Using Attribute Importance Rankings within Discrete Choice Experiments: an application to Valuing Bread Attributes.

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Abstract

In this paper we present results from a Choice Experiment (CE) incorporating respondent debriefing ranking information about attribute importance employing a modified Mixed Logit using Bayesian methods. Our results indicate that a CE debriefing question that asks respondents to rank the importance of attributes, as opposed to simply indicating attendance or non-attendance, helps to explain the resulting choices. We also examine how mode of survey delivery (online and mail) impacts model performance and find that our results are not substantively affected by the mode of survey delivery. We conclude that the ranking data is a complementary source of information about respondent utility functions within CE.

Key Words: Choice Experiment, Attribute Non-Attendance, Survey Mode
JEL: C11, C25, L66

1. Introduction

There is a rapidly growing literature that examines how respondents interact and use the attributes employed within Choice Experiments (CEs). For example, Hensher et al. (2005) explain that it is normally assumed that when a survey participant undertakes a CE they employ all attributes. However, there are reasons to assume that respondents may employ less than the full set of attributes when making choices. This has become known as Attribute Non-Attendance (ANA). It is now well known that respondents, when prompted, often state that they ignore some of the attributes presented to them in CEs.

A central issue within the stated ANA literature has largely been on whether respondents really ignore attributes and what the implications of this would be for Random Utility Models. For example Campbell et al. (2008) argue that non attendance may be symptomatic of discontinuous preferences. With exceptions (Balcombe et al., 2011), the majority of papers seem to suggest that respondents do not fully ignore attributes that they state that they do not attend. Essentially, it seems that people that indicate non-attendance for attributes seem to have place lower importance on those attributes when making choices, but do not ignore them altogether. While the initial goal of the non-attendance literature was to determine whether people have employed simplification strategies, this literature has resulted in demonstrating that asking debriefing questions about attribute attendance is an important source of information about peoples utility functions, even if people do not fully ignore attributes (Scarpa et al., 2009 and 2010).

Here we investigate a potentially useful alternative to asking non-attendance debriefing questions. Instead of asking people whether they have ignored (or used) attributes we ask them to rank the attributes in order of importance to them. This should not be confused with a ranking approach for alternatives. Our approach still requires discrete choice but with a single importance ranking question after all the choices have been completed. We show how this information can be used in a parsimonious way by modifying the Mixed Logit. We believe that this provides a potentially richer assessment of attribute use and importance than a dichotomous non-attendance question.

Our application is a CE study into the attributes of bread, including a functional ingredient and a health claim. As such it adds to a growing literature examining consumer attitudes towards foods modified with functional ingredients as well as the provision of information to help consumers make informed health choices (eg., Cowburn and Stockley, 2005, Grunert and Wills, 2007, Mazzocchi et al., 2009, Balcombe et al, 2010, Hellyer and Haddock-Fraser, 2011, and Hellyer et al., 2012). Indeed, the CE employed in this paper has previously been employed by Bitzios et al. (2011) to address these issues. However, in this paper we extend the previous analysis by employing attribute ranking data as well as additional data collected online. Specifically, the CE collected data using two modes of survey delivery – mail and online. There already exist several studies that examine if the mode of CE delivery impacts resulting model estimates (eg, Savage and Waldman, 2008, Olsen, 2009, Lindhjem and Navrud, 2011 and Windle and Rolfe, 2011). Our analysis adds to this literature by examining if there are differences in model results and performance for the mail and online survey data.

We estimate models employing Bayesian methods. We discuss two alternative ways of incorporating ranking data, one of which is new to the literature. We first assess if rank data are consistent with marginal utilities estimated independently of the ranking data. We then employ a modified Mixed Logit that incorporates the ranking data. We will refer to this as the "contraction approach". We make model comparisons employing model marginal likelihoods.

The structure of the paper is as follows. In section 2 we briefly describe the CE employed in this study. We then introduce and develop the econometric models we use to estimate our data. In section 4 we describe our data and report model results. In Section 5 we provide a summary and conclude.

2. The Choice Experiment: Design and Data

The CE employed in this paper was designed to provide WTP estimates for various types of bread with assorted attributes. The data employed had two modes of delivery, a mail version and an online version. Bitzios et al. (2011) analysed the mail version data only using a latent class approach, and did not employ the ranking data as we do in this paper. Since the two versions of the survey employed in this paper differed only in their mode of delivery, a full description of the design of the CE can be found in Bitzios et al. (2011) including the approach to attributes selection, experimental design and choice card format. A brief description of the attributes and levels employed in the CE are provided in Table 1.

