THE INFLUENCE OF ATTRIBUTE CUTOFFS ON CONSUMERS' CHOICES OF A FUNCTIONAL FOOD

Yulian Ding[1], Michele M. Veeman[2] and Wiktor L. Adamowicz[3]

[1]PhD Candidate, [2]Professor Emerita and [3]Professor, Department of Rural Economy, University of Alberta, Edmonton, Alberta, Canada T6G 2H1

michele.veeman@ualberta.ca

EAAE THE ECONOMICS OF FOOD, FOOD CHOICE AND HEALTH
1st joint eaae/aaea seminar
AAEA Agricultural & Applied Economics Association

2010

Selected Paper
prepared for presentation at the 1st Joint EAAE/AAEA Seminar

"The Economics of Food, Food Choice and Health"
Freising, Germany, September 15 – 17, 2010

ABSTRACT

This study investigates evidence of non-compensatory preferences by incorporating attribute cutoffs into the modeling of consumer choices in the context of food with health-related attributes (omega-3 content) that may be associated with fortification or may result from genetic modification (GM). Data for this study were collected through a nation-wide internet-based survey drawn from a representative panel of Canadian households maintained by a major North American marketing firm. In addition to querying respondents on their perceptions and attitudes regarding food and health, choices of canola oils are elicited using a stated choice experiment in which product alternatives are identified based on attributes of price, country of origin, omega-3 content and GM/non-GM derivation.

Consumers' choices for functional canola oil products are examined in three steps. Initially, a conditional logit (CL) model is estimated assuming that no cutoffs apply in decisions on canola oil choices. Respondent's self-reported cutoffs are then incorporated into the CL model and a random parameters logit (RPL) model, applying a utility model which penalizes rather than eliminates a desired alternative when a cutoff violation occurs. In the third step, the problem of endogeneity associated with attribute cutoffs is examined by linking respondents' self-reported cutoffs to their demographic characteristics.

Results from estimations of models with/without cutoffs show that consumers value omega-3 content in canola oils but dislike GM-derived ingredients in canola oil products. These Canadian respondents prefer canola oils produced in Canada to those produced in the United States. Regarding attribute cutoffs, it is found that consumers suffer a utility loss when violating their self-reported attribute cutoffs. Comparisons between models with/without attribute cutoffs suggest that incorporating cutoffs into the compensatory utility model significantly improves the model fit. Cutoff endogeneity is examined by predicting cutoffs based on respondents' demographic characteristics. Using predicted cutoffs as instruments for self-reported cutoffs, this study provides some evidence that self-reported cutoffs may be endogenous and that researchers should consider using approaches that account for the potential endogeneity.

Keywords: decision strategy, attribute cutoff, functional food **JEL** codes: C25; C93; D1

1. Introduction

Traditional economic theory assumes that consumers are rational, utility-maximizing decision makers, with complete information about choice tasks. Lancaster (1966) extended traditional consumer theory by assuming that consumers obtain utility from the characteristics of a good rather than the good per se. Further extending this concept, the linear compensatory choice model, which assumes that consumers evaluate the attributes of alternative products/services and the trade-offs between attributes when they choose among alternatives, has been widely used in studying consumers' choice behavior (e.g., McFadden, 1974). Some scholars, however, argue that consumers have cognitive limits in processing information (e.g., Simon, 1955; Tversky and Kahneman, 1974) and note evidence that choice heuristics are commonly used in consumers' decision-making processes (Bettman et al., 1991; Payne et al., 1988).

Swait (2001) maintains that non-compensatory decision strategies are commonly used in decision making. Using a non-compensatory decision strategy, the decision maker bases his/her assessment of an alternative on just some of the attributes of the alternative instead of making tradeoffs between all attributes of an alternative (Elrod et al., 2004). Previous literature has documented a variety of non-compensatory decision rules, such as elimination-by-aspects[1] (EBA) (Tversky, 1972), lexicographic decision strategies[2] (Wright, 1975), and conjunctive and disjunctive decision rules[3] (Elrod et al., 2004). Recognizing the common use of non-compensatory decision strategies, some have questioned the robustness of a linear compensatory choice model in predicting consumer behavior under various choice settings (e.g., Johnson and Meyer, 1984).

