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Traffic Lights and Food Choice: A Choice Experiment Examining the Relationship Between Nutritional Food Labels and Price

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ABSTRACT

In this paper we investigate how consumers respond to the UK food label Traffic Light System (TLS). Employing a Choice Experiment (CE) we find that consumers appear to behave in a manner consistent with our expectations regarding the impact of the TLS nutrition label. In particular, we identify a strong preference on the part of respondents to avoid a basket of goods containing a mix of foods with any "Red" lights. We have also found that consumers have a hierarchy of importance in terms of perception of the various nutrients examined and clear behavioural differences associated with particular socio-economic characteristics confirming early research on the use of nutrition labels. Overall our results indicate significant heterogeneity in the attitudes and responses of consumers to food labels within and across socioeconomic strata in terms of the magnitude of WTP.

Keywords: Nutrients, Traffic Light System, Choice Experiment, Bayesian Mixed Logit
JEL Classification: I18, C35, Q18

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1. Introduction

There is an ever-growing awareness and understanding of the relationship between food and the role it plays in health and well being. The importance of this relationship is increasing as the health implications of a poor diet in the UK have become ever more apparent (HMSO, 2007). There are now a whole raft of policy approaches that address this issue including various health campaigns such as the Food Standards Agency (FSA) "The eatwell plate" (FSA, 2007), the FSA "6g per day of salt intake" and the Department of Health "5-a-day campaign" for fruit and vegetable consumption. All of these campaigns have been accompanied by a drive to have food labelled in a manner that provides important dietary information for consumers. In terms of nutritional food labelling the UK has voluntarily adopted the Traffic Light System (TLS)[1] which indicates levels of four key nutrients ie, Fat, Sugar, Saturates and Salt, which are found in processed food.

The TLS system is relatively simple with a Red light indicating a very high level of a specific nutrient, Amber a medium amount and Green low. The choice of colour is based on the content of each of the nutrients per 100 grams of any food type that can then be converted into a per portion quantity. Thus, for any food the resulting quantities of these nutrients are measured then compared against the TLS which in turn provides the colour coding on the food packaging. In practice, the TLS is meant to aid consumers in getting the balance of products right in terms of their overall diet. It can be used a means to keep a check on the amount of food being consumed that is high in one or more of the nutrients identified.

There already exists a large literature that has examined many varied aspects of the TLS and nutritional labels in general. Both Cowburn and Stockley (2005) and Grunert and Wills (2007) provide comprehensive reviews of the literature on consumer use and response to nutrition information on food labels. They both observe

[1] If a specific nutritional claim is made it is necessary for producers to adhere to the appropriate EC Directive in terms of label format. Within the UK food labelling is regulated by EC Directive 90/496/EEC.

that within the literature it has been established that the use of label information can alter overall food purchase behaviour. Furthermore, existing research indicates that most consumers are interested in nutrition information and that they use nutrition labels. However, as many researchers note the actual use of nutrition labels in actual food choice is almost certainly lower than consumers claim in surveys.

In addition, it has been observed that when consumers are confronted by complex food choices in terms of food selection they are less able to make informed choices. For example, Black and Rayner (1992) noted that consumers struggle to understand how to process information when they are shown several nutrients simultaneously. Indeed there is evidence that consumers will employ a heuristic that sees food choices made in terms of a specific nutrient. Evidence from New Zealand reported by Mhurchu and Gorton (2007) indicates that consumers do not understand how to balance the consumption nutrients in their diet and often make choices based on the fat content of food regardless of other nutrient levels. Grunert and Wills (2007) note that in terms of nutrition information interest, calories and/or fat are frequently cited of being of most interest to consumers followed by salt and sugar.

Given these important observations about how consumers cope when making complex food choices as well as preferences for specific nutrients we aim to reveal the relative value that consumers attached to specific nutrients. To do this we examine the TLS from a different perspective to that previously undertaken in the literature. We conduct a Choice Experiment (CE) to examine consumers' willingness-to-pay (WTP) for reductions in the various nutrients as indicated by the TLS, that is Fat, Saturates, Sugar and Salt, in terms of a basket of shopping. This analysis allows us to reveal the relative values placed on the reduction of each specific nutrient in terms of going from Red to Amber and from Amber to Green.

The reason why we employ a basket of goods as opposed to specific products is that the TLS is designed to help food purchase choice as part of a healthy diet.[2] Consumers need to consider the mix of all food being purchased and consumed and assess consumption against the ideal dietary requirement. Thus, there is nothing

[2] Indeed providing this information as part of the shopping experience may well help to improve the overall effectiveness of the TLS.

preventing a consumer from eating a bag of crisps, or a piece of cheese, as long as they compensate for these food types with moderation elsewhere in their diet. Importantly previous research on nutrition labels has identified that consumers find it difficult to employ nutritional label information to place a specific food item within an overall dietary plan (Cowburn and Stockley, 2005). In related research on health claims on food Wansink and Chandon (2006) note that consumers who select a healthy food option frequently over compensate with some sort of indulgence, yielding a negative impact in terms of their dietary intake. For these reasons simply focussing on a single food item within a CE could lead to behavioural outcomes that will not capture how the TLS should be used in helping to achieve a healthy diet.

The emphasis here on a basket of goods as opposed to specific product is not without precedent. For example, a basket of goods as a means to assess dietary goals has previously been employed by Jetter and Cassady (2006) who examined the US Department of Agriculture Thrifty Food Plan diet guide that employs a specific basket of food items. Furthermore, most consumers will engage with the TLS as part of the weekly shopping experience and it is within this context that we should examine the impact of the nutrition label.