[Approximate Position of Table 1]

The survey had four different versions (24 options that were presented to respondents in four blocks of six choice cards). The survey was composed of six sections. The first section gave information and explained the concept of functional foods. The second section included some warm-up questions on bread eating behaviour and bread facts knowledge. The third section explained the choice task using an example with the fourth section presenting the actual choice exercises that had to be completed. The next section included questions related to attitudes towards food including the ranking of attributes. The final section collected socio-economic individual specific information.

The specific ranking question that we asked was as follows:

For your choice card responses please rank from 1 (Most Important) to 7 (Least Important) the attributes which affected your choices. No two attributes should receive the same rank number.

- *Type of bread*
- *Production method of grain*
- *The presence of functional ingredient*
- *Whether it is sliced or unsliced*
- *The texture of bread*
- *The potential health benefit*
- *Price of bread*

The online version of the survey was implemented using SurveyMonkey an online survey software and questionnaire tool (www.surveymonkey.com/). We employed an opt-in approach to survey participation. To attract survey participants we placed a link to the survey on the University of Kent website, advertised via the news section of the University's website. The advertisement provided a link for respondents to the survey. We also placed a link on the Home Grown Cereals Authority website which was advertised via their e-club "Crop Research News". For both sites the link to the specific version of the survey was modified every few days to ensure that we obtained a balance of responses across the four blocks of choice cards we had employed with the postal version of the survey instrument. The mail survey had 341 useable responses and the online survey returned 318. A comparison of both mail and online respondents is provided in Table 2.

[Approximate Position of Table 2]

Table 2 shows that we have more female respondents than males for both survey modes, and that the proportion of females is higher for the online version of the survey. The actual proportion of females in the UK is just under 51 percent. Our mail sample has an above average age compared to the UK average of 39, whereas the online sample has a lower average age. The average income of respondents (excluding non-responses) is just over £31,000 for mail and £33,000 for online which is reasonably close to average income in the UK.

Notably, the online survey attracted proportionally more females than the mail survey and generally the online participants were considerably younger. The online participants also tended to be slightly more highly educated, paid and in work, and health conscious.

In terms of the rankings also presented in Table 2 it is evident that Type of Bread is clearly identified as the most important attribute by respondents. This is followed by Texture, Price and Health Benefit. Functional ingredients and Production Methods are clearly viewed as being of low importance by respondents. These rankings are broadly the same across the two modes of delivery. In Section 4 the importance rankings will be used within the estimation of the Mixed Logit. As we will see the marginal utilities estimated using the discrete choice data will be in accordance with the rankings summarised in Table 2. Moreover, these rankings are able to be used in the estimation of marginal utilities.

3. Model Specification and Estimation

3.1. The Standard 'Mixed Logit'

The utility (U) that the *jth* ($j = 1, ..., J$) individual receives from the *ith* choice ($i = 1, ..., I$) in the *sth* choice set ($s = 1, ..., S$) is assumed to be of the form

$$U_{ijs} = \dot{x}'_{ijs}\dot{g}\left(\beta_j\right) + e_{ijs} \tag{1}$$

where $\dot{x}_{ijs}$ denotes the $K \times 1$ vector of attributes presented.

Next, let y_{ijs} denote an indicator variable that equals one if the *jth* individual indicates that they would choose the *ith* option within the *sth* choice set, and zero if they would not. The set of all stated choices by respondents is denoted as $Y = \{y_{ijs}\}_{i,j,s}$. The error e_{ijs} is 'extreme value' (Gumbel) distributed, is independent of $\dot{x}_{ijs}$, and is uncorrelated across individuals or across choices. β_j is a ($k \times 1$) vector describing the preferences of the *jth* individual and obeys

$$\beta_j = \alpha + u_j \tag{2}$$

where u_j is a independently and identically normally distributed vector with variance covariance matrix Ω. The function $\dot{g}\left(\beta_j\right) = \left(\dot{g}_1\left(\beta_{1j}\right), ..., \dot{g}_K\left(\beta_{Kj}\right)\right)$ is a dimension preserving transformation of the vector β_j. For example, by using a exponential transformation for a given attribute coefficient, the marginal utility for that attribute becomes log normal. The errors $\{u_j\}$ are assumed to be uncorrelated across individuals. It is also common to condition the marginal utility in [2] on variables that characterise the respondent, as we discuss below.