A number of non-compensatory decision strategies involve the use of attribute cutoffs. For example, the conjunctive decision strategy implies that decision makers discard an alternative if it does not meet the threshold of any one of the attributes (Elrod et al., 2004). A large body of

[1] Using an elimination-by-aspects (EBA) decision strategy, decision makers would evaluate alternatives based on a set of aspects. One aspect is examined at a time and the alternatives that do not include the aspect are rejected. The process continues till only one alternative is left.

[2] Using a lexicographic decision strategy, decision makers would first rank the importance of attributes and then evaluate alternatives starting from the most important attribute. The alternative that surpasses other alternatives on the most important attribute is chosen. Otherwise, the process continues till one alternative is chosen.

[3] The conjunctive decision rule rejects alternatives that do not meet all the attribute thresholds, while the disjunctive decision rule accepts those alternatives that surpass at least one of the attribute thresholds.

literature on decision making suggests that attribute cutoffs are often used by consumers to simplify their choices (Huber and Klein, 1991; Bettman et al., 1991; Tversky, 1972). By implementing cutoffs, decision makers exclude alternatives that do not exceed the relevant attribute cutoffs from their choice sets at a screening stage and then choose only from the alternatives remaining in the reduced choice set (Huber and Klein, 1991). Where this is the case, taking attribute cutoffs into consideration in choice models is of importance in providing a more precise specification of consumers' decision making processes and allowing researchers to study consumer's choices in a more realistic manner (Swait, 2001; Elrod et al., 2004).

Numbers of studies have employed linear compensatory utility models to examine consumers' preferences for foods derived from modern agricultural biotechnology, commonly referred to as genetically modified (GM) foods (e.g., Burton et al., 2001; Onyango et al., 2006). It has been recognized that consumers differ considerably in their acceptance of GM foods (Hu et al., 2004; Siegrist et al., 2005). Some people refuse to consider consumption of food with GM ingredients, while others may have no concern about this issue (Siegrist et al., 2005). A growing body of literature on consumption decisions regarding foods with GM ingredients takes consumers' preference heterogeneity into consideration by using latent class (LC) models and random parameters logit (RPL) models (Hu et al., 2004; Christoph et al., 2006; Onyango et al., 2006). However, so far, little work has been done to link heterogeneous consumer preferences to the use of attribute cutoffs in decision making in studying consumers' choices for GM/non GM food. It is reasonable to postulate that consumers may encounter cutoff constraints when they choose between food products with/without GM ingredients. This study incorporates attribute cutoffs into the modeling of consumer choices in the context of food with health-related attributes (omega 3 content) that may be associated with genetic modification. As well, we examine the problem of endogeneity that may be associated with attribute cutoffs (Swait, 2001) by linking cutoffs to respondents' demographic characteristics.

2. Literature review

There is growing interest in understanding processes underlying consumers' decision-making. Payne et al. (1988) pointed out that individuals tend to adjust their decision strategies in response to varying choice tasks and time pressures to be effective in decision making. It remains a challenging task to understand when and why a decision strategy is chosen. Some argue that the selection of a decision strategy is determined by the costs and benefits associated with particular instances of decision making (e.g., Shugan, 1980). For example, based on assessments by a small group, Russo and Dosher (1983) found that decision makers selected those decision strategies which minimized their cost (effort) to make particular choices.

