University of Alberta

Three Essays on Genetically Modified Food Labelling and Consumer Behaviour

by

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DEDICATION

This work is dedicated to my parents Xiaoru Liu and Hua Hu and my sister Wenyue Hu. Their forever love and support is beyond the reach of any language.

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Chapter 1 Introduction

Background

Modern agricultural biotechnology, referred to here as genetic modification (GM), has developed rapidly in the previous decade. For crop products, in 1990, virtually no GM crops were grown commercially in the western world. By the end of 2002, GM or transgenic crops were grown on more than 58 million hectares of land (ISAAA 2003). Canada's federal government has approved about 10 varieties of GM crops and more than 50 different types of GM foods, including corn, canola, soybean and potato (CFIA 2004). Canada, together with Argentina, the United States, and China produce more than 99% of the world's GM food (ISAAA 2003). The extent of genetic modification in agricultural products is expanding in several senses. First, more products are subject to GM testing and may appear in the market in the near future. For example, GM wheat is being tested in Canada and discussion is ongoing on whether it should be commercialized (CFIA 2004). Second, in addition to the first generation of GM technology, which refers to applications designed to reduce farm costs by varieties that strengthen plant disease resistance, impart herbicide resistance, or generate yield improvements (Runge and Jackson 1999), second generation GM technology has started to appear which will have a direct effect on products' final consumer characteristics (Rousu et al. 2003).

Usually new technology comes with uncertainties and concerns. This is especially true for the GM technology. The development and application of GM technology has generated a great deal of controversy, and even the proper name of this new technology has not been settled (Huffman 2003). Since the beginning of the GM phase, different entities from all aspects of society, particularly represented by pro-GM biotechnology companies and anti-GM environmental groups, have addressed issues concerning animal welfare, ethics, environment, economics and trade, and human health (Veeman 2001, Einsiedel 2002, Hossain et al. 2003, Hobbs 2003, Huffman 2003). One such issue is the labelling of GM food. There are currently two major types of GM labelling policies being used in the world: mandatory labelling in the European Union, Australia and most of Asia, and voluntary labelling in the United States and Canada. In the context of mandatory labelling, all products that contain GM ingredients must be labelled, while under a voluntary labelling regime, food producers can choose whether to label their products. Proponents of mandatory labelling argue that consumers have the right to know what is in their food and mandatory labelling is the only way that this information can be efficiently declared to consumers. Supporters of voluntary labelling however argue that the social cost of mandatory labelling is too high and the labelling of something that has unproven adverse effects is not necessary. Discrepancies in these two types of labelling requirements have already caused an international trade dispute (Huffman 2003).

What makes the debate complicated is the lack of research or scientific support. Despite their importance, issues associated with GM labelling and consumer behaviour have rarely been the focus of social science or economic research. The objective of this thesis is to attempt to fill this void. Specifically, using consumers' stated choices for pre-packaged sliced bread, this thesis addresses various issues associated with the labelling of GM food and consumer behaviour, with the hope of providing a timely contribution to the general discussion. In three separate but closely related papers, the following issues are investigated: consumers' behaviour under different labelling systems and the value of information revealed in these labelling policies; behavioural interpretation of impacts from consumers' psychological status; and heterogeneity and variability in choices and implied welfare measures.

Research Methodology and Plan

The analysis in this thesis is conducted within a random utility framework. However, each paper explores a unique aspect of the basic model based on random utility theory in the context of GM food choice and GM labelling.

The first paper examines how different GM labelling policies may affect consumers' choice of pre-packaged sliced bread. It also attempts to recognize the heterogeneity among consumers' tastes relative to various bread attributes and identification of the presence/absence of GM ingredients in bread products. Most of the current debate on labelling policies focuses on the cost side while the benefit of labelling, especially to the end consumers, is often neglected. A welfare measure adjusted from the conventional approach is applied in the paper to calculate the value of information revealed in each labelling policy. Built on simulation techniques, the adjusted measure of the value of information can reflect consumers' uncertainties associated with a GM attribute in bread. The benefit of the two labelling policies in terms of average market prices for bread products is also calculated in the paper. This provides a readily accessible guideline from the benefit side for policy makers to apply benefit-cost analysis to GM labelling.

The second paper extends current economic analysis of consumer behaviour by incorporating conclusions from studies in psychology. In the context of GM bread, consumers may be uncertain about the presence/absence of GM ingredients. The information revealed in a label will help them to reduce this uncertainty. However, different labelling policies may cause the revealed product attribute to differ from consumers' perceived attribute (price or quality). The difference between the actual and perceived attribute level creates an effect commonly known as the reference point effect. In this paper, a method to capture these reference point effects is designed and applied in a testable economic model. Account is taken for heterogeneity as well as possible sources for reference point effects. The value of information, defined in a similar way as in the first paper, is also calculated.

In the third paper, again using consumers' choice of GM bread as a vehicle, general practices for modeling heterogeneity in consumers' choice behaviour are enhanced. In addition to consideration of heterogeneity in consumers' sensitivities around reference point effects, this paper recognizes other factors that may cause choices to vary, such as context effects, the complexity of choice tasks, or consumers' demographic characteristics. This paper presents a method that provides a much richer explanation of consumers' choice behaviour by jointly considering taste heterogeneity together with choice variability.

Data

Data for this research were collected through a stated preference survey. As mentioned previously, the food product that is selected for study is pre-packaged sliced bread with possible genetically modified ingredients. There are two major reasons that bread was chosen as the target product. First, bread is commonly consumed by Canadians so there is no need to explain the product. Thus, the biases associated with unfamiliarity and the explanation itself are reduced. Second, GM bread is not currently approved by the government of Canada for production or sale in the market. This is expected to limit some pre-existing biases before the survey. These biases may include the possibility that consumers may have formed some beliefs on the product prior to the survey and therefore do not trust the hypothetical products described in the survey. In this case, choices reported by these consumers may not reflect their true assessments.

Before the formal survey was implemented, focus group discussions were conducted during May to August 2002 at the University of Alberta. The focus groups consisted of members of the general public recruited through the population research lab of the University of Alberta. The purpose of these focus group discussions was two-fold. The first purpose was to determine the product attributes to be used in the survey. The following attributes were determined to be the most important: brand name, type of flour, freshness, presentation and price. All but freshness and presentation were included as attributes. Freshness and presentation were standardised in the product descriptions. We by explicitly telling consumers in the survey questionnaire that "the bread you buy is FRESH and WELL PRESENTED (i.e., no damaged slices, packaging, etc.)." The second purpose of the focus group discussions was to find out whether consumers might have difficulties in responding to the questionnaire as this was initially planned.

The formal survey was carried out in December 2002 and completed in January 2003. There are four sections in the survey: First, information on respondents' usual bread purchase habits (price and quality) and their general perceptions on food safety issues was collected[1]; second, a stated preference choice-based conjoint experiment was conducted. The attributes and levels within each attribute are shown in Table 1.1. Following Louviere et al. (2000), these attributes were brought into a fractional factorial design. The design considered the main and first-order interaction effects between attributes. The first two alternatives in a choice set were described by attributes and the last alternative was a "choose-none" option. A total of 64 choice sets were produced by the design. The two labelling contexts, together with a base situation (where any type of label may appear), were applied to the resulting design and yielded 192 ($=64\times3$) choice sets. Under each of these three labelling conditions (each has 64 choice sets), choice sets were blocked into 8 segments with each segment comprising 8 choice tasks. Each individual was randomly assigned to one of the three labelling conditions with one segment (comprising 8 choice tasks) of the overall 64 choice sets. In the third section, participants' attitudes to GM-related issues were obtained, and lastly, respondents' social economic and demographic characteristics were collected.

The survey was conducted online. Computer-aided surveys are becoming increasingly popular in many areas. Computers enable interactive or randomized survey approaches, which is particularly relevant to choice-based conjoint experiments. These features cannot be achieved through traditional paper-based surveys. Although face to face and live telephone surveys may yield similar outcomes as computer-aided surveys, they are only capable of cruder measures[2] than may be available with computer aided technology and survey results may be affected by the interviewer at the point of the survey. A sample survey questionnaire is attached in Appendix A. Although a potential draw-back related to internet-based surveys is that respondents are required to have access to the internet when they complete the survey, it is believed that internet usage is fairly common among Canadians (Statistics Canada 2004). This particular draw-back associated with internet-based surveys, although recognized, did not outweigh the benefits of the approach.

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[1] Following Burton et al. (2001), in this section, questions asking for respondents' perceptions on the presence of GM attribute were carefully blended with questions on other attributes to avoid anchoring effects.

[2] This is mainly due to the interviewer bias introduced by survey enumerators (Rea and Parker 1997).

The survey was presented to a sample of Canadian consumers from a representative panel composed of more than 40,000 households. The panel is administered by a professional marketing company. Invitation letters were sent to those individuals who showed interests in food-related surveys when they registered in the panel and when each respondent signed into the survey, they were given a unique PIN number for identification purposes. The survey was kept active until we obtained our target sample size. A total of 882 completed surveys were collected. Approximately half of these responses included the survey experiment on which this thesis study is based[3]. Figure 1.1 shows some sample characteristics. Compared with the overall general Canadian population, we conclude that the sample is reasonably representative. However, there are several differences that are noteworthy. The sample used in this study had a lower proportion of younger individuals but a higher percentage of individuals aged between 55 and 64. Apart from those who did not report their yearly income, low income families were under-represented and high income families were over-represented. The sample also contained a higher-than-standard proportion of individuals that had received higher education.

Organization

The remainder of the thesis is set out as follows. Chapters 2 though 4 each address a research topic outlined earlier in this chapter: consumers' behaviour under different labelling systems and the value of information revealed in these labelling policies; behavioural interpretation of impacts from consumers' psychological status; and heterogeneity and variability in choices and implied welfare measures. The fifth chapter concludes this thesis and puts forward possibilities for further development.

[3] The other half of the sample are used in a different study.

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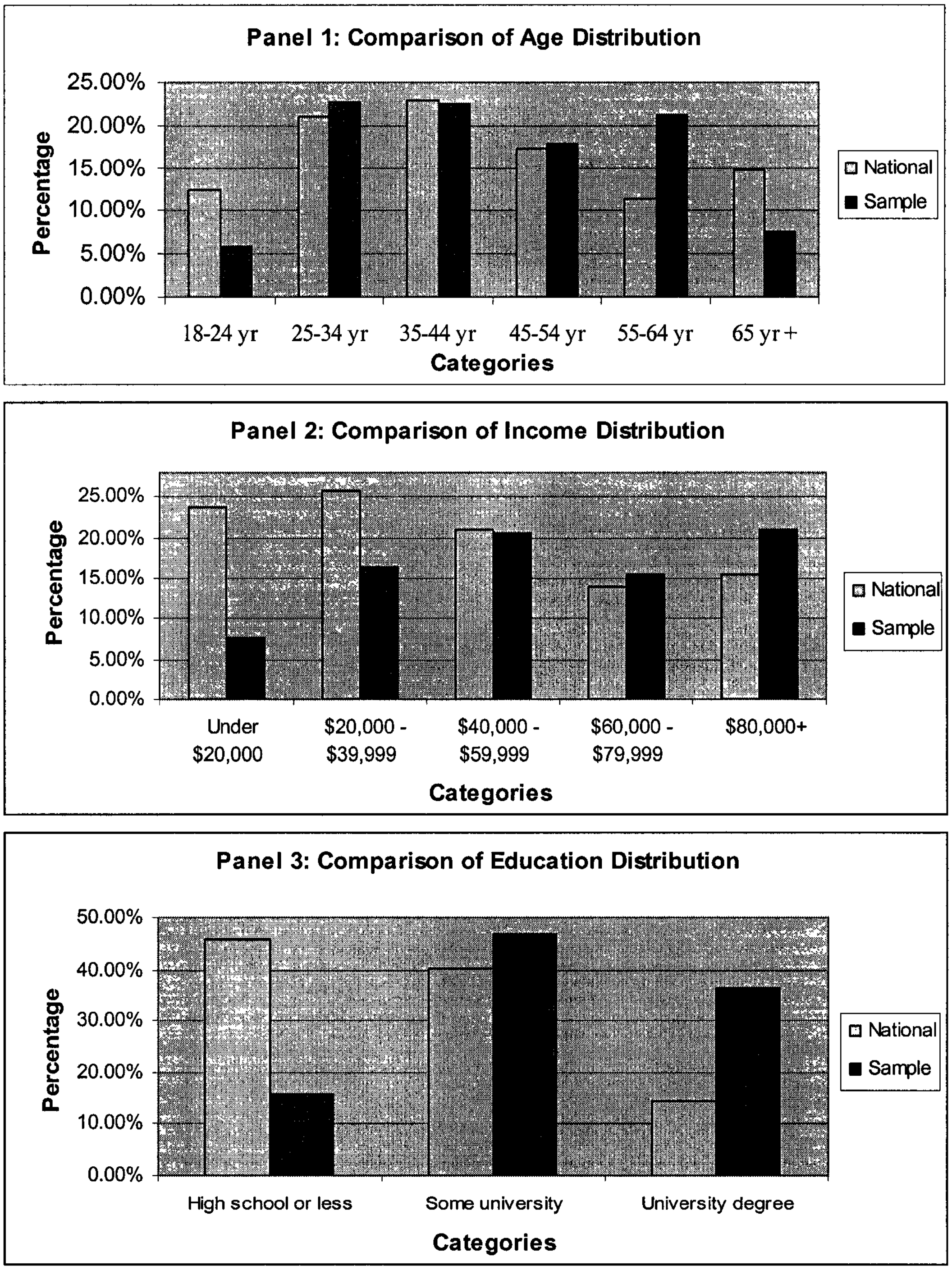
Table 1.1: Pre-packaged Sliced Bread Attributes and Levels with Each Attributes

Attributes	Level 1	Level 2	Level 3	Level 4
Brand Name	store brand	national brand	-	-
Type of Flour	white	partial (60%) whole wheat	(100%) whole wheat	multi-grain
Price (CND)	$0.99	$1.49	$2.49	$3.49
GM or not	GM ingredients present	GM ingredients absent	not specified (as in the mixed labelling scenario)	-

Figure 1.1: Comparison of the Distribution of Demographics of the Sample to Canadian Population



Chapter 2 Labelling Genetically Modified Food: Heterogeneous Consumer Preferences and the Value of Information

Overview

One facet of public debate associated with genetically modified (GM) food has focused on labelling policy for products derived from GM processes. This paper reports analysis of the effects of different GM labelling policies on consumers' choices of pre-packaged sliced bread. Substantial heterogeneity among consumers' tastes for various bread attributes, including the presence/absence of GM ingredients in bread products is found to exist from data on consumers' choices. A simulation-based bias-adjusted measure is applied to estimate the value of information revealed to consumers by different labelling procedures for the GM attribute. This indicates that the information provided to consumers in a mandatory labelling context is considerably more valuable than in a voluntary labelling context. In a final section, estimated consumer benefits from labelling policies are expressed in terms of average market prices for bread products, providing a measure of benefits against which potential cost increases associated with labelling policies may be compared in the context of benefit-cost analysis of GM labelling.

Introduction

Associated with the increasing use of agricultural biotechnology in international agriculture (ISAAA 2003), there is lack of unanimity about the nature and magnitude of benefits and costs to consumers of GM food (Fernandez-Cornejo and McBride 2002; Eurobarometer 2001). Consequently, there is much interest internationally in the manner in which information related to GM may best be provided, as evidenced by a variety of policies that either require or encourage labelling (Veeman 2001). Labelling can be viewed as a means of providing information to enable consumers to make informed choices, and there is much debate about the merits or otherwise of different labelling policies. This study attempts to answer two important questions associated with the labelling of GM food: how consumers behave under different labelling policies; and how much they value the information revealed in different labelling contexts.

To address the first question, a flexible mixed logit (ML) model based on random utility theory is adopted to explain consumers' choice behaviour under different labelling policies. The ML model has the advantage of relaxing constraints in simple analytical models such as the conditional logit (CL) model. In addition, the ML model explicitly describes the (unobserved) heterogeneity in consumer preferences. To address the second question; i.e., the value that consumers place on information provided through different labelling approaches, this study builds on the existing welfare literature by calculating the "value of information" associated with the declaration of the GM attribute in different labelling contexts. Previous research on the value of information has been conducted in a contingent referendum framework (e.g., Roosen et al. 2001). In contrast, the analysis in this study is based on Canadian consumers' stated choice behaviour for pre-packaged sliced bread with a credence attribute — the GM attribute.

Compensation variation (CV) has been widely adopted in the literature as a measure to use in evaluating welfare changes induced by policy variations. However, CV measurement is biased when policy changes will not affect actual product attributes but simply change the amount of product information circulated or the way the product is presented (Foster and Just 1989). This is the situation in the labelling of GM food. The potential bias associated with conventional CV approaches measuring the value of labelling GM food is avoided in this paper by adjusting the welfare measures appropriately taking into account the credence nature of the GM product. A simulation-based approach is described and applied to calculate welfare changes based on different averaging methods. Accurate estimates of the value of information have potentially important implications for future policy and market and development of GM food, since analysis of labelling policies requires that knowledge.

Current Practice and Research on GM Food Labelling

Views on labelling requirements for food with GM ingredients tend to be polarized. Two types of labelling practices are currently being used: mandatory labelling and voluntary labelling. With mandatory labelling, all products that contain genetically modified ingredients are required to be clearly and prominently labelled (CFIA 2001).

For example, a label may read "this product contains GM ingredients", which is defined as positive labelling by Runge and Jackson (1999). A voluntary labelling regime, on the other hand, gives the right to food producers to choose whether or not to label their products, as long as the information they provided is true, and not misleading or deceptive (Caswell 2000).

If GM products are subject to a voluntary labelling regime, suppliers will have no incentive to label their products unless the positively labelled item is viewed by the producer to have an attribute that appeals to a consumer, such as a "functional food" with health benefit or a product that can be claimed to have an environmental or public good benefit obtained through genetic modification. Similarly, negative labelling statements, "this product does not contain GM ingredients", will likely appear on products under a voluntary labelling regime as a negative label may resolve the uncertainties involved with genetic modification and make those products more attractive. Table 2.1 describes different situations under mandatory and voluntary labelling policies for products that either contain or do not contain GM ingredients.

The European Union has adopted a mandatory labelling scheme for food being sold in their markets, and is moving to a requirement that all products that have GM ingredients higher than 0.9% of the product weight must be explicitly labelled (European Commission 2003). Although the Canadian government has not yet finalized regulation for the labelling of foods obtained or not obtained through genetic modification, a voluntary labelling system is expected to be adopted (CFIA 2003; Veeman 2003). Opponents of mandatory labelling argue that since the impacts of GM products (to human health and the environment) are not clearly known, the positive statement (this product contains GM ingredients) required by mandatory labelling is not able to provide enough product information (Runge and Jackson 1999, Kinsey 1999) or may act as a warning. On the other hand, advocates of mandatory labelling claim that consumers have the right to know how foods they are eating are produced (Friends of the Earth 2001)

Research on the impact of GM labelling can be categorized into two groups. The first school examines the impact of the existence of a food label, and the format of the label, on consumers' behaviours using methods of stated choice (Wohl 1998; Blend and Ravenswaay 1999; and Levy et al. 2001), contingent valuation (Roosen et al. 2001), or experimental auctions (Noussair et al. 2002; Rousu et al. 2002; and Huffman et al. 2003). The second line of research focuses on effects on consumer from various types of information (such as health or environmental implications) contained in a label and the labelling context (such as whether or not a third-party verified label) (Teisl and Roe 1998; Roe et al. 2001; Loureiro and Hine 2001; and Huffman et al. 2002).

However, these studies are not comprehensive. First, almost none of these studies have undertaken rigorous econometric analysis of consumer behaviour. Simple qualitative statistics or choice models, such as the conditional logit model or the ordered probit model, were often utilized in these analyses. Although the conditional logit model and ordered probit models are fairly robust in terms of forecasting (McFadden 1999), such simple choice models are often based on strong and unrealistic behavioural restrictions such as the independence of irrelevant alternatives, often known as the IIA property in choice models. Louviere et al. (2000) reviewed these behavioural restrictions and pointed out that these should be considered and tested before analysis. Second, previous studies on labelling effects did not fully investigate various issues concerning the measurement of consumers' welfare. This study seeks to avoid these pitfalls by applying a flexible mixed logit model and calculating an adjusted CV measure based on the theoretical method outlined by Leggett (2002). A specific dollar value is obtained for information under the two labelling policies considered in the study—mandatory and voluntary labelling.

Data

A panel of 882 consumers across Canada completed an internet-based survey during the period December 2002 to January 2003. A key component of the survey is a split sample repeated choice experiment. About 50% (437 out of 882) of the surveyed consumers were randomly selected to participate in this choice experiment (the others were assigned to a different survey task). In each choice situation, three choice alternatives were presented to respondents. The first two alternative choices were sliced bread "products" varying across four attributes determined through focus group discussions: brand name, type of flour, price, and whether the product contains GM ingredients. The third alternative was to "buy none of these two products."

The inclusion of the option "no-choice" is important in a choice task and has been widely adopted in the literature, especially in environmental economics and marketing studies (e.g., Adamowicz et al. 1998; Carson et al. 1994). A choice experiment should provide an environment as close as possible to real choice situations (Batsell and Louviere 1991), where consumers always have the right of not purchasing. If an option of not choosing any of the alternatives given in the experiment is provided, consumers are not forced to make a choice, especially when all alternatives in a task are undesirable, and therefore, the observed choice probabilities are a better reflection of the actual probabilities. The second major benefit associated with including a no-choice option in the design is that it allows the researcher to analyse the demand of the commodity under study in general by examining consumers' decisions of whether to purchase any of the products (Batsell and Louviere 1991).

There are several ways to present the no-choice option in choice experiments. The option can be specified as "buy none of the products", as used in this paper. If the product currently purchased is known, the "no-choice" option can be presented as remaining with the current purchasing option (e.g., Huennemeyer et al. 2004). This is a slightly different strategy that results in the choice experiment being a "switching task" that describes when consumers will change their product choices for a new suite of attributes. A third way to present the no-choice option is as any fixed generic option (e.g., Swait et al. 1994). Although presented differently, these approaches all share similar properties by allowing the respondents not to choose any specific alternatives offered in the experiment. There is no clear theoretical guidance on which formulation should be used. Researchers ought to determine the most suitable approach in each individual study (Ruby et al. 1998). We focus our discussion on the approach used in this paper. Despite its benefits, there are, however, also some challenges associated in including a no-choice option as well. The most prominent challenge is that when respondents choose this option, no attributes are associated with this choice and it is difficult to code and model this behaviour in empirical analysis. The next section of this paper discusses potential approaches to handle this difficulty.

Table 2.2 shows the levels of the attributes used in this paper. Based on these attributes, a main and first-order interaction effect fractional factorial design was implemented and this design created sixty-four choice sets. It is not possible to ask one individual to evaluate all sixty-four choice sets, therefore, these sixty-four choice sets were further blocked into eight groups. Each respondent was randomly assigned to one of the eight groups with each contained eight choice sets. The order of the choice situations was also randomized[1]. Respondents were asked to choose one option from the three alternatives (including the "buy none of them" option) in each choice set.

Three labelling scenarios were created within this experiment: a mandatory labelling scheme; a voluntary labelling scheme; and the base scenario representing no specific regulation on GM labelling. The base scenario contains all possible GM labels, including positive/negative labels for the presence/absence of GM ingredients and no label at all. Then 437 respondents were assigned into one of these three scenarios. The base scenario was added to the survey to allow direct comparison between the effects of mandatory and voluntary labelling on consumers' preferences. Figure 2.1 presents two sample choice sets under the mandatory and voluntary labelling schemes respectively.

Treatment of the No-Choice Option

Since no actual product attributes are associated with the no-choice option, it is not straightforward to evaluate this option in an empirical model. There are several ways proposed in the literature to treat this option. In this section, these approaches are reviewed.

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[1] Layton and Brown (2000) proposed a simple way to test the ordering effect from choice situations but this is not the focus of the analysis reported here.

A direct way to model the no-choice option is to treat it similarly to other alternatives offered in a choice task. To reflect the fact that there are no attributes associated with this option, marginal utilities of the attributes are assumed to be zero. Because utilities are ordinal, the absolute scales of utilities do not have any meaning for analysis. It is the differences between utilities associated with choosing different alternatives that decides consumers' choices. Therefore, utilities must be normalized for their scales (Train 2003). An alternative specific constant (ASC) serves this purpose. In addition to the utility represented through an alternative's attributes, the ASC incorporates how much *more/less* the utility is associated with that alternative when compared with a different alternative. It is therefore a quantity measuring relative differences between utilities. An ASC for the no-choice option can be included in the model to capture how much difference the utility associated with this option (non-participation) is relative to the product options (participation). The magnitude of the no-choice option ASC is therefore the relative utility associated with that option.