3.2. Modifying the Model Using Ranking Data

In this CE we have observations $\{z_{jk}\}$ which represent the rank of the *kth* attribute by the *jth* respondent. As outlined above, each respondent was required to rank the data on a scale from one through R. Respondent were required to assign a unique rank to each attribute (they were not allowed ties). with one being the highest ranked (most important) attribute and R being the lowest.[1] In common with the treatment of

[1] In the case where a given attribute is categorical so that the coding uses dummy variables then the number of attributes to be ranked (R) will be smaller than K. Each of the dummy variables associated with a given attribute will recieve the same rank.

non-attendance data, we could choose to extend [2] so as to treat the rank as an explanatory variable for β_j. More specifically:

$$\beta_j = \alpha_o + \alpha_1 z_{jk} + u_j \tag{3}$$

This 'covariate approach' is potentially unsatisfactory because by treating the variance term of β_j as invariant to the ranking of an attribute we ignore the fact that it is not only a shift in the mean that would be expected but that people with very low rankings of some attributes are more likely to have marginal utilities clustered around zero. In order to take account of this we propose an alternative, where we define utility as in [1].

First, let us define the matrix $\Lambda_j = diag(\lambda_{j1}, ...\lambda_{jK})$ which has the elements

$$\lambda_{jk} = (1-\tau) + \tau \frac{(R - z_{jk})}{R-1} \tag{4}$$

where τ is a parameter that is to be estimated and is free to vary between zero and one. As $\tau \to 0$ this implies that the ranking data is unimportant in determining the mean and variance of the coefficients. At the other extreme, $\tau = 1$ implies that the lowest ranked attribute has zero marginal utility. It then follows that the individual marginal utilities are modelled by assuming $g\left(\beta_j\right) = \left(g_1\left(\beta_{1j}\right), ..., g_K\left(\beta_{Kj}\right)\right)$ where g_k is a transformation (e.g. an exponential) and likewise defining the elements of $\dot{g}\left(\beta_j\right)$

$$\dot{g}_k\left(\beta_{kj}\right) = \lambda_{jk} g_k\left(\beta_{kj}\right) \tag{5}$$

We note that for the highest ranked attribute $\lambda_{jk} = 1$ regardless of the value of τ. Without this condition the model would not be identified. We shall subsequently refer to this as the 'contraction approach'. We can write this in vector form using

$$\dot{g}\left(\beta_j\right) = \Lambda_j g\left(\beta_j\right) \tag{6}$$

3.3. Estimation of the Contraction Model

The contraction model is simple to estimate using Bayesian methods, since it can be specified in a similar way to the standard Mixed Logit, with the normal latent variables being multiplied by the shrinkage terms. If we define

$$g\left(\beta_j\right) = \Lambda_j^{-1} \dot{g}\left(\beta_j\right) \tag{7}$$

where as before:

$$\beta_j \sim N\left(\alpha, \Omega\right) \tag{8}$$

Viewing utility in this way we have

$$U_{ijs} = \left(\dot{x}'_{ijs}\Lambda_j\right) g\left(\beta_j\right) + e_{ijs} \tag{9}$$

By defining

$$x'_{ijs} = \dot{x}'_{ijs}\Lambda_j \tag{10}$$

the non-stochastic component of utility is defined conventionally as

$$V_{ijs} = x'_{ijs} g\left(\beta_j\right) \tag{11}$$

and the posterior densities for the parameters $\left\{\beta_j\right\}, \alpha, \Omega$, and τ, are obtained by observing that the probability of i being chosen in the circumstance js is the standard logit probability

$$p_{ijs} = \frac{e^{V_{ijs}}}{\left(\sum_i e^{V_{ijs}}\right)} \tag{12}$$

If the observed choices are defined by $y_{ijs} = 1$ where the ith option is chosen in circumstance js and $y_{ijs} = 0$ otherwise, then the likelihood of all the observed choices (Y) is

$$f\left(Y|\tau, \alpha, \Omega\right) = \prod_i \prod_j \prod_s p_{ijs}^{y_{ijs}} \tag{13}$$

