38GBP, 0.68GBP, 0.98GBP, and 1.28GBP), while 'GM content' entered as a mixed distribution such that NonGM captures the differences between 'zero' and 'nonzero' GM content in chicken feed while GMCont captures a cardinal measure of GM content taking the values 1%, 5%, 10%, and 30%.

The MN model was run in GuassX using a self programmed code.[2] After accounting for missing data or individuals that do not consume eggs the sample size was reduced from 312 to 240 individuals. These individuals provided data for 1753 choices.[3] The estimated MN logit coefficients are presented in Table 1. All the estimated parameters have the expected impact on utility and are highly significant. The characteristics of 'free-range', 'organic', and 'certification' have a significant and positive impact on *V*. Also, The impact on *V* of price of price negative and highly significant. Moreover, the impact on *V* of obtaining 100% GM free eggs is positive (given by the coefficient on the 'NonGM' dummy) while the effect on *V* of an increase in GM content is negative and significant. Finally, the implicit ranking of the attributes based on the marginal WTP values (or part-wholes) suggests that total avoidance of GM content is the most important determinant of choice followed by the characteristics of 'free range' and 'organic' (see Table 6).

7. Multinomial logit with individual characteristics

Next, preference heterogeneity was introduced into the basic MN logit model by including individual characteristics in *V*. Identification of the effects of these characteristics requires that they are interacted with the profile attributes. Various combinations of demographic and

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[2] All computer codes can be provided by the authors upon request.

[3] That is the 240 times 8 choices per individual yields 1920 total choices made. After accounting for missing data this number is reduced to 1753.

attributes were used. Table 1 presents the results from a specification that includes interactions terms between the five attitudinal variables extracted from the factor analysis and the choice specific attributes. Using the Swait-Louviere log-likelihood test it can be seen that the models with interaction effects outperforms the simple model.[4] We see that the factors of "Mistrust and disbelief" and "Environment concerns" have the highest impact on the probability of choosing s particular brand. Yet, the direction of this impact remains ambiguous.

8. Specification and estimation of Latent Segment Model

Estimation of the LS model first required the specification of the variables affecting segment membership (i.e. the vector α_s in Eq. 14). After experimentation with various specifications the five factors obtained from the factor analysis along with the socio-economic characteristics of income (in logarithmic form) and education were used (in dummy variable form such that '1' for university degree and '0' otherwise. Secondly, the specification for the choice or utility portion of the model was determined in the same lines as was established in the MN logit model described above. Note that the LS model assumes that individual characteristics affect choice indirectly through their impact on segment membership. Hence, all such variables are included only in the specification of the segment membership function.

The programme for maximizing the likelihood of the LS model was coded in GaussX for Windows. Both the BHHH and the BFGS algorithms for maximizing the log-likelihood of Eq. 17 were used. Starting values were obtained by using the BFGS algorithm. Also, following Swait (1994) and Boxall and Adamowicz (1999) we assumed independence across multiple responses from the same individual.

The LS model was run for the two, three, four, and five segment case. The log-likelihood, $\bar{\rho}^2$, *AIC* and *BIC* statistics of the 1, 2, 3, 4, and 5- segment solutions are presented Table 3. First of all we can see that the log-likelihood and $\bar{\rho}^2$ statistics improve as more segments are added. This clearly supports the presence of multiple segments in the sample. Determination of the optimal number of segments requires a balanced assessment of the information in Table 3. Based on this assessment it is clear that the 3-segment solution provides the best fit to the data. First, we see can see that though the AIC statistic decreases as more segments are added

[4] The test statistic is given by 2(2100.36-1813.72)=573 and the df are 30. We can easily reject that the

to the model, the decrease is much smaller from the 3- to 4- segment and 4- to 5- segment solutions than the decrease from 2- to 3-segment solutions. Further, the increase in the $\overline{\rho}^2$ statistics is substantially levelled off after the 3-segment solution. Finally, the BIC criteria is minimised at segment three.

9. Interpretation and assessment of three segment model

Having selected the model with the optimal number of latent segments we now turn to the interpretation and assessment of the three-segment model. Table 2 displays the results from both the segment membership and utility coefficients. The model exhibits an overall highly satisfactory fit with almost all the coefficients being highly significant.