Given the design of our CE and the statistical methods we employ to analyse the data we make several contributions to the literature on TLS and nutritional labels in general. First we do not focus on individual products but instead consider dietary choice at the basket level. As a result our analysis reveals the relative weighting of the key nutrients as revealed by our WTP estimates. Second, our results provide information about the degree of asymmetry in response to changes in consumer choice in relation to the colours. That is the relative magnitude of moving from Red to Amber is much greater than that from moving from Amber to Green. This is an important insight into how consumers respond to the TLS which if may help to explain how the food supply chain is responding to the dietary demands of consumers by modifying its processed foods products. Third, the use of a CE to undertake research of nutrition labelling is novel. Most of the existing CE applications in the literature (e.g., Teratanavat and Hooker, 2006, and Bond et al, 2008) have been used to examine health claims on food packaging as opposed to nutritional information. Thus, they examine presence or absence of claim or the strength of a claim for a specific product. In our CE the nutritional label represents the amount of each nutrient within a basket of goods using colour.

On the methodological front our paper adds to a small literature that having employed a CE to generate stated preference data then estimates the resulting Mixed Logit (MXL) model using Bayesian methods. In addition, the model is estimated in WTP space as opposed to preference space, which as Balcombe et al. (2009) explain there are a number of important benefits that emerge as a result of this approach. Finally, we also employ a model specification that allows respondents to be indifferent to the choices presented. We take this approach because of the observation that many consumers employ a simple heuristic when making food choices with respect to nutrients.

The structure of this paper is as follows. We begin by reviewing the literature on the TLS as well as economic issues related to nutritional labels of specific interest to our study. In Section 3 we describe the design and implementation of the survey instrument used in our CE. Then in Section 4 we describe the method of analysis we employ in this paper. In Section 5 we present our survey results and in Section 6 we provide a summary and conclusions in Section 6.

2. Literature Review

2.1. The TLS

The TLS has been the subject of ongoing research and development by the FSA since 2004 (see www.food.gov.uk for more details). As noted by Drichoutis et al. (2006) the development of the TLS can partly be explained as a response to difficulties which consumers had with earlier nutrition label systems. However, the emergence of the TLS has not been a simple or cooperative process on the part of the public and private sectors. Lang (2006) describes in detail the struggle that the FSA have had in bringing the TLS into operation. He notes that research has found that consumers find the TLS easy to use, especially when compared to alternative nutrient food label formats. Yet despite the clear public health motivation for implementing the scheme the food industry, broadly defined, has at times been less than cooperative and frequently openly hostile. For example, some in the food industry have advocated the use of a Guideline Daily Amounts (GDA) system that relates food intake to a total daily target.

There have also been ongoing debates about the use of front or back of packet labels. Overall, in comprehensive reviews of the literature Cowburn and Stockley (2005) and Grunert and Wills (2007) report that research suggests that front-of-label information should be simple with the more complex detailed nutritional information presented on the back. By presenting information in this way consumers are able to make a quick decision at the point of purchase as well as being able to examine in more detail at their leisure specific nutrient details.

Overall there appears to be general support for the use of TLS amongst many health professionals in the UK. For example, the Children's Food Campaign (2007) supports the use of the TLS. They note that the TLS can be employed by consumers very quickly. Other more complex labelling systems increase the risk of widening existing inequalities in food choice. This is because a large proportion of the UK public finds it difficult to understand what many of the numerical values employed on food labels imply about healthy eating.

However, some researchers are less positive about the TLS. For example, Feunekes et al. (2008) examined front-of-pack nutrition labelling for various label formats including the TLS. They conducted survey work across four European countries. Their first study looked at three specific products with each survey participant shown three out of the six nutritional labelling systems being examined. The respondents had to rate the each of the label systems based on liking, comprehension, credibility and perceived healthiness. In general the TLS performed very well except in terms of perceived healthiness per product category. This result led Feunekes et al. to question the overall value of the TLS.

It also needs to be appreciated that although consumers may well prefer simply information presented on the front of packages this does not mean that they react to it (Verbeke, 2005). In fact some evidence available about how consumers actually use the TLS is suggests that there can be a degree of confusion and in some cases not use of the TLS at all. For example, Grunert and Wills (2007) noted that the when it comes to actual use of the TLS not everybody responds to Red as intended because taste overrides considerations related to health. They also note that even though the TLS is a relatively simply nutritional labelling system, consumers can struggle to understand it when attempting to construct a meal.

Finally, there is indirect evidence that consumers do use the TLS. Several food retailers, including Sainsbury's and Waitrose, have adopted the TLS. Based on this there is some evidence which is reported by Grunert and Wills (2007), albeit somewhat weak, that suggests that by adopting the TLS these retailers have subsequently found it advantageous to reformulate certain products, so as to remove the Red light. This would suggest that consumers are responding to the TLS and retailers have responded as they see a change in the mix of products being purchased.

2.2 Economics and Nutritional Labels

There is a large literature that has examined various economic issues associated with the liking, use, understanding and development of nutritional labels. In addition to the material already cited other examples in the literature include Drichoutis et al. (2005, 2006), Gracia et al. (2007), Kim et al. (2000), Loureiro et al. (2006), Verbeke (2005), Variyam (2008), Weaver and Finke (2003).

In general it has been established in the literature that consumers are interested in the provision of nutrition information although the extent and detail of this information as demanded by consumers varies by product as well as context. In a comprehensive review of the literature Drichoutis et al. (2006) observe that most research indicates that consumers do respond to nutritional labels but mostly in a negative manner. That is, consumers appear to wish to avoid things that are considered bad for them. This effect is compounded when it is reinforced with a public health campaign such as those employed in the UK. They also observe that consumers respond to health claims associated with food consumption, as opposed to nutrient labels like the TLS, which can partly help to explain the explosion of functional food products.

In terms of explaining consumer use of labels Drichoutis et al. (2006) note that the findings in the literature to date do not provide a clear set of conclusions. There is no *a priori* reason to expect any specific relationship between income, age or working status to affect the use of labels. There is, however, evidence to suggest that being female and being educated are positively related to label use. Furthermore, having time to shop, being concerned about diet for various reasons such as a diet-disease relation and having prior knowledge about nutrition are all positively related to label use. Finally, as might be expected consumers who are price sensitive are less likely to be interested in and use labels.