Conditionally on Λ_j, the steps for generating latent variables $\left\{\beta_j\right\}$ along with α and Ω can be estimated using Markov Chain Monte Carlo (MCMC) steps as in the standard Mixed Logit (e.g. Train and Sonnier, 2005). That is, having normalised the attributes $\left(x_{ijs} = \dot{x}'_{ijs}\Lambda_j\right)$ the conditional distributions for β_j along with α and Ω are defined in the usual way (in terms of x_{ijs}). However, since τ is estimated, the normalised attributes need to be updated at each iteration, and the posterior distributions for τ is also required. The precision matrix has a Wishart prior $W\left(I, k+4\right)$ where k is the dimension of the covariance matrix. The precise priors that we use have a mean of zero for α and a diagonal covariance matrix for α with a variance of 100 for each of the effects common to all models. For the covariate terms in the model using the ranking data (model 2) the variances were set to 10. Thus, the prior variance for α was set so as to be relatively uninformative for the estimates, and small enough so that the penalty for additional parameters in the model would not be very restrictive.

Therefore, it follows that the posterior distributions for τ is

$$f\left(\tau|Y, \alpha, \Omega\right) \propto f\left(Y|\tau, \alpha, \Omega\right) f\left(\tau\right) \tag{14}$$

where τ has uniform prior over the unit interval [0,1]. Estimation proceeds by iterating through the sequence of conditional draws: $\left\{\beta_j\right\}|\alpha, \Omega, \tau Y$; $\alpha|\left\{\beta_j\right\}, \Omega, Y$; $\Omega|\left\{\beta_j\right\}, \alpha, Y$; $\tau|\alpha, \Omega, \left\{\beta_j\right\}, Y$. The conditional posterior distributions for the first three components are the same as in Train and Sonnier (2005). The conditional posterior distribution for τ is obtained from [14]. These can be sampled using Metropolis Hastings steps with a random walk proposal density.

4. Results

In the following section we examine the relative performance and results of three competing models across the two data sets (Mail and Online). The three models which we employ differ in their treatment of the ranking data. The first model (Model 1) makes no use of the ranking data. The second model (Model 2) uses the ranking data as a covariate on marginal utilities, thus allowing the mean to depend on the rankings of attributes (as in [3]) The third model (Model 3) uses the ranking data in the manner described in Section 3.3.

4.1. Model Comparisons.

We begin by examining relative model performance. The results for the logged marginal likelihoods (MargLL) are presented in Table 3.

[Approximate Position of Table 3]

For completeness we also present the maximum log likelihood (MaxLL) (calculated using the simulation method with Halton Sequences) visited by the sampler. From a Bayesian perspective the MargLLs are sufficient for us to make model comparisons (Balcombe et al., 2009). Comparisons should only be made vertically (we are not comparing between online and mail surveys). The larger the MargLL, the 'more preferred' a model. The exponential of the difference between the MargLL for two models gives the 'Bayes Factor' between two models when each is considered equally plausible *a priori*. For example, models which have a difference of 3 in the MargLL would indicate that the model with the larger MargLL is over 20 times more likely to be the true model after incorporating the sample information. The MargLL implicitly takes into account whether one model has more parameters than another, so no adjustment needs to be made to the MargLL in order to make model comparisons.

As the results show, in most cases the differences between the MargLLs between competing models are quite large. For both the mail and online data Model 3 is preferred to Model 2 which in turn is preferred to Model 1. As can also be seen from the MaxLL within Table 3, there is also a very large improvement in the MaxLL when comparing Model 3 with Model 1, even though there is only one additional parameter. Since Model 3 nests Model 1, one could calculate a classical p-value using a likelihood ratio statistic that would reject the restriction that $\tau = 0$ at very low levels (p<0.001). The results therefore seem unequivocal. Using the ranking data improves model performance whether ranks are used as covariates, or in the contraction approach outlined in Section 3. However, as can also be seen there is a very big improvement in MargLLs using the contraction approach over the covariate approach.

4.2.Parameter Estimates

4.2.1. Standard Mixed Logit

We first present the results of the parameter estimates of the standard Mixed Logit (Model 1) in Table 4.