Another way to analyse the effects of the no-choice option is to assume that correlations among alternatives are systematically different regarding whether the alternative is a no-choice option. This issue examines the substitution pattern of choices. A nested logit model can be employed for this purpose, where the no-choice option can be specified as a degenerate branch and other alternatives in the choice task can be specified as another branch[2]. This method is not fundamentally different from the ASC approach in that it still estimates the zero-coded attributes associated with the no-choice option but with a different way to model the correlations between alternatives. Haaijer (1999) compared the results of modeling the no-choice option using a logit model with the ASC specification and a nested logit model. Their conclusion, based on various scenarios, is that the ASC approach is superior to the nested logit approach. Given this evidence, the next section proceeds by using the logit model with an ASC specification

[2] A different way to think about the effects of the no-choice option is to view respondents as self-selecting whether they would like to purchase any bread. This introduces the issue of endogeneity associated with the no-choice option. Von Haefen and Adamowicz (2003) proposed a hurdle model to capture this type of issues in the context of discrete choices. Given that most Canadians consume bread, we expect the self-selection problem is minimal in this study.

for the no-choice option. Results from the nested logit model are briefly described below and examined in detail in an appendix.

Econometric Models

Given the attributes of pre-packaged sliced bread specified in this study, the indirect utility of respondent i choosing alternative (product) j can be written in a random utility framework as:

$$U_{ij} = \beta_1 Buyno + e_j, \quad j = \text{no-choice}$$

$$\begin{aligned} U_{ij} = {} & (1 - Buyno)(\beta_2 Storeb_j + \beta_3 White_j + \beta_4 Partial_j + \beta_5 Whole_j \\ & + \beta_6 GMO_j + \beta_7 NOGMO_j + \beta_8 \Pr ice_j \\ & + \beta_9 MGMO + \beta_{10} VNOGMO) + e_j, \qquad j \neq \text{no-choice} \end{aligned} \tag{1}$$

where $\beta's$ are parameters to be estimated; e_i is an unknown (to the analyst) error term; *Buyno* is a dummy variable having a value of 1 if respondent i chose to buy none of the bread products and is otherwise zero. $Storeb_j$ equals one if bread j is a store brand otherwise $Storeb_j$ equals 0. The attribute type of flour is dummy-coded into three separate variables, *White*, *Partial*, and *Whole* representing white, partially whole wheat, and whole wheat bread (The level multigrain is omitted to avoid singularity in the models). $Price_j$ is the price of product j. The GM attributes of sliced bread are effects coded into two variables *GMO* and *NOGMO* indicating whether product j is explicitly shown as containing or not containing GM ingredients. It is noteworthy that although variables *GMO* and *NOGMO* are realized through a label on the product, they are different from an indicator of the type of labelling scheme under which a product is labelled.

To compare the impacts of different labelling schemes on consumers' behaviour, labelling context variables enter as interaction terms. As labelling policies are aimed at the GM attribute, they are expected to directly interact with the impact of variables *GMO* and *NOGMO*. Defining *Mand* and *Volun* as two dummy variables representing mandatory labelling and voluntary labelling respectively, the labelling effect can be analyzed through the interactions with variables *GMO* and *NOGMO* in equation (1).

Interaction terms between labelling context variables with other attributes are not included in this study for two reasons. First, understanding of consumers' choice behaviour for bread with GM ingredients under different labelling contexts is unlikely to be much further be advanced by these terms and, secondly, because this would involve a large number of coefficients to be estimated. Consequently only the two terms *MGMO* (the interaction between mandatory labelling indicator and *GMO*) and *VNOGMO* (the interaction between the voluntary labelling indicator and *NOGMO*) are included in the consumer's indirect utility function. Further description of the explanatory variables used in the analysis can be found in Table 2.3.

If one assumes that the distribution function of the unknown error term e_i is defined around a finite parameter vector, a probability expression can be derived. Specifically, if e_i is iid distributed and has an extreme value type 1 (EV1) distribution, the probability of respondent i choosing product j, P_{ij}, can be expressed in a familiar multinomial conditional logit (CL) form:

$$P_{ij} = \frac{\exp(\mu V_{ij})}{\sum_{k=1}^{K} \exp(\mu V_{ik})}, \tag{2}$$

with X_j representing the explanatory variables in equation (1); $V_{ij} = \beta' X_j$ is the deterministic part of the indirect utility function in equation (1); k is an index denoting the products for a consumer to choose from in any one choice situation (k = 1,…, K, where K = 3 in this study); and μ is a scale parameter which is traditionally normalized to one in a CL model.

Recent developments in economics and consumer research have suggested the importance of understanding heterogeneity in determining consumer preferences (e.g., Chang et al. 1999; Bell and Lattin 2000). Vriens et al. (1996) and Fennell et al. (2003) noted that to simply include consumer household variables into the analysis is not generally a sufficient way to capture heterogeneity. The mixed logit (ML) model, developed by Jain et al. (1994), Bhat (1998), Revelt and Train (1998) and Train (1998), is very general, has the ability to accommodate a wide range of heterogeneity in consumers' decision making and can provide a tremendous amount of information that is not directly available from a traditional CL model (Allenby and Rossi 1999). McFadden and Train (2000) proved that a mixed logit model can approximate any random utility model. This approach has been applied in many contexts, and is especially useful when considering models of repeated choice by the same decision maker[3] (Brownstone and Train 1999), which is the case studied here.

The mixed logit model assumes that consumers' choices are conditional on the specification of the distribution of the coefficients. In other words, rather than being fixed, the coefficients of attributes are assumed to be distributed across the sampled individuals according to a set of parameters. Specifically, let θ denote the distribution parameters of coefficient β. Then the probability of individual i choosing alternative j could be written as:

$$\overline{P}_{ij} = \int P_{ij} f(\beta \mid \theta) d\beta, \tag{3}$$

where P_{ij} is given in equation (2) and $f(\beta \mid \theta)$ is the probability density function for coefficient β defined over a vector of parameters θ. The log-likelihood function[4] is:

$$LL = \sum_{i=1}^{N} \sum_{j=1}^{J} c_{ij} \ln\left(\overline{P}_{ij}\right), \tag{4}$$

where c_{ij} is an indicator, which equals one if individual i chose alternative j, and otherwise equals zero. The integration expression for $\overline{P}_{ij}$ usually does not have a closed form and therefore the likelihood function in equation (4) cannot be efficiently estimated with Maximum Likelihood estimation. However, the probability $\overline{P}_{ij}$ can be simulated according to density $f(\beta \mid \theta)$.

[3] Different specifications of the distribution function of the coefficients and different interpretations produce different models. These models include the popular random parameter logit models, varying effect logit (RPL or VEL) models, hierarchic choice models and latent class models.

[4] For panel data with repeated choices, the estimation of a logit model can be undertaken with Berkson's proportionate transformation estimation or a normal linear discriminant analysis, where one does not have to define a log-likelihood function or can define it in a different way. In this study, we take a more traditional ML estimation route. Under certain conditions, these three methods are equivalent (McFadden 1999).

For any given value of θ_0, one can obtain a series of $\beta(\theta)$ from the distribution described by θ_0, denoted as $\beta_d^{\theta_0}$ (d = 1, 2, …, D), where d is the number of draws from $f(\beta \mid \theta)$. The next sub-section as well as Appendix 2.1 describes how to choose a random coefficient and determine its distribution. Using β^f to represent the non-random (fixed) coefficients, the simulated probability and log-likelihood of individual i choosing alternative j given θ_0 can be written as:

$$\widetilde{P}_{ij} = \frac{1}{D}\sum_{d=1}^{D} \frac{\exp[(\beta_d^{\theta_0}, \beta^f) X_j]}{\sum_{k=1}^{J} \exp[(\beta_d^{\theta_0}, \beta^f) X_k]} \tag{5}$$

$$SLL = \sum_{i=1}^{N}\sum_{j=1}^{J} c_{ij} \ln\left(\widetilde{P}_{ij}\right) \tag{6}$$

In this study, each individual answered a sequence of eight choice questions. The ML model above needs to be extended to analyze this multi-period panel data. Assuming a consumer's taste (β_i) is constant throughout the choice process[5], equation (6) can be re-written to include the panel factor t as:

$$SLL = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J} c_{itj} \ln\left(\widetilde{P}_{itj}\right) \tag{7}$$

By allowing the coefficients of attributes to vary across individuals, the mixed logit model can reveal the existence of taste heterogeneity among sampled individuals. Traditional CL models ignore these variations, and in this sense, compared with a ML model, the maximum likelihood estimation based on a CL model is indeed a quasi-maximum likelihood estimation (McFadden 1999).

[5] This assumption is likely to be applicable, given the "short" panel in this study. The eight choices for each individual were made in a short period of time and the impact of time on taste change is ignored. This being said, taste variation can be modeled during the course of eight choices made by a respondent, although this is not done here. Specifically, a second stochastic term can be added in β_i. If this term varies across choice situations but is independent across individuals, choices in different choice situations are correlated within one individual but the taste varies.

Estimation Results

Table 2.4 presents the estimation results. Before interpretation, estimation results from the nested logit and the CL model were compared to examine treatment of the no-choice option. No significant differences in the attribute values (the ratio of the coefficient of an attribute against the coefficient of price) were found between these two models. Appendix 2.2 reports the nested logit model estimation results and interpretation. For the CL model, all coefficients are statistically significant at the 5% significance level, except *VNOGMO*. Not choosing one of the bread products in a choice task had a negative impact on consumer's utility indicated by the negative sign of *Buyno*. Variable *Storeb* had a negative coefficient which implies that store brand sliced breads were not preferred relative to national brands. Variables *White*, *Partial*, and *Whole* are all associated with significant and negative coefficients, indicating that compared with the omitted attribute (multigrain), these three attributes are less preferred by consumers.

Variables *GMO*, *NOGMO* and *Price* all had coefficients with the expected sign. Consumers strongly preferred bread without GM ingredients and avoided bread with GM ingredients. The variable *MGMO* shows the impact on a consumer's utility when a bread product containing GM ingredients is labelled under the mandatory labelling regime rather than under the base case. *MGMO* is significantly negative indicating that a consumer will discount the utility brought by a GM bread product further when it is in a mandatory labelling regime compared with the base case. However, variable *VNOGMO* is not significantly different from zero, indicating that consumers value the attribute *NOGMO* relatively the same when the product is under a voluntary labelling regime compared with the base case.

Next, a mixed logit model was estimated with the coefficients for *Buyno*, *White*, *Partial*, *Whole*, and *GMO* following a normal distribution and *-1*Price* following a lognormal distribution[6]. The fit of the ML model was significantly improved from the CL model, with log-likelihood function of -2616.614 and pseudo-R^2 of 0.286, indicating

[6] See Appendix 2.1 for a discussion on how to determine which coefficient should be specified as random and what distribution they should follow.

a fairly good model fit (Domencich and McFadden 1975). The estimated standard deviations of the random coefficients were all highly significant. This further demonstrated that the inclusion of a mixing structure for the selected coefficients in the CL model was necessary. As the price coefficient has a lognormal distribution, the mean and standard deviation (not standard error) of the coefficient itself is given by $-\exp\left(0.348+(0.645)^2/2\right)=$ -1.744 and $\sqrt{\exp(0.645)^2-1}=0.718$, respectively.

The fixed coefficients in the ML model had very similar effects on utility as those in the CL model. For random coefficients, the significant standard deviations associated with these coefficients indicate that there exist strong variations among the respondents' "taste" on: what type of flour the bread is made from; whether the bread contains GM ingredients; and the price of the bread. On the issue of how much "disutility" is introduced by buying none of the bread products, respondents varied considerably as manifested by the large standard deviation associated with the variable *Buyno*. In a CL model, a positive (negative) coefficient of an attribute indicates that all sampled individuals treat that particular attribute as desirable (undesirable). An insignificant coefficient simply means that the attribute associated with the coefficient is not important to all consumers. However, in a ML model, more insight on taste heterogeneity is obtained from the random coefficients. For a normally distributed coefficient with a positive (negative) mean estimate, we can calculate the share of the sampled respondents that hold a negative (positive) view of that attribute.

In the ML model, attributes (excluding the price variable) with normally distributed coefficients are: *Buyno*, *White*, *Partial*, *Whole*, and *GMO*. Given a random variable $\beta \sim N(b,\sigma^2)$, the probability of $\beta<0$, $\Pr ob(\beta<0)$, equals $\Phi\left(\frac{0-b}{\sigma}\right)$, where Φ is the distribution function of a standard normal distribution. The probability of $\beta>0$, $\Pr ob(\beta>0)$, is $1-\Pr ob(\beta<0)$. The probabilities of $\beta<0$ (> 0) can be interpreted as the percentage of respondents that hold a negative (positive) view on an attribute. Based on this method, the percentage of respondents that value each attribute positively versus negatively is reported in Table 2.5. A total of 98.8% of the respondents had negative values associated with "buy none of the breads" option indicating that almost all respondents disliked the choice of not buying any bread. Even though from the mean coefficient estimates of the ML model, respondents preferred multigrain bread the most, there was a considerable group that would actually prefer the other three types of bread. There were 33.6%, 23.4% and 40.9% of respondents who preferred white, partially whole wheat and whole wheat bread over multigrain bread respectively. Similarly, despite the large negative mean coefficient associated with the GMO attribute, holding other factors constant, 23% of the sampled respondents would prefer a loaf of bread with GM ingredients. This verifies the large discrepancy among consumers' evaluation of GM attributes ranging from negative to neutral and to supportive as reported in some recent studies (Hossain et al. 2003, Huennemeyer et al. 2004).

The results of the CL and ML models support a consistent interpretation of consumers' preferences for bread attributes. Consumers preferred multi-grain bread more than the other three types of bread and/or bread explicitly labelled as not containing GM ingredients. They did not prefer bread with a store brand, containing GM ingredients and/or with a higher price. The two models also provide a generally consistent explanation for the impacts of different labelling policies on consumers' utilities associated with purchasing bread compared with a common base situation. In both models, mandatory labelling significantly worsens the negative impact of GM ingredients to consumers' utility compared with the base case[7]. On the other hand, neither model showed a significant impact on consumer choices from the voluntary labelling policy. In other words, consumers' bread purchasing behaviour is unlikely to be as affected by a voluntary labelling policy as in a mandatory situation.

It is worthwhile to point out that we are examining the impact of different labelling policies on consumers' preferences, rather than the implied welfare or value of information. Although the estimated coefficients for various labelling context effects are

[7] Note that as bread without GM ingredients is not labelled in a mandatory labelling regime, a mandatory labelling policy is not expected to affect bread products that do not contain GM ingredients. For a similar reason, bread with GM ingredients is unlikely to be labelled in a voluntary labelling regime and therefore only products without GM ingredients are assumed to be affected by voluntary labelling.

informative, they cannot represent a readily quantified measure of the impact of the information contained in labels[8]. Given the (average) negative impact of the identification of the GM attribute to consumers' utilities, the results suggest that disclosure of the presence of GM ingredients should always be associated with a positive value. However, from the model estimates, the coefficient of mandatory labelling of GM ingredients itself is negative. It would seem that the conventional welfare analysis would find that the mandatory labelling of GM implies a negative welfare measurement. This paradox cannot be solved if one does not make appropriate adjustment to the conventional welfare calculation. In the following sub-section, we explain this adjustment and calculate the appropriate welfare measures of labelling policies using the value of information approach.

Value of Information

Theoretical Welfare Measures

Compensating variation (CV) can be used to calculate consumers' welfare associated with changes in products attributes. By definition, CV is the monetary value that sets a consumer's utility invariant before and after the specified change. Assume X and X' are vectors of attributes before and after the change; E represents the expenditure under these two situations; and $\bar{u}$ represents the utility level, CV can be written as:

$$CV = E(X',\bar{u}) - E(X,\bar{u}) \tag{8}$$

In the context of discrete choices, if the analyst assumes that consumers will participate in the market; i.e., consumers choose alternatives with non-empty attributes either before or after the change, CV can be calculated in the context of a CL model involving multi-attributes. Hanemann (1983 and 1985) developed the expression:

$$CV_{MNL} = \left\{ \ln\left[\sum_{j=1}^{J} \exp(\beta X')\right] - \ln\left[\sum_{j=1}^{J} \exp(\beta X)\right]\right\} \Big/ -\beta_{price}, \tag{9}$$

[8] Attribute marginal values can be calculated. However, these values are not the precise measures of consumers' welfare from choosing bread products. Particularly, when obtaining the marginal value for an attribute (or attribute interacted with a labelling context), one has to assume that all other attributes are fixed at their current level and welfare implications over multiple attribute changes cannot be calculated (Boxall and Macnab 2000).

This approach has two implicit assumptions that are sometimes ignored when it is applied to analyze welfare changes. First, consumers under consideration should have perfect knowledge about attribute changes. Consumers' behaviour (or choices) is determined by their perception of attributes of a commodity and if they are not aware of the changes, their perception of attributes will not be consistent with the actual attributes. Therefore, welfare measures calculated using actual changes will be incorrect (Foster and Just 1989). The second assumption is that changes in attributes must be actual changes rather than changes incurred based on consumers' improved product knowledge.

In this study, the welfare implications of labelling policies are simulated by comparing consumers' choices under mandatory or voluntary labelling regimes with the situation when neither of these policies are in place. Due to different implications of the two labelling policies, the same product is labelled differently and thus seems different to consumers. However, the actual qualities under consideration are exactly the same before and after the application of the labelling policy. In other words, changes in attributes caused by different labelling requirements are a reflection of changes in the amount of consumer information but not the actual changes of product attributes. This violates the second assumption of the CV formula specified by Hanemann (1983, 1985) and therefore equation (9) is not directly applicable in this situation.

When extra information is available to reveal (rather than change) an attribute, the interpretation of the associated welfare is not straightforward (Foster and Just 1989; Teisl and Roe 1998). This difficulty is more noticeable when the information reveals an undesirable attribute. As implied by the negative coefficient of an undesirable attribute in the utility function, it is expected that a welfare loss would occur when an undesirable attribute appears. However, if consumers wish to avoid this undesirable attribute, its revelation (through a label) will enable consumers actually to choose not to consume this attribute. Information revealing this attribute should therefore have a positive value to consumers. Foster and Just (1989) argued that in this type of situation, the appropriate welfare measure is compensating surplus, not compensating variation. They termed the difference between compensating surplus and CV as "the cost of ignorance".

Leggett (2002) extended the theoretical discussion by Foster and Just (1989) and proposed a bias-adjusted CV measure to replace the conventional CV formula:

$$CV'_{MNL} = CV_{MNL} + \sum_{j=1}^{J}\left(\left(P_j^1 \mid \Delta V_j^1\right) - \left(P_j^0 \mid \Delta V_j^0\right)\right) \Big/ -\beta_{price}, \qquad (10)$$

where P_j^0 and P_j^1 are probabilities, based on perceived attribute levels, that alternative j is chosen before and after the change, respectively; ΔV_j^0 is the difference in utility based on perceived and actual attributes before the change and ΔV_j^1 is the similar difference defined after the change. This general expression accounts for situations in which consumers do not have perfect information about the change of attributes (either before or after the change or in both stages) or when attributes do not actually change but information changes. In the latter case, assuming utilities can be written in terms of a linear combination of product attributes, equation (10) reduces to:

$$CV'_{MNL} = CV_{MNL} - \sum_{j=1}^{J}\left(P_j^0 \mid (\beta X'_j - \beta X_j)\right) \Big/ -\beta_{price} \qquad (11)$$

This is, thereafter, named "the value of information". Using LF_{MNL} to represent the second term in the right hand side of equation (11), we can rewrite the adjusted CV measurement as:

$$CV'_{MNL} = CV_{MNL} + LF_{MNL} \qquad (12)$$

Given equation (12), one can solve the paradox raised earlier. When extra information is given to reveal that some bread may contain GM ingredients, the "revealed" GM attribute is likely to cause CV_{MNL} to be negative as the GM attribute is not desired by most of the consumers. However, in this situation, LF_{MNL} would be positive and if the absolute value of LF_{MNL} is greater than CV_{MNL}, CV'_{MNL} would be positive, where CV'_{MNL} is the value of the information that reveals the presence of GM ingredients. In our context, CV'_{MNL} is the value of the information under the mandatory labelling policy. Note from (9) and (11) that when an undesirable attribute is labelled, the more undesirable is that attribute, the more negative will be CV_{MNL}, however, in this case LF_{MNL} will be more positive.

In a voluntary labelling context, information that indicates the absence of GM ingredients will generate a positive measure of CV_{MNL} but a negative measure of LF_{MNL}. That is, in the adjusted CV calculation for voluntary labelling, the traditional CV measurement for an actual attribute improvement will be adjusted downward. The value to consumers associated with a voluntary labelling policy CV'_{MNL} will be smaller than the value predicted by CV_{MNL}. The measure of LF_{MNL} in this case represents the cost to consumers of making potential sub-optimal choices when relevant information is not fully released. When information reveals a favourable attribute after the choices are made, consumers cannot go back in time to adjust their choices according to the new information. Therefore, favourable information will not generate as large a gain of utility as in the case when there are actual favourable attribute changes and consumers know these changes from the beginning.

Simulation Scenarios

Due to the fact that there are no actual GM regulations on the labelling of bread products currently in Canada, hypothetical policy changes are created to examine the value of information provided under mandatory and voluntary GM labelling policies. To make simulation results close to the actual situation, before simulating policy changes, a hypothetical bread market is created to reflect bread choice options available in a real market. A market search was conducted in two major Canadian grocery stores in August 2003 in Edmonton, Alberta. Observations of retail market-level breads were obtained[9] and according to these observations, necessary grouping and classifications were applied to ensure that the bread products arbitrarily selected in further analysis conducted below are representative, within a reasonable limit of complexity.

[9] See Appendix 2.3 for a discussion of these findings.

In order to simulate changes in consumers' welfare from potential introduction of the two different GM labelling policies, a total of 16 bread products were chosen to represent the range of bread alternatives that consumers face in a retail store setting. These 16 bread products are categorized by the attributes *brand name* and *type of flour* and the distribution is cross-tabulated in Appendix 2.3. Among these 16 bread products, welfare simulations were conducted for policy-induced changes in two situations: only one product is affected and multiple products are affected. These two situations represent cases when only a small proportion or a significant proportion of bread in the market is affected by labelling policies.

A total of 8 products were chosen for the case involving multiple product changes. Of these, 4 products out of the 8 had a store brand name and the other 4 had a national brand name. Each group of 4 products covered all four bread flour types. Prices were assumed to be constant and were defined by the median real price observed for each bread by flour type. The base case is when no products are specifically labelled as either containing or not containing GM ingredients[10]. The change in consumers' welfare caused by the changes to bread attributes can be evaluated under numerous different scenarios. For the current study, four scenarios were chosen:

1. Due to the requirement of a mandatory labelling policy, a label "this product contains GM ingredients" is simulated to appear on one nationally branded white bread.
2. One nationally branded white bread is simulated to be labelled as "this product does not contain GM ingredients" reflecting a voluntary labelling environment.
3. Due to the requirement of a mandatory labelling policy, a label "this product contains GM ingredients" appears on the eight previously defined bread products..
4. Eight bread products that are previously defined are now being labelled as "this product does not contain GM ingredients" reflecting a voluntary labelling environment.

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[10] Although the third labelling scenario incorporated in the choice experiment and in this simulation (in addition to mandatory or voluntary) is the situation where any type of label may appear, the coefficients obtained from the choice models allow us to perform the comparisons between mandatory/voluntary labelling with no label at all by substituting appropriate values for variables *MGMO* and *VNOGMO*.

Simulation Results

Welfare measures are calculated based on an average consumer buying one of any of the 16 different products in one grocery trip. Such measures can be viewed as the expected welfare (Breffle and Morey 2000). Standard deviations of welfare measures implied by the CL model can be obtained through the procedure described by Krinsky and Robb (1986). For the ML model, the calculation involves an additional layer of simulation. We define draws from the multivariate normal density implied by the ML model estimates as the *parameter simulation* and draws for specific coefficients from the result of each parameter simulation as the *coefficient simulation*[11]. As the distribution of welfare measures under the ML model is the combination of a normal distribution and a lognormal distribution (given by equation (9) and (11)), the resulting distribution has unknown properties. Special attention should be paid to this issue before obtaining a naïve "mean" measure of the distribution.

One of the best ways to reveal the properties of an unknown distribution is to plot its density function. Non-parametric kernel densities of welfare measures obtained after one of the R=1000 numbers of coefficient simulations[12] under the second and the third scenarios are presented in Figure 2.2. There are significant differences between the densities in the two panels of Figure 2.2. Under scenario 2, the density function is relatively wide and is only slightly skewed to the right. This indicates that the mean and median of the distribution will be similar. However, under scenario 3, the shape of the density function looks very much like a lognormal distribution: tight to the left of the peak and heavily skewed to the right. This suggests that the mean will be significantly larger than the median. It should be noted that the inconsistency between the mean and the median of welfare measures associated with a coefficient simulation is not expected to appear when the price coefficient is fixed at its mean level because the resulting welfare measures will be normally distributed.