Literature on decision making has documented numbers of factors which influence selection of decision strategies, including the choice environment, the characteristics of the decision maker, the complexity of the choice task and time pressure (Swait and Adamowicz, 2001; Payne et al., 1988; Wright, 1974). Payne et al. (1993) provide a comprehensive literature review on the influence of choice environments on decision making. Facing a decision task, individuals tend to vary in their abilities to process information and often exhibit cognitive limits in decision making (Heiner, 1983). De Palma et al. (1994) found evidence that an individual's ability to process information affects his/her judgment of the optimal choice and selection of the decision strategies. The importance of the complexity of a decision task in determining the selection of decision strategies has been demonstrated in a number of studies (e.g., Johnson and Meyer, 1984; Tversky and Shafir, 1992; Heiner, 1983). Johnson and Meyer (1984) found that respondents are more likely to use elimination strategies when choice size increases. Tversky and Shafir (1992) concluded that individuals tend to defer their decision making or to seek new options when they face strong conflicts between alternatives. It is a common finding that the tendency for an individual to use simplified decision strategies increases when the decision tasks become more complex (Payne et al., 1988; Wright, 1974).

An attribute cutoff is the minimum acceptable level that an individual sets on an attribute (Huber and Klein, 1991). Previous literature suggests that attribute cutoffs are frequently used by decision makers (Huber and Klein, 1991; Klein and Bither, 1987). The tendency to use an attribute cutoff increases as the choice task becomes more complex (Payne, 1976), or when decision makers are under time pressure or exposed to more distractions (Wright, 1974). However, eliciting information on cutoff usage in decision making remains a challenge. Previous literature identifies attribute cutoffs based on self-reported values (Swait, 2001), process tracing methods (Klein and Bither, 1987), and observed choices (Elrod et al., 2002). Regarding elicitation of cutoffs from respondents, there is no agreement on when and how to query respondents about this. Swait (2001) identifies respondents' cutoffs based on a single cutoff-related question, but suggests that multiple questions may be useful to reduce measurement errors. Process tracing approaches, which include verbal protocols and information boards (these record respondents' search for information on choice alternatives), provide methods by which researchers may attempt to follow decision makers' cognitive processes (Ford et al., 1989). However, these approaches may also interfere with respondents' decision making (Elrod et al., 2002) and are not practical unless the research is conducted in a laboratory setting (Swait, 2001). Green et al. (1988) examine the consistency between respondents' self-reported cutoffs and their subsequent choices. These authors find that while respondents frequently violated self-reported cutoffs, they were less likely to violate a cutoff associated with an important attribute (Green et al., 1988).

Turning to the literature on the development of models to accommodate the use of cutoffs in decision making, some studies assume that decision making involves two stages and model attribute cutoffs using a two-stage decision model (Swait and Ben-Akiva, 1987; Robert and Lattin, 1991). It is hypothesized that at the first stage, decision makers screen the alternatives and eliminate from further consideration those that fail to meet cutoff levels; at the second stage, decision makers choose from the remaining alternatives (Robert and Lattin, 1991). However, the two-stage choice model is very difficult to estimate (Swait, 2001). In contrast, Swait (2001) incorporates attribute cutoffs into the linear compensatory utility model. This model penalizes cutoff violations, but does not reject alternatives that violate cutoff constraints (Swait, 2001). Elrod et al. (2004) propose an integrated model which allows for compensatory, conjunctive and disjunctive decision strategies. This model requires no information on self-reported cutoffs. Instead, information on cutoffs is obtained based on observed choices. Violations of cutoffs are not allowed in this approach.