[Approximate Position of Table 4]

We consider this model because our first interest is about whether there is a relationship between the importance rankings (reported in Table 1) and the size of the coefficients when they are estimated independently of the ranking data. Within Table 4 we report, for both online and mail data, the estimates and standard deviation of α along (in results columns 1,2, 4 and 5) with the estimates (the mean of the posterior) for the diagonal elements of Ω (in results columns 3 and 6). These are referred to as 'the mean of the variances'. Whereas α determines the means of the latent variables, the variances Ω_{ii} determine how diffuse these marginal utilities are across the population. If $\sqrt{\Omega_{ii}}$ is large relative to α_i (unless the utility is transformed) then a significant part of the population will have differently signed marginal utilities.

As can be seen from Table 4 and Table 2 the average importance scores tend to correspond with the size of the coefficients which, given that they are mainly dummies, are able to be compared. This is particularly evident with regard to the bread type. We see that whether a bread is wholegrain or brown has a very large average marginal utility, though this does differ substantially across the population (the variance estimates reflecting respondent heterogeneity are high). Examining the importance rankings in Table 2 we see that bread type was considered the most important attribute on average. Likewise, the next most important attribute (texture) also seems to have a relatively large effect on peoples utility given the coefficients in Table 4. The third most important ranked attribute is the health benefit which seems to have a large role in peoples choices given the quite large marginal utility (0.819) and relatively small standard deviation for this estimate (0.12).

4.2.2. Rankings as Covariates

When we look at the impact of the rankings when they are included as covariates on the marginal utilities in Table 5, this also confirms that the importance rankings seem to be strongly correlated with the marginal utilities.

[Approximate Position of Table 5]

For this exercise we took the (1 to 7 score) as the covariate so as to make the results easier to interpret. We would expect that marginal utility which was positive would have a 'significant' positive ranking coefficient. As we can see for bread types, price and health benefit, this is indeed the case. The only counter intuitive results seem to be the case for firmness, whereby although the effects included in the models were positive, those indicating that they have high importance for these attributes were estimated to have lower utilities (as shown by the fact that the dummy covariates have negative signs)

4.2.3. Contraction Model

Finally, we turn to the estimates of the model using the contraction approach which is presented in Table 6.

[Approximate Position of Table 6]

The contraction coefficient estimates are at the bottom of this table. The estimates for the contraction coefficients are approximately 0.94 and 0.80 for the mail and online versions respectively. A coefficient of 0.94 indicates that if a respondent ranks an attribute the lowest, then they would have a marginal utility of 6% of that which they would otherwise be predicted to have. Both estimates are high suggesting that people have very small marginal utilities for those attributes they rank as having low importance. While both surveys give comparable results, those in the mail version have a significantly greater contraction coefficient.

4.2.4. WTP Estimates

The values of α within Tables 4, 5 and 6 cannot be directly compared. For example, α coefficients in Table 4 will tend to be larger in absolute value since they do not take account of the fact that the coefficients will be scaled downwards for each individual in Table 6. It would be possible to obtain a rescaling of the α coefficients at the mean. However, this is effectively done by through the WTP estimates using the rescaled estimates which are presented in Table 7, which contains the WTPs for all three models.

[Approximate Position of Table 7]

The WTPs are estimated using simulation from the distribution of the latent coefficients and contraction coefficients. In Table 7 we see that the estimates are, for the most part, fairly robust to changes in method and survey mode. If we compare Models 1 and 3, we can see that there is a tendency for downward absolute revision in WTP estimates. However, it is not dramatic. This was not the case where the score was used as a covariate (Model 2) which tended to have slightly higher WTPs. Nonetheless, the overall picture remains similar. According to these results, it is striking that people are prepared, on average, to pay a large premium for wholegrain breads (anywhere from around £1.46 to £2.18) taking the lowest and highest estimates. However, the best performing model (Model 3) gives the lowest estimates (£1.46 to £1.76 Mail or Online respectively). The most noticeable difference between the Mail and Online results is in the WTP results for organic. For the Mail results we found very small or even negative WTP for organic bread, whereas this result was given a premium of 30 pence for the Online. Slightly larger values were found online for a functional ingredient and for a health benefit. Over all models and survey modes, the health benefit was given a higher WTP than for the functional ingredient or organic, with an estimate of an average 60 pence premium for the health benefit. However, we would again note that the respondents were more homogeneous in their liking for the health gain, whereas there was a great deal of heterogeneity across the population about liking for organic or functional ingredients.