[11] See Appendix 2.4 for a detailed description of these simulations.
[12] Recall, for each observation of the parameter simulation, a number of S=1000 coefficient simulation replications are calculated

The discrepancies between the mean and the median of welfare measures within each replication of the parameter simulation indicate that overall welfares based on means or medians can be different. For the case under scenario 3 (Panel B of Figure 2.2), assuming the price coefficient is allowed to be random, Figure 2.3 displays the kernel density of R numbers of the welfare measures when each observation is the mean or median over S replicates of welfare measures from the coefficient simulation. It can be observed that there is a significant shift of the distribution. The shapes of both of the densities are nearly normal (i.e. mean equals median), which is guaranteed by the central limit theorem when R is large. The overall mean for welfare measures from the parameter simulation based on medians of each coefficient simulation is significantly smaller than that based on the means. For scenario 2 (Panel A of Figure 2.2), the overall welfare measure based on means or medians does not deviate significantly.

Although the overall welfare measures based on means or medians of the coefficient simulation can be different, there is no strong theoretical preference for either. Some authors favour the method using the median as it captures the "voting" nature of these welfare measures (Hanemann and Kanninen 1996). In this study, we report results based on both methods when the price coefficient in the ML model is either fixed or random, in the anticipation that this can provide more insights into the issue. Panel A in Table 2.6 gives the estimated CVs and their associated standard deviations for models under the conventional approach given by Hanemann (1983). Panel B of Table 2.6 contains the adjusted welfare measures (Leggett 2002), representing the value of information under each simulated scenario. Overall, welfare measures obtained from the ML model have greater variances compared with the corresponding measures derived from the CL model. This is because CV estimates calculated from the ML model coefficients incorporate variations from both the parameter simulation and coefficient simulation process, while the CV estimates calculated through a CL model contains only the variation from the coefficient simulation (see Appendix 2.4).

Although values reported in Panel A are the results of incorrectly treating "changes" of attributes introduced by new information under different policy requirements as actual attribute changes, some interesting trends can be observed. Firstly, in both models, when the presence of GM ingredients is known (as in scenario 1 and 3), consumers will generally experience a welfare loss. The more breads that are labelled as containing GM ingredients due to the requirement of a mandatory labelling regime, the larger are the losses. Secondly, if in a voluntary labelling regime where a loaf of bread could be labelled as containing no GM ingredients, consumers will not have welfare gains associated with this underlying information if it is not revealed. Again, however, the amount of gain from information revealed increases along with the number of bread products that are affected and labelled as containing no GM ingredients.

The results displayed in Panel B of Table 2.6 are estimates of the values of information. These differ significantly from values estimated under a conventional CV calculation. All estimated values of information are now non-negative. If one out of the 16 bread products must be labelled as containing GM ingredients in the mandatory labelling regime, the value of information is \$0.02 per loaf (in Canadian dollars) in the CL model and \$0.00 to \$0.09 in the ML model, depending on which method of calculation is used. On the other hand, if one product can be labelled as containing no GM ingredients under a voluntary labelling regime, the value of that item of information does not matter as much to consumers as does the information revealing the existence of GM ingredients in a mandatory labelling regime. Both models (and both methods under fixed or random price coefficient in the ML model) yield a smaller value for information that is provided from labels under the voluntary labelling context.

Continuing with Panel B, in the third scenario, eight bread products are labelled as containing GM ingredients as a result of the mandatory labelling requirement. The information revealing this to consumers is valued at \$0.15 in the CL model and \$0.30 to \$0.58 in the ML model depending on the calculation method. Finally, in the last scenario, if these eight products do not actually contain any GM ingredients and can be so labelled under a voluntary labelling regime, consumers again would place a smaller monetary value on this compared with the information in the mandatory labelling context. The average willingness to pay for that information is around \$0.01 to \$0.05 in the CL and the ML models respectively. There is a discrepancy between the values of information calculated from the two models under the third scenario. It can be argued that although the absolute difference is large, the relative difference is not much bigger or may even be smaller than in the other scenarios (for example in scenarios 1 and 4). This issue can be further investigated by cross-comparing results in the two panels of Table 2.6. These comparisons are documented in Appendix 2.5.

Another interesting perspective of the welfare analysis of the different labelling policies is to determine how much prices for marketed bread products could rise until the welfare gain consumers obtained from the value of information is offset to zero. Undoubtedly there will be costs associated with the introduction and maintenance of any labelling policies. Ultimately, most of the costs are likely to be reflected in the final product price. An understanding of consumers' benefit from GM labelling in price terms can provide policy makers with an assessment of the extent to which the costs of labelling policies can be absorbed in market prices.

To evaluate this issue, since the 16 products in the simulation have different prices, price changes are calculated as percentage increases from each individual product's original price level. Table 2.7 reports the estimated price increases, based on consumers' welfare estimates as reported in Table 2.6, from both the CL and the ML models. In most of the situations associated with voluntary labelling, the implied price increase is small, i.e., less than or around 1%. However, based on the welfare estimates, consumers' tolerance for potential price increases under the mandatory labelling regime is much higher than that under the voluntary labelling regime. For example, when there is only one product that may be affected by a labelling policy and a random price coefficient from the ML model is used to calculate the means of coefficient simulations, overall the market price can increase by close to 3% under the mandatory labelling regime. However, with a voluntary labelling policy, the market price cannot be increased by more than 1% to attract the same amount of purchases, regardless of the extra information the voluntary labelling policy may provide.

Under the third scenario, since eight products are directly affected by the mandatory labelling policy, consumers' welfare gains from the information provided by labels are the largest among all four scenarios. There is an obvious asymmetric welfare effect compared with the fourth scenario. In fact, to maintain consumers break-even before and after GM labelling policy changes suggested in scenarios 3 and 4, prices can increase more than ten times more in scenario 3 than in scenario 4. Mandatory labelling is expected to incur more costs than is the case for voluntary labelling (Huffman et al. 2002). However, the information consumers obtained from mandatory labelling is more highly valued too. Bread market prices can increase by 3.7% (from the CL model) or by close to 15% (from the ML model) without offsetting the value of label information. On the other hand, even if multiple bread products are labelled as containing no GM ingredients under a voluntary labelling regime, based on this study, consumers will not treat this information as very valuable and therefore will not pay higher prices for it.

In summary, the magnitude of consumers' welfare increased with mandatory labelling and also as more bread products were affected by a labelling policy, no matter whether the actual bread attributes changed or the amount of product information due to labelling requirements had been changed. Interestingly, the magnitude of consumer welfare changes associated with the "GM attribute" was consistently larger than the magnitude of welfare changes associated with the "non GM attribute". This asymmetric effect almost always applied, as seen from comparison of the welfare values in scenario 1 to scenario 2 and scenario 3 to scenario 4 in both models with or without adjustment. This asymmetric effect of gains and losses associated with GM ingredients through different labelling policies could be viewed as another manifestation of Kahneman and Tversky's prospect theory, in that consumers value gains and losses according to an asymmetric value curve (Kahneman and Tversky 1979).

Possible reasons for the asymmetric values of information provided under mandatory and voluntary labelling policies could be that consumers may treat risks associated with GM food differently in that they are willing to pay disproportionately to avoid a potentially risky product (GM product). On the other hand, consumers may simply treat the information provided by negative statements in the voluntary labelling regime as a marketing gimmick and discount the value associated with it. In fact, in a descriptive part of the survey from which data for this study were gathered, when asked whether respondents believed that a voluntary label would be used as a marketing tool, more than 70% of the respondents strongly or somewhat agree. Further research is warranted in investigating the mechanisms/reasons behind the asymmetric effects observed here.

Conclusions and Implications

Using a controlled choice experiment, this analysis attempts to understand consumers' preferences for pre-packaged sliced bread with possible genetically modified ingredients under two labelling policies: mandatory labelling and voluntary labelling. We focus on how the two different labelling schemes affect consumers' choices and how consumers evaluate the information implied under these two policies. Both conventional and mixed logit models are applied in the analysis. The results indicate that consumers prefer bread with national brand names and bread that is multi-grain. Bread with GM ingredients significantly decreases the value of this product while information that the bread does not contain GM ingredients increases the value of the product. The mixed logit model reveals that there exist substantial heterogeneities in consumers' tastes on various attributes including the price.

The two labelling contexts have diverse impacts on consumers' stated purchasing behaviour of bread products. Compared with a base case of no specific labelling policies, respondents exhibited a moderate degree of utility loss as shown by choices in situations of mandatory labelling of GM ingredients in bread products, while the disclosure of the absence of GM ingredients in bread products encouraged by a voluntary labelling regime does not have a significant impact on consumers' utility. Estimates of the welfare implications of the two labelling policies are also obtained in four succinct simulated scenarios. The conventional approach for calculating welfare is not appropriate in this situation as it incorrectly predicts negative values associated with the information provided under mandatory labelling rather than recognising the distinction between information provided and the nature of the attribute that is identified. Instead, the value of information is derived using an adjusted approach that recognises this distinction.

In all situations, the value of information is positive. The largest absolute differences occur in the third scenario where eight products are directly affected by mandatory labelling. In general, consumers value the information more when more products in the market are directly affected by labelling policies. Consumers value information provided under the mandatory labelling policy significantly more than information given under a voluntary labelling policy. The implied price increases that can offset the extra benefit brought by information under various labelling requirements are also calculated. These possible price increases imply a similar situation: the more products that are directly affected by labelling policies, the higher prices overall consumers are willing to pay. Evidently, to keep consumers at the same utility level, prices can be higher for bread under mandatory labelling policies than under the alternate voluntary situation.

Bread is widely consumed in Canada and can be viewed as a representative of other commonly consumed food items that could contain GM ingredients. The method used in this study has potential applicability to other food products as well. The use of GM ingredients in wheat products has not been authorised in Canada but discussion on this were ongoing when this study was being conducted. This study provides a contemporary contribution to the understanding of GM labelling. The analysis of the welfare provided through the value of information presented in this research can potentially be applied to quantify the benefit of various labelling policies to consumers. This information is potentially useful as an estimate of the benefit associated with labelling in any benefit-cost analysis of the policy.

The asymmetric effects found in this study in the welfare estimates between mandatory and voluntary labelling contexts have important implications, both from a public policy perspective and a research point of view. It should be recognised that in addition to the differences between label wordings under these two labelling contexts, labelling may have a more profound impact on consumers' choices and welfare.

Mandatory labelling may involve higher costs than voluntary labelling however, the associated benefit are also higher. Careful benefit-cost analysis is required to evaluate the overall social welfare impact of these two labelling schemes. Furthermore, the asymmetric impacts on welfare measures from different labelling policies may be deeply rooted in consumers' social, economic, and psychological differences. Insights from behavioural economic research may shed light on the reasons and source of these asymmetric effects. This is a direction that is explored in the next chapter.

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Table 2.1. Illustration of mandatory and voluntary labelling for GM/non-GM products

	A product contains GM ingredients	A product does NOT contain GM ingredients
Mandatory Labelling	*required labels*	
	This product contains GM ingredients	No label (no requirement)
Voluntary Labelling	*possible labels*	
	No label (expected)	This product does not contain GM ingredients

Table 2.2. Levels within Each Attribute of Pre-Packaged Sliced Bread

Attributes	Level 1	Level 2	Level 3	Level 4
Brand Name	store brand	national brand	-	-
Type of Flour	white	partial (60%) whole wheat	(100%) whole wheat	multi-grain
Price (CND)	$0.99	$1.49	$2.49	$3.49
GM or not	GM ingredients present	GM ingredients absent	not specified (as in the mixed labelling scenario)	-

Table 2.3. A Summary of the Variables Used in the Analysis.

Attribute	Definition
Buyno	= 1 if an individual chose to buy none of the bread products. Otherwise = 0.
Storeb	= 1 if the bread has a store brand. Otherwise = 0.
White	= 1 if the bread is white bread. Otherwise = 0.
Partial	= 1 if the bread is partial whole wheat. Otherwise = 0.
Whole	= 1 if the bread is whole wheat. Otherwise = 0.
GMO	= 1 if the bread is labelled as containing GM ingredients. Otherwise = 0.
NOGMO	= 1 if the bread is labelled as not containing GM ingredients. Otherwise = 0.
Price	the actual price.
MGMO	= 1 if a bread is under mandatory labelling and contains GM ingredients. Otherwise = 0.
VNOGMO	= 1 if a bread is under voluntary labelling and does not contain GM ingredients. Otherwise = 0.

Table 2.4. Estimation Results

Attribute	CL	
	Coeff.	Std. Error
Buyno	-2.865***	0.115
Storeb	-0.221***	0.052
White	-0.781***	0.083
Partial	-0.617***	0.078
Whole	-0.222***	0.077
GMO	-0.706***	0.109
NOGMO	0.358***	0.101
Price	-0.708***	0.033
MGMO	-0.256**	0.130
VNOGMO	-0.169	0.129
pseudo-R2	0.109	
LL	-3267.702	

Attribute	ML	
	Coeff.	Std. Error
random parameters in utility function		
Buyno	-6.610***	0.276
White	-2.389***	0.237
Partial	-1.190***	0.129
Whole	-0.405***	0.119
GMO	-1.637***	0.238
Price (lognormal)	0.348***	0.050
fixed parameters in utility function		
Storeb	-0.428***	0.074
NOGMO	0.806***	0.160
MGMO	-0.644**	0.283
VNOGMO	-0.224	0.213
standard deviations of random parameters		
Sd-Buyno	2.919***	0.186
Sd-White	5.640***	0.328
Sd-Partial	1.645***	0.146
Sd-Whole	1.779***	0.165
Sd-GMO	2.259***	0.180
Sd-Price	0.645***	0.034
pseudo-R2	0.286	
LL	-2616.614	

*, **, *** indicates significant at the 10%, 5%, and 1% significance level respectively.

Table 2.5. Positive/Negative Shares of Attributes With Normally Distributed Coefficients

Coefficient of Attribute	Percentage	
	Positive	Negative
Buyno	1.2%	98.8%
White	33.6%	66.4%
Partial	23.4%	76.6%
Whole	40.9%	59.1%
GMO	23.4%	76.6%

Table 2.6. Welfare Simulation Results (per Loaf per Choice Occasion) #

Panel A: Conventional Measures

Scenarios	CL	ML			
		Fixed Price Coefficient		Random Price Coefficient	
		Mean of Means	Mean of Medians	Mean of Means	Mean of Medians
	a	b	c	d	e
Mandatory Labelling: One Labelled as GM	-$0.04* (0.00406)	-$0.01 (0.11107)	-$0.01 (0.10273)	$0.00 (0.26043)	$0.00 (0.17918)
Voluntary Labelling: One Labelled as NO-GM	$0.01 (0.00725)	$0.04 (0.11226)	$0.03 (0.10306)	$0.06 (0.26360)	$0.03 (0.18109)
Mandatory Labelling: Eight Labelled as GM	-$0.47* (0.03721)	-$0.20 (0.11569)	-$0.16 (0.11003)	-$0.22 (0.25759)	-$0.20 (0.17646)
Voluntary Labelling: Eight Labelled as NO-GM	$0.13* (0.06573)	$0.13 (0.12148)	$0.18 (0.11316)	$0.23 (0.27130)	$0.20 (0.18989)

Panel B: Adjusted Measures - Value of Information

Scenarios	CL	ML			
		Fixed Price Coefficient		Random Price Coefficient	
		Mean of Means	Mean of Medians	Mean of Means	Mean of Medians
	f	g	h	i	j
Mandatory Labelling: One Labelled as GM	$0.02* (0.00379)	$0.07 (0.11339)	$0.00 (0.10290)	$0.09 (0.26576)	$0.00 (0.17946)
Voluntary Labelling: One Labelled as NO-GM	$0.00 (0.00128)	$0.01 (0.11149)	$0.02 (0.10274)	$0.03 (0.26173)	$0.01 (0.18065)
Mandatory Labelling: Eight Labelled as GM	$0.15* (0.02683)	$0.42* (0.11376)	$0.40* (0.10720)	$0.53* (0.22045)	$0.30 (0.19073)
Voluntary Labelling: Eight Labelled as NO-GM	$0.01 (0.00651)	$0.03 (0.11191)	$0.03 (0.10235)	$0.04 (0.26147)	$0.05 (0.18067)

* Significant at the 5% significance level.

All values reported are in Canadian dollars.

Table 2.7. Percentage Increase of Price to Offset the Value of Information

Scenarios	CL	ML			
		Fixed Price Coefficient		Random Price Coefficient	
		Mean of Means	Mean of Medians	Mean of Means	Mean of Medians
Mandatory Labelling: One Labelled as GM	0.522%*	2.469%	0.000%	2.740%	0.000%
Voluntary Labelling: One Labelled as NO-GM	0.033%	0.438%	0.391%	0.918%	0.491%
Mandatory Labelling: Eight Labelled as GM	3.705%*	14.172%*	13.821%*	14.516%*	10.681%
Voluntary Labelling: Eight Labelled as NO-GM	0.185%*	0.898%	0.949%	1.180%	1.573%

* Significant at the 5% significance level.

Figure 2.1* Example of Choice Set under Mandatory and Voluntary Labelling

Features	Option A	Option B	Option C
Brand Name	National brand (such as "Old Mill" and "Wonder")	Store brand (such as Safeway and IGA brands)	I would not buy any bread at all
Type of Bread	100% whole wheat	60% whole wheat	
Ingredients	Wheat flour, water, yeast, vegetable oil, sugar, salt Contains genetically modified/engineered ingredients.	Wheat flour, water, yeast, vegetable oil, sugar, salt.	
Price	$1.49	$2.49	

* According to the definition of mandatory labelling, products that contain GM ingredients must be labelled.

Features	Option A	Option B	Option C
Brand Name	National brand (such as "Old Mill" and "Wonder")	Store brand (such as Safeway and IGA brands)	I would not buy any bread at all
Type of Bread	100% whole wheat	60% whole wheat	
Ingredients	Wheat flour, water, yeast, vegetable oil, sugar, salt.	Wheat flour, water, yeast, vegetable oil, sugar, salt. Does not contain genetically modified/engineered ingredients.	
Price	$1.49	$2.49	

* According to the implication of voluntary labelling, only products that do not contain GM ingredients are likely to be labelled.

Figure 2.2. Kernel Density of Welfare Measures (Value of Information) after a Representative Coefficient Simulation When Price Coefficient is Allowed to be Random in a ML Model

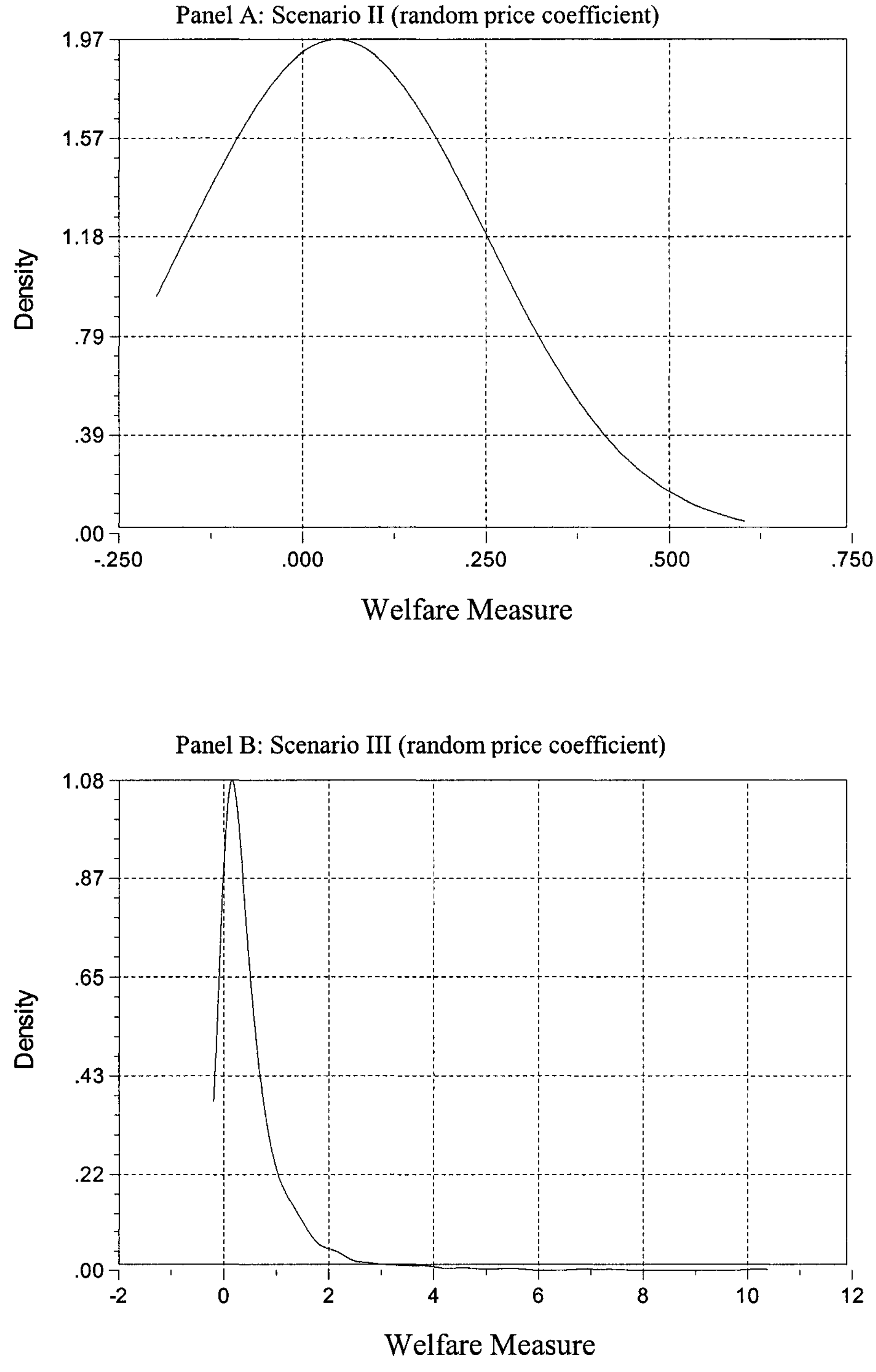
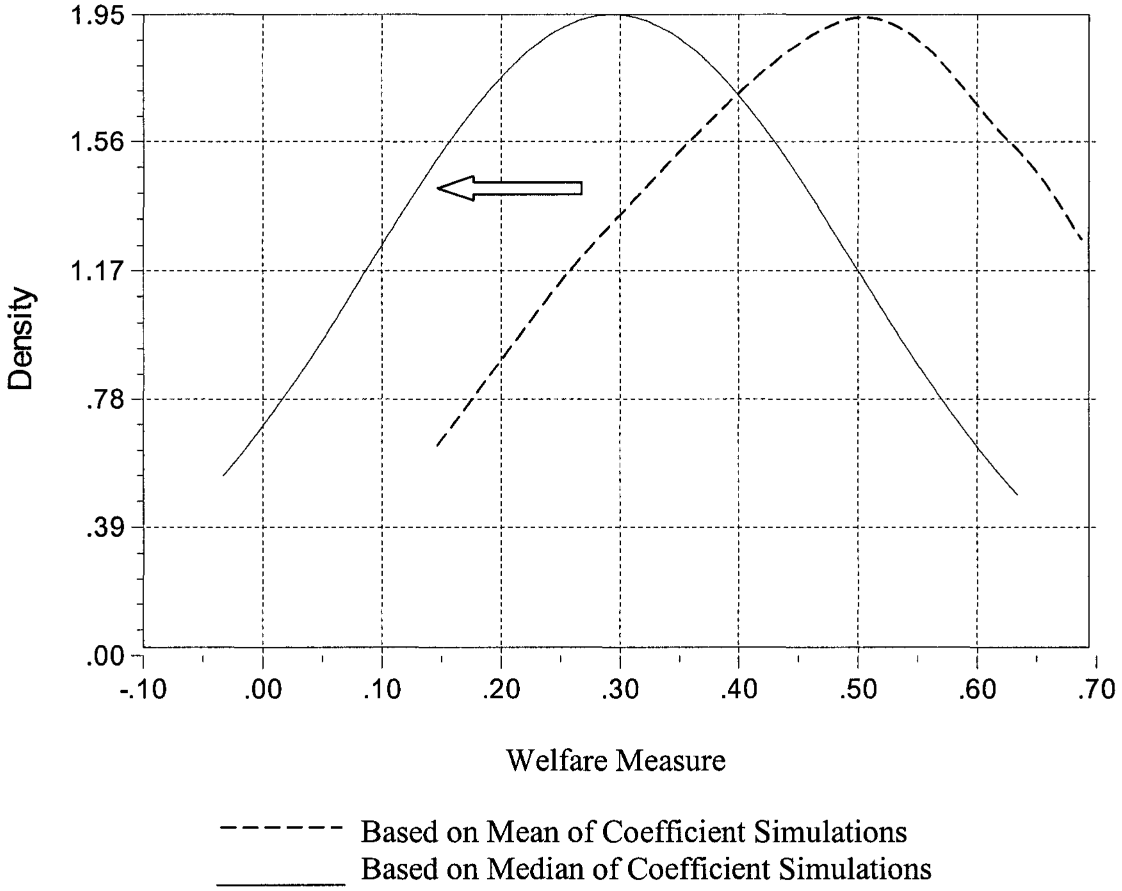


Figure 2.3. Kernel Density for Welfare Measures Based on Different Average Methods for Coefficient Simulations



Appendix 2.1: Specification of Random Coefficients

Before the estimation, a specification test was conduct to detect which parameter (s) is (are) likely to have a mixing structure. Following McFadden and Train (2000), a vector of artificial variables av_{iq} was created as:

$$av_{ijq} = \frac{1}{2}\left(x_{ijq} - \bar{x}_{iq}\right)^2, \text{ where } \bar{x}_{iq} = \sum_{j=1}^{J} x_{ijq} P_{ij}, \text{ for } q = 1,2,...,Q \qquad \text{(A2.1.1)}$$

P_{ij} is the predicted probability of respondent i choosing alternative j given by the conditional logit model. This vector of artificial variables is then included in the CL model as additional variables. The LR test rejects the null hypothesis that the artificial variables are jointly insignificant, which indicates that the model's fit will be improved by adding in mixing structures. To investigate which particular coefficient may be specified with a random component, a t-test is used for the coefficient of each individual artificial variable corresponding to each coefficient in the utility function. Because the coefficients in the utility function are assumed to be independent of each other, the power of this specification test is relatively low and McFadden and Train (2000) pointed out that 1 rather than 2 should be used as the critical value for determining whether an artificial variable is significant; i.e., whether the corresponding coefficient should be randomized.