In more recent research Loureiro et al. (2006) employed a survey designed to reveal consumer willingness-to-pay (WTP) for a nutritional label on a box of cookies. The WTP values were derived by employing a Contingent Valuation (CV) survey instrument that used a dichotomous choice question format. The survey was conducted in Spain and the sample size was 400 individuals. The motivation behind this research stems from the fact that the EU have been considering the adoption of mandatory food labels on food much like the Nutritional Labelling and Education Act (NLEA) introduced in the US in 1994. This study found that consumers were WTP 11 percent more for a product with this information, although as would be expected this varied by type of consumer. In related research Gracia et al. (2007) used different data from the same survey as Loureiro et al. to see which consumers value the potential introduction of mandatory nutrition labels. Analysing the data by employing a three-equation multivariate probit model they reveal that individuals with food related health problems know more about nutritional labels, and being knowledgeable makes an individual more likely to use a label and that label users do consider mandatory labels as beneficial.

In terms of proximity to our research the survey methods and model estimation employed by Berning et al. (2008) is reasonably close. They employ a CE to examine how the provision of nutritional information on the grocery store shelf label is valued by consumers. The CE employed a number of nutrition label designs and information sets. The purpose of the CE was to reveal consumer preferences regarding label design. Berning et al. used a single product in their CE, a can of tomato soup, and they employed attributes including price, a nutrition label both of which varied in terms of prominence as well as a star rating for the product. Employing a face-to-face survey method a total of 410 individuals participated. The data was analysed using a MXL model employing Classical methods assuming normal distributions for all random parameters in one model and triangular in another. The main finding is that participants express a positive preference for nutrition information on the product shelf, although greater amounts of information do not result in increased use or understanding.

In addition to the research that has employed specific consumer surveys to examine issues of nutritional label use there have also been a number of studies that have examined actual food purchase behaviour (eg, Kim et al., 2000, Weaver and Finke, 2003 and Variyam, 2008). These papers have all made extensive use of the US Department of Agriculture's 1994-1996 Continuing Survey of Food Intakes by Individuals as well as the Diet and Health Knowledge Survey. The reason why this particular part of the literature is relevant to our research is that it has provided insights into the relative importance of nutrients being consumed once nutritional labelling has been introduced. The findings of Kim et al. suggested that significant effects from label use on the consumption of fats, cholesterol, sodium and fiber. However, Variayam has produced results that challenge these findings by employing a difference-in-differences method of estimation so as to deal with issues of self-selection in the data. The findings of this study raise doubts about the extent to which the introduction of the NLEA resulted in changes in nutrient intake except for fiber and iron. Thus, these results indicate only a minimal response on the part of the public to nutritional labels. However, Variayam does acknowledge certain weaknesses with the especially the fact that label effects may vary across socio-economic groups. Furthermore, Variayam observes that the measure of benefit employed does not take account of potential substitution amongst nutrients being consumed. Clearly an analysis that examines the degree of correlation of preference for nutrients can provide insights into this particular issue.

There is also a related literature that has examined the impact of health claims on food packaging. Health claims differ from nutrition labels in that a specific benefit from consumption of the food product is described. With nutrition labels there need be no explicit health claim made, it is left up to the consumer to use the information provided to make a choice that might result in a healthier diet. This basic difference means that health claims are easily examined by data generated by a CE and as a result there are several applications in the literature. This occurs because a CE that considers a health claim need not adjust the product which can be vehicle used to test the health claim. However, with nutrition labels once the mix of nutrients changes this implies a different product and the change in product can confound the choice being made by the survey respondent. For example, Teratanavat and Hooker (2006) and Bond et al. (2008) have both examined how specific health claims impact consumer choice and the resulting WTP for a product. Teratanavat and Hooker employed a CE to examine how much consumers value particular aspects of new and novel food products such as functional food. Bond et al. conducted a similar study expect with a different product. Both papers estimate MXL models employing Classical methods. As is common in literature Bond et al. assumed that their MXL model specification had a fixed (not random) price parameter. As we explain in Section 4 below this is a less than satisfactory assumption.

3. Choice Experiment Design and Data

3.1. Designing and Implementing the Choice Experiment

Our CE was design and implemented so as to examine consumers' WTP for reductions in the nutrients incorporated in the TLS. As we have previously explained we decided to design our CE around a basket of goods as opposed to specific food items. We did this because the TLS is designed to help consumer food choice as part of achieving a healthy diet. As we will explain the final design of the CE we employed allows us to estimate the WTP of each specific nutrient in terms of going from Red to Amber and from Amber to Green.

A critical decision was to frame the choices in terms of a basket of goods rather than a specific item. Our rationale was that a specific item would not reflect the purchasing behaviour of the individual in a general enough way. For example, the response of consumers to the nutrients in a meat pie or ready meal would hardly reflect their responses to a range of items. Consumers are obviously ready to tolerate high levels of nutrients in some items but not others. Our piloting suggested that consumers could readily conceptualize a representative basket.

We began our CE survey instrument design process by presenting a number of draft choice cards to a small group of participants (ie, students and staff). From this we developed our set of CE attributes and the associated levels which we then used to conduct a focus group exercise. The nutrients and the associated TLS colours constituted our main CE attributes. In keeping with the TLS we included four nutrients: Salt, Sugar, Fat and Saturates. Next we devised our basket of goods based on the report produced by Synovate (2005) for the FSA. Based on the mix of goods in our hypothetical basket we then referred to the National Statistics (2007) publication, Family Food in 2005-06 to establish the expected cost of this basket of goods for an average UK household. This yielded a value of £20. Having established the status quo price we determined the number of price points used in the survey. We decided to employ five price points with £20 as the mid point. The other price points used in the CE are £15, £18, £25 and £30. Importantly, we allowed the cost of the basket to be lower than the status quo. We considered it important to offer this option because some consumers may well be far more price sensitive than health sensitive, a behaviour observed in previous CE.

In terms of the survey instrument we began by briefly explaining to participants that the government has introduced a TLS signalling the impact of certain food ingredients on health. We then explained the system in simple to understand language. We then provided an explanation of the task involved in the CE. This is shown in Figure 1.