5 Summary and Conclusions

This paper introduced a new way of using respondent debriefing ranking information about attribute importance in the context of a discrete choice experiment for the attributes for bread. The importance rankings were incorporated into the Mixed Logit using Bayesian estimation methods. However, the methods introduced here could also be implemented classically. Our results indicate that a CE debriefing question that asks respondents to rank the importance of attributes helped to explain the resulting choices and thus improved estimates of respondent utility functions. We explored incorporating the ranking information in two different ways: as a covariate explaining marginal utilities and a 'contraction' of the utility towards zero where the degree of contraction was estimated. The second approach proved to be the preferred one, although the covariate approach also improved model performance relative to using no information at all. We also found that the mode of survey delivery (online and mail) did not substantively alter our conclusions either with regard to the use of debriefing information or with regard to the estimates of marginal utilities and WTP. The results indicated that attributes which were ranked the lowest by respondents had a very small marginal utility to those respondents. With regard to the determinants of people's WTP for attributes of bread, the largest premiums were, on average, attached to 'wholegrain' closely followed by 'brown', but with a very large variation across the population with many consumers preferring white bread. Organic production received only a small premium on average, as did 'functional ingredients'. However, a health claim was valued highly, by the vast majority of the population.

The research here has built upon the literature on non-attendance which has shown that debriefing questions about attribute knowledge can assist our understanding of respondent utility functions in a way that is complementary to the observation of discrete choices. One ranking exercise by respondents is a relatively low cost exercise and we would advocate its use more generally. The results regarding contractions based on rankings may depend, inter alia, on the number of attributes in the choice experiment. We believe this warrants further investigation. There is also further work to be done on how best formally incorporating other forms of information into the estimation process using multiple debriefing questions and sources based on observation of respondents during the choice process.

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Table 1: Attributes and Levels Employed in the Choice Experiment

Attributes	Description	Levels
Type of Bread	Breads offered in the hypothetical market	White, Wholemeal Brown, 50-50, Rye
Method of Production	Who grain used in bread produced	Conventional, Organic
Functional Ingredient	An ingredient that can potentially deliver nutritional benefits	Yes, No
Sliced/Unsliced	Indicates if bread sold sliced or not	Medium, Thick, Unsliced
Texture	Consistency of the bread	Soft, Firm, Crunchy, Springy
Health benefit	If bread promotes health	Yes, No
Price	Cost (in £) of standard 800gr loaf of bread	0.7, 1, 1.3, 1.6, 1.9, 2.2

Table 2: CE Descriptive Statistics

	Units	Sample Avg	Mail Avg	Online Avg	Difference
Socio-Economics					
Gender	Female=1	0.71	0.64	0.81	-0.18
Age	Years	44.27	52.66	33.65	19
Children	Number	0.45	0.47	0.42	0.05
Education	1 to 5	2.27	1.72	2.9	-1.18
Income	£000's	32.12	31.02	33.61	-2.59
Exercise Regularly	Yes = 1	0.6	0.62	0.58	0.04
Health Conscious	Yes = 1	0.72	0.69	0.76	-0.07
Gluten Intolerance	Yes = 1	0.04	0.05	0.04	0.02
Work	Work = 1	0.57	0.54	0.6	-0.06
Rank Scores (1 high, 7 low)					
Bread Type		2.03	1.89	2.19	-0.3
Production Method		4.99	5.2	4.76	0.44
Functional Ingredient		5.13	5.29	4.96	0.33
Sliced		4.24	4.11	4.37	-0.26
Bread Texture		3.73	3.67	3.81	-0.14
Health Benefits		4.13	3.99	4.22	-0.23
Bread Price		3.78	3.85	3.7	0.15

Table 3: Marginal Log Likelihoods and Max Log Likelihoods

	Mail		Online		
	MargLL	**MaxLL**	**MargLL**	**MaxLL**	**No. of Parameters**
Model 1	-2083.66	-1968.86	-2058.92	-1954.64	104
Model 2	-2061.48	-1901.44	-2057.56	-1904.61	117
Model 3	-1994.19	-1889.72	-2016.16	-1911.78	105

Table 4:Standard Mixed Logit Results (Model 1)