The labelling of each segment is, like the labelling of factors, a subjective processes based on the overall fit of the model and relative significance and magnitude of the coefficients in the latent segment membership function. The segment membership coefficients for the first segment were normalised to zero in order to be able identify the remaining coefficients of the model. All other coefficients are to be interpreted relative to the normalised or base-line first segment.

Observing the membership and utility coefficients if Segments 2 and 3 we label them ‘food cautious’ and ‘ethical opponents’ respectively. Further, based on the coefficients of these two segments we were able to assess the characteristics of Segment 1 and label it the ‘food optimists’ segment (see Kontoleon 2003 for details of how segments were interpretd). Lastly note that no segment is characterised purely by one type of concern. The model allows for attitudes to overlap since it acknowledges that individuals (or segments of individuals) are complex and multifaceted entities.

The relative size of each segment (or market share) can be estimated by inserting the estimated segment coefficients into Eq. 14. This will provide the series of probabilities that each individual *n* belongs to each of the three segments. Individuals are assigned to one of the three segments on the basis of their largest probability score. We thus find that 53.5% of the sample is classified into the ‘food optimist’ segment that includes individuals that are cautiously in favour of GM foods. Moreover, 38.8% can be classified into the ‘food safety cautious’ segment that includes people that are against GM foods on environmental and health

significance of the contribution of the interaction effects is equal to zero.

risk concerns. Lastly, the marker share of the 'ethical opponents' segment is 7.7%. This includes individuals that oppose GM foods on ethical grounds and have a relatively stronger propensity to object to even traces of GM content in food (i.e. traces of GM content bellow 1%). We can thus conclude that roughly half of the sample is open to the possibility of consuming GM foods while the other half has rather a strong negative predisposition towards GM foods.

These results are in line with other GM food segment studies that have used non- behaviour based cluster analysis techniques. For example Verdrume *et al.* (2001) 'cautious and food Neophobics', 'enthusiasts' and 'green opponents' segments directly correspond to the 'food safety cautious' 'ethical opponents', and 'food optimist' derived here. The results are also in line with the segments obtained by studies by Baker and Burnham (2001) and Baker and Crosbie (1993). All of these studies use some form of cluster analysis to distinguish consumer segments in relation to GM foods. The segments revealed via the LS model, however, are based on a behavioural model of choice. This makes the information more operationally valuable than those obtained from simple cluster analysis (Ben-Akiva *et al.* 1997).[5, 6]

Moreover, we can compare the LS model with the MN logit model that includes interacted individual characteristic. Using the Swait and Louviere log-likelihood test we find that the former outperforms the latter . The chi square statistic is 78.46 which can reject the null that the MN is the correct specification at the 1% level. Hence, based on statistical criteria the LS model outperforms the MN model with interacted individual characteristics in accounting for preference heterogeneity.

We can further appreciate the policy usefulness of the LS model by comparing the part-worth values (or the marginal rate of substitution between income and a change in the attribute in

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[5] Still, the affinities of our results with those obtained from cluster analysis studies provide a form of external validity and/or convergent validity. Also, Hossain *et al.* (2002b) have conducted a qualitative study in which they assess consumer acceptance of various types of GM foods in the US. One of the foods they investigate is in fact eggs laid by hens that have been feed with GM chicken feed. They find that roughly 50% of the sample would be willing to purchase these eggs while 50% would not. This is an interesting finding since it suggests that consumer preference across the Atlantic may not be as different as argued by many. GM opponents in Europe are usually much more vocal and dominate the public debate to the extent that they have influenced policy decisions.

[6] Recent valuation work on the welfare impacts of introducing GM foods have investigated preference heterogeneity by focusing on demographic characteristics such as age and sex (e.g. James and Burton 2001). Yet, the large number of qualitative studies on GM foods have found that attitudinal and motivational (as

question) of the 3-segment model with those obtained from the single segment MN logit model (with and without individual characteristics). Table 6 presents segment part-worth values from both models. These were calculated in accordance with McFadden (1999). Note that calculation of segment specific marginal welfare measures presupposes that we have assigned respondents to segments. Initial inspection of this table shows that the implicit ranking of the value of each attribute changes from one segment to the other (see Table 6).[7] Hence, the overall results from the LS model provide useful policy input into the discussion over GM food market segmentation and food product labelling. It is clear that any policy decisions made on the basis of the single segment model would not reflect the richness and heterogeneity in utility attributes that exists in the sampled population.