Table A.2.1.1 reports the t-ratios of these artificial variables and reveals that the coefficients of the following variables should be random: *Buyno*, *White*, *Partial*, *Whole*, *GMO* and *Price*. Variable *Price* should be expected to have a negative impact on consumers' utility, therefore, the opposite of the price coefficient is assumed to have a lognormal distribution and other random coefficients are assumed to be normally distributed, given that a normal distribution is the most commonly used distribution in the literature.

Table A.2.1.1. Mixed Logit Specification Test Result

Artificial Variables	Coeff	Std. Er.	t-ratio
av_BUYNO	4.519*	0.701	6.444
av_STOREB	0.194	0.250	0.775
av_WHITE	3.422*	0.364	9.393
av_PARTIAL	0.810*	0.320	2.528
av_WHOLE	1.373*	0.363	3.786
av_GMO	1.533*	0.474	3.237
av_NOGMO	0.297	0.504	0.588
av_PRICE	0.222*	0.052	4.244
av_MGMO	-0.508	0.572	-0.888
av_VNOGMO	-0.553	0.626	-0.883

* Indicates a random coefficient

Appendix 2.2: Nested Logit Model Treatment for the No-Choice Option

For the nested logit model, given nest n and a total of K' alternatives in the nest, the conditional probability of individual i choosing alternative j is:

$$P_{ij|n} = \frac{\exp(\beta' X_{j|n})}{\sum_{k'=1}^{K'} \exp(\beta' X_{k'|n})} \qquad \text{(A.2.2.1)}$$

The inclusive value is:

$$IV_{ij} = \ln\left(\sum_{k'=1}^{K'} \exp(\beta' X_{k'|n})\right) \qquad \text{(A.2.2.2)}$$

For the degenerate no-choice option, $P_{ij|n} = IV_{ij} = 1$. The unconditional probability of individual i choosing alternative j is then:

$$P_{ij} = \frac{\exp(\gamma IV_{ij})}{\sum_{k=1}^{K} \exp(\gamma IV_{ik})} \qquad \text{(A.2.2.3)}$$

The result is reported in Table A.2.2.1. It can be seen that the utility parameter estimates and model fit are very similar to the conditional logit model. The inclusive value parameter for not choosing any bread alternatives "nobread" is fixed at one in order for the model to be identified. A LR test shows that the coefficient of the inclusive value for "bread" is significantly different from one. This indicates that the correlation between the other two alternatives in a choice task is greater than that between any of those two alternatives and the no-choice option.

Table A.2.2.1. Nested Logit Model Analysis of the No-Choice Option

	Coeff.	Std. Error
BUYNO	-2.596***	0.136
STOREB	-0.234***	0.056
WHITE	-0.839***	0.090
PARTIAL	-0.661***	0.084
WHOLE	-0.263***	0.084
GMO	-0.707***	0.120
NOGMO	0.402***	0.114
PRICE	-0.760***	0.039
MGMO	-0.403**	0.157
VNOGMO	-0.167	0.146
IV parameters		
BREAD	0.743***	0.079
NOBREAD	1	-
pseudo-R^2	0.111	
LL	-3263.258	
LR (df =1) test of $IV_{BREAD=1}$	8.89	

** and *** indicates significant at the 5% and 1% significance level respectively.

Appendix 2.3: Observations of the Current Canadian Bread Market (August 2003)

A study of available breads was conducted by observation in two major Canadian grocery stores in August 2003 in Edmonton, Alberta. On average, the following findings of the current pre-packaged sliced bread market were observed:

1. The ratio between bread products that have store brand and national brand is around 1: 2.
2. The ratio among white bread, partially whole-wheat bread, whole-wheat bread and multigrain bread is about 2 : 1 : 3 : 2.
3. The price for white bread ranges from $0.99 to $2.49 with median of $1.49.
4. The price for partially whole-wheat bread ranges from $0.99 to $2.49 with median of $1.49.
5. The price for whole-wheat bread ranges from $0.99 to $2.49 with median of $1.49
6. The price for multigrain bread ranges from $2.49 to $3.49 (and some are more than $3.49) with median of $3.49
7. In general, prices for national brands are relatively higher than those for store brands.

Sixteen bread products are created based on these findings for the actual market and the nature of their attributes are given in the following table.

Table A.2.3.1. Distribution of a Simulated Sliced Bread Market

Categories	White	Partially Whole-Wheat	Whole-Wheat	Multigrain	Sum
Store Brand	1	1	2	1	5
National Brand	3	1	4	3	11
Sum	4	2	6	4	16

Appendix 2.4: Welfare Measure Standard Deviation Simulations in a ML model

Train (1998) described how to calculate the CV in a ML model representing the average welfare of one grocery trip for an average consumer. This is the CV in a simple CL model integrated out of the density (over sampled consumers) of the random parameters:

$$CV'_{ML} = \int CV'_{MNL} f(\tilde{\beta} \mid \theta) d\tilde{\beta}, \qquad \text{(A.2.4.1)}$$

where $\tilde{\beta}$ is a vector of random parameters in the ML model defined through the distribution parameters θ. Since the expression in equation (A.2.4.1) does not have an exact analytical form, it must be approximated. A simulation approach can be conducted in two steps. First, a large number (R) draws of the ML model parameters reported in Table 2.4 are taken from a multivariate normal distribution according to the estimated parameters and their covariance from the simulated maximum likelihood estimation of the ML estimation. We define this step as *parameter simulation*, which is similar to the simulation in a CL model. Second, after each draw in R, the values of these parameters are used to construct the empirical densities (which are asymptotically normal) for the six random coefficients, and S (S is large) draws are taken from these empirical densities for each individual coefficient. We define this step as *coefficient simulation*. Together with the values of those fixed coefficient obtained directly from the parameter simulation, welfare measures can be calculated based on formula (11).

The result of each individual coefficient simulation is not directly relevant to the final welfare measure. The final mean and standard deviation of the welfare measurement under a ML model could be obtained by using a similar process as described for the CL after all coefficients are obtained. Ideally, both R and S should be sufficiently large (especially for R) to guarantee that a draw from a multivariate normal distribution is an appropriate assumption for the parameter simulation. In this study, we use 1000 for both R and S.

In this study, the coefficient for the price variable price is assumed to be lognormally distributed to comply with the theoretical sign of price in choice probabilities. When the entire distribution of the lognormal distribution is used for welfare calculations, its substantial long tail tends to bias the welfare estimates downward, given the fact that a welfare measure under a discrete choice model is (roughly) inversely proportional to the coefficient of price (Layton and Brown 1998; Chen and Cosslett 1998). However, there is even a more serious potential problem associated with a random price coefficient with almost any type of uncensored distribution. When the price coefficient is sufficiently close to zero, which is likely for a normally distributed or a lognormally distributed coefficient, the welfare measures will approach infinity (Revelt and Train 1999). This effect will bias the welfare measure upward. To make it more confounding, there is no method to detect which of these two sources of bias is dominating in a particular situation. Hensher and Greene (2003) proposed a process to remove the first type of bias: when drawing from a lognormal distribution, the last two percentile of that distribution can be truncated to reduce the "long tail" problem[13]. For the second problem associated with a random price coefficient, there is no definite answer either. We compare cases when the price coefficient is allowed to vary according to its lognormal distribution and when it is fixed at the mean level.

[13] This approach is rather *ad hoc*. There is no guidance from theory on how much of the tail one should truncate. We investigated its potential in this study: For each loop of the parameter simulation, a total number of S draws are obtained for the coefficient of price. These draws are first sorted in ascending order, after which the last X percent (X has been specified as 2, 4, and 10) of the series are disregarded and then the series is resorted. Therefore, a total number of (1-X%)*S replicates for each random coefficient are obtained within each parameter simulation. Finally, the mean from the parameter simulation is retrieved to compare with the situation when no truncation was carried out. However, we found no significant differences.

Appendix 2.5: Comparison of Welfare Measures Simulation Results

There are at least three contrasts that can be drawn by comparing these results. First, under either the conventional approach or the value of information approach, the result under the ML model is different when the price coefficient is held fixed or random. The largest gaps are observed in the third scenario (where eight products are labelled as containing GM ingredients), especially when the median is used in the conventional calculation (in column c and column e) and when the mean is used in the adjusted approach (in column g and column i). Second, depending on whether the mean or the median is used in the ML model, welfare measures tend to be different. This is particularly true for the third scenario irrespective of the conventional or the adjusted approach and no matter whether the price coefficient is held fixed or random. Compared with CV estimates obtained through the CL model, two of the four groups suggest that using medians rather than means in the ML model provides a more consistent measure (compare column f versus h or g; compare column f versus j or i). The other two groups give mixed evidence (compare column a versus c or b; compare column a versus e or d). Finally, similar to the situation under the CL model, in the ML model there exists a significant difference between the conventional CV measures and the value of information, whether or not the price coefficient is held fixed. This can be seen through comparisons of columns b-g, c-h, d-i, and e-j.

Through these analyses, a general conclusion that can be reached when calculating welfare measures is that, the CL and the ML models can produce fairly different results. Such differences persist even when the price coefficient is held constant under the ML specification. This implies that these differences are mostly due to the disparities between the simulation processes that underlie these two situations. Similar discrepancies in welfare calculations under the CL and the ML models have been documented in other studies as well (e.g. Bhat 1996). Researchers should be aware of this possibility and act accordingly in deriving a reliable range of welfare measures.

Chapter 3 Reference Point Effects and Consumer Choice of GM Food

Overview

Reference point effects are investigated in the context of Canadian consumers' choice of bread with possible GM ingredients. In addition to a price reference point, this paper also develops consumers' reference points on a quality attribute with credence properties—whether or not the product contains GM ingredients. A flexible choice model is used to capture the existence, as well as the source, of both reference point effects. Consumers' welfare implications from changes in GM labelling policy are considered in terms of their policy-induced reference point effects. The results indicate that for the GM based food attribute, for which attitudes are diverse, the reference point effects that have typically applied for price changes are not evident. This may due to the uncertainties associated with the GM attribute and variety-seeking behaviour. Differences in both the magnitude and the distribution of the welfare measures associated with alternate labelling policies are found.

Introduction

Consumer goods can be divided into three categories: search goods (Nelson 1970), experience goods (Nelson 1970; Leland 1979), and credence goods (Darby and Karni 1973). Credence attributes can arise when a good is produced by inputs with stochastic properties or the result of consuming the product is unknown (Darby and Karni 1973). Since genetically modified (GM) foods have unknown properties regarding human health (Veeman 2001) and the environment (Forge 1999; Adele et al. 2001), foods containing or not containing GM ingredients can be viewed as credence goods. Consumers' choices of foods that may or may not include GM content are made under uncertainty.

Based on neoclassical economic theory, expected utility theory is often applied to analyze consumers' economic behaviour under uncertainty. However, there is a significant amount of evidence from the literature indicating that individuals sometimes tend to behave "irrationally" or "abnormally" relative to the predictions of expected utility theory (see McFadden 1999 for an excellent review). The seminal work by Kahneman and Tversky (1979) and its elaboration into reference-dependence preference theory (Tversky and Kahneman (1991)) brought the behavioural and psychological aspects of human decision-making into economic analysis. The theory suggests that the apparent inconsistency between individuals' actual behaviour and prediction based on expected utility is due to the unrealistic assumptions inherent in the expected utility theory rather than to individuals' irrational behaviour. McFadden (2002) noted that traditional predictive choice analysis, parallel to expected utility theory, could benefit from adopting the results and derivations found in behavioural choice analysis.

In this study, reference point effects drawn from the theory of reference-dependent preferences are investigated. Using Canadian consumers' stated choices of pre-packaged sliced bread, reference points are constructed around the price and GM attributes. The presence or absence of GM ingredients is revealed through different types of GM labelling, which represent current policies in labelling requirements that apply in different countries. Given consumers' uncertainties surrounding the GM attribute, it is not clear *a priori* how they will react to actual presence/absence of GM ingredients in food compared with whether they perceive that GM ingredients are present (i.e., relative to their reference level).

The analyses in this paper are developed in the framework of the random utility model (RUM) from the realm of predictive choice analysis, a model which can accommodate a large range of choice behaviour. In particular, a mixed logit model is adopted that incorporates variables measuring reference point effects associated with the price and GM attributes. Heterogeneity surrounding these reference point effects is explicitly modeled, which allows us to analyze the source of reference point effects. Finally, dependent on their reference levels, consumers' welfare measures are calculated in four hypothetical scenarios involving changes in GM labelling policies.

Theory

Since the developments by Kahneman and Tversky (1979); Tversky and Kahneman (1991) and Tversky and Wakker (1995), prospect theory has increasingly been applied in interpreting choices under uncertainty and has become a core theory with a variety of extensions (such as rank-dependent utility theory (Quiggin 1982, Lopes 1984, 1987 and 1990) and others (Birnbaum 1997; Birnbaum and Navarrete 1998)). Kahneman and Tversky (1991) formalized the implications of their prospect theory to individual's decision making. This is widely referred to as reference-dependent preference theory—all preferences are defined over certain reference points. Depending on a reference point, a gain for one person may be taken as a loss by others and may induce different reactions by different people. For the same individual, a shift of the reference point at different stages of a decision process will change his or her valuation benchmark and cause behaviour changes.

Kahneman and Tversky (hereafter referred to as KT) defined the overall value of a prospect V as

$$V(x,p;y,(1-p)) = \pi(p)v(x) + \pi(1-p)v(y) \tag{1}$$

where π is the weighting function that depends on the probability of prospect x, p. The weighting function is different from the definition of a simple probability. It measures the desirability of a prospect due to its possible outcomes, and generally π (p) + π (1-p) < 1. v is the value function and x and y denote outcomes or wealth changes respectively. KT assume that $v(0) = 0$ in that if a prospect does not change a consumer's wealth level, he or she will not have a gain or loss in utility. Furthermore, KT assume that $\pi(0) = 0$ and $\pi(1) = 1$, indicating either a definitely impossible case or a must-occur case respectively. Equation (1) can be shown to nest the specification of expected utility by imposing certain conditions on π and v. KT described the value function v as showing how a particular change of wealth can be evaluated by an individual, and described it as an S-shape projection of wealth *changes* on values.

The value function has three major unique properties that differ from expected utility theory assumptions (Laibson and Zeckhauser 1998). First, decision makers exhibit risk aversion when the outcome involves gains (Tversky and Kahneman 1991). This is represented by a concave value function over the domain of gains. However, a convex value function over the region of losses demonstrates that these individuals are risk seeking when the outcome refers to losses. Second, the value functions for both gains and losses display diminishing sensitivity over the magnitude of change in wealth. Third, the asymmetric distribution of the value function over regions of gains and losses (steeper for losses than for gains) indicates that the same amount of absolute changes in gains and losses will result in different subjective values for the decision maker.

It is necessary to point out that in KT's value function, the focus is on the *change* of the current level of wealth. This includes the augmentation (positive or negative) of wealth, as well as the original level of wealth before the change. In contrast, expected utility only includes the final stage; i.e., only uses the *result of the change* in wealth as the argument of the utility function. Neilson (1998) solved two further anomalies in decision making by constructing a useful three-argument value function which includes effects from original wealth, accumulated changes of wealth, and the current change of wealth. For a summary of the properties of the weighting function, see Laibson and Zeckhauser (1998).

Both the value function and the weighting function are subjective measures, which implies that they vary across individuals. The value function incorporates changes of wealth rather than its final stage. For each individual there must be a normalized "zero" on his or her wealth scale so that the value function can be built on gains or losses relative to that zero point. KT defined this point as the reference point of decision making. In other words, the value function is defined conditional to a certain reference point. As the reference point is subjective, each individual is likely to have a different level of reference and, therefore, to have a different view on gains and losses. Decisions suggested by reference-dependent preferences can be assumed to obey the properties of the value function and the weighting function.

Based on their discussion on reference-dependent utility theory, Tversky and Kahneman (1991) generalized the theory to include multiple reference points in a single decision making process. They concluded that if a choice could be viewed as a composite package of its attributes, then each attribute may be described by a value function specific to that attribute. The value function will carry all the characteristics of that particular attribute. Therefore, a decision maker will likely judge the value (or attractiveness) of each attribute according to its perceived reference point and choices are made relevant to each individual reference point. The extension to multiple reference points implies that in a product market, in addition to the single price reference point, consumers are likely to draw their choices based on other quality reference points as well.

Although prospect theory was developed to describe consumers' choices under uncertainty, the properties of the value function (e.g., the induced reference point effect) have been found to apply in general choice behaviour and have been verified by revealed preference studies and laboratory experiments (e.g., Jullien and Salanie 2001; Munro and Sugden 2002)[1]. In economic studies, if a consumer's utility of choosing a product is determined by the product's attributes, the utility can be written as a function of these attributes. The decision makers (consumers) are assumed to know their preferences and utility obtained from a product perfectly, but that utility is not fully observed by an analyst. The indirect utility of consumer i choosing product j, from the view of a researcher, could be written as:

$$U_{ij} = X_{ij}\alpha_i + e_i, \qquad (2)$$

where X_{ij} is a vector of factors that may affect consumer i's utility, including choice-specific or individual-specific factors and e_i is an error term denoting the fact that an analyst does not observe a consumer's utility perfectly.

Equation (2) is a standard representation of random utility theory; $X_{ij}\alpha_i$ is the deterministic portion of the utility and the error term e_i is the random portion. Since a consumer's favoured product is represented by a higher utility level than other product alternatives to that consumer, the utility associated with it can be viewed as a measure of the attractiveness of a product when a series of its characteristics (X_{ij}) are compared with the characteristics of another alternative (X_{ik}). Comparing the meaning of a utility function with the definition of a value function $v(x)$, which is a measure of the value of an

[1] Levy and Levy (2002), however, showed that predictions of prospect theory do not always dominate in all situations. These authors review studies that either support or oppose prospect theory.

asset, determined by the change in wealth relative to another state or asset to an individual, it is not difficult to see that the utility function in a random utility framework can be readily specified as a value function in prospect theory. The value function is not defined over the state of wealth but rather the change in wealth. This generates the reference point effect. The utility function could also feature the changes of factors and a representation of the reference point effect. Since the framework of random utility produces a rich platform for various analytical tools for studying consumer preferences (Manski 1999), this study focuses on the reference point effect in utility functions defined under the random utility framework.

Modeling of the Reference Point Effect

Prospect theory has been empirically proven to be superior to expected utility theory in explaining human behaviour in many situations other than in laboratory experiments (Jullien and Salanie 2001; Munro and Sugden 2002). In the marketing literature, the existence of a reference point effect has long been recognized. Early works include Winer (1986), Lattin and Bucklin (1989), and Kalwani and Yim (1992). Other studies focus on different ways of capturing and measuring the reference point effect (e.g., Kalyanaram and Little 1994; Chang et al. 1999; Bell and Lattin 2000; and Niedrich et al. 2001). However, these studies did not explore the generalized multiple reference point effect speculated by Tversky and Kahneman (1991) and, therefore could not fully explain consumers' preferences and heterogeneity.

As early as 1993, Hardie et al. proposed a pioneering economic model to capture the reference point effect with both the price reference point and brand loyalty as a quality reference point for refrigerated orange juice. Using household scanner panel data, the authors applied the price and brand of a consumer's last purchase as the reference points for a current purchase. The effect of loss aversion was also taken into account. A similar analytical approach was adopted by Suzuki et al. (2001) to study transportation choices. Ordonez (1998) also examined how a reference price may affect consumers' product choices. She postulated that a reference price was generated endogenously through the quality of a product by each individual consumer. Ordonez (1998) found differences in this reference price for products with higher price and higher quality compared to products with lower price and lower quality.

The studies noted above that examined multiple reference point effects have some common drawbacks. First, they all used market-level data, which only reflected purchasing behaviour and prices, since typically no data on household characteristics or perceptions were available. However, consumers' preference heterogeneity is a crucial issue in analyzing the effect of reference-dependence, as well as in general choice analysis (Chang et al. 1999; Bell and Lattin 2000). Second, previous studies did not address the implication of consumers' uncertainty about the quality of the product on preferences, such as is expected to apply in purchasing food with credence attributes. In this study, uncertainties about the GM attribute may have impacts on the reference point effect. This paper explicitly explores the implications of reference point effects in consumers' preferences for a food item with possible GM attributes. The drawbacks of previous studies are avoided by a carefully designed analysis. The food product chosen is sliced bread. Individual-specific variables (such as GM perceptions, GM knowledge and other demographic variables) are obtained to describe heterogeneity in consumers' choices. A better understanding of consumers' choices in this situation is expected to provide a better understanding of the effect of different labelling alternatives on consumer preferences.

Data and Construction of Reference Points

The data used in this study are similar to those used in Chapter 2. They are obtained from a survey on consumers' perceptions and purchasing behaviours for pre-packaged bread with possible GM ingredients. The sample size is 437 respondents. As the majority of the data used in this analysis are also used in Chapter 2, only the unique portion of the data is described. This is the construction of reference point measures. For a more detailed description of the data, see the relevant section in Chapter 2.

Before entering the choice experiment, each consumer was asked how much he or she would usually pay to buy a loaf of sliced bread. Respondents were also asked whether or not they believed that the sliced bread that they normally buy contains GM ingredients. Each respondent faced a series of questions about the type of bread that they normally purchased and was asked to give their best estimate of the queried features. The answers to these questions yield each consumer's perceived price level and perception on the presence of GM ingredients. These questions were asked only once based on the assumption that these perceptions are held constant throughout the entire survey. The characteristics that were elicited could be defined, using the language of Munro and Sugden (2002), as each consumer's customary purchase. The perceived levels of customary price and perceived GM content are each taken as the consumer's reference points for price and GM ingredients. In the choice experiment, each product is described by its attributes including price and GM ingredients (for the third alternative "buy none" in a choice situation, these attributes are zeros). For chosen products these are the actual attribute levels. The difference between the reference and the actual levels of price and presence of GM ingredients serves as the basis for generating the two reference point effects for each respondent.

Following Hardie et al. (1993), the gain and loss variables are constructed based on the analysis in Table 3.1. Specifically, they are calculated as follows: for the price variable, as noted above, the reference point is obtained from the question preceding the choice experiment and denoted, in the case of the reference price as P_r. Let the price of the bread in an alternative be represented by P_a, then: if $P_a \leq P_r$, PG (price gain) = 1 and PL (price loss) = 0. On the other hand, if $P_a > P_r$, PG = 0 and PL = 1. For the reference point of GM attribute, GM_r, when an individual perceives that the bread he or she usually purchases has GM ingredients, $GM_r = 1$, otherwise $GM_r = 0$. The actual presence of GM ingredients (GM_a) in a loaf of bread is described in the choice experiment. When a product is explicitly labeled as containing GM ingredients, $GM_a = 1$, otherwise $GM_a = 0$. Since GM ingredients trigger the credence attribute property, as a researcher one can not directly assume that GM ingredients are undesirable and associated with a loss, while the absence of GM ingredients is associated with a gain. These are assertions that should be tested rather than assumed. However, for convenience, we define GMG = 1 and GML = 0 when $GM_r - GM_a = 1$ and when $GM_a - GM_r = 1$, GML = 1 and GMG = 0. According to these definitions of gain and loss, for the third (no choice) alternative in each choice occasion, the gain = loss = 0 for both price and the GM attribute.