	Mail			Online		
	Mean α	**St Dev α**	**Mean of Variance**	**Mean α**	**St Dev α**	**Mean of Variance**
Price (log-normal)	-0.441	0.223	1.723	-0.287	0.258	2.552
Bread (relative to White)						
Wholegrain	2.328	0.310	13.304	1.761	0.238	6.104
Brown	1.506	0.252	7.911	1.297	0.221	5.712
50/50	1.232	0.207	2.224	0.931	0.210	1.431
Rye	-0.429	0.339	14.736	-0.039	0.288	12.208
Method Production	-0.090	0.111	0.395	0.385	0.105	0.500
Functional Ingredient	0.250	0.112	0.226	0.227	0.103	0.196
Sliced (relative to Thin)						
Thick	0.083	0.124	0.482	-0.050	0.114	0.281
Unsliced	-0.217	0.134	0.583	-0.244	0.126	0.509
Texture (relative to Soft)						
Firm	0.327	0.158	0.997	0.331	0.141	0.617
Crunchy	0.134	0.148	1.065	0.220	0.133	0.534
Springy	0.251	0.150	0.590	0.353	0.139	0.677
Health Benefits	0.819	0.112	0.437	0.579	0.107	0.430

Table 5:Impact of Rank on Mixed Logit (Model 2)

	Mail		Online	
	Mean α	**St Dev α**	**Mean α**	**St Dev α**
Price (log-normal)	-0.773	0.124	-0.612	0.136
Bread (relative to White)				
Wholegrain	0.387	0.172	0.317	0.107
Brown	0.308	0.140	0.223	0.100
50/50	0.163	0.116	0.085	0.079
Rye	0.268	0.181	0.315	0.130
Method Production	0.204	0.059	0.185	0.046
Functional Ingredient	0.172	0.066	0.076	0.056
Sliced (relative to Thin)				
Thick	0.007	0.055	-0.043	0.048
Unsliced	0.010	0.061	-0.110	0.053
Texture (relative to Soft)				
Firm	-0.104	0.073	-0.145	0.068
Crunchy	-0.021	0.077	-0.059	0.067
Springy	-0.162	0.073	-0.180	0.069
Health Benefits	0.336	0.054	0.206	0.049

Table 6: Model Results With Contraction (Model 3)

	Mail			Online		
	Mean α	**St Dev α**	**Mean of Variance**	**Mean α**	**St Dev α**	**Mean of Variance**
Price (log-normal)	2.307	0.271	2.919	0.779	0.259	2.680
Bread (relative to White)						
Wholegrain	2.838	0.324	16.598	2.215	0.279	7.849
Brown	1.830	0.274	10.831	1.579	0.264	7.649
50/50	1.563	0.228	3.131	1.186	0.244	2.504
Rye	-0.597	0.403	21.630	0.079	0.351	16.527
Method Production	0.284	0.262	1.858	0.807	0.194	1.220
Functional Ingredient	0.878	0.223	0.834	0.566	0.194	0.542
Sliced (relative to Thin)						
Thick	-0.083	0.195	1.184	-0.046	0.163	0.479
Unsliced	-0.439	0.207	2.053	-0.508	0.200	1.722
Texture (relative to Soft)						
Firm	0.155	0.232	1.868	0.370	0.203	1.222
Crunchy	-0.315	0.253	3.931	0.207	0.204	1.470
Springy	-0.069	0.213	1.293	0.287	0.207	1.335
Health Benefits	1.624	0.172	0.653	1.150	0.160	0.603
	Mean	**St Dev**		**Mean**	**St Dev**	
Contract Coefficient	0.938	0.037		0.794	0.064	

Table 7: Median WTP Estimates

	Mail			Online		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Price (log-normal)	1.000	1.000	1.000	1.000	1.000	1.000
Bread (relative to White)						
Wholegrain	1.687	1.848	1.465	1.970	2.181	1.768
Brown	1.086	1.159	0.906	1.432	1.531	1.200
50/50	0.906	0.947	0.852	1.066	1.097	0.950
Rye	-0.292	-0.371	-0.237	-0.065	-0.079	0.058
Method Production	-0.060	-0.056	0.025	0.396	0.391	0.293
Functional Ingredient	0.172	0.212	0.112	0.212	0.251	0.193
Sliced (relative to Thin)						
Thick	0.056	0.004	-0.010	-0.051	-0.082	-0.017
Unsliced	-0.146	-0.217	-0.063	-0.226	-0.292	-0.197
Texture (relative to Soft)						
Firm	0.232	0.227	0.032	0.325	0.397	0.183
Crunchy	0.098	0.099	-0.025	0.213	0.219	0.103
Springy	0.181	0.197	-0.010	0.369	0.410	0.144
Health Benefits	0.596	0.633	0.502	0.554	0.648	0.595