10. The Random Parameters logit and Covariance Heterogeneity models

We now turn to compare the results from the LS model with those derived from the random parameter logit (RPL) and Covariance Heterogeneity (CovHet) models. The rationale behind these model was described in Section 2. Details of their formulation can be found in Louviere *et al.,* 2000 and Green, 1997). The estimation process was undertaken in LIMDEP (Version 7.0.2) following the guidelines of Green (1998, pp. 540-542) and Louviere *et al.* (2000, pp. 200-201). The best-fit results from these models is presented in Table 4 and Table 5. (see Kontoleon 2003 for a more detailed discussion of these models).

Formal comparison of the RPL and LS models is complicated by the fact they are non-nested models. We use the test presented in Ben-Akiva and Swait (1986) for comparing for non-nested probabilistic choice models (see Kontoleon 2003 for details). The test rejects the null hypothesis that the RP logit model is the true specification. Hence, the RP logit model (and the estimation complexity it requires) appears to be superfluous. This result may reflect the fact that (for this particular study) the LS model provided added information that was not conveyed in the RP logit model. For example, though the coefficients on individual characteristics in the RP model were highly significant, they are considerably less interpretable and operationally useful than those obtained for each segment under the LS model. Also, the statistical supremacy of the LS model is implying that individual characteristics are affecting choice *indirectly* (through the segment membership function)

opposed to purely demographic) variables are more appropriate in explaining differences in choice. The current study provides one of the first attempts to incorporate such latent constructs in a quantitative model of choice.

[7] Note that the absolute (as opposed to relative) magnitude of the part-worth values seems quite large and are not as such to be used for policy purposes. What is useful from this table is to see how (qualitatively) the relative importance of part-worth values changes across segments.

rather than directly through the utility function. Lastly, we can see from Table **6** that the implicit ranking of the marginal WTP values (i.e. part-worth values) derived from the RP logit model differs from that derived from the LS model. This reinforces the need to use the best-fit LS model for policy purposes since the two types of models led to different conclusions regarding the distributional impacts of GM foods.

Further, by running a covariance heterogeneity (CovHet) and then comparing it to the LS model we can investigate whether individual characteristics are more suitable for explaining heterogeneity in 'variance' instead of taste (see Section 2.3). Once again the two models are non-nested so we employ the Ben-Akiva and Swait (1986). On the basis of this test we reject the null hypothesis that the CovHet model is the correct specification. It is therefore, more likely that (for this particular study) the LS model that uses individual characteristics to explain parameter differences (or preference heterogeneity) across types of segments of individuals provides a better fit to the data than the CovHet model that uses individual traits to explain consistency (or variability) of individual choices. Finally, we can see from Table 6 that the implicit ranking of the marginal WTP measures for the two types of models differs and hence it is not inconsequential for policy purposes which model is used.

11. Concluding remarks

There are both statistical and behavioural arguments for accounting for preference heterogeneity in random utility discrete choice models. The former concern the accuracy of the estimated parameters while the latter have to do with the policy relevance of the results. The current paper presented an alternative approach to account for preference heterogeneity in random utility models, the latent segmentation (LS) model. The model was applied to a data set derived form a choice experiment investigating the impact that the introduction of GM foods would have on individual food purchasing decisions. The analysis compared the LS model with other specifications and found that it outperformed all rival models on statistical grounds. Further, the implicit ranking of the estimated implicit prices varied considerably across models signifying that care must be taken when choosing appropriate specification for treating heterogeneity. Also the LS model was shown to provide much more rich policy information, and hence, in this instance, was found to be superior on policy grounds. This is so because the latent segmentation model yields information on the viability of creating segregated food production and distribution networks as well as niche markets for novelty or functional foods. In addition, the model provides information that is useful in understanding the distributional impacts of alternative GM food policies. Both of these considerations are vital in discussions currently underway on future of GM foods. We believe that further research on such latent class models that integrate information from choice models with latent constructs and socio-economic factors will provide highly useful information that will enrich the policy discussions on labelling, GM certification, and market segregation issues.