Our data set has 437 consumers. A total of 9.2% of these consumers usually pay a price of $0.99 or less for a loaf of bread. Consumers who usually pay $1 to $1.99, $2 to $2.99 and $3 to $3.99 for a loaf of bread account for 60%, 27.5% and 3.4% of the sample respectively. In terms of consumers' perceptions on the presence/absence of GM ingredients in their bread, 40.7% of the sampled consumers believed that their bread contained GM ingredients and the rest did not think that this was the case. These 437 consumers, each responded to eight choice situations, and each choice situation contained two alternatives that were described by their attributes[2]. This gives a total of 6992 "products" in the survey. Based on the definition of gains and losses in price and GM ingredients in this study, 11% of the alternatives created a gain and 17% created a loss in GM content while 72% of the alternatives did not involve any gains or losses in terms of GM content. For price, 31% and 42% of the alternatives involved gains and losses in price respectively while the balance of the alternatives (27%) remained neutral (neither gain nor loss). These features demonstrate that there is likely to be a significant amount of variation in the measures of gains and losses created by the methods used in this study.

Econometric Models

Based on random utility theory, the indirect utility of individual i choosing alternative j in the t-th choice situation can be specified as (index t is omitted for the simplicity of presentation):

$$U_{ij} = \beta_1 Buyno + e_j, \quad j = \text{no-choice}$$

$$\begin{aligned} U_{ij} = (1-Buyno)(&\beta_2 Storeb_j + \beta_3 White_j + \beta_4 Partial_j + \beta_5 Whole_j + \beta_6 GMO_j \\ &+ \beta_7 NOGMO_j + \beta_8 MGMO_j + \beta_9 VNOGMO_j + \beta_{10} GMLOSS_j \\ &+ \beta_{11} NOGMGAIN_j + \beta_{12} Price_j + \beta_{13} PriceG_j + \beta_{14} PriceL_j \\ &+ \beta_{15} PriceGS_j + \beta_{16} PriceLS_j) + e_j \quad j \neq \text{no-choice}. \end{aligned} \tag{3}$$

[2] In order to obtain a measure of each consumer's reference level for the GM attribute, survey questions were used to ensure that consumers report their perceptions, either based on their true belief (Q2a) or based on their "best guess" (Q2b).

Variables Buyno, Storeb, White, Partial, Whole, GMO, NOGMO, MGMO, VNOGMO, and Price are all described in Chapter 2 and their definition is not repeated here. Recall that variables GMG and GML are two dummy variables, described in the previous section, indicating whether a choice option involved a gain or a loss in GM content.

Variable GMLOSS in equation (3) is created by interacting variables GMO with GML while variable NOGMGAIN is created by interacting variables NOGMO with GMG. The basis for these is that a loss in GM attribute can only occur when the actual alternative contains GM ingredients and, similarly, a gain in the GM attribute can only occur when the actual alternative does not contain GM ingredients. Dummy variables PG and PL, also discussed in the previous section, represent gains and losses in price respectively. Accordingly, variables PriceG and PriceL are interaction terms between variable Price and PG and PL respectively. Although PG and PL are both dummy variables, since Price is continuous, the variables PriceG and PriceL are also continuous. Quadratic forms of these terms, PriceGS and PriceLS are also included in the analysis. Finally, e_j is an error term reflecting the unobserved (from the analyst's point of view) factors in consumer i's choice for alternative j.

The indirect utility function in equation (3) mimics the value function in prospect theory. Testing the parameters provides evidence on whether consumer choices exhibit the properties predicted in prospect theory. Specifically, the value function should be concave in the gain domain and convex in the loss domain, with diminishing sensitivities. For the price reference point effect, one would expect the coefficient of PriceGS to be negative and the coefficient of PriceLS to be positive. For the GM reference point effect, due to the feature that the variables representing gain and loss over GM ingredients (GMLOSS and NOGMGAIN) are dummy variables, the curvature property of the indirect utility function is not testable. It is the expectation that the value function is steeper over losses than it is over gains, indicating an asymmetric response of consumers toward gains and losses. If this prediction is valid, one would expect the magnitude of the coefficient for PriceL is greater than that for PriceG. At this stage, we do not know whether consumers will view the unexpected presence of GM ingredients as a loss or whether they will view the unexpected absence of GM ingredients as a gain. However, if so, we would expect that the magnitude of the coefficient of GMLOSS is greater than that for NOGMGAIN.

With the assumption that the error term in equation (3) has a Gumbel distribution, the probability of consumer i choosing alternative j can be written as a conditional logit (CL) model. However, the CL model assumes the restrictive IIA property and is not suitable for estimating using panel data such as in the data set here. In addition, the CL model ignores heterogeneity among sampled consumers' preferences. The mixed logit (ML) model, often also referred to as the random parameter logit model (Ben-Akiva et al. 1993 and Train 1998), was developed to alleviate the drawback of the IIA assumption of the CL model, and also explicitly models preference heterogeneity. Following Train (1998), the probability implied by a ML model can be defined as:

$$\overline{P}_{ij} = \int P_{ij} f(\beta) d\beta \,, \tag{4}$$

where P_{ij} is the expression for the probability in the CL model and $f(\beta)$ is the density function of the random parameters. The ML model does not have a closed analytical form and simulation can be used in estimation (Ben-Akiva and Lerman 1985 and Train 1998). The simulated log-likelihood function is:

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} c_{ij} \ln\left(\widetilde{P}_{ij}\right) \tag{5}$$

where $c_{ij} = 1$ if j is picked by individual i but otherwise $c_{ij} = 0$, and $\widetilde{P}_{ij}$ is the simulated probability. Chapter 2 provides a more detailed discussion on the simulation procedure and properties associated with simulated log-likelihood.

Relative to the appropriate density functions for random coefficients, there is no determined theory to rely on (McFadden and Train 2000). In this study, the major interest is to determine whether there are heterogeneities among consumers' responses towards gains and losses in both price and GM attribute (coefficients $\beta_{10} - \beta_{16}$ in (3)). These responses are subsequently referred to in this paper as weights. To capture the heterogeneities, observed household characteristic variables are included to explain variations in weights for gains and losses, while the rest of the unobserved heterogeneities are assumed to be captured by a stochastic disturbance.

These random coefficients can be expressed as follows:

$$\beta = b_0 + \sum_{k=1}^{K} b_k d_k + \varepsilon \qquad (6)$$

where b_0 is a constant, capturing the average weights when holding other factors invariant and setting the mean of the stochastic term ε to zero; d_k is a vector of observed household characteristic variables that serve as the covariates for the mean estimate of β; b_k is the vector of coefficients associated with d_k; ε is the stochastic term associated with the weight. This is assumed to be normally distributed with a mean of zero and standard deviation b_s for all random coefficients β in the paper[3]. The first two terms in equation (6) in combination give the mean weights of the sampled consumers on various gain and loss measures, while the standard deviation, b_s, reflects how much the individuals in the sample differ from each other in terms of these weights.

To control the degree of complexity of estimation, three variables are postulated to capture the observed heterogeneity (d_k) among the mean estimates of β: respondent's age, household income, and respondent's knowledge of GM[4]. Table 3.2 summarises the definitions and descriptive statistics of the variables including the bread attributes, labelling scenario interacted variables, reference point effect measures, and the three household variables.

Estimation Results

Although the CL model is not the most desirable approach for analyzing the choice data, it does provide a reasonable base model for interpretation. The second column of

[3] There is no theoretical basis as a guide on which particular distribution ε should follow. A normal distribution is chosen due to its convenient moment and conjugation properties and since it is the most popular distribution used in the relevant literature (Hensher and Greene 2003 and Train 2003 Chapter 6).
[4] Efforts were made to incorporate other demographic and perception variables such as (education and attitude toward GM in food products) into vector d_k. However, the ML model often suffers from difficulties in converging and this applied in these cases.

Table 3.3 presents the estimation results of the CL model based on expression (3). The model is highly significant with an adjusted pseudo-R^2 of 0.114[5]. Similar to the discussion in Chapter 2, an alternative way to treat the no-choice option can also be investigated through the approach of a nested logit model, in the context of consideration of reference point effects. This procedure is followed and results from the nested logit model version are given in Appendix 3.1. The conclusion from comparing results between the CL and the nested logit models is also similar to that drawn from Chapter 2: although the nested logit model predicts closer correlation between the two bread alternatives than between any of these two alternatives relative to the no-choice option in a choice task, the marginal values of attributes are quite similar from the two models.

In the CL model, not buying any of the bread products generates a negative value for consumers as reflected by the negative coefficient of the variable Buyno. Compared with a national brand, a loaf that is store-branded is associated with a negative utility. Multigrain bread is the most preferred type of bread given the negative coefficients associated with the other bread type variables (white, partially whole wheat, and whole wheat). Bread with GM ingredients cause a significant drop in purchasing probabilities and breads that are explicitly labelled as GM-free significantly increase consumers' utility and thus increase the probability of their purchase. In this particular model, the labelling context interacted variables MGMO and VNOGMO do not appear to be highly significant (MGMO is significant at the 10% significance level).

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[5] It is noteworthy, however, that although the quadratic term PriceGS has a negative coefficient and PriceLS has a positive coefficient, as expected, they are both insignificant. This indicates that we fail to observe any curvature properties of the indirect utility function. However, this conclusion needs to be interpreted carefully. By saying that we *fail* to observe the curvature properties, we do not mean that they do not exist. Further investigation of the data revealed that variables PriceGS and PriceLS have strong correlations with PriceG and PriceL (higher than 0.9 coefficient of correlation) such that multicollinearity may be a significant issue. Generally, if a variable is completely continuous, one would not expect the correlation between its quadratic and linear form to cause serious statistical problems. In our case however, both PriceG and PriceL are created by multiplying price with a dummy variable. The multicollinearity due to the lack of full continuity in these variables may be severe enough to warrant close attention, since the presence of multicollinearity will induce overstatement of coefficients' significance and may even introduce a wrong sign. Considering this problem, variables PriceGS and PriceLS are dropped from further analysis and the second column of Table 3.3 reports the CL result of removing these two variables. The results of these two models are not qualitatively different.

Price has a significant negative coefficient as would be expected, indicating that when the price is higher, the purchasing probability is lower. The gain in price is negative but not significant. On the other hand, the loss in price is highly significant. These findings indicate that consumers do not attach a strong weight to price gains, but they discount the loss considerately and these effects should be included in the overall effect of price. These results verify prospect theory's prediction that for at least the price attribute, the consumers' value function (indirect utility function) has a different slope depending on whether it is defined over the gain or loss domain. However, the prediction from prospect theory is not directly analogous to the gain or loss as defined over the GM attribute. The parameter for NOGMGAIN (when a product was perceived to contain GM ingredients but was labelled as GM-free) is positive but not significant. However, when a choice involved an unexpected presence of GM ingredients, it introduced a significant amount of utility increase to consumers as shown by the significant positive coefficient of GMLOSS (when a product was perceived not to contain GM ingredients but was labelled as GM).

This result is somewhat surprising. Given the fact that variable GMO has a significant negative coefficient, indicating that on average consumers view the GM attribute as undesirable, one would expect that that the estimated coefficient of GMLOSS should also be negative as the unexpected presence of an undesirable attribute should further decrease utility. However, this is not the result found from the CL model in this analysis.

This apparent anomaly may be explained in the following way: the respondents who believe that their bread currently does not contain GM ingredients may be less averse to the presence of GM ingredients. Or more specifically, there may be two subgroups among these respondents who do not think their bread contains GM ingredients: those who think that GM ingredients are undesirable and that their absence is critical in making a purchase, and a second subgroup containing consumers that treat the GM attribute no differently than a peripheral quality attribute (do not have a concern about GM content). For respondents in the second subgroup, the appearance of the GM attribute in bread may even increase the variety that they can choose from and thus cause their utility to increase. As reflected by the results of the analysis outlined above, it appears that, the second subgroup dominated in our sample[6]. Alternatively, since GM foods are still relatively new in the market, it may not be surprising that reference points for these products are not well formed yet. One can further notice that the combined coefficients of variables GMO and GMLOSS is still negative indicating that the overall effect of the GM attribute is to decrease consumers' utility.

The fourth column in Table 3.3 presents the results of the ML model. The log likelihood function and adjusted pseudo-R^2 indicate a moderate improvement in model fit relative to the CL model. Except that variable MGMO is now significant at the 5% significance level (rather than at 10% in the CL model), all other fixed coefficients have the same interpretation as in the CL model[7]. Four variables are assumed to be associated with a normally distributed random coefficient: PriceG, PriceL, NOGMGAIN, and GMLOSS. These random coefficients are further specified with heterogeneity in the mean according to equation (6). The constant term, b_0, is significant for the weight of PriceL indicating that, in addition to the covariates included in the specification of reference point effect coefficients, the remaining average effect of PriceL is not zero. Average weights (b_0) of other reference point effect coefficients are not significantly different from zero.

Three household characteristic variables were used as covariates for the mean estimates of the reference point effect weights. We obtain the overall mean of these weights based on the estimate of the b coefficients. Equation (6) is evaluated based on an average consumer; i.e., a consumer that has the age, income and GM knowledge level

[6] Some insights on this issue might have been obtained by directly asking respondents how important they think the presence of GM ingredients is to their purchasing decisions. This question was not asked in the survey.

[7] A general check of the reliability of the ML model estimation result can be performed by comparing the normalised coefficients between the CL and the ML model. Normalisation is achieved by taking ratios of other coefficients and the price coefficient (Brownstone and Train 1999). Except for variable VNOGMO, the differences between these ratios in the CL and ML models are less or very close to 10% of the ratios themselves. We conclude that the estimates from the CL and ML models are generally consistent, except of course that the CL model does not provide estimates of random parameters.

indicated by the sample mean. Simulations are used to obtain the standard error associated with each β. The simulation procedure is straightforward. First, the covariance matrix between the b coefficient estimates was preserved from the estimation; denote this as Σ_b. Second, vectors of parameter the b estimates are drawn from the multivariate normal distribution $MN((b_0, b_1, b_2, b_3, b_s), \Sigma_b)$ through a Cholesky decomposition. For each draw, we calculate $\bar{\beta} = b_0 + \sum_{k=1}^{3} b_k \bar{d}_k$, where $\bar{d}_k$ is the sample average household characteristics. Finally, standard deviations are obtained from the standard deviation between the $\bar{\beta}$ estimates after each draw. Table 3.4 presents the results after 1000 simulations. Analogous to the findings for the CL model, the overall price gain and NOGMGAIN are not significantly different from zero, while the price loss weight is strongly significant and negative and GM loss is positive and significant.

The results obtained from the simulation are supportive of the structure of the average indirect utility function presented in Figure 3.1. The dashed line in this figure represents the standard shape of the value function suggested by prospect theory. Given that curvature of the value function (indirect utility function) cannot be successfully modeled from the data used in this analysis, the dotted line indicates the slope of the indirect utility function with respect to price and GM attributes without any reference point effect. For price, the dotted line over the gain and loss domain is a straight line. When reference point effects are added, a significant shift occurs in the loss domain, which leads to an asymmetry, shown by the steeper slope of the solid line over loss than over the gain. For the GM attribute, the dotted line indicates the slope of the average indirect utility function over the GMO and NOGMO attribute. A simple LR test reveals that the magnitude of the slope for GMO is greater than that for NOGMO. After the reference point effect is included, as indicated by the solid line, the coefficient of NOGMO is not changed, but the coefficient for GMO approaches zero for those individuals who have experienced an unexpected appearance of the GM attribute in bread. The reaction depicted in Figure 3 for the effect of the GM attribute is at odds with the anticipated shape of the value function.

We now turn to an explanation of the sources of heterogeneity surrounding the reference point effect measures. In Table 3.3, consumers' GM knowledge does not seem to have a significant impact on any of the weights. Income is significant in explaining the weight for NOGMGAIN. The lack of significance of b_0 for NOGMGAIN implies that higher income families that expect that GM bread is already in the market may be more sensitive to the positive utility given by the "no GM ingredients" attribute. This could reflect that higher income families tend to be more sensitive to food quality and opt not to buy food with uncertain features such as GM ingredients. Thus an unexpected absence of GM ingredients seems to matter more for richer families. Income also has a positive effect in the mean weight for price loss. The interpretation of this is, however, different to the impact of income on the weight for NOGMGAIN. Since the constant is negative and significant, a positive income effect will make price loss effect less salient. In other words, families with higher household incomes are less likely to "suffer" from losses in price, or a higher than normal price. This can be expected, given that higher income families are expected to be less price sensitive.

Finally, respondent's age has a significant positive effect on his or her weight on price loss. Similar to the interpretation for income effects, for older consumers, the price loss weight changes from being very negative (which applies with younger consumers) and moves closer to zero as age increases, indicating that older consumers are less sensitive to price loss than younger consumers. Relative to related literature, it is of interest that, in an experimental auction setting, List (2003) found that neoclassical economic theory predicts relatively well for consumers with more market experience while prospect theory functions better for consumers with less market experience. If age could be viewed as a proxy for market experience, our study supports that less experienced (younger) consumers behave more in accordance with prospect theory (are more sensitive to price loss).

The coefficient (b_s) for the stochastic term associated with each random weight is estimated jointly with other parameters and this coefficient represents the standard deviation among the sampled consumers surrounding a particular weight. All standard deviations are significant, indicating that in addition to the covariates we included in the analysis, there are other unobserved factors that make consumers assign different weights on gain and loss measures.

Welfare Simulations

In this component of the analysis, we calculate the value of information associated with GM labelling policies in the four scenarios in a market consisting of the 16 bread products that were specified earlier in Chapter 2. The four scenarios are as follows:

1. Due to the requirements of a mandatory labelling policy, a label "this product contains GM ingredients" appears on one nationally branded white bread.
2. One nationally branded white bread is being labelled as "this product does not contain GM ingredients," reflecting a voluntary labelling environment.
3. Due to the requirements of a mandatory labelling policy, a label "this product contains GM ingredients" appears on the previously defined eight bread products.
4. Eight previously defined bread products are now being labelled as "this product does not contain GM ingredients," reflecting a voluntary labelling environment.

With the reference point effects, these welfare calculations become more complicated then those in Chapter 2. For each given price, depending on their personal reference price levels, respondents may either be gaining, losing or breaking-even at that price. Similarly for the GM attribute, when different breads are labelled (either as containing or not containing GM ingredients) in various scenarios, different respondents will have different levels of GMLOSS or NOGMGAIN depending on their perception of the normal situation of their customary bread purchase that was determined at the beginning of the survey. Furthermore, given a certain level of departure from a reference level, respondents have different weights (coefficients) attached to that reference point effect defined through the covariates in the mean weight and the unobserved heterogeneity across the sample. These factors make it difficult to calculate the value of information through simulations based on an "average" consumer or several representative consumers. Consequently, we adopt the approach of sample enumeration (Train 2003, Chap 2) for this assessment. In sample enumeration, the value of information is calculated for each individual in the sample under each scenario. These individual values are then analyzed to obtain the properties, such as the mean and the standard deviation, of the welfare measure across the sample.

For the CL model, the conventional compensating variation (CV) and the biased-adjusted "value of information" are given by Hanemann (1983) and Legett (2002) respectively as:

$$CV_i^{Conventionaal} = \left\{ \ln\left[\sum_{j=1}^{J} \exp(\beta X'_{ij})\right] - \ln\left[\sum_{j=1}^{J} \exp(\beta X_{ij})\right]\right\} \Big/ -\beta_{price} \qquad (7)$$

$$CV_i^{ValueofInformation} = CV_i^{Conventional} - \sum_{j=1}^{J}\left(P_{ij}^{beforechange}(\beta X'_{ij} - \beta X_{ij})\right) \Big/ -\beta_{price} \qquad (8)$$

Given a welfare measure CV, either for the traditional measure or for the value of information, individual i's welfare measure under the ML model can be written as:

$$E(CV_i) = \int CV_i f(\beta_r(b_0, b_k) \mid b_s) f(b_0, b_k, b_s, \beta_f \mid L) d\beta_r d\beta_f \qquad (9)$$

where β_r are random coefficients whose distribution is determined by covariates and standard deviation across the sample; β_f are fixed coefficients; and L is the Cholesky factor of the overall parameter covariance matrix. Equation (9) can be evaluated by simulation.

Von Haefen (2003) showed that welfare measures conditional on each consumer's observed choices are more robust than in the unconditional case in various scenarios. In other words, conditional (on choices) parameter distributions can be used to replace the unconditional distribution in (9) to achieve better estimation of welfare. However, drawing from the conditional distribution usually requires one or several components of the Gibbs sampler to apply the Metropolis-Hastings (M-H) algorithm in a MCMC process. The M-H algorithm can be time-consuming, especially considering that we need to simulate each individual's welfare in the sample. We therefore propose a sequential variant of von Haefen's approach.

From a Bayesian perspective, the conditional distribution is equivalent to the posterior distribution of parameters of a subgroup of consumers (who have the same preferences reflected by choices in the survey) using the sampled population distribution as a prior. Following Revelt and Train (2000), the posterior distribution is obtained by applying Bayes theorem:

$$f'(\beta_r(b_0, b_k) \mid b_s) = \frac{P_{ij}}{\overline{P}_{ij}} f(\beta_r(b_0, b_k) \mid b_s) \tag{10}$$

This posterior distribution incorporates consumer i's previous choices and all covariate personal characteristic information. We then use f' to replace f for the simulation of (9) using 2000 replications. Table 3.5 reports both the conventional welfare measures and the value of information after sample enumeration[8].

The conventional welfare measure calculated using either the CL or the ML model shows that the welfare associated with mandatory labelling is negative. As discussed in Chapter 2, this is not a correct measure of the true welfare associated with GM labelling. The adjusted approach reveals the value of information. These adjusted welfare measure results from the CL and the ML model estimates are generally consistent except in the fourth scenario, where the ML model predicts a value five times higher than from the CL model. The likely reason for this discrepancy is the relative difference between the coefficient associated with variable VNOGMO in the two models. In both models the value of information in the mandatory labelling regime is higher than that in the voluntary labelling scenario. When eight breads are affected by the labelling requirement, the value of information to consumers increased in each of the mandatory and voluntary labelling situations.

The sample standard deviation measures in Table 3.5 describe by how much the sampled consumers vary in terms of their individual valuations of information in the four

[8] It is of note that this sequential method ignores the correlation between individual level parameters and other fixed parameters in the utility function. Therefore, although the means of various welfare measures will not be affected, the variance estimates are not precise. If we greatly reduce the number of replications for each individual's simulation, an approach similar to Von Haefen (2003) may be applied. However, we would be trading off unbiasedness for loss of efficiency due to the reduced number of replications if this approach was chosen.

scenarios. The sample standard deviation is smaller than the sample mean in the mandatory labelling scenarios, indicating that the majority of consumers value the information under a mandatory labelling requirement positively. For example, comparing the mean and the standard deviation in the first scenario under the ML model, one can see that 93% of the sampled consumers attach a positive value to the information. Similarly, in the third scenario from the CL model, more than 99.9% of consumers attach a positive value to the information from mandatory labelling. On the other hand, standard deviations in the voluntary labelling scenarios are (except one) all greater than the mean, showing that there is a great deal of "disagreement" among the sampled consumers on whether the information provided through a voluntary label is valuable. The proportion of consumers that value the information positively under a voluntary labelling regime ranges from 73% in the fourth scenario from the ML model to 56% in the second scenario from the CL model.

Related to the explanation discussed in the previous chapter, under the mandatory labelling regime, products that contain GM ingredients will be so labelled. If consumers believe there are uncertainties associated with GM foods (in terms of impacts on human health, the environment, and other aspects), the requirement that producers label GM product, may lead to trust in the provision of information and accredit a similar amount of value to the information. For voluntary labelling, some consumers regard the information as informative and valuable. However other consumers place less value on the information. The reasons for this could be that they simply do not trust the information statement perhaps because they think such a label claiming "the product does not contain GM ingredients" is a marketing tool. If this is the case, there might be some room for the government to focus on improving public understanding of the label and labelling system. The second chapter of this thesis provides more discussion on this issue and it is likely to be an interesting future research direction.

Summary

Although developed in the context of choice under uncertainty, prospect theory is demonstrated in this analysis to be also relevant in explaining consumers' choice behaviour. This chapter focuses particularly on reference point effects derived from prospect theory. A utility function incorporating reference point effects is constructed and testable hypotheses relating to these effects are evaluated. In addition to a price reference point, reference points are also developed on a quality attribute with credence properties—whether or not the product contains GM ingredients. The uncertainties associated with GM ingredients contribute to the interest in determining whether reference points occur for this attribute. The results show a reference point effect around price is as predicted in prospect theory. However, reference point effects around the GM attribute cannot be explained as simple gains or losses from the reference level. General predictions from prospect theory may not be directly applied to the GM attribute. This may be due to the uncertainties associated with the presence/absence of the attribute or to variety-seeking behaviour.