Although there is growing interest in incorporating cutoffs into choice modeling, the issue of endogeneity of self-reported cutoffs has received little attention. Swait (2001) argues that attribute cutoffs are not exogenous to choices but are jointly determined with choices. There is empirical evidence that attribute cutoffs are not fixed and that individuals adjust their cutoffs during their decision making (e.g., Klein and Bither, 1987; Huber and Klein, 1991). Huber and Klein (1991) conclude that individuals adjust their cutoffs when they have more information about the attributes and decision tasks, while Klein and Bither (1987) observe different cutoffs to apply with differences in the utility structures that different people may employ. Given endogeneity that may be associated with respondents' self-reported cutoffs, incorporating self-reported cutoffs directly into the modeling of consumers' choices may generate biased estimates. This study models consumers' choices for canola oil products with potential health and risk attributes, allowing the use of attribute cutoffs in decision making. Moreover, we examine the issue of cutoff endogeneity by instrumenting respondents' self-reported cutoffs with predicted cutoffs. We predict respondents' cutoffs based on their demographic characteristics, which are exogenous to their choices.

3. A utility model with compensatory cutoffs

Intuition and casual observation suggest that people may not always adhere to their self-stated cutoffs. Instead, they may view these as statements of desired cutoff levels which they are willing to modify. Consequently, individuals may suffer a utility penalty rather than completely eliminate a desired alternative. We follow this chain of reasoning in adopting the model developed by Swait (2001), which penalizes rather than rejects an alternative that violates cutoff constraints. The model proposed by Swait (2001) extends the linear compensatory utility model in two aspects: first, it allows for the use of attribute cutoffs in decision making; second, it allows for violations of cutoffs. The following is a brief description of the model (for further details, see Swait, 2001).

Suppose individual n faces a choice task of choosing one alternative from choice set C, which contains several alternatives. Each alternative is characterized by K attributes, Z_i= $[X_i, p_i]'$; p_i denotes the price of alternative i and X_i represents the other ($K-1$) attributes of alternative i. Individual n obtains utility $U_{ni}(X_i, p_i)$ by consuming alternative i. We also assume that individual n is subject to an income constraint M_n. The utility maximization problem for individual n is:

$$\max \sum_{i \in C} \delta_{ni} U_{ni}(X_i, p_i)$$

$$\text{s.t.} \quad \sum_{i \in C} \delta_{ni} = 1, \ \delta_{ni} \in \{0,1\}, \ \sum_{i \in C} \delta_{ni} p_i \le M_n, \ \forall i \in C \qquad (1)$$

where δ_{ni} is a choice indicator. If individual n chooses alternative i, $\delta_{ni} = 1$; otherwise, $\delta_{ni} = 0$.

Model (1) represents a linear compensatory utility model. Considering that individual n may have constraints for the acceptable range of an attribute, we define a_K and b_K as the lower and upper bounds for the K attributes, where $a_K = [a_1, a_2, \cdots, a_k]'$, $b_K = [b_1, b_2, \cdots, b_k]'$, $-\infty < a_k \le b_k < +\infty$. By incorporating non-compensatory cutoffs into model (1), the optimization problem becomes:

$$\max \sum_{i \in C} \delta_{ni} U_{ni}(X_i, p_i)$$

$$\text{s.t.} \sum_{i \in C} \delta_{ni} = 1, \ \delta_{ni} \in \{0,1\}, \ \sum_{i \in C} \delta_{ni} p_i \le M_n, \ \forall i \in C$$

$$\delta_{ni} a_K \le \delta_{ni} Z_i \le \delta_{ni} b_K \qquad (2)$$

Model (2) requires that individual n can only choose an alternative which meets the attribute constraints. As suggested by Green et al. (1988), individuals often violate their self-reported cutoffs. Allowing decision makers to violate the attribute constraints at a cost, the extended model takes the following form:

$$\max \sum_{i \in C} \delta_{ni} U_{ni}(X_i, p_i) + \sum_{i \in C} \sum_{k} \delta_{ni} (\lambda_k g_{ik} + \gamma_k h_{ik})$$

$$\text{s.t.} \sum_{i \in C} \delta_{ni} = 1, \ \delta_{ni} \in \{0,1\}, \ \sum_{i \in C} \delta_{ni} p_i \le M_n, \ \forall i \in C \qquad (3)$$

where g_{ik} and h_{ik} denote the amounts of violations, $g_{ik} = a_k - Z_{ik}$ and $h_{ik} = Z_{ik} - b_k$; λ_k and γ_k are parameters indicating utility penalties.