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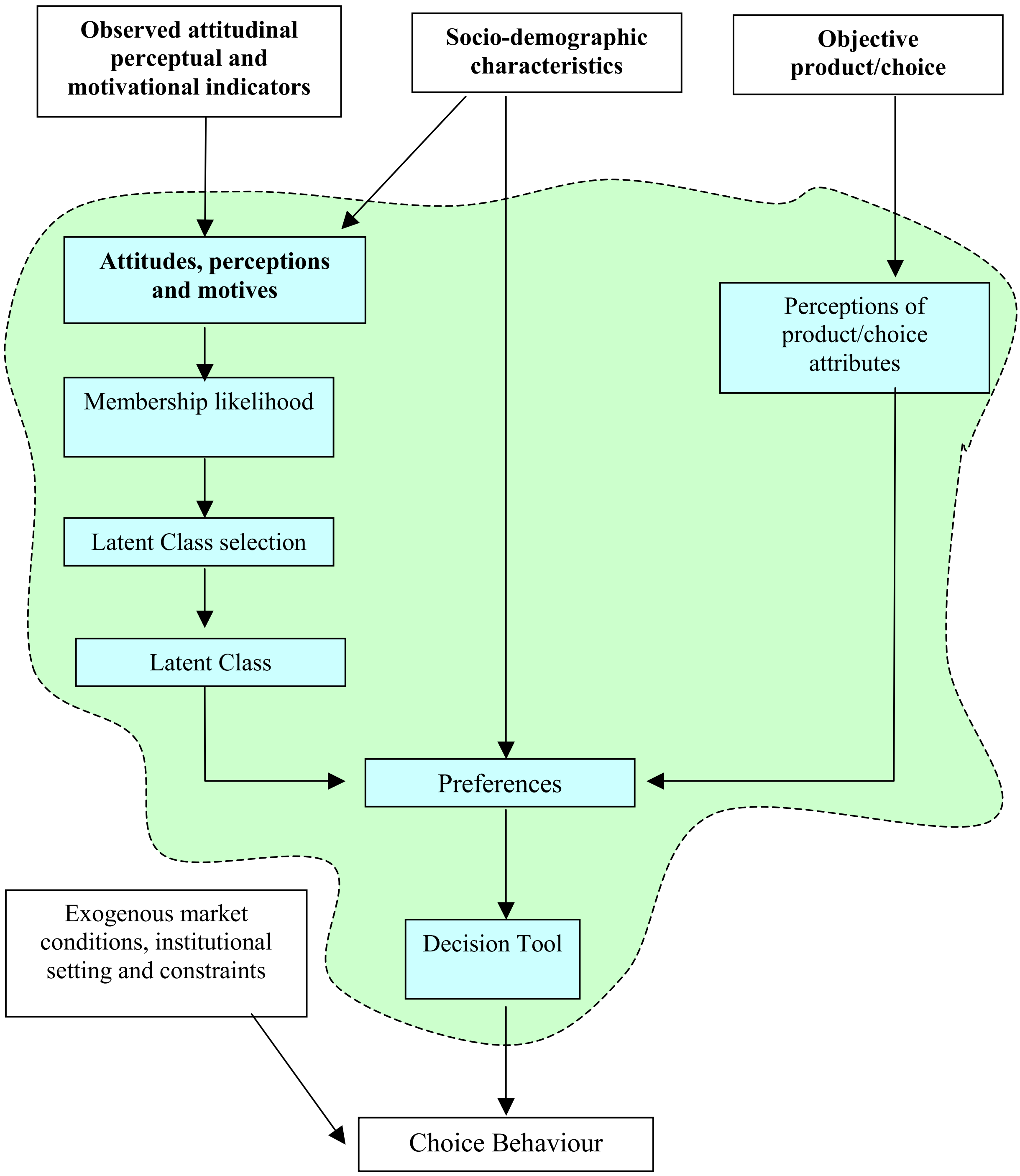
13. Appendix 1: Figures and Tables

Figure 1 A Structural model of latent segmentation and choice (adapted from McFadden (1986), Ben Akiva *et al.* (1997) and Swait (1994)).