The analysis reported in this chapter differs from previous studies in that it explains the source of reference point effects through consumers' personal characteristics by adopting a flexible mixed logit model. It is found that different consumers do have different sensitivity towards reference point effects. Estimates of the value of information to consumers under mandatory and voluntary labelling policies are derived in the context of various scenarios recognising the reference point effects. These results show that in a mandatory labelling regime, consumers are relatively consistent in terms of the revealed value of information provided by labelling. However, in a voluntary labelling framework consumers value the information revealed much less than in the mandatory labelling case, and also tend to differ significantly in terms of the magnitudes of their valuation. This may suggest that from the perspective of the benefit associated with information revealed through labelling, mandatory policy is preferred to voluntary policy since voluntary labelling generates lower and more variable values to consumers. The labelling enforcement agency may improve the efficiency of voluntary labelling by reducing the proportion of consumers who may trust or value less the information revealed through voluntary labelling. This also provides issues for further study of the role of the labelling enforcement agency on consumer acceptance and valuation of policies.

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Table 3.1. Description of the Construction of Gain and Loss Measures

	Gain	Loss	No Gain or Loss
Price	If perceived price is higher than the actual price	If perceived price is lower than the actual price	If perceived price and the actual price are equal
GM Ingredients	If perceived as GM bread but actually is non-GM bread	If perceived as non-GM bread but actually is GM bread	Perceived and actual attribute regarding GM ingredients are the same

Table 3.2. Model Variable Descriptions

Variable Name	Variable Description
Price	A continuous variable representing actual price
Buyno	Alternative specific constant representing the utility associated with choosing to buy none of the bread
Storeb	=1 if the bread has a store brand. Otherwise = 0.
White	=1 if the bread is white bread. Otherwise = 0.
Partial	=1 if the bread is partial whole wheat. Otherwise = 0.
Whole	=1 if the bread is whole wheat. Otherwise = 0.
GMO	=1 if the bread is labelled as containing GM ingredients. Otherwise = 0.
NOGMO	=1 if the bread is labelled as not containing GM ingredients. Otherwise = 0.
MGMO	=1 if the context is mandatory labelling and the bread contains GM ingredients. Otherwise = 0
VNOGMO	=1 if the context is voluntary labelling and the bread does not contain GM ingredients. Otherwise = 0.
PG	=1 if the alternative involves a gain in price. Otherwise = 0.
PL	=1 if the alternative involves a loss in price. Otherwise = 0.
PGS	=square of PG*Price
PLS	=square of PL*Price
GMG	=1 if the alternative involves a gain in GM ingredients. Otherwise = 0.
GML	=1 if the alternative involves a loss in GM ingredients. Otherwise = 0.
Age	A continuous variable representing respondents' age
Income	A continuous variable representing respondents' income
Know	=1 if a respondent has answered all five GM knowledge questions correctly. Otherwise = 0.

Table 3.3. Coefficient Estimates

CL Model			ML Model		
	Coefficient	Std. Error		Coefficient	Std. Error
PRICEG	-0.0507	0.0645	Constant in Price Gain	0.4423	0.3034
			Age	-0.8242	0.5514
			Income	-0.1768	0.2737
			Knowledge	-0.0194	0.1565
			Sd. Of Price Gain	0.7170***	0.1086
PRICEL	-0.2201***	0.0411	Constant in Price Loss	-0.6675***	0.1481
			Age	0.5140**	0.2532
			Income	0.2827**	0.1363
			Knowledge	0.0837	0.0755
			Sd. Of Price Loss	0.5294***	0.0438
NOGMGAIN	0.1223	0.1304	Constant in GM Gain	-0.6010	0.6877
			Age	-0.1795	1.4231
			Income	1.3248**	0.5143
			Knowledge	0.0136	0.3494
			Sd. Of GM Gain	0.8150***	0.2210
GMLOSS	0.5337***	0.1277	Constant in GM Loss	0.6963	0.6177
			Age	-0.9763	1.1069
			Income	0.6612	0.6246
			Knowledge	-0.2548	0.3360
			Sd. Of GM Loss	1.3415***	0.1714
Buyno	-2.5415***	0.1585	Buyno	-3.0777***	0.1538
Storeb	-0.2243***	0.0523	Storeb	-0.2524***	0.0604
White	-0.7744***	0.0836	White	-0.8432***	0.0648
Partial	-0.5943***	0.0787	Partial	-0.6906***	0.0773
Whole	-0.2057***	0.0777	Whole	-0.2186***	0.0735
Price	-0.4190***	0.0740	Price	-0.5449***	0.0659
GMO	-1.0391***	0.1368	GMO	-1.2288***	0.1272
NOGMO	0.3279***	0.1134	NOGMO	0.3944***	0.0582
MGMO	-0.2380*	0.1308	MGMO	-0.3258**	0.1437
VNOGMO	-0.1845	0.1295	VNOGMO	-0.1410	0.1401
pesudo-R^2	*0.114*		*pesudo-R^2*	*0.161*	
LL	*-3241.766*		*LL*	*-3070.900*	

*, **, and *** indicates significant at the 10%, 5%, and 1% significance level respectively.

Table 3.4. Simulated Random Coefficients

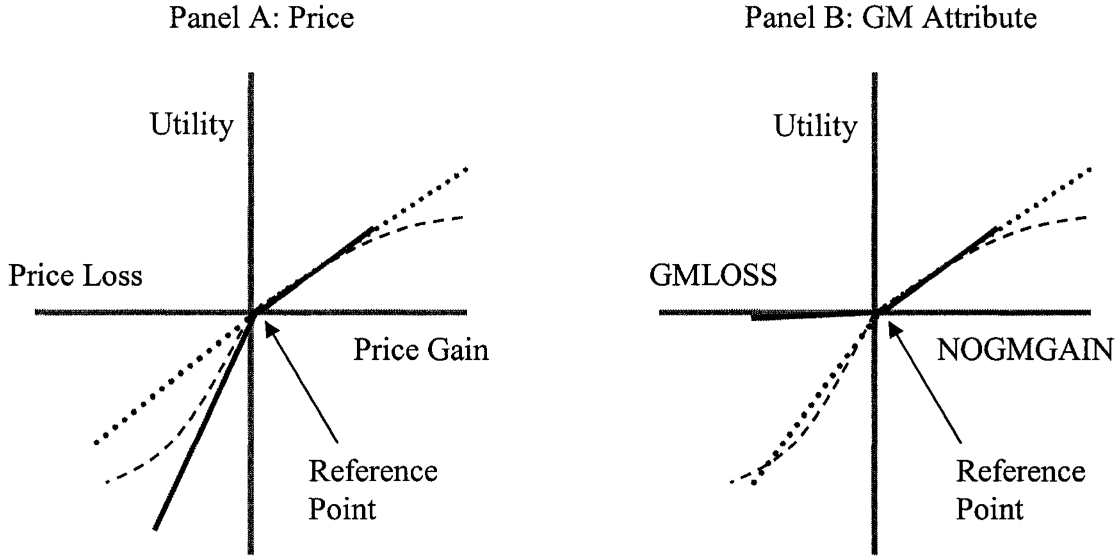
	Coefficient	Standard Deviation
Price Gain	-0.0251	0.1073
Price Loss	-0.3011*	0.0519
No GM Gain	0.1002	0.1796
GM Loss	0.5847*	0.1647

* Significant at the 5% significance level.

Table 3.5. Welfare Measures Based on Sample Enumeration

Scenarios	CL				ML			
	Conventional		Value of Information		Conventional		Value of Information	
	sample mean	sample std. dev.	sample mean	sample std. dev.	sample mean	sample std. dev.	sample mean	sample std. dev.
Mandatory Labelling: One Labelled as GM	-\$0.08	0.04905	\$0.08	0.05404	-\$0.06	0.02593	\$0.08	0.04945
Voluntary Labelling: One Labelled as NO-GM	\$0.05	0.05357	\$0.01	0.05219	\$0.05	0.04365	\$0.02	0.02869
Mandatory Labelling: Eight Labelled as GM	-\$1.08	0.10921	\$0.69	0.20900	-\$0.81	0.20984	\$0.78	0.45965
Voluntary Labelling: Eight Labelled as NO-GM	\$0.30	0.12309	\$0.04	0.05612	\$0.44	0.48041	\$0.21	0.32241

Figure 3.1. Graphic Interpretation of Reference Point Effects



Notes
The dashed line represents the shape of the value function suggested by prospect theory.

The dotted line represents the result when reference point effects are ignored. For price, the dotted line is the coefficient of the variable "price", which is a straight line across the gain and loss domain. For the GM attribute, the dotted line represents the coefficient associated with variable "GMO" over the gain domain and in the loss domain, the dotted line represents the coefficient associated with variable "NOGMO."

The solid line represents the result found in this paper that includes reference point effects.

Appendix 3.1: Nested Logit Model Treatment for the No-Choice Option with Consideration of Reference Point Effects

The formula and estimation issues for the nested logit model were introduced earlier in Chapter 2, therefore estimation results are directly presented in the following table. Similar to the findings from exploring this issue in Chapter 2, this model indicates that the two bread alternatives are more closely correlated to each other than they are to the no-choice option. However, the normalised attribute coefficients (ratio of a coefficient to the price coefficient) are very similar to the CL model.

Table A.3.1.1. Nested Logit Model Analysis of the No-Choice Option with Reference Point Effects

	Coefficient	Std. Error
PRIG	-0.051	0.069
PRIL	-0.216***	0.044
NOGMGAIN	0.118	0.140
GMLOSS	0.578***	0.142
BUYNO	-2.451***	0.155
STOREB	-0.233*	0.054
WHITE	-0.812***	0.089
PARTIAL	-0.623***	0.083
WHOLE	-0.231***	0.082
PRICE	-0.457***	0.082
GMO	-1.071***	0.148
NOGMO	0.352***	0.122
MGMO	-0.320**	0.150
VNOGMO	-0.179	0.139
IV parameters		
BREAD	0.847***	0.084
NOBREAD	1	-
pseudo-R^2	0.116	
LL	-3240.278	
LR (df =1) test of $IV_{BREAD=1}$	2.98	

*, **, and *** indicates significant at the 10%, 5%, and 1% significance level respectively.

Chapter 4 Decomposing Unobserved Choice Variability In the Presence of Consumers' Taste Heterogeneity

Overview

Heterogeneous tastes across a sample of consumers can be captured by random coefficients in a mixed logit (ML) model. However, there are other types of factors that may cause choices to vary, such as context effects or the complexity of choice tasks. These factors may not directly affect taste. This paper presents a method that jointly considers taste heterogeneity as well as choice variability, which is often broadly termed unobserved heterogeneity. Data from a stated preference choice experiment for bread with potential genetically modified ingredients are used. Taste heterogeneity around reference-dependent attributes is revealed by random coefficients in the utility function while the remaining choice variability is modeled through the scale function, assuming choice context, fatigue effect, and demographic characteristics as covariates. Results demonstrate that modeling other sources of choice variability in addition to taste heterogeneity moderately increases the model fit.

Introduction

In the previous two chapters, we examined consumers' reactions to different GM labelling policies and to "gains" and "losses" in terms of product price and GM ingredients. In this chapter, heterogeneities in consumers' tastes are explicitly modeled in mixed logit models through the distribution of coefficients associated with variables of interest. The method is proven to be useful in revealing the central tendencies of the variations of consumers' tastes. Valuable insights can also be obtained by decomposing the taste coefficient into several additive covariates to analyse the source of heterogeneity. Any significant taste heterogeneity that can not be explained by covariates included in the model is usually classified as unobserved (Hensher and Greene 2003). It is not difficult to see that holding other factors constant, the more knowledge one can collect about the heterogeneity, the better an economic model may explain and predict behaviour. This raises the question of how one can, to the fullest extent, use relevant information contained in observed consumers' choices to get a better understanding of unobserved heterogeneity.

By modeling taste heterogeneity through random coefficients in a mixed logit (ML) specification, a researcher will implicitly have to make a behavioural assumption that all the differences in consumer choices can and will be reflected by their taste variations[1]. This is likely to be an over-simplified assumption. Louviere et al. (2002) argued that unobserved heterogeneity, such as that described in a ML model, is just one of the many types of factors that cause choices to vary. These researchers used the term "variability" to account for reasons for choices to vary other than taste heterogeneity. We follow this terminology in the analysis here.

The variability in choices (within one individual or across individuals) may come from such factors as task complexity, the response mode, survey locations, time pressures or other aspects of the decision process (Louviere 2001). Literature in behavioural economics and psychology has made advances in recognising factors that form consumers' decisions (Payne et al. 1992 and Rabin 1998). McFadden (1998) provided a synthesis of these factors, collecting these into four overlapping categories: context effects, reference point effects, availability effects, and superstition effects. Reference point effects were investigated in the previous paper. In this chapter, the influence of context effects (including the fatigue effect) and demographic factors as a representation of these issues, are explored in accounting for other variability in choices, in addition to taste heterogeneity.

The importance of unobserved variability to the estimation of economic models has been investigated during the past decade. Variations in taste parameters cannot fully incorporate overall variability in choices (Louviere 2001). Researchers have formulated a systematic approach in order to model unobserved variability by taking advantage of the random (to the analyst) disturbance term in individuals' utility specifications (e.g., Swait and Louviere 1993; Swait and Adamowicz 2001a and b). After summarizing

[1] The ML model can also be specified as an error component model by collecting the stochastic portion of random coefficients into the error term of the indirect utility function (Brownstone and Train 1999). Sharing the same computational property as the random coefficients ML model, the error component model can be used to model the variance structure of choices. However, this approach is only adopted to explicitly model a specific heteroskedastic substitution pattern (Train 2003, p160).

relevant literature, Louviere (1996) concluded that once unobserved variability is explicitly controlled, many utility parameter differences across different studies may become negligible, hence a large proportion of the heterogeneity around taste (as seen in utility parameters) will be accounted for. In order to use unambiguous and succinct language, in the following discussion of the paper we follow the general terminology used in the literature by naming the error term of the random utility model (RUM) as the random component and the random term in a random parameter as the stochastic component. We model the overall choice variability through the random component, while explicitly accommodating taste heterogeneity through the stochastic component of random coefficients.

Modeling Choice Variability and Taste Heterogeneity

The random component in a RUM is the representation of all factors that affect individuals' choices that is known to those individuals but are unobservable from the analyst's perspective (McFadden 1974)[2]. Louviere et al. (2002) noted that since the random component coalesces all pertinent sources of unobserved variability that contribute to the differences in choices, one can achieve a valuable understanding of choice variability by explicitly modeling the covariance structure of the random component in a RUM. Hensher et al. (1999) appraised efforts along this line of research. Some researchers modeled the statistical impact of the unobserved (sometimes uncontrollable) variability in choices made under different scenarios. Examples include Adamowicz et al. (1994), Louviere et al. (1993), and Brownstone et al. (2000). These studies treated the random component purely as a scale factor to normalise estimation obtained from different data sources in order to support cross-evaluation of the validity of various results.

Although sharing the same modeling structure, another set of researchers considered the scale parameter derived from analysis of the random component as a behavioural vehicle by adding decision making factors to the scale parameter. Swait and Louviere

[2] Recent consumer behavioural research outlines new advances in constructing a RUM by assuming that occasionally consumers themselves are uncertain about their own choices due to factors such as learning by doing or strategic behaviour (Ben-Akiva et al. 2002).

(1993) reduced disparities between parameter estimation from different choice tasks to investigate the apparent difference in consumers' cognitive process. Other researchers have specified more direct models to elicit factors that contribute to the variability in choices. Hensher et al. (1999) used consumers' responses to the average value of different alternatives to explain choice variability. Hensher et al. (2001) investigated the impact of the number of choice sets as a measure of the effect of complexity in consumer choice. Bradley and Daly (1994) explicitly measured the fatigue level in choice situations as an explanatory variable for choice variability. Swait and Adamowicz (2001a and b) generalised the fatigue effect and incorporated the choice environment and a measure of complexity as covariates for the scale differences. Using a set of revealed preference (RP) data, Swait and Stacey (1996) modeled the impact of inter-purchase time and state-dependent on consumers' choice behaviour. Louviere and Hensher (2001) concluded that factors like consumers' demographic characteristics, choice environment and context, geographical and spatial allocations, and time factors can all be potential elements accounting for the variability of consumers' choices.

The researchers noted above have explored theoretical and empirical methods to explicitly model choice variability. They all treat the random component as the overall cause of the variability in choices by modeling only the scale parameter. However, one can consider decomposing choice variability by assuming that the stochastic component explains the unobserved heterogeneity and the random component integrates the rest of the choice variability. Swait and Adamowicz (2001b) pointed out that these two effects often come hand in hand in a choice model. It might be more appropriate to model and interpret some forms of choice variability as taste heterogeneity and vice versa. Insofaras unobserved heterogeneity and variability are coupled, joint estimation will be more efficient than independent estimation.

Swait and Bernardino (2000) outlined a potential approach for accomplishing this goal. Through a nested logit (NL) model, these authors accommodate taste heterogeneity across different alternatives in different nests while controlling the scale factors (inclusive value in a NL model) among nests. They concluded that if the differences across nests are not appropriately treated, it is likely that taste differences would seem to dominate. However, there are some limitations associated with using the NL model. First, as is well known, the underlying behavioural implication indicated by a NL model may not be consistent with utility maximization when the estimated scale parameters (inclusive values) fall beyond the range of [0,1] (McFadden 1978). An example is given by Swait et al. (2003). Swait and Bernardino (2000) also noted that more complicated specification of the NL, for example a random parameter version, may confound the interpretation of the nesting structure. Second, the NL model requires that the random component has a generalized extreme value distribution, which is more restrictive than the distributions of the multinomial probit (MNP) or the ML model. Therefore, the NL model (and other models in the generalized extreme value (GEV) model family) can only partially relax the IIA assumption, and has difficulties in handling panel data (Train 2003 p111).

Louviere (2001) and Louviere et al. (2002) commented that since the impacts of the stochastic and random components are usually confounded, generally it requires special treatment to separate them. With the development of the ML model, taste heterogeneity can be uniquely modeled. Moreover, the ML model is flexible enough to allow any type of choice covariance structure (McFadden and Train 2000)[3] and provides a promising way to separate taste heterogeneity and choice variability.

Brownstone et al. (2000) estimated a ML model with explicit consideration of the scale parameter. These authors did not address the scale factor as a manifestation of the unobserved choice variability. Rather, they estimated the scale factor as a purely statistical nuance to enable the merging of data sets from a revealed preference (RP) and stated preference (SP) survey. Breffle and Morey (2000) modeled anglers' unobserved heterogeneity and variability jointly under a ML framework. They allowed taste coefficients to vary across sampled individuals and estimated models with three types of

[3] McFadden and Train (2000) demonstrated that this can be achieved by specifying appropriate distributions for the random coefficients in a model. However, they continued the argument with the note that such a generalisation of the ML model is most likely only feasible in theory. In practice, researchers usually choose distributions that are relatively convenient to work with, which in turn prohibits to some extent the model's ability to capture *any* arbitrary type of covariance structure.

different scale function specifications: individual scales (where the model has difficulties in converging), group-wise scales, and a random scale. The random scale approach is, again, a purely statistical treatment to account for the scale differences. For the group-wise scale specification, prior to estimation, these authors divided anglers into eight groups based on three demographic characteristics: age, fishing experience and fishing club status and compared the differences in the implied eight scales. However, this pre-estimation cluster analysis is not efficient for determining the appropriate magnitude of scales.

The analysis in this chapter differs from these previous studies. A ML model is adopted to account for taste heterogeneity across the sample, and choice variability is jointly considered by estimating a scale function. The scale function has a clear behavioural interpretation in that it is a function of choice context, choice set complexity (fatigue effects) and respondents' demographic characteristics: gender and whether or not the respondent received post-secondary education. These factors affecting choice variability are treated as endogenous to decision-making and are estimated jointly with all other parameters in the ML model.

Econometric Models

In a typical choice experiment, respondents are often assigned to a series of choice occasions with each consisting of several alternatives. They are asked to state their preferences (usually indicated as the most preferred alternative) in each choice occasion (Swait and Adamowicz 2001a). This structure gives a string of stated choices for each individual and therefore constitutes a set of panel observations. According to random utility theory, the indirect utility of individual i choosing alternative j can be specified as:

$$U_{ijt} = \beta_i X_{ijt} + \varepsilon_{ijt}, \qquad (1)$$

where t indexes choice occasions and β_i is a vector of coefficients representing taste. β_i is allowed to be different for each individual respondent to incorporate heterogeneity associated with taste. ε_{ijt} is the random component, which can be viewed as a union of all other effects that cause choice variability (Louviere 2001). If the analyst can assume a cumulative distribution function, in particular a Gumbel distribution, for the random component that is defined over a finite parameter vector, the probability of individual i choosing alternative j at the t[th] choice occasion can be written as:

$$\overline{P}_{ijt} = \int \frac{\exp(\lambda_{ijt}\beta_i X_{ijt})}{\sum_k \exp(\lambda_{ikt}\beta_i X_{ikt})} f(\beta)d\beta = \int P_{ijt} f(\beta)d\beta \qquad (2)$$

There are several noteworthy points in this specification. First, ε_{ijt} is specified as independent across individuals. Second, $\overline{P}_{ijt}$ represents the choice probability under the mixed logit model. As the second equality shows, $\overline{P}_{ijt}$ is the conventional conditional logit probability P_{ijt} integrated over the density of the random parameters. Third, $f(\beta)$ is the probability density function for random coefficients. To keep our notation clean, β_i is used in equation (2), although not all coefficients in equation (1) need to be specified as random coefficients[4]. $f(\beta)$ gives the density of those coefficients that are random. Also, random coefficients can be assumed to be distributed independently, or to have a joint multivariate distribution, and in this latter case $f(\beta)$ can be generalised to represent the joint density function of the random coefficients.

Fourth, λ_{ijt} is the scale parameter that accounts for the overall unobserved variability of choices. It is the inverse of the standard deviation of the model. In a multinomial logit model, the scale parameter is typically normalized to one to allow the identification of the utility parameters. As discussed earlier, however, variability may occur from various sources such as the nature of the alternatives, individuals' demographic characteristics, or survey context. Therefore, the most general form to use to represent the scale parameter is $\lambda_{ijt}(Z_{ijt})$, which indicates that this is a function rather than a single parameter, and may vary across alternatives, survey respondents, or choice situations[5].

[4] In fact, Ruud (1996) showed that if all coefficients, including constant terms, are randomized, serious identification problem may arise and cause the model estimation to be unstable.

[5] In theory, if the scale parameter is specified as λ_{ijt}, this may also correlate with the random coefficient in that they are distributed jointly following a multivariate distribution function. This idea is appealing because the unobserved heterogeneity and variability in choices are expected to be naturally interrelated. A

For β_i, in addition to the mean and standard deviation of the stochastic component, one can specify covariates to model that shift the mean in response to various explanatory variables. In general, one can define:

$$\beta_i = b_0 + b_q Y_{iq} + b_e e_i, \qquad (3)$$

where Y_{iq} is a vector of individual-specific variables and $e_i \sim N(0,1)$. Similarly, we desire to explicitly model the source of unobserved variability in choices. Therefore $\lambda_{ijt}(Z_{ijt})$ can be defined as follows:

$$\lambda_{it} = \exp(\gamma_w Z_{itw}) = \frac{1}{\sigma_{it}}, \qquad (4)$$

where Z_{itw} is a vector of w variables representing the differences across choice sets and γ_w indicates the corresponding scale function parameters. Note that the modeling of the scale parameter is simplified by letting Z_{itw} vary only across choice situations and individuals, but not over alternatives. Variables Z_{itw} enter the scale in their exponentiated form to guarantee non-negative estimates of model variance, as λ_{it} is the inverse of the standard deviation. Equations (3) and (4) can be substituted back into (2) to complete the probability expression.

Obviously, the integral in equation (2) does not have a closed form and is usually evaluated by simulation[6]. Conditional on the d-th random draw of β_{id}, the simulated probability can be written as:

$$\tilde{P}_{ijt} = \frac{1}{D}\sum_{d=1}^{D} \frac{\exp(\lambda_{it}\beta_{id}X_{ijt})}{\sum_k \exp(\lambda_{it}\beta_{id}X_{ikt})} \qquad (5)$$

The corresponding simulated log-likelihood function is:

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person or a group of individuals as a whole is not likely to distinguish between and separately evaluate a variety of factors in making choices. Therefore, a joint distribution may be a more realistic representation of the actual behavioural process. However, due to the multiplicative nature of the scale and coefficient parameters, identifying and estimating such a joint distribution is not straightforward. Although such an analysis is in our future research agenda, we did not pursue this specification in the current study.