{Approximate Position of Figure 1}

An important facet with this description of the CE task was that we needed to make it clear to all survey participants that although the choices are **hypothetical** that we needed them to make their choices as if real. Furthermore, we also needed to establish the legitimacy of the cost element in the choice set so that the resulting WTP are as realistic as possible. The development of the information provided in this part of the survey instrument was the result of extensive pre-testing with focus group participants as well as critically discussions with academic colleagues who are experts in food marketing.

An example of the choice card used in the CE is presented in Figure 2.

{Approximate Position of Figure 2}

Having defined our set of attributes (number of attributes by number of levels) it was then necessary to generate the choice sets that would be employed in the CE. Employing a full factorial design, ensuring a balance across all attributes yielded a total of 24 choice sets. To keep the survey task manageable and to avoid response fatigue we blocked the 24 choice sets into four groups of six. Thus, each respondent only answered six choice sets.

In terms of the design, the status quo option, always Option 1, we offered the survey participants two alternative options. We generated the alternative options, always labelled two and three, randomly from the original set of 24, but always ensuring a balance in terms of attribute levels across the design. We also included a "Don't Know" as part of the choice set.

3.2. Survey Returns

The survey was distributed in the mail to some 3,000 UK households. The mail survey was single shot. Survey participants were offered a simple financial incentive to complete the survey. We received 477 returns deemed useable in the analysis we present. We begin our analysis of our survey returns by examining various socio-economic descriptive statistics that are reported in Table 1.

{Approximate Position of Table 1}

Beginning with various socio-economic data we have an average age of respondents is 48 years. This is slightly higher than the average age in the UK which is 39 in 2007. Also it is slightly higher than reported in related research. For example, Loureiro et al (2006) have a sample average of 46.8 years and Berning et al (2008) report 42.4 years. In terms of income our sample average (excluding zero responses which accounted for some 20 percent of the sample) is £24,500. The distribution of income was reasonably evenly distributed. In comparison to population data for the UK average income for non-retired households was £37,600 in 2006/07 and the average for all households including retirees is £30,000. Thus, the reported levels of income are a little below the UK average.

Next turning to the gender mix is we had 81 percent females and 19 percent males. Again this is slightly higher than in related surveys that frequently report rates of female participation in the range of 60 and 70 percent. In terms of actual shopping data for the UK the Department of Transport (2007) report that females make on average 37 percent more food shopping trips than males. Thus, we consider that we have an over-representation of females in our survey albeit only marginally higher than reported in related research. When estimating our models we allow for group effects for gender and other demographics, thus this over-representation does not induce bias in our results. However, when generating an average WTP for our sample (rather than gender specific), this would be biased in favour of females. Accordingly, to illustrate the effect of this bias in our data we present results at the end of our analysis that correct for this imbalance. We assume a 50:50 gender mix which is in keeping with current UK demographics.

In terms of marital status some 73 percent of respondents are married. 67 percent of respondents did not have children living at home. Currently within the UK there are estimated to be 33 percent single households and just over 60 percent of households have no children. Turning to the number of children in the household our sample has on average 0.6. The level of educational achievement in our sample some 30 percent have level of university education (undergraduate and/or postgraduate). Finally in Table 1 we can see that 60 percent of our sample is employed. Note the "Other" category includes those who are retired as well as those who are in various forms of unpaid work such as full time childcare.

Finally, in addition to collecting various socio-economic statistics and participation in the CE we asked survey respondents a number of questions concerning food and health issue. Of our sample of respondents some 94 percent consider themselves to be health conscious. In terms of food label use the vast majority of respondents claim read food labels some of the time. We also asked survey participants to rank the nutrients that appear on the FSA TLS. Ranking, Salt, Sugar, Fat and Saturated Fats on a scale of 1 to 4 in terms of most to least important in terms of wellbeing we found the following average scores: Salt = 2.4; Sugar = 2.9; Fat = 2.6; and Saturates = 2.1. These indicate that Saturates followed by Salt are considered the most important in terms of making a negative impact on the wellbeing of respondents.

4. Econometric Methods

The main objective of this paper is to estimate the consumer WTP from a CE designed to avoid high levels of nutrients as indicated by the TLS. To analyse our CE data we employ Bayesian methods to estimate the MXL model following Balcombe et al. (2009).

Formally, let $x_{j,s,n}$ denote a $k \times 1$ vector of attributes from the CE presented to the jth individual ($j = 1, \ldots\ldots, J$) in the sth option ($s = 1, \ldots., S$) of the nth choice set ($n = 1, \ldots., N$). Next assume that $U_{j,s,n}$ be the utility that the jth individual attains from $x_{j,s,n}$. In addition, let $y_{j,s,n}$ be an indicator variable that is equal to one if the jth individual chooses the sth option within the nth choice set, and zero otherwise. Finally, define $f(x)$ and $f(x_j)$ to denote the density and conditional density functions and $F(x)$ and $F(x_j)$ to be the associated cumulative distributions.

An individual j is assumed to receive linear utility from the sth choice in the nth choice set, although the parameters may be transformed. Consequently, the utility function is of the form

(1) $U_{j,s,n} = x'_{j,s,n} t(\beta_j) + e_{s,j,n}$

where β_j is a $(k \times 1)$ vector describing the preferences of the jth individual and $t(.)$ is some transformation of the parameters. The error term $e_{s,j,n}$ is assumed to be extreme value (Gumbel) distributed, independent of $x`_{s,j,n}$ and uncorrelated across individuals or choices.

The function $t(.)$ can take a number of forms (see Balcombe et al., 2009). Specifically, we employ the censored normal for random parameters except the price of the basket, such that the preference distribution is censored from below at zero, with a mass point occurring at zero. By censoring the normal distribution from below at zero yields a mass point at zero so that with β normally distributed with mean b and variance σ the transformation is $t_n = max(0,\beta)$. Values of b and σ, and hence t, are estimated giving the population proportions massed at zero and above zero. With respect to price we employ a log-normal transformation $t(\beta)=exp(\beta)$ with the distribution bounded below at zero and with zero probability mass at zero.