Notes: shaded segment includes latent or unobservable constructs.

Table 1. Multinomial Logit model: with and without individual characteristics

	Basic MN logit				MN logit with individual characteristics			
	Coefficient	Std. Error	t-Stat	P-Value	Coefficient	Std. Error	t-Stat	P-Value
ASCS1	-0.124	0.130	-0.952	0.341	0.128	0.137	0.934	0.350
Living condition	0.808	0.047	17.293	0.000	0.940	0.056	16.770	0.000
Pesticides	0.310	0.040	7.733	0.000	0.464	0.045	10.317	0.000
NonGM	0.945	0.101	9.343	0.000	1.172	0.112	10.455	0.000
GMCont	-0.013	0.004	-3.226	0.001	-0.044	0.007	-6.436	0.000
Information	0.098	0.038	2.543	0.011	0.134	0.045	2.996	0.003
Price	-0.909	0.137	-6.621	0.000	-1.445	0.146	-9.896	0.000
					-	-	-	-
LC*Ethical resistance	-	-	-	-	-0.061	0.054	-1.131	0.258
Pes*Ethical resistance	-	-	-	-	0.156	0.043	3.627	0.000
NonGM *Ethical resistance	-	-	-	-	0.905	0.113	7.981	0.000
GMCont*Ethical resistance	-	-	-	-	-0.040	0.006	-6.888	0.000
Inf*Ethical resistance	-	-	-	-	0.071	0.044	1.590	0.112
Price*Ethical resistance	-	-	-	-	-0.678	0.096	-7.091	0.000
	-	-	-	-	-	-	-	-
LC*Mistrust and disbelief	-	-	-	-	0.152	0.056	2.702	0.007
Pes*Mistrust and disbelief	-	-	-	-	0.262	0.046	5.647	0.000
NonGM *Mistrust and	-	-	-	-	0.802	0.121	6.638	0.000
GMCont*Mistrust and	-	-	-	-	-0.014	0.005	-2.698	0.007
Inf*Mistrust and disbelief	-	-	-	-	0.055	0.047	1.156	0.248
Price*Mistrust and	-	-	-	-	-0.695	0.100	-6.939	0.000
	-	-	-	-	-	-	-	-
LC*Environment concerns	-	-	-	-	0.315	0.061	5.168	0.000
Pes*Environment concerns	-	-	-	-	0.129	0.047	2.721	0.007
NonGM *Environment	-	-	-	-	0.273	0.127	2.153	0.031
GMCont*Environment	-	-	-	-	-0.021	0.005	-4.145	0.000
Inf*Environment concerns	-	-	-	-	-0.020	0.049	-0.418	0.676
Price*Environment	-	-	-	-	-0.357	0.107	-3.352	0.001
	-	-	-	-	-	-	-	-
LC*Cost and bargain	-	-	-	-	-0.155	0.058	-2.653	0.008
Pes*Cost and bargain	-	-	-	-	-0.117	0.049	-2.382	0.017
NonGM *Cost and bargain	-	-	-	-	0.081	0.127	0.643	0.520
GMCont*Cost and bargain	-	-	-	-	0.011	0.005	2.000	0.046
Inf*Cost and bargain	-	-	-	-	-0.112	0.051	-2.201	0.028
Price*Cost and bargain	-	-	-	-	-0.067	0.105	-0.637	0.524
	-	-	-	-	-	-	-	-
LC*Food safety concerns	-	-	-	-	-0.134	0.058	-2.335	0.020
Pes*Food safety concerns	-	-	-	-	-0.152	0.049	-3.118	0.002
NonGM *Food safety	-	-	-	-	-0.302	0.128	-2.362	0.018
GMCont*Food safety	-	-	-	-	0.009	0.005	1.805	0.071
Inf*Food safety concerns	-	-	-	-	-0.061	0.051	-1.208	0.227
Price*Food safety concerns	-	-	-	-	0.301	0.105	2.864	0.004
Log of Likelihood	-2084.4501				-1800.02			
Number of Observations	1753				1753			