[6] When the number of random variables is relatively small, Gaussian quadrature can also be used and may achieve convergence faster than simulation (Breffle et al. 1999).

$$SLL = \sum_{i=1}^{N} \sum_{t}^{n_i} c_{ijt} \ln\left(\widetilde{P}_{ijt}\right), \qquad (6)$$

where n_i denotes the number of choices individual i makes in the survey, and $c_{ijt}=1$ only when alternative j is chosen by individual i in the t-th occasion. Although SLL is a biased estimator of the true likelihood, it is efficient when the number of draws is large enough (Lee 1992; Hajivassiliou and Ruud 1994). A numerical difficulty associated with maximising SLL in MLE is however that the implied Hessian is not guaranteed to be globally positive definite. Therefore the standard errors of estimated parameters are usually calculated from an approximated Hessian (Brownstone and Train 1999), such as the average outer product of gradients. Therefore, it is helpful to determine the analytical expressions for the maximisation gradients. These gradients are provided in Appendix 4.1.

Data

The data employed for this analysis are the same as those used for the previous two studies. Survey design, bread attributes, and reference point effect measures have been described previously, and these descriptions are not repeated here, although issues that are crucial to this particular analysis are highlighted. For equation (3), we incorporate three variables into Y_{iq}: respondents' age, income, and GM knowledge level. The GM knowledge level is a dummy variable, which equals one if a respondent correctly answers all five binary knowledge questions that were included in the descriptive part of the original survey. In theory, researchers can add any variables that they consider to be important in explaining heterogeneity in Y_{iq}. However, an excessively long list of covariates will unnecessarily complicate the estimation and lead to unstable results (Breffle and Morey 2000). Therefore, after several trials (removing non-significant variables), we limited our specification to this set of three variables.

In terms of parameterising vector Z_{itw} in equation (4), three types of variables are included. First, we propose to assess model choice variability that is rooted in the survey context. Since the survey includes three contexts defined by different types of GM labelling environments, variables capturing these labelling contexts are natural candidates for the scale function. Two dummy variables representing each of the mandatory and voluntary labelling contexts are therefore selected. Second, following Hensher et al. (2001) the choice task number (1-8) is included in Z_{itw} to approximate task fatigue or cumulative complexity[7]. A general hypothesis is that as the task overall becomes increasingly complex, as indicated by the task number moving from 1 to 8, consumers' preferences are likely to become less consistent (Swait and Admowicz 2001b).

Third, following Swait and Stacey (1996), variables describing respondents' demographic characteristics are utilised as a further reflection of unobserved choice variability. It is known that all relevant information/factors affecting choices must be processed by respondents before any actual choices are made (McFadden 2001). Different individuals, characterised partly by their demographic characteristics, are therefore likely to vary systematically in their different manners of processing information and making choices (de Palma et al. 1994; Hensher et al. 1999). Two demographic variables are included: gender and college participation experience[8]. Definitions of all relevant variables used in the analysis are summarised in Table 4.1.

Estimation and Results

Questions often faced by practitioners for estimation of a ML model are which coefficients in the utility function should be randomised and what type of distribution should be utilised to describe the stochastic component. McFadden and Train (2000) developed a test to help identify which variable should be associated with a random coefficient. However, the power of the test is low, and the critical value is difficult to retrieve. In regard to what type of distribution should be used for random coefficients, the choice is likely to be a judgement call, if not completely arbitrary. In many cases, the assumed distributions are dependent on the particular problem being examined and the covariance structure that researchers want to establish for the overall random component

[7] Different researchers have proposed different measures of task complexity. See Swait and Adamowicz (2001a and b) for a review of these methods.

[8] Other demographic variables can also be used. The effects of the two variables currently included in this study are robust across specifications we have used. In theory, variables used to explain heterogeneity in taste parameters can also be included. However, treating the same variable as both the taste and the scale (context) covariate will make the interpretation of its effect impossible.

of the model. In this study, we assume normally distributed random coefficients for the four reference point effect measures. The estimation results are presented in Table 4.2. It is commonly known that in order to identify the scale function, a base case scenario must be specified (Swait and Louviere 1993) enabling other scale measures to be compared with the base case. The base case will have zero values for all related covariates, and as determined by equation (4), the scale parameter for the base case was one.

The model is significant and the fit improves slightly over the model without the specification for the scale function (-3065.968 versus -3070.900 in *LL* function). All orthogonally designed bread attribute variables are highly significant. General implications of the estimates are: the higher the price, the less attractive a loaf of bread is to consumers; consumers prefer to buy bread rather than not, and in particular, they prefer nationally branded multigrain bread over white, partially whole wheat, or whole wheat bread; the presence of GM ingredients is associated with large utility loss and the absence of GM ingredients results in utility gain. All standard deviation estimates for the four random coefficients are significant, indicating that there is still a significant amount of heterogeneity that cannot be explained by the constant (b_0) and the three covariates we used in the specification of the β_i estimates. Knowledge about GM is not significant in any of the random coefficients. However, respondents' age has a positive impact on the negative price loss coefficient, suggesting that older consumers can cope with price losses better than relatively younger consumers. Higher family incomes alleviate consumers' loss of utility associated with a price loss; higher family incomes also increase the utility for consumers when GM ingredients are not present in bread.

In the specification of the scale function, except for the dummy variable indicating a mandatory labelling scenario, all other parameters are at least marginally significant. Since the scale parameter is the inverse of the standard error of the model and the exponential function given in equation (4) is monotonically increasing in its argument, the larger a parameter in the scale function, the smaller is the implied model standard deviation (variance). The coefficient of the voluntary labelling scenario dummy variable is positive in the scale function. This implies one of two things: first, compared with a situation where no particular labelling policies are applied for GM bread products, the variance between consumers' choices is smaller in a voluntary labelling regime; or second, our model explains the unobserved variability in the voluntary labelling scenario better. In other words, as researchers, we can be more confident in predicting consumers' behaviour under the voluntary labelling scenario, than in the situations where there is no labelling or in the mandatory labelling scenario[9].

This result is in accordance with our expectation. When no particular labelling rules apply, it is possible that the market may contain different products with all the possible labels (positive, negative, or a mixture of these two). In this situation, more products may appear to be different, and consumers may be overwhelmed by the variety. This can be interpreted as more different products increasing the complexity of choice tasks, resulting in less consistent choices (Mazzotta and Opaluch 1995). For the mandatory labelling scenario, the presence of GM ingredients can be a cause of uncertainties in terms of human health and the environment. A consumer is not likely to obtain sufficient information to resolve these uncertainties from a label that lists some ingredients with GM content (i.e., with stochastic qualities). Kinsey (1999) argues that from a consumers' perspective, a positive GM label statement in a mandatory labelling scenario may be viewed to work no better than no label at all.

Swait and Adamowicz (2001b) pointed out that consumers' uncertainties can lead to inconsistent choices and therefore a larger variance in utility functions. In our case, holding other factors fixed, consumers' choices under a mandatory labelling environment are just as "noisy" as in the scenario of no labelling requirement. On the other hand, in a voluntary labelling scenario, consumers are given definite information in terms of the GM ingredients (this product contains no GM ingredients). Thus consumers may be more certain about the quality of their chosen alternative which may indicate less volatility in terms of information presentation. These factors may significantly lower

[9] The variances of choices under the no labelling requirement and mandatory labelling scenarios are not statistically different, indicated by the non-significant coefficient for the mandatory labelling dummy variable in the scale function.

variation among choices in the voluntary labelling scenario, as indicated by the variable *Volun* in the scale function.

In terms of the effect of fatigue and cumulative complexity, it seems possible that choices may be more variable at the beginning of the task but more consistent at the end, not because consumers are not certain about their own preferences but due to an unfamiliarity effect. At the beginning of the survey, respondents are "novice consumers" in that they may not be familiar with the product (or some of its attributes) in the survey or they may never have seen any type of choice experiment. As choices are made consecutively, consumers will start to obtain more experience in choices and learn from their own previous choices (Hampton 1998). As this learning effort accumulates toward the end of the survey, consumers are expected to have more stable choices, leading to less choice variability (variance) overall.

Another opposing possibility is that when the tasks become complex, consumers may start to feel tired of or less interested in the task and may take two opposite types of actions. With one of these, consumers may simplify their choices by always selecting the alternative that is the easiest to evaluate. This effect is generalised as the "simplifying heuristic" in the behaviour literature (Dhar 1997; Foster and Mourato 2002). In our situation, the "buy none" option has no product attributes associated with it and one may expect that consumers are likely to choose this option more often when they are applying the simplifying heuristic; Dhar (1997) termed this "status quo" bias. The status quo bias will lead to a smaller choice variance.

Alternatively, another type of action associated with complex tasks can be termed the "pick any" effect. With this effect, consumers tend to pick an alternative simply to finish the choice task without making much effort to go through all the alternatives to select the one that best represents their preferences. An extreme situation of the "pick any" effect would be when tasks get so complex that consumers make completely random choices without referring to any product attributes (Louviere 2001). In this study, the variable "task" provides an approximation of the impact of survey fatigue on consumer choices as the task number. Its effect is negative and significant in the scale function, indicating that as the choices proceeded, respondents made more inconsistent choices. Although the results from our model are consistent with the "pick-any" effect, it is possible that all behavioural processes discussed under the fatigue effect may coexist. Thus, more precisely, in this study, the pick-any effect was the one found to be dominant. Distinguishing the mechanism that actually functioned behind the observed result is worthy of further research[10].

Gender is highly significant in shifting respondents' choices in this study. Holding other factors constant, male consumers tend to make more variable choices than female consumers. In other words, the model predicts female consumers' choices better than for males. Consumers' education level is marginally significant in explaining choice variability. Generally speaking, choices made by consumers that had received some post-secondary education are more consistent.

Table 4.2 reports the estimates of the b and γ parameters in equation (3) and (4). These are not the actual random coefficients or the scale parameter. To obtain the mean and standard error estimates associated with the estimates of β and λ, simulations can be used. To take the covariance between estimated parameters in the model into account, given the mean Y_{iq} variables, a vector of corresponding $b's$ can be drawn from the multivariate normal distribution $MN(\theta, \Sigma_\theta)$, where θ is a vector of the means of the estimated parameters and Σ_θ is the correlation matrix between the parameters. Table 4.3 reports the simulated mean and standard deviations associated with the four random coefficients after 2000 replications.

The simulated coefficient associated with the effect of price gain is not significant while the simulated coefficient for price loss is negative and significant. This verifies the asymmetric price reference point effect. A similar result was not observed for the GM

[10] The effect of a squared term of the fatigue measurement was also investigated. However, the model failed to converge.

attribute. The simulated coefficient for gain with the no-GM attribute (when a product was labelled as no-GM while respondents believed that the product contained GM ingredients before the choice) is not significant. However, the simulated coefficient for loss of the GM attribute (when a product was labelled as GM while respondents believed that the product did not contain GM ingredients) is significant but positive. As discussed in the last chapter, these findings do not necessarily disprove the existence of reference point effects for GM content or absence: whether GM ingredients are present or absent is a credence attribute with uncertain properties. Consumer responses to this attribute may not follow a standard pattern and the definition of gain or loss associated with GM ingredients may not be viewed similarly by all consumers. A detailed interpretation of similar findings can be found in Chapter 3 of this thesis.

For the scale parameter, a similar simulation approach can be conducted. Before the simulation, we classified the effects from variables in the Z_{itw} vector into six groups: a) Mandatory labelling with low fatigue (variable "fatigue" reflects the number of choice tasks a respondent has completed out of the 8 choice tasks. With low fatigue, the variable is the average of the first four tasks, which is 2.5); b) Voluntary labelling with low fatigue; c) no labelling requirement with low fatigue; d) Mandatory labelling with high fatigue (here "fatigue" = 5.5, which is the average of the last four tasks); e) Voluntary labelling with high fatigue; and f) no labelling requirement with high fatigue. We define a representative consumer as a male consumer with some post-secondary education experience. Due to the exponential function used to define the scale parameter, a draw of 1 from the multivariate normal distribution can cause the scale parameter to be unreasonably large (e.g., in group f, $\exp(5.5) = 148$). Therefore, the parameter for the variable "task" is fixed at the mean (i.e., -0.0265) and parameters for variables "mand", "volun", age, and education are drawn from the multivariate normal distribution. Table 4.4 reports these six different scale parameters. Since the parameters for "task" are fixed and in scenarios where no labelling was involved, the effects from variables "mand" and "volun" will not be reflected in the simulation either. The only variations are from the draws of coefficients associated with age and education variables. Therefore we chose not to report the standard deviations associated with the overall scale estimates of the two no labelling scenarios.

All four testable scale parameters are significantly different from one. These scale parameter estimates can be compared with the base case (where scale is equal to one) or be interpreted relative to each other. Within either the low effort or the high effort scenario, voluntary labelling is associated with the lowest implied model standard deviation; i.e., the estimation in the voluntary labelling scenario is subject to the least choice variability. In the situation of no labelling requirements, variances among choices are noticeably larger than in the two specified labelling situations.

Conclusions and Discussion

A random parameter specification of the ML model is used to analyse consumers' taste heterogeneities associated with various product attributes. Covariates are added into the model to explain sources of taste heterogeneity. Usually, all the variability in choices that cannot be captured by taste heterogeneity is treated as unobserved heterogeneity. This study demonstrates that in addition to taste heterogeneity, other factors may also cause variability in choices. Using a ML model, we show that the scale parameter can be specified as a function of factors that may affect the variances in utilities associated with different choices. The selected factors of GM labelling context variables, a task fatigue effect proxy, and two demographic variables are included in the scale function to represent, respectively, a context effect, a fatigue effect and human cognitive and perception transformation differences.

This study demonstrates the use of reference point effects and the heterogeneity in consumers' evaluations that is associated with them. It also shows that unobserved heterogeneity can be further explained by explicitly modeling other sources of variability in choices through the scale function. The model shows only slight improvement in terms of the model fit, despite several significant covariates in the scale function. This is not completely consistent with the findings of some previous studies that have analyzed the relationship between choice variability and specific taste heterogeneity, in that once the scale parameter was explicitly considered, the degree of heterogeneity was greatly reduced or even disappeared (Kamakura et al. 1996; Swait and Bernardino 2000; Hensher et al. 1999; Louviere et al. 2002). However, a general conclusion can be derived that by simply estimating either heterogeneity through coefficients or variability through the random component, a researcher may miss effects of some factors that can otherwise be discovered by jointly modeling both sources.

This study shows that unobserved heterogeneity can be separated from unobserved variability and that both may have significant impacts on choice predictions. However, as there are numerous factors that may affect consumers' choice behaviour and these often overlap with each other (McFadden 1999), it is difficult to distinguish their effects and include them into the modeling process. In the analysis presented in this study, only several representative effects are investigated. Although it is infeasible to incorporate all factors that are relevant to human decision making into a study, adding more effects to the model may enable us to explain choice variability better. Nevertheless, there is likely to be a limit on how many covariates can be included into the scale function while still ensuring the model to be identifiable.

Another related issue is how to specify the covariate structure for taste heterogeneity and choice variability. A specific treatment, such as the choice context, may affect either taste or choice variability, or both (Louviere 2001). As has been demonstrated in the results in this chapter, the behavioural interpretations of one variable can be quite different, depending on whether the variable is defined as a covariate for explaining taste heterogeneity or for the scale function to explain choice variability. Similarly, rather than entering GM labelling context variables in the scale function, these can be first interacted with attribute variables and entered directly into the utility function with random coefficients. The interpretation as well as the inclusion in the analysis will be different in these cases. Any solution to such questions of appropriate treatment will, to some extent, rely on the individual researchers' experience and judgement, and perhaps also on trial estimations. Alternatively, since it may be difficult to make such judgements, one could let taste parameters correlate with the scale function. With no need to make a clear-cut differentiation between heterogeneity and variability covariates it is possible that more efficient estimation may be achieved. This approach was considered for this study but has not been pursued at this stage of research.

Finally, it is noteworthy that the method proposed and applied in this study is not limited to a ML model. Other flexible models may be adopted depending on the research goal. These could include a mixed latent class model (if the purpose is to classify consumers rather than to know the preferences of the entire population or each specific individual); a mixed probit model (which may shorten the estimation process) or a pure probit model (which may allow direct parameterisation of the model's covariance structure). These all provide grounds for future research effort.

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Table 4.1. Model Variable Descriptions

Variable Name	Variable Description
Price	A continuous variable representing actual price
Buyno	Alternative specific constant representing the utility associated with choosing to buy none of the bread
Storeb	=1 if the bread has a store brand. Otherwise = 0.
White	=1 if the bread is white bread. Otherwise = 0.
Partial	=1 if the bread is partial whole wheat. Otherwise = 0.
Whole	=1 if the bread is whole wheat. Otherwise = 0.
GMO	=1 if the bread has GM ingredients. Otherwise = 0.
NOGMO	=1 if the bread does not contain GM ingredients. Otherwise = 0.
PG	=1 if the alternative involves a gain in price. Otherwise = 0.
PL	=1 if the alternative involves a loss in price. Otherwise = 0.
GMG	=1 if the alternative involves a gain in GM ingredients. Otherwise = 0.
GML	=1 if the alternative involves a loss in GM ingredients. Otherwise = 0.
Age	A continuous variable representing respondents' age
Income	A continuous variable representing respondents' income
Know	=1 if a respondent has answered all five GM knowledge questions correctly. Otherwise = 0.
Mand	=1 if the context is a mandatory labelling. Otherwise = 0.
Volun	=1 if the context is a voluntary labelling. Otherwise = 0.
Task	A continuous variable representing the task number
Male	=1 if the respondent is a male. Otherwise = 0.
College	=1 if the respondent received some post-secondary education. Otherwise = 0.

Table 4.2. Estimation Result

	Without Scale Function		With Scale Function	
	Coefficient	Std. Error	Coefficient	Std. Error
Reference Point Effect Measures with Random Parameters				
Constant in PG	0.4423	0.3034	0.3725	0.2954
PG-Age	-0.8242	0.5514	-0.6420	0.5266
PG-Income	-0.1768	0.2737	-0.1688	0.2708
PG-Know	-0.0194	0.1565	-0.0492	0.1594
Std. Dev. PG	0.7170***	0.1086	0.7450***	0.1091
Constant in PL	-0.6675***	0.1481	-0.7176***	0.1417
PL-Age	0.5140**	0.2532	0.5644**	0.2490
PL-Income	0.2827**	0.1363	0.3136**	0.1319
PL-Know	0.0837	0.0755	-0.0906	0.0761
Std. Dev. PL	0.5294***	0.0438	0.5362***	0.0443
Constant in GMG	-0.6010	0.6877	-0.4663	0.6005
GMG-Age	-0.1795	1.4231	-0.2121	1.2856
GMG-Income	1.3248**	0.5143	1.1113**	0.4608
GMG-Know	0.0136	0.3494	0.0503	0.3375
Std. Dev. GMG	0.8150***	0.2210	0.7960***	0.2267
Constant in GML	0.6963	0.6177	0.5346	0.5533
GML-Age	-0.9763	1.1069	-0.8208	1.0418
GML-Income	0.6612	0.6246	0.8392	0.6143
GML-Know	-0.2548	0.3360	-0.2544	0.3387
Std. Dev. GML	1.3415***	0.1714	1.2875***	0.1737
Attribute Variables with Fixed Coefficient				
Price	-0.5449***	0.0659	-0.5584***	0.0821
Buyno	-3.0777***	0.1538	-3.0934***	0.2761
Storeb	-0.2524***	0.0604	-0.2208***	0.0620
White	-0.8432***	0.0648	-0.8711***	0.0863
Partial	-0.6906***	0.0773	-0.7108***	0.0923
Whole	-0.2186***	0.0735	-0.2556***	0.0757
GMO	-1.2288***	0.1272	-1.4360***	0.1305
NOGMO	0.3944***	0.0582	0.3042***	0.1013
MGMO	-0.3258**	0.1437	-	-
VNOGMO	-0.1410	0.1401	-	-
Scale Function Parameters				
Mand	-	-	0.0881	0.0610
Volun	-	-	0.1177**	0.0496
Task	-	-	-0.0221*	0.0127
Male	-	-	-0.0797***	0.0217
College	-	-	0.0508**	0.0256
Adj. R^2	*0.161*		*0.168*	
LL	*-3070.900*		*-3065.968*	

*, **, *** indicates significant at the 10%, 5%, and 1% significance level respectively.

Table 4.3. Simulated Random Coefficients

	Coefficient	Std. Dev.
Price Gain	-0.0208	0.1123
Price Loss	-0.3123*	0.0596
No GM Gain	0.1075	0.1726
GM Loss	0.5890*	0.1628

* Significant at the 5% significance level

Table 4.4. Overall Simulated Relative Scale Parameters

Groups	Mean Scale Parameter	Std. Dev.	Implied Std. Dev. ($1/\lambda$)
Mandatory/Low fatigue	1.1379*	0.0846	0.8788
Voluntary/Low fatigue	1.1723*	0.0734	0.8530
No Labelling/Low fatigue	0.9035	-	1.1068
Mandatory/High fatigue	1.2321*	0.0916	0.8116
Voluntary/High fatigue	1.2693*	0.0795	0.7878
No Labelling/High fatigue	0.8345	-	1.1983

* Significantly different from 1 at the 5% significance level.

Appendix 4.1: Analytical Gradients for ML with Parameterization of the Scale Factor

Recall the probability of individual i choosing alternative j in the t-th choice occasion is: $P_{ijt} = \frac{\exp(\lambda_{ijt}\beta_i X_{ijt})}{\sum_k \exp(\lambda_{ikt}\beta_i X_{ikt})}$, with random coefficients $\beta_i^r = b_0 + b_q Y_{iq} + b_e e_i$, fixed coefficients β^f, and λ_{ijt} is simplified as $\lambda_{it} = \exp(\gamma_w Z_{itw})$. $P_{ijtd} = \frac{\exp(\lambda_{ijt}\beta_{id} X_{ijt})}{\sum_k \exp(\lambda_{ikt}\beta_{id} X_{ikt})}$,

where β_{id} is the vector of random coefficients subject to the d-th draw from its density.

$\widetilde{P}_{ijt} = \frac{1}{D}\sum_{d=1}^{D} \frac{\exp(\lambda_{it}\beta_{id} X_{ijt})}{\sum_k \exp(\lambda_{it}\beta_{id} X_{ikt})}$, and the simulated log-likelihood is

$SLL = \sum_{i=1}^{N}\sum_{t}^{n_i} c_{ijt} \ln(\widetilde{P}_{ijt})$.

The gradient of the simulated log-likelihood with respect to parameters b's is:

$$g_b = \frac{\partial SLL}{\partial b} = \sum_{i=1}^{N}\sum_{t}^{n_i} \frac{\partial \ln(\widetilde{P}_{ijt})}{\partial b} = \sum_{i=1}^{N}\sum_{t}^{n_i} \frac{1}{\widetilde{P}_{ijt}} \frac{\partial \widetilde{P}_{ijt}}{\partial b} = \sum_{i=1}^{N}\sum_{t}^{n_i} \frac{1}{\widetilde{P}_{ijt}} \frac{1}{D}\sum_{d=1}^{D} \frac{\partial P_{ijtd}}{\partial \beta_{id}} \frac{\partial \beta_{id}}{\partial b}$$

In this expression,

$\frac{\partial P_{ijtd}}{\partial \beta_{id}} = P_{ijtd}\left(\lambda_{it} X_{ijt} - \sum_{k=1}^{K} P_{iktd}\lambda_{it} X_{ikt}\right)$, and

$\frac{\partial \beta_{id}}{\partial b} = \begin{bmatrix} 1 & Y_{i1} & Y_{i2} & \dots & Y_{iq} & e_{id} \end{bmatrix}^T$.

Substitute these to the expression of g_b, we have:

$$g_b = \sum_{i=1}^{N}\sum_{t}^{n_i} \frac{1}{\widetilde{P}_{ijt}} \frac{1}{D}\sum_{d=1}^{D} P_{ijtd}\left(\lambda_{it} X_{ijt} - \sum_{k=1}^{K} P_{iktd}\lambda_{it} X_{ikt}\right) \begin{bmatrix} 1 \\ Y_{i1} \\ Y_{i2} \\ \dots \\ Y_{iq} \\ e_{id} \end{bmatrix}. \qquad \text{(A4.1.1)}$$

Similarly, the gradient with respect to the scale parameters is:

$$g_\gamma = \sum_{i=1}^{N} \sum_{t}^{n_i} \frac{1}{\widetilde{P}_{ijt}} \frac{1}{D} \sum_{d=1}^{D} P_{ijtd} \left(\beta_{id} X_{ijt} - \sum_{k=1}^{K} P_{iktd} \beta_{id} X_{ikt} \right) \begin{bmatrix} Z_{it1} \exp(\gamma_1 Z_{it1}) \\ Z_{it2} \exp(\gamma_2 Z_{it2}) \\ \ldots \\ Z_{itw} \exp(\gamma_w Z_{itw}) \end{bmatrix}. \quad \text{(A4.1.2)}$$

For the non-random coefficients β^f, the gradient is much simpler:

$$g_{\beta^f} = \sum_{i=1}^{N} \sum_{t}^{n_i} \frac{1}{\widetilde{P}_{ijt}} \left(\lambda_{it} X_{ijt} - \sum_{k=1}^{K} P_{ikt} \lambda_{it} X_{ikt} \right). \quad \text{(A4.1.3)}$$

Chapter 5 Conclusion and Extensions

The development of the techniques of genetic modification through the application of modern agricultural biotechnology brings opportunities and controversies that have seldom been seen in the history of agricultural production. Consequently, careful research is needed to evaluate public concerns for effective risk communication and public policy development. Labelling is an important and potentially efficient policy tool to inform consumers in the market for GM food. Most current references to the benefits and costs associated with GM labelling are viewed from producers' perspectives, and focus on the costs associated with labelling, especially for mandatory labelling. The analysis in this thesis is directed towards both improving understanding and quantification of consumer benefits associated with different labelling policies. This is accomplished by analyzing consumers' stated preferences for a selected GM product—pre-packaged sliced bread.