The reason why we employ a bounded distributions is because we consider it necessary to accommodate indifference on the part of survey respondents in our CE. If we allow a respondent to be indifferent with respect to some attributes this implies that we are allowing marginal utility to be equal to zero for these attributes. The reason for wishing to allow indifference is that we do not believe that respondents are negatively disposed to particular attributes. But for the case of food and choice based on nutrient content it is highly likely that certain individual's will be indifferent to some of the attributes because of health concerns or dietary requirements and/or restrictions. Their choices will be driven by a subset of the attributes and there is evidence from the literature to support this view (eg., Black and Rayner, 1992, and Grunert and Wills, 2007).

Another important feature of the MXL model we employ is that we estimate our model in WTP space. Balcombe et al. (2009) observe it may be appropriate to estimate the MXL in WTP space, as opposed to in preference space which is the conventional approach adopted in the literature. In order to estimate the MXL in WTP space we can employ a reparameterisation of the form:

(2) $$t(\beta_j) = t_1(\beta_{1j})(1, t_2(\beta_{2j}), \ldots\ldots\ldots t_k(\beta_{kj}))'$$

which means that the quantities $t_2(\beta_{2j}), \ldots\ldots\ldots t_k(\beta_{kj})$ are the Marginal Rates of Substitution (MRS) with the numeraire being the first attribute, which will always be the price or cost attribute within the given CE. There are important benefits to be gained from adopting this approach to MXL model estimation. Specifically, when we estimate the MXL model in preference space we first estimate marginal utilities and the various MRS are derived from these. However, by estimating in WTP space the MRS are estimated directly and this can significantly reduce the instability associated with WTP estimates derived in preference space. The instability is avoided as the need to derive estimates based on the ratio of random variables, which are by construction volatile, is no longer necessary. The instability WTP estimates derived in preference space has been found to be particularly problematic when the payment vehicle (price or cost attribute) is variable and not bounded above zero. As a result this has lead to researchers fixing the payment coefficient (eg, Bond et al, 2008) which is an *ad hoc* approach to resolving the instability. However, fixing the price coefficient may violate other modelling requirement as well as being behaviourally inappropriate if we assume that individuals' responses vary independently of socio-economic characteristics.

To implement the Bayesian approach to estimation of the MXL we simulate the posterior distribution of the mean and variance/covariance of the preference parameters $\{\beta_j\}$. In the Bayesian literature the algorithm used to undertake the simulation is referred to as the "the sampler". A detailed description of the algorithm, in this case Gibbs with a Metropolis-Hastings (M-H) Step which is based on Balcombe et al. (2009) is provided in an Appendix.

For the analysis we present we have generated all posterior distributions by mapping 10,000 draws from the posterior sampler. As is common practice in Bayesian econometrics we have paid particular attention to the performance of the sampler to ensure convergence has been achieved. To test for convergence we initially observe the values of the parameters sequentially generated by the sampler. If our model is correctly specified and performing appropriately our parameters should move away from their initial starting points and by the time that the burn has finished they should be stable about a mean. To ensure that there is minimal dependence in the sampled values we estimate the autocorrelation coefficients for the sequential values generated by the sampler. To minimise problems of dependence we draw every kth value (in this model we took very 1 in 500 values) in a sequence generated by the sampler where the number of draws is set so as to minimise the degree of dependence. Following Koop (2003) we formally test for convergence by employing a modified t-test for which the null hypothesis is no-difference between the first and second half of the sampled values (with a sub-set of values removed from the middle).[3]

5. Results

Our preferred specification allows for potential heterogeneity in all the parameters characterising preferences. As a result of model examination and behavioural expectations regarding indifference we present results for a MXL estimated in WTP

[3] Details of the likelihood and priors employed in the estimation are provided in an appendix to the paper.

space. To allow for the possibility of indifference to the various attributes we have employed a censored normal distribution for all parameters except the price of the basket of goods which we have modelled as a log-normal distribution.

The model specification we estimate takes the following form

(3)

$$U_i = \beta_{i,1}(\Pr ice_i + \beta_{i,2} SatAG_i + \beta_{i,3} SatRG_i + \beta_{i,4} FatAG_i + \beta_{i,5} FatRG_i + \beta_{i,6} SugAG_i + \beta_{i,7} SugRG_i + \beta_{i,8} SaltAG_i + \beta_{i,9} SaltRG_i + \beta_{i,10} StatusQuo_i) + e_i$$

where Price is the cost of the basket, Sat is saturates, Fat is fat, Sug is sugar, Salt is salt and StatusQuo is a dummy variable to see if respondents showed a bias toward selecting the default option. For each of the nutrients we have estimated the change from Amber to Green (A/G) and Red to Green (R/G). These parameters provide us with a measure of how much our survey respondents are WTP to reduce their exposure to higher levels of the various nutrients. Finally, Status Quo captures Option 1 in all choice sets which we devised based on an examination of current consumption activity and the levels of the various nutrients being consumed. Each of the parameters is then conditioned on a set of socioeconomic characteristics as discussed in Section 3. In this case each parameter is expressed in terms of

(4) $$\beta_{ij} = a_{0,j} + a_{1,j} Gender_i + a_{2,j} Age_i + a_{3,j} Children_i + a_{4,j} Education_i + u_i$$

These estimates can then be used to construct the WTP estimates for groups by Gender, Age, Children and Education. In each case respondents are separated into two groups within each of these categories: Male/Female, Young/Old, With/Without Children and Less/More Educated. Finally, the error terms (u_i in equation 4) can be correlated. This would be expected because we would expect that people that responded more with respect to a particular nutrient (e.g. Salt) would also be more responsive with respect to the other nutrients also (e.g. Fat).

Our results and the resulting WTPs based on this specification are reported in Table 2.

{Approximate Position of Table 2}

In Table 2 we report the mean, standard deviation and median of the resulting posterior densities. The reason for reporting both the mean and median is that for the indifference model these represent quite different aspects of the underlying distribution. If over 50% of consumers are indifferent to an attribute the median might be zero, but the mean may still be (potentially) quite large. As a result Balcombe et al. (2009) advocate that researchers report both the mean as well median. In the resulting analysis we generally focus on the median, although for this data set the differences are minor.