Table 2. Three Latent Segment Model

Variable	Coeff	Std. Error	t-Stat	P-Value	
Segment 2: segment function coefficients					
Constant2	-0.315	0.131	-2.411	0.016	**Food Cautious**
Ethical resistance	1.616	0.151	10.707	0.000	
Mistrust and disbelief	1.728	0.200	8.638	0.000	
Environment concerns	0.686	0.148	4.637	0.000	
Cost and bargain concerns	-0.429	0.147	-2.917	0.004	
Food safety concerns	1.637	0.207	7.890	0.000	
Dummy Education	-1.219	0.243	-5.005	0.000	
Log Income	0.189	0.055	3.424	0.001	
Segment 3: segment function coefficients					
Constant2	-4.387	0.242	-18.151	0.000	**Ethical Opponents**
Ethical resistance	4.294	0.815	5.272	0.000	
Mistrust and disbelief	1.294	0.399	3.241	0.001	
Environment concerns	-1.898	0.548	-3.463	0.001	
Cost and bargain concerns	2.586	0.513	5.044	0.000	
Food safety concerns	-0.766	0.399	-1.923	0.055	
Dummy Education	3.870	0.795	4.866	0.000	
Log Income	-1.149	0.341	-3.366	0.001	
Segment 1: utility function coefficients					
ASCS1	2.106	0.231	9.115	0.000	**Food Optimists**
Living condition	0.755	0.056	13.442	0.000	
Pesticides	0.163	0.049	3.353	0.001	
NonGM	-0.141	0.136	-1.040	0.298	
GMCont	-0.017	0.005	-3.699	0.000	
Information	0.012	0.047	0.254	0.799	
Price	-1.464	0.186	-7.873	0.000	
Segment 2: utility function coefficients					
ASCS2	-5.611	0.164	-34.309	0.000	**Food Cautious**
Living condition	8.105	0.273	29.685	0.000	
Pesticides	3.241	0.426	7.601	0.000	
NonGM	2.054	0.682	3.014	0.003	
GMCont	-3.471	0.752	-4.618	0.000	
Information	2.228	0.257	8.658	0.000	
Price	-5.718	0.490	-11.670	0.000	
Segment 3: utility function coefficients					
ASCS3	2.636	0.858	3.071	0.002	**Ethical Opponents**
Living condition	0.010	0.284	0.036	0.971	
Pesticides	1.316	0.508	2.589	0.010	
NonGM	3.324	1.152	2.886	0.004	
GMCont	-2.312	0.636	-3.636	0.000	
Information	0.788	0.370	2.129	0.033	
Price	-5.679	1.829	-3.104	0.002	
Log of Likelihood			-1653.5777		
Number of Observations			1753		

Table 3 Criteria for determining optimal number of segments

Number of segments	Parameters (P)	Logarithm Likelihood (LL)	ρ bar2	AIC	BIC
1	8	-2084.45	0.139	4184.90	2106.37
2	24	-1737.29	0.275	3522.57	1803.05
3	40	-1653.58	0.303	3387.15	1763.19
4	56	-1620.35	0.310	3352.71	1773.81
5	72	-1587.87	0.315	3319.74	1785.18

1）N=240 individuals

2） AIC (Akaike Information Criterion) is -2（LL-P）.

3） ρ bar2＝{1-AIC/2LL(0)}

4） BIC(Bayesian Information Criterion) is -LL+（P/2）*ln（N）.