This thesis follows a three-paper mode. The first paper, Chapter 2, focuses on and provides answers to two questions: how different GM labelling policies may affect consumers' choices and what is the value of information revealed in different labelling policies. Although Canada has decided to adopt a policy of voluntary labelling for GM food, the experimental data of this study allows analysis of how Canadian consumers would also behave under a mandatory labelling approach. It is found that strongly diverse opinions are held by different consumers on the attractiveness of various bread attributes, particularly for the GM attribute. Although GM ingredients are viewed as a negative attribute by a majority of consumers, the presence of this attribute significantly increased some consumers' utility. When only products that contain GM ingredients are labelled, as in a mandatory labelling environment, consumers' utilities were further decreased. This decline of utilities was not observed for voluntary labelling. Consumers valued information revealed through a mandatory regime much more than that that under a voluntary regime. This is true no matter whether a small or a large proportion of the products in the market is affected by the policy. To assist in potential benefit-cost analysis of GM labelling, the value of information is also represented relative to average product prices. It is generally considered that the costs of mandatory labelling will be higher than the costs of voluntary labelling. Even so, our study indicates that the benefits to consumer from mandatory labelling are higher than from voluntary labelling. The objection to mandatory labelling on the grounds that it is too costly needs to be reassessed given the evidence of relatively high consumer benefits shown in this paper.

In paper two (Chapter 3), explanations of individual's judgment and decision making behaviour based on literature from psychology are incorporated into conventional random utility theory in the context of GM labelling and GM food choices. Consumers' utilities are no longer assumed to depend solely on static states of attributes, but rather on changes in these as well. Based on these concepts, reference point effects formalized in prospect theory are incorporated in the developed model. This gives an opportunity to model a much richer range of consumers' choice and decision making. Results indicate that changes of bread price from consumers' reference levels did cause changes in their utility, and that this effect depended on whether the change incurred a gain or a loss. A price loss had a much larger impact on utility than the same amount of price gain. For the GM attribute however, it is found that standard predictions from prospect theory did not apply. Further analysis showed that this outcome is the result of the uncertainties and heterogeneity associated with consumers' perceptions of the GM attribute. The choice model used in the paper also provides a means to analyze sources of the heterogeneity around respondents' reference point effects. It is found that age and income are significant sources of consumers' sensitivity toward reference point effects. The value of information calculated in this analysis reflects that consumers are more consistent in terms of their valuation of the information revealed under the mandatory labelling than under the voluntary labelling. Comparing the estimates of the value of information in this analysis with those reported in the previous paper, it can be noticed that although the general nature of the measures reflected in the two papers is the same, the two sets of estimates of the value of information differed moderately.

In the third paper, presented in Chapter 4, the focus is more general issues of modeling choice heterogeneity and variability. This paper further extends the methods used in the second paper. The results demonstrate that in addition to modelling the existence of reference point effects and taste heterogeneity associated with attributes in the utility function, consumers' choice variability can be simultaneously modeled by parameterizing the scale parameter in the logit model. Unlike most previous studies that have statistically examined the scale factor in a random utility model, the model in this paper is built directly upon behavioural observations. In its specification, this model includes human factors, such as consumers' demographic characteristics, as well as factors related to the choice environment, such as choice context and complexity. Consequently it is able to provide behavioural interpretations for the basis of choice heterogeneity and variability. This paper provides a baseline approach for further research in that different behavioural factors may be included in the model for different purposes. The approach may be useful for researchers and food marketers who want to understand not only individual choice consequences but also the decision process.

Overall, the emergence of GM food raises a series of complicated and often controversial questions. This thesis does not address all the issues related to GM food but focuses on questions related to GM labelling. Studies on other facets of this topic are certainly desirable. Methodologically, one natural extension of this thesis will be to model reference point effects more closely. This would involve making the reference point endogenous to choices. In the data set of the current study, all choices are made in a relatively short period of time (in one survey), so that it is a reasonable assumption that consumers' reference points do not change. However, over time, consumers' reference points may change along with their familiarity with these products in the market. It will be of interest to see the long run effect of GM food marketing on consumers' reference levels, and consequently on their choices.

As the third paper shows, it is possible to learn about consumer behaviour by further exploring more flexible and realistic behavioural models. A possible extension of the third paper is to model the scale factor (choice variance) as changing over time for each consumer, perhaps as they become more exposed to GM food. This involves developing a model that allows random or fixed scale parameter estimations, which would complicate the modelling task, since as the model becomes more complex, identification and programming in the framework of maximum likelihood may become burdensome. However, with the resumed interest in applications involving Bayesian econometric techniques, many models previously classified as "unestimable" are now becoming a routine task. The issue of estimation therefore may become less of a problem in the future.

Another issue for further research relates to the stated preference choice data used in this thesis. Due to the hypothetical nature of stated preference choice data in this thesis, biases such as strategic behaviour and anchoring or context effects may be present. Other methods, such as auctions, may be utilized to examine different types of behaviour. There is an emerging body of literature discussing the theory and application of experimental auctions in economic evaluation studies. It is often believed that the dominant strategy in auctions is to reflect the true willingness to accept a product and therefore control the bias associated with strategic behaviour. However, there are tradeoffs associated with the choice of an auction format relative to a stated preference method. These include the unusual decision context of the auction versus the relatively more familiar context of state preference methods and the cost of implementing auction methods on representative samples relative to these costs for stated preference surveys. More importantly, when studying GM food that may already be in the market, revealed preference data on consumers' actual choices may be collected. It will be interesting in future to compare the difference, if any, between these two types of data and possibly to combine them to reach a better understanding of decision processes.

Appendix A: University of Alberta GM Foods Survey Questionnaire
(Paper Draft)

Introduction at Site
Welcome!

Thanks again for agreeing to take part in this research.

As you go through the survey, please take time to answer each question, as you can only move from one page to the next after answering all questions. **To go forward or backward, please use the next page/pervious page buttons at the bottom of each page, NOT the Forward/Back button on your browser.**

There are two parts to this survey – a purchase simulation and a questionnaire. **We ask that you complete all parts of the purchase simulation in one session.** If at any time after that you wish to stop the questionnaire and complete it at a later time, please click on the Stop button located at the bottom of the questionnaire, and come back to it at your convenience. When you return to the survey site you will be required to enter your PIN and the questionnaire will begin again where you left off.

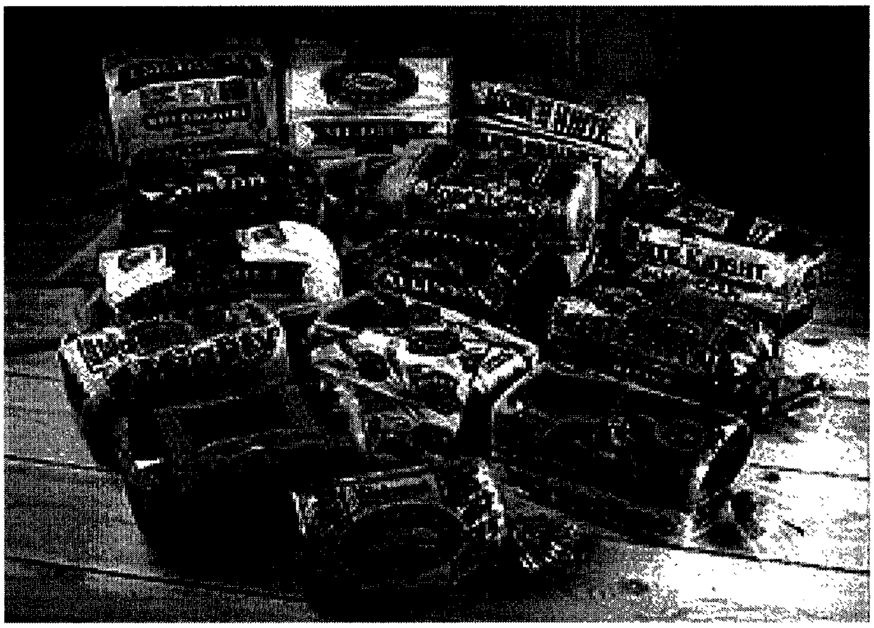
[Screener]

S1. Which of the following types of bread do you ever purchase? **CHECK ALL THAT APPLY**

Sliced, pre-packaged store brand
Sliced, pre-packaged national brand
Fresh bakery bread
Make my own
Never buy bread
DK/NS

CONTINUE IF SLICED PRE-PACKAGED STORE BRAND AND/OR SLICED PRE-PACKAGED NATIONAL BRAND, ALL OTHERS THANK & TERMINATE

In this survey, we are interested in your choices of pre-packaged sliced loaf bread that you typically buy at the grocery store. By "sliced loaf bread" we mean the bread that is often purchased for breakfast or sandwiches, like the breads shown in the picture below. We will ask you questions about your preferred bread choices, and your opinions about your bread's nutrition contents and health aspects.



[QUESTIONNAIRE]

[Your Typical Bread Purchase]

Q1. We would like to start this survey by learning more about pre-packaged bread that you normally buy in the grocery store. Please tell us about your **typical bread purchase**. Assume that the bread you buy is **fresh** and **well presented** (i.e. no damaged slices, packaging, etc.).

We understand that you might purchase a variety of different types of bread at different times. However, for the purpose of this study, please indicate which characteristic you **most often** select for each feature of loaf bread presented below [i.e., brand, type of flour, loaf consistency, price, thickness of slices and shape] when purchasing bread.

a) **BRAND: I most often purchase... CHECK ONE ONLY**

National brand [sliced, pre-packaged, for example, Dempster's, Wonderbread, Ovenjoy, Olafson, Healthy Way, etc.]

Store brand [sliced, pre-packaged, for example, President's Choice, Western Family, Safeway, IGA, etc.]

b) **PRICE: I <u>most often</u> purchase... CHECK ONE ONLY**

$0.99 / 600g loaf
$1.00 to $1.99 / 600g loaf
$2.00 to $2.99 / 600g loaf
$3.00 to $3.99 / 600g loaf
$4.00 or more / 600g loaf

c) **TYPE OF FLOUR: I <u>most often</u> purchase... CHECK ONE ONLY**

White
Partly whole wheat [60%]
Whole wheat [100%]
Multigrain

d) **LOAF CONSISTENCY: I <u>most often</u> purchase... CHECK ONE ONLY**

Dense loaf consistency

Soft loaf consistency

e) **BREAD CRUST: I <u>most often</u> purchase... CHECK ONE ONLY**

Light brown, soft crust

Mid brown, crunchy crust

f) **THICKNESS OF SLICES: I <u>most often</u> purchase... CHECK ONE ONLY**

Regular slices

Thick slices

g) **SHAPE OF SLICES: I <u>most often</u> purchase... CHECK ONE ONLY**

Sandwich loaf, square slices

Rounded-top slices

Q2. a) For the following question, even if you are not sure of the answer, we are interested in your <u>perceptions</u> of the bread you most often buy. Based on what you know or what you think, is the bread you **most often** buy ... **[RANDOMIZE ORDER OF PRESENTATION]**

Yes
No
DK/NS

a) Low in fat
b) High in nutrition
c) High in fibre
d) Low in sodium

e) Organic
f) Free of genetically modified/engineered ingredients
g) Free of pesticide residues

ASK Q2b FOR ALL ITEMS DK/NS IN Q2a

b) We understand that you are not sure about whether the bread you buy has these characteristics. However, we would like you to choose a "yes" or "no" based on your perceptions or what you think is most likely. Do you think the bread you most often buy is.....

Probably Yes
Probably No

POSSIBLE ITEMS [INSERT ALL DK/NS FROM Q2a]

a) Low in fat
b) High in nutrition
c) High in fibre
d) Low in sodium
e) Organic
f) Free of genetically modified/engineered ingredients
g) Free of pesticide residues

Q3. How important are the following pre-packaged sliced bread features to you when choosing a loaf of sliced bread to buy in the grocery store?

Very important
Somewhat important
Not very important
Not at all important
DK/NS

a) Brand name
b) Type of bread (e.g., white, whole wheat, multigrain)
c) Price of bread

[PURCHASE SIMULATION]

PLEASE TAKE TIME TO CAREFULLY READ THE FOLLOWING INSTRUCTIONS BEFORE PROCEEDING

In this section you will be presented with a series of purchase options for pre-packaged bread. Each option will include a description of different features. For each purchase simulation, you will be asked to indicate your preferred choice

FOR EACH SCENARIO please imagine that you are planning to purchase pre-packaged bread. You will have a number of different options presented to you on the following screens.

- **Please choose ONLY ONE OPTION on each screen**
- **Assume that the options on EACH SCREEN are the ONLY ones available**
- **DO NOT COMPARE OPTIONS ON DIFFERENT SCREENS**

You may encounter a few options that seem counter-intuitive (e.g. a lower price but a higher quality in your personal opinion). Be assured that **this is not an error** but part of the design of the survey. Simply choose the one bread option that you prefer most based on its characteristics.

Q4. Now suppose you are shopping for sliced bread. The following choices are the ONLY ONES AVAILABLE to you in the grocery store. Again, the bread you buy is FRESH and WELL PRESENTED (i.e. no damaged slices, packaging, etc.).

Please examine each choice below, keeping in mind that, in a real-life-situation, you are paying for the product that you choose. Please choose ONE AND ONLY ONE of Option A, Option B or Option C. Please make the choice that closely reflects your real decision.

I would purchase...

Option A
Option B
Option C

EXAMPLE ONLY Case 1 ***(other cases omitted)***

Features		**Option A**		**Option B**		**Option C**
Brand Name		National brand (such as "Old Mill" and "Wonder")		Store brand (such as Safeway and IGA brands)		I would not buy any bread at all
Type of Bread		100% whole wheat		60% whole wheat		
Ingredients		Wheat flour, water, yeast, vegetable oil, sugar, salt Contains genetically modified/engineered ingredients.		Wheat flour, water, yeast, vegetable oil, sugar, salt.		
Price		$1.49		$2.49		

[Consumer Attitudes Towards GM/ GE Ingredients in Food Products]

Q5. Below is a list of possible food safety issues. For each, please indicate how much of a health risk you feel *it is to you personally.* **[RANDOMIZE ORDER OF PRESENTATION]**

High risk
Moderate risk
Slight risk
Almost no risk
DK/NS

a) Bacteria contamination of food
b) Pesticide residuals in foods
c) Use of hormones in food production
d) Use of antibiotics in food production
e) BSE (mad cow disease)
f) Use of food additives
g) Use of genetic modification / engineering in food production
h) Fat and cholesterol content

Q6. We would like to get your opinion on possible environmental safety issues that might result from modern agriculture. Please indicate how much of a risk you personally believe each issue represents. **[RANDOMIZE ORDER OF PRESENTATION]**

High risk
Moderate risk
Slight risk
Almost no risk
DK/NS

a) Water pollution by chemical run-offs from agriculture
b) Soil erosion through agricultural activity
c) Genetic modification / engineering
d) Resistance to herbicides and pesticides
e) Adverse effects of agriculture on biodiversity
f) Agricultural waste disposal (e.g., animal manure)

[Knowledge About Genetic Modification / Engineering in Food Products]

Q7. We will now ask you several questions about the technology that is referred to as *"genetic modification (GM)" or "genetic engineering (GE)"*. We appreciate your answers as they help us to better understand how familiar the public is with this topic.

For each of the following statements please indicate whether you believe the statement is *"true"*, *"false"* or that you *"don't know"*. **[RANDOMIZE ORDER OF PRESENTATION]**

True
False
DK/NS

a) Genetic modification/ engineering can only be applied to plants, but not to animals.
b) By eating a genetically modified/ engineered food, a person's genes will also become modified.
c) Canola, corn, soybean and potato are amongst the genetically modified/ engineered crops currently produced in Canada.
d) Genetically modified/ engineered food items are currently available in Canadian supermarkets.
e) All of the food items in Canadian supermarkets contain genetically modified/ engineered ingredients.
f) Canadian food regulations require the labelling of food items which contain genetically modified/ engineered ingredients.

Q8. How well informed would you say you are about genetically modified/ engineered foods? Would you say...?

Very well informed
Somewhat informed
Not very informed
Not at all informed
DK/NS

[Potential Benefits and Risks of GM Foods]

Q9. We would like to get your opinion on issues about applications of genetic modification/ engineering *(GM/ GE)* ***in food production***. Following is a list of opinion statements. The statements refer to GM/ GE foods derived from ***animals*** (such as meat, dairy products, milk, eggs, etc.) as well as derived from crops (grains, oils seeds, etc). In the statements below, we will treat these distinctions as two separate issues.

Please read each statement carefully and indicate your agreement or disagreement with the statement. **[RANDOMIZE ORDER OF PRESENTATION]**

Strongly agree
Somewhat agree
Somewhat disagree
Strongly disagree
DK/NS

a) The human health benefits of GM/ GE crops outweigh the human health risks.
b) I would sample foods from GM/ GE crops to find out whether I like them.
c) Foods derived from GM/ GE animals are simply not necessary in Canada.
d) Foods derived from GM/ GE crops are less risky for humans than foods derived from GM/ GE animals.
e) I would prefer cheaper foods derived from GM/ GE crops over more expensive GM-free products.
f) Canada should advance the general field of GM/ GE technologies to prevent or cure diseases.
g) The overall benefits for the environment of GM/ GE crops outweigh the overall environmental risks.
h) Increased GM/ GE crops in Canada will lead to a harmful concentration of corporate power.
i) GM/ GE in agriculture is unnatural.
j) GM/ GE applied to livestock will worsen animal welfare.
k) Overall, I am more sceptical of GM/ GE applications in livestock than in crops.
l) Feeding animals with GM/ GE feed is not a concern.
m) All things considered, benefits of GM/ GE in food production outweigh risks.

[Sources of Information About GM Food Products]

Q10. In the past year, how often have you discussed aspects of genetically modified / engineered foods with others? Would you say.... **CHECK ONE RESPONSE ONLY**

Frequently
From time to time
Never
DK/NS

Q11. Suppose you wanted to obtain trustworthy information about genetically modified/ engineered food products. Please indicate how trustworthy you consider each of the following sources to be.
[RANDOMIZE ORDER OF PRESENTATION]

Very trustworthy
Somewhat trustworthy
Not very trustworthy
Not at all trustworthy
DK/NS

a) Canadian Government
b) The food industry
c) Farmers' associations
d) Family / friends

e) Research institutions (e.g., universities)
f) Consumer associations

Q12. In the past year, how often have you discussed aspects of genetically modified / engineered foods with others? Would you say.... **CHECK ONE RESPONSE ONLY**

Frequently
From time to time
Never
DK/NS

Q13. Suppose you wanted to obtain trustworthy information about genetically modified/ engineered food products. Please indicate how trustworthy you consider each of the following sources to be.
[RANDOMIZE ORDER OF PRESENTATION]

Very trustworthy
Somewhat trustworthy
Not very trustworthy
Not at all trustworthy
DK/NS

g) Canadian Government
h) The food industry
i) Farmers' associations
j) Family / friends
k) Research institutions (e.g., universities)
l) Consumer associations

Q14. We would like to gain an understanding about your actions with respect to GM food products. Please check either "Yes" or "No" for each of the following statements. **[RANDOMIZE ORDER OF PRESENTATION]**

Yes
No
DK/NS

a) The possibility of genetically modified/ engineered content affects my food choices.
b) I purposefully buy food at organic stores to avoid genetically modified/ engineered foods.
c) I donate money to organizations which oppose genetically modified/ engineered foods.
d) I donate money to environmental protection organizations.
e) I have lobbied against genetically modified/ engineered foods.

[Labelling Of GM Foods]

Q15. The following statements concern your opinion regarding the regulation of genetically modified/ engineered foods. Currently, discussions are going on in Canada as to whether or not food that contains genetically modified/ engineered ingredients should be labelled. Food labelling can be either mandatory or voluntary.

Mandatory labelling requires all producers to clearly and prominently label any product that contains genetically modified/ engineered ingredients. Under a voluntary labelling scheme, producers can choose to label or not to label products that contain genetically modified/ engineered ingredients as long as the information they provided is true, and not misleading or deceptive.

Please indicate your level of agreement or disagreement with each of the following statements. **[RANDOMIZE ORDER OF PRESENTATION]**

Strongly agree
Somewhat agree
Somewhat disagree
Strongly disagree
DK/NS

a) The public is sufficiently involved in the regulation of genetically modified/ engineered foods.
b) Even if food prices were higher, the consumers' "right to know" warrants a mandatory labelling scheme.
c) The decision about introduction of genetically modified/ engineered foods to Canada should be left to experts.
d) There is no need for mandatory labelling of genetically modified/ engineered foods if the final product quality is the same.
e) Voluntary labelling might be used as a marketing tool rather than providing useful consumer information.
f) Stricter regulations for approving genetically modified/ engineered foods are better than a mandatory labelling system for genetically modified/ engineered foods.
g) Overall mandatory labelling is preferable to voluntary labelling.

[Demographic Information]

The following questions are designed to tell us a little about you. This information will only be used to report comparisons among groups of people. Your identity will not be linked to your responses in any way.

Q16. Are you...

Male or Female

Decline to respond

Q17. What is your age?

RECORD NUMBER OF YEARS [**RANGE 18 TO 120**]
Decline to respond

Q18. How many people, including yourself, live in your household?

RECORD NUMBER [**RANGE 1 TO 20**]
Decline to respond

Q19. How many children live in your household?

None
RECORD NUMBER [**RANGE 1 TO 20**]
Decline to respond

ASK Q19 IF ONE OR MORE IN Q18
Q20. And how many children living in your household fall into each of the following age groups?

a) 1 to 4 years
RECORD NUMBER [**RANGE 0 TO 20**]

b) 5 to 11 years
RECORD NUMBER [**RANGE 0 TO 20**]

c) 12 to17 years
RECORD NUMBER [**RANGE 0 TO 20**]

Q21. What is the highest level of education that you have completed? **CHECK ONE ONLY**

Never attended school
Grade school (grades 1 to 9)
Some high school
High school graduate
Post secondary trade or technical school certificate/degree
Some university or college
College diploma/degree
University undergraduate degree
Some post graduate university study
Post graduate university degree (e.g., Masters or Ph.D.)
Decline to respond

Q22. Which of the following best describes your employment status? **PLEASE SELECT ONE ONLY**

Working full- or part-time [**PLEASE SPECIFY OCCUPATION**]
Full- or part-time student
Do unpaid work from home/ homemaker
Retired
Decline to respond

Q23. For classification purposes, what is your total household income before taxes? **CHECK ONE ONLY**

Less than $10,000
$10,000 - $19,999
$20,000 - $29,999
$30,000 - $39,999
$40,000 - $49,999
$50,000 - $59,999
$60,000 - $69,999
$70,000 - $79,999
$80,000 - $89,999
$90,000 - $99,999
More than $100,000
Decline to respond

Q24. How often do you buy organic food products? **CHECK ONE ONLY**

Regularly
Occasionally
Never
DK/NS

Q25. Are you a member of or associated with any consumer group that focuses on issues of food safety?

Yes
No
Decline to respond

Q26. Are you a member of or associated with any environmental group? **CHECK ONE ONLY**

Yes
No
Decline to respond

Participant Debriefing

Dear Survey Participant:

Once again, we would like to take the opportunity to thank you for participating in this survey. Your contribution is much appreciated.

At this point we would also like to explain more about this research. The study is being conducted by the Department of Rural Economy at the University of Alberta in Edmonton, AB. The purpose is to better understand how people view potential risks and benefits of genetically modified/ engineered foods, their likely choices in a purchase context, and the effects of information on choices. The results of this study will be reported in terms of averages only and individual responses will be confidential. The report of these results will be publicly available and may help to improve Canadian food policies.

We point out that at this point in time, genetically modified/ genetically engineered wheat is not approved for use or sale in the Canadian market, and the products suggested in this survey are HYPOTHETICAL products not currently available in the Canadian market.

Again, please be assured that all information from your personal responses will be treated with strict confidentiality and will not be made available to anyone other than the researchers. Participant's responses will not be individually identified. If you have any questions about the interview or the study in general and its results, please contact the investigators at the address and telephone number listed below.

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