From the results presented in Table 2 we can see that the change from Red to Green (R/G) yields a much larger estimate for all nutrients compared to the change from Amber to Green (A/G). This implies that there is a strong aversion to Red for all nutrients. This asymmetric response is in keeping with those reported by Drichoutis et al (2006). We can also see that the largest mean and median estimates are for Salt and the smallest for Fat. This finding is interesting given the high profile campaign employed by the FSA in the UK to draw attention to salt in the diet and the associated health effects of excessive consumption.[4]

In addition, for Fat (A/G) the median is equal to zero indicating that a large number of consumers are indifferent to the change in the level of this nutrient. This implies that consumers are concerned about reducing high levels of Fat in their diet but far less concerned about reducing Fat significantly. We can also see that the status quo parameter estimate is positive indicating a positive preference for this preference for this option. However, the relative magnitude of the estimate is much smaller than any of the Red to Green changes for all the nutrients.

Overall we note that the resulting WTP estimates are reasonably large. For example, the WTP estimate for moving from Red to Green for Salt is £19. Although this is higher than we anticipated the magnitude of the estimate can be partly linked to the price attached to the basket of goods. It will be important in subsequent research to examine this aspect of the CE design in more detail to see if modifying the basket of goods and associated price has a significant impact on the associated WTP.

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[4] The FSA have a stated objective of reducing average salt consumption of adults in the UK to 6g a day by 2010. This objective comes from the Scientific Advisory Committee on Nutrition who where concerned about excessive salt consumption and related health problems such as high blood pressure and the associated increased risk of strokes and cardiovascular disease. To achieve this objective the FSA launched its first Salt Campaign in September 2004, it has engaged with various food organisations asking them to reduce the salt content of food, and in March 2006 it published targets for reductions in salt consumed by consumers backed up by high-profile TV ads.

Next we report the correlation structure between the regression coefficients. Our estimates are shown in Table 3

{Approximate Position of Table 3}

The results in Table 3 show that the regression coefficients for the various food ingredient attributes are all negatively related to price. Furthermore, as we might expect, all the ingredients are positively correlated. However, there is an interesting pattern for Saturates, especially R/G with, in that the correlation estimates are much smaller than for all the other nutrients. Thus, reductions in nutrient consumption of Salt, Sugar and Fat are not matched by anywhere near the same reduction in Saturates. Overall, our correlation estimates provide support for our CE in terms of respondents interacting appropriately with the task required.

We next report results for the same model specification including a number of key socio-economic variables in our model which are interacted with each of the parameters in the model as described by equation (3). The socio-economic variables we have employed are gender (male or female), age (young (less than 46) or old ((more than 46)), children in then household (yes or no), and level of education (school or higher). By including these socio-economic variables we are able to provide estimates of how these various characteristics impact the WTP estimates. Unfortunately we have not included income in the analysis because of the relatively large number of undisclosed responses in the survey returns.

{Approximate Position of Table 4}

The first thing to note in Table 4 relates to the differences between Men and Women. It is very clear that Men have lower estimates across the board compared to Women. This implies that Women are WTP more to avoid nutrient quantities labelled Red and Amber compared to Green. These differences equate to Men being WTP almost a third less than Women. The second set of results in Table 4, refer to differences associated with Age. On the whole there appear to be only minimal differences between our Age categories which suggests' that this socio-economic characteristic is not that important in terms of explaining WTP.

In the lower part of Table 4 reports results for differences in WTP depending on if a household includes children. Although the differences are not that large there is evidence to suggest that households with children are WTP more to consume food with lower levels of all nutrients compared to those without children. Finally, we examine how the level of education affects WTP. As we might expect from existing results in the literature those respondents with a higher level of education are WTP more to have lower levels of nutrients.

The final part of our analysis presents results when we take account of the bias in the sample of the high proportion of females (81 percent). By imposing an equal sample weight of 50 percent we have recalculated the model results. Our results are reported in Table 5.

{Approximate Position of Table 5}

The revised results in Table 5 are compared against the original results reproduced from Table 2. As can be seen, by re-weighting the sample to increase/decrease the proportion of males/females we have reduced all the resulting WTP estimates. This result is not that surprising given the results we have previously considered regarding Gender and presented in Table 4. However, these results do indicate that if we wish to extrapolate from our results to those of the general public it will be necessary to ensure that we correctly reflect current socio-economic and demographic characteristics.

6. Summary and Conclusions

In this paper we have developed and analysed a CE to examine how consumers respond to the TLS introduced by the FSA. Overall our results indicate a very strong preference on the part of UK consumers to reduce the quantity of any nutrient identified with a Red Light. From this response we can conclude that the role of the TLS to inform consumers appears to be understood. We have also identified that consumers are most concerned by Salt and Saturated Fats when it comes to judging nutrient content and much less so by Fat and Sugars. In addition, we have identified that particular parts of the population respond differently to the TLS in a manner that we would expect from previous research on the use of nutrition labels. Overall our results provide an interesting hypothesis that can be tested with actual purchase data. That is if we examine actual food purchase data can we see a strong movement away from Reds, and much smaller movement from Amber to Green. Secondly, if there is a preference regarding nutrients are these being revealed in actual food purchase behaviour.

These findings provide strong support for the use of the TLS in terms of consumer understanding and planned shopping behaviour. If the policy agenda is encourage consumers to move away from purchasing items with very high levels of unhealthy nutrients, then this is a significant finding. However, it is difficult to know if the hypothetical behaviours identified will be replicated in actual shopping behaviour. This is, of course a problem with all stated preference methods and studies. Currently, anecdotal evidence suggests that this is the case but further research combining revealed and stated preference data (data from actual purchase behaviour and data generated by a hypothetical CE) could significantly enhance our understanding of this issue. In addition, it is unclear if the consumers are really responding to the information content associated with the TLS or whether we are simply observing a decision based on the colour scheme used. Further research to examine the extent to which information as opposed to colour of the TLS guides decisions is worthy of further consideration. Indeed, it may well be the case that a key difference between the TLS and other schemes are that the colours not only provide information but convey a strong normative message. This would go some way to explaining the very high WTPs we observe.