Table 4 Random Parameter Logit model

Variable	Coefficient	Standard Error	t-stat	p-value
	Random parameters in utility functions (mean values)			
ASC	-2.144	0.586	-3.661	0.000
Living condition	0.828	0.047	17.458	0.000
Pesticides	0.336	0.041	8.224	0.000
NonGM	0.987	0.103	9.569	0.000
GMCont	-0.014	0.004	-3.323	0.001
Information	0.092	0.039	2.378	0.017
Price	-0.884	0.141	-6.279	0.000
	Non-random parameters in utility functions			
Ethical resistance	-0.612	0.064	-9.588	0.000
Mistrust and disbelief	-0.415	0.069	-5.994	0.000
Environment concerns	-0.212	0.075	-2.818	0.005
Cost and bargain concerns	-0.011	0.073	-0.153	0.878
Food safety concerns	-0.281	0.074	-3.772	0.000
Education dummy	0.417	0.122	3.431	0.001
Income (logs)	0.233	0.076	3.052	0.002
	Derived standard deviations of parameter distributions			
SD_ASC	0.008	0.058	0.139	0.890
SD_Living condition	0.010	0.038	0.267	0.790
SD_Pesticides	0.001	0.035	0.035	0.972
SD_NonGM	0.001	0.059	0.015	0.988
SD_GMCont	0.000	0.003	0.039	0.969
SD_Information	0.003	0.034	0.076	0.940
SD_Price	0.010	0.049	0.205	0.838
Log likelihood function			-1980.643	
Replications for simulated probabilities			500	
Number of observations			1753	

Table 5 The CovHet Model

Variable	Coeff	Std. Error	t-Stat	P-Value
		Utility Parameters		
ASC	0.032	0.175	0.184	0.854
Living condition	0.791	0.063	12.494	0.000
Pesticides	0.271	0.041	6.641	0.000
NonGM	1.022	0.107	9.555	0.000
GMCont	-0.013	0.005	-2.491	0.013
Information	0.082	0.046	1.780	0.075
Price	-0.999	0.186	-5.379	0.000
		Covariates of scale function		
Constant	0.944	0.107	8.829	0.000
Ethical resistance	0.844	0.107	7.857	0.000
Mistrust and disbelief	0.255	0.114	2.241	0.025
Environment concerns	-0.151	0.100	-1.519	0.129
Cost and bargain concerns	-1.005	0.144	-6.987	0.000
Food safety concerns	0.272	0.127	2.133	0.033
Log Income	0.944	0.107	8.829	0.000
Dummy Education	-0.222	0.183	-1.215	0.224
Log-Likelihood		-1931.015		
Chi-squared		998.3176		
Sample Size		1753		

Table 6 Part-worth values for alternative multinomial choice models

	MN logit model				Three Segment LS Model								RP Logit Model		CovHet Model	
	Model without individual Characteristics		Model with individual Characteristics		Food Optimist Segment		Food Cautious Segment		Ethical Opponent Segment		Single weighted estimate from 3-segment model		Model with individual Characteristics		Model with individual Characteristics	
	£	Rank	£	Rank	£	Rank	£	Rank	£	Rank	£	Rank	£	Rank	£	Rank
Living conditions[a]	0.89	(2)	0.65	(2)	0.516	(1)	1.417	(1)	0.002	(5)	0.826	(1)	0.937	(2)	0.791	(2)
Pesticides[b]	0.34	(3)	0.32	(3)	0.111	(2)	0.567	(3)	0.232	(3)	0.714	(2)	0.380	(3)	0.271	(3)
NonGM[c]	1.04	(1)	0.81	(1)	-0.096	(3)	0.359	(5)	0.585	(1)	0.366	(3)	1.117	(1)	1.022	(1)
GMCont[d]	-0.01	(5)	-0.03	(5)	-0.012	(4)	-0.607	(2)	-0.407	(2)	-0.273	(4)	-0.016	(5)	-0.013	(5)
Information[e]	0.11	(4)	0.09	(4)	0.008	(5)	0.390	(4)	0.139	(4)	0.157	(5)	0.104	(4)	0.082	(4)

Notes:

Bold numbers in parentheses denote implicit ranking of choice attributes.

[a] *Calculated as the marginal WTP to have free range eggs*
[b] *Calculated as the marginal WTP to have organic eggs*
[c] *Calculated as the marginal WTP for reducing GM from 1% to the 0% content level*
[d] *Calculated as the marginal WTP for reducing GM from 30% to the 1% content level*
[e] *Calculated as the marginal WTP to have information (labelling) on egg boxes*