Appendix – Likelihood and Priors

Following Balcombe et al. (2009) we can assume that the parameters β_j are ordered. Thus, they may contain fixed parameters $c`_j$ as well as random parameters $b`_j$

$$\beta`_j = (c`_j, b`_j)$$

Both sets of parameters can be conditioned on appropriate socio-economic variables for any individual where preferences are determined by a vector z_j, which is an $(h\times1)$ vector of variables. Thus, defining $Z_j = I_k \otimes z_j$, the components of $\beta`_j$ are defined as:

$$c_j = Z`_j\alpha_c$$
$$b_j = Z`_j\,\alpha_b + u_j$$

where u_j is a independently and identically normally distributed vector with variance covariance matrix Ω.

Next define the set of all stated choices by an individual as $Y = \{y_{j,s,n}\}_{j,s,n}$, the set of characteristics describing all respondents by $Z = \{z_j\}_j$, the set of options given to the jth individual is $X_j = \{x_{j,s,n}\}_{s,n}$, the set of all option sets given to all respondents is $X = \{X_j\}_j$ and the set of all data is $D = \{Y,Z,X\}$. Finally, we describe the collection of all parameters describing the model as $\Theta = (\alpha,\Omega)$ the set $\{b_j\}_j$ denoted as B refers to B as latent data. Note, for notational convenience the multiple integral

$\int_{\beta_n} .... \int_{\beta_1} db_1 .... db_n$ is expressed as $\int_B \; dB$.

Given this notation we can we can define the probability that an individual j will make a given set of choices. Formally,

$$p_j = \prod_{n=1}^{N} \prod_{s=1}^{S_n} \left(\frac{e^{t(\beta_j)' x_{j,s,n}}}{\sum_{s=1}^{S_n} e^{t(\beta_n)' x_{j,s,n}}} \right)^{y_{j,s,n}}$$

Therefore, we can express the likelihood function for the choices made (given a selection of a model t) as:

$$L(\Theta|D,t) = \int_B \left(\prod_{j=1}^{J} p_j \right) dF(B|\Theta,Z)$$

Thus, the posterior distribution of the parameters $\pi(\Theta|D,t)$ (in a Bayesian framework) is:

$$\pi(\Theta|D,t) \propto L(\Theta|D,t)\pi(\Theta)$$

Where $\pi(\Theta)$ is the prior distribution for the parameters that are independently normal for the parameters α_c and α_b and Inverse Wishart (IW) for Ω. More specifically for the prior for α we assume

$$(\alpha_c', \alpha_b')' = \alpha \sim f_N(\alpha|\mu, A_0)$$

where μ is the mean and A_0 is a diagonal matrix. With respect to the prior is Ω

$$\Omega \sim f_{IW}(\Omega|T_0, \nu_0)$$

For the priors we employ the hyper parameters which are set *a priori* are μ, A_0, T_0 and v_0. Our choice of priors is determined by reference to the literature as well as our own experiments with the data to check for robustness of results generated.

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Table 1: Survey Descriptive Statistics

Socio-Economic Data	**Variable**	
Age (Years)	Average Age in sample	48.34 (13.3)
Income (£ 000's)	Average Income in sample	24.5 (21)
Gender	Male Female	19% 81%
Marital Status	Married Single Other	73% 11% 16%
Number of Children in Household Children	0 1 2 3 4	67% 13% 14% 5% 1%
Educational Achievement	School to 16 A Level or equivalent Further Education University Undergraduate University Postgraduate Higher	25% 11% 32% 18% 12% 2%
Employment Status	Employed Self-Employed Unemployed Other	48%, 12% 15% 25%

Table 2: MXL Results for Indifference Model

Attributes	Posterior Parameter Estimates		
	Mean	Standard Deviation	Median
Price	1.720	1.504	1.297
Saturates-A/G	0.437	0.424	0.355
Saturates-R/G	1.727	0.591	1.741
Fat-A/G	0.120	0.197	0.000
Fat-R/G	1.208	0.519	1.207
Sugar-A/G	0.381	0.372	0.311
Sugar-R/G	1.422	0.437	1.438
Salt-A/G	0.263	0.310	0.151
Salt-R/G	1.932	0.540	1.959
SQ	0.366	0.316	0.323

Table 3: Mixed Logit Correlation Matrix

	Price Coefficient	Saturates (Amber)	Saturates (Red)	Fat (Amber)	Fat (Red)	Sugar (Amber)	Sugar (Red)	Salt (Amber)	Salt (Red)	Status Quo
Price Coefficient	1.000									
Saturates (Amber)	-0.362	1.000								
Saturates (Red)	-0.216	0.288	1.000							
Fat (Amber)	-0.368	0.534	0.193	1.000						
Fat (Red)	-0.414	0.558	0.289	0.725	1.000					
Sugar (Amber)	-0.371	0.524	0.211	0.742	0.768	1.000				
Sugar (Red)	-0.379	0.564	0.228	0.699	0.754	0.764	1.000			
Salt (Amber)	-0.334	0.472	0.143	0.682	0.653	0.658	0.623	1.000		
Salt (Red)	-0.395	0.483	0.327	0.659	0.724	0.687	0.677	0.656	1.000	
Status Quo	0.206	-0.276	-0.154	-0.300	-0.329	-0.316	-0.283	-0.341	-0.344	1.000

Table 4: MXL Results – Socio-Economic Variables

Attributes	Women				Attributes	Men		
	Mean	Stdv	Median			Mean	Stdv	Median
Price	1.751	1.516	1.330		Price	1.560	1.365	1.181
Sat-A/G	0.465	0.431	0.394		Sat-A/G	0.319	0.373	0.187
Sat-R/G	1.847	0.537	1.842		Sat-R/G	1.203	0.548	1.200
Fat-A/G	0.117	0.195	0		Fat-A/G	0.121	0.197	0
Fat-R/G	1.278	0.497	1.276		Fat-R/G	0.883	0.489	0.874
Sug-A/G	0.394	0.374	0.327		Sug-A/G	0.344	0.356	0.257
Sug-R/G	1.518	0.387	1.519		Sug-R/G	0.995	0.404	0.993
Salt-A/G	0.274	0.317	0.162		Salt-A/G	0.210	0.281	0.056
Salt-R/G	2.051	0.470	2.050		Salt-R/G	1.387	0.508	1.385
SQ	0.383	0.316	0.352		SQ	0.292	0.291	0.229
Attributes	Older				Attributes	Younger		
	Mean	Stdv	Median			Mean	Stdv	Median
Price	1.692	1.475	1.277		Price	1.708	1.473	1.291
Sat-A/G	0.463	0.432	0.392		Sat-A/G	0.406	0.415	0.308
Sat-R/G	1.722	0.565	1.729		Sat-R/G	1.722	0.613	1.742
Fat-A/G	0.123	0.199	0		Fat-A/G	0.116	0.193	0
Fat-R/G	1.283	0.509	1.284		Fat-R/G	1.124	0.517	1.125
Sug-A/G	0.401	0.376	0.341		Sug-A/G	0.354	0.360	0.273
Sug-R/G	1.498	0.416	1.509		Sug-R/G	1.346	0.444	1.368
Salt-A/G	0.278	0.317	0.172		Salt-A/G	0.246	0.304	0.117
Salt-R/G	2.038	0.501	2.041		Salt-R/G	1.826	0.550	1.854
SQ	0.415	0.323	0.387		SQ	0.323	0.298	0.275

Attributes	Children				Attributes	No Children		
	Mean	Stdv	Median			Mean	Stdv	Median
Price	1.853	1.584	1.402		Price	1.652	1.414	1.255
Sat-A/G	0.419	0.421	0.329		Sat-A/G	0.444	0.429	0.363
Sat-R/G	1.926	0.566	1.933		Sat-R/G	1.625	0.587	1.641
Fat-A/G	0.112	0.190	0		Fat-A/G	0.123	0.207	0
Fat-R/G	1.267	0.508	1.270		Fat-R/G	1.172	0.521	1.176
Sug-A/G	0.350	0.358	0.267		Sug-A/G	0.396	0.372	0.334
Sug-R/G	1.495	0.414	1.504		Sug-R/G	1.385	0.446	1.405
Salt-A/G	0.270	0.317	0.155		Salt-A/G	0.259	0.309	0.143
Salt-R/G	2.037	0.510	2.055		Salt-R/G	1.876	0.550	1.908
SQ	0.333	0.304	0.284		SQ	0.381	0.318	0.346
	Higher Education					School Education		
	Mean	Stdv	Median			Mean	Stdv	Median
Price	1.693	1.458	1.276		Price	1.697	1.461	1.280
Sat-A/G	0.479	0.438	0.409		Sat-A/G	0.411	0.416	0.316
Sat-R/G	1.901	0.591	1.910		Sat-R/G	1.633	0.574	1.656
Fat-A/G	0.103	0.183	0		Fat-A/G	0.125	0.200	0
Fat-R/G	1.212	0.515	1.211		Fat-R/G	1.192	0.517	1.195
Sug-A/G	0.382	0.369	0.309		Sug-A/G	0.377	0.369	0.304
Sug-R/G	1.493	0.433	1.509		Sug-R/G	1.388	0.435	1.406
Salt-A/G	0.285	0.321	0.182		Salt-A/G	0.254	0.308	0.139
Salt-R/G	2.062	0.530	2.082		Salt-R/G	1.861	0.533	1.893
SQ	0.367	0.315	0.329		SQ	0.369	0.316	0.332

Table 5: MXL Results Indifference Model – Re-weighted for Gender

	Re-Weighted Sample			Base Sample		
Attributes	Posterior Parameter Estimates			Posterior Parameter Estimates		
	Mean	Standard Deviation	Median	Mean	Standard Deviation	Median
Price	1.656	1.441	1.256	1.720	1.504	1.297
Sat-A/G	0.392	0.402	0.290	0.437	0.424	0.355
Sat-R/G	1.525	0.542	1.521	1.727	0.591	1.741
Fat-A/G	0.119	0.196	0	0.120	0.197	0.000
Fat-R/G	1.081	0.493	1.075	1.208	0.519	1.207
Sug-A/G	0.369	0.365	0.292	0.381	0.372	0.311
Sug-R/G	1.256	0.395	1.256	1.422	0.437	1.438
Salt-A/G	0.242	0.299	0.109	0.263	0.310	0.151
Salt-R/G	1.719	0.489	1.717	1.932	0.540	1.959
SQ	0.337	0.303	0.291	0.366	0.316	0.323

Figure 1: The Choice Experiment Survey Description Page

Section C: Survey Description

We are going to ask you 6 questions concerning food choice.

You simply indicate the basket you would buy if offered these options in a shop.

The options presented relate to an individual's weekly basket of food which might include:

- Ready meals
- Chicken burgers/pizzas
- Pasta ready meals/curry ready meals
- Cake/crisps
- Cereal bars/breakfast cereals

We describe the basket of food using the Traffic Light System and cost.

The cost of the basket is for a typical UK consumer for one week's shopping.

This is, on average, about £20.

In the survey, an option would be described as follows:

Food Basket	***Option A***
Salt	Green
Sugar	Green
Fat	Amber
Saturates	Green
Price	£20

This column represents the nutrient content in a basket of goods. We simply call this basket Option A. Using the Traffic Light System we code each nutrient. Finally, £20 is the price for buying this basket of goods

Figure 2: Sample Choice Card

CHOICE CARD 1				
Food Basket	***Option 1***	***Option2***	***Option3***	
Salt	Amber	Red	Green	**Don't Know**
Sugar	Amber	Green	Amber	
Fat	Red	Amber	Red	
Saturates	Amber	Amber	Red	
Price of basket	£20	£25	£30	
Tick ONE and only one box				