Model (3) can capture a variety of decision strategies (Swait, 2001). For example, when there are no violations of attribute cutoffs, i.e., $g_{ik} = h_{ik} = 0$, this model becomes a compensatory utility model (i.e., model (1)). Model (3) can also accommodate a conjunctive decision strategy (in which an alternative is eliminated for not meeting the cutoff constraints on any one of its attributes) by setting the appropriate utility penalty (λ_k, γ_k) to $-\infty$ (Swait, 2001).

4. Data

Data employed for this study were collected through a 2009 Canada-wide internet-based stated choice survey. This survey investigates Canadian consumers' choices of canola oils with selected attributes. Canola oil is chosen as the identified food product since this is commonly consumed by Canadian households and allows avoidance of biases associated with product unfamiliarity. Moreover, canola is Canada's major oilseed crop and canola oil is widely used as a food product and ingredient.

The survey simulates market purchases using a stated choice experiment. We identify the attributes and levels of canola oil products based on the objectives of this study and focus group discussion. Four attributes are considered important. These are price, country of origin, omega-3 content and GM/nonGM derivation. The definitions of the attributes and levels are presented in Table 1. The survey uses a fractional factorial design which considers both the main effects and two-way interactions between attributes. Each choice set consists of three options: two canola oil products and a "no purchase" option. We conducted two pre-tests to test the validity of the survey design and the levels of the attributes. The questionnaire was revised based on analysis of the pre-test data. The recruitment for and application of the final survey were carried out by a marketing company that has a representative Canadian consumer panel composed of 80,000 households with more than 150,000 individuals. Two rounds of invitations were sent to the panelists by the company's Online Project team. A total of 2,857 panelists participated in the survey with full completion of 1,009 surveys.

Tables 2 to 4 provide demographic characteristics available for the analysis sample and the Canadian population. Table 2 shows the distributions of different age groups for the sample and the Canadian population. The sample consists of people who are at least 18 years old and can be compared with Statistics Canada's Census year data (for 2006) on the Canadian population 18 years and over. Relative to age, the sample is slightly biased towards older people compared to the general adult population in 2006. The proportion of people with some college education and above in the sample is higher than for the 2006 Canadian population aged 20 years and over[4] (see Table 3). The geographic distribution of survey respondents is similar to that of the Canadian population (see Table 4). Comparing income levels between the sample and the Canadian population: the sampled respondents have an average household income of $61,751.15, which is somewhat lower than the average household income of $69,548 indicated by the 2006 Canadian Census (Statistics Canada, 2006 Census (d)). Regarding gender distribution, there are more females than males in the sample, 58.4% versus 41.6%. However, given that the survey focuses on food consumption and women tend to do more of the household grocery shopping, this is considered to be relatively realistic. Overall, observable demographic characteristics of the sample are judged to reasonably match the adult food-buying Canadian population.

The focus of this study is to incorporate attribute cutoffs into the modeling of consumers' food choices. Respondents were asked a series of short questions on their stated preferences for the attributes employed in the choice experiment, specifically for the four attributes of country of origin, omega-3 content/characteristics, GM/nonGM derivation and price. Cutoffs were queried prior to the choice experiment, so that self-reported cutoffs would not be affected by the attribute levels appeared in the that experiment, using a set of four questions which correspond to the four attributes. These are worded as: (1) "When purchasing canola oil, which of the following statements best represents how the country of origin influences your purchase decision?" ; (2) "Which of the following statements best describes your attitudes toward buying foods with fortified ingredients?"; (3) "Which of the following statements best describes your behavior when it comes to buying foods that have ingredients that are genetically modified or genetically engineered?"[5]; (4) "When you purchase a bottle of canola oil, say 1 litre in size, is there always a maximum price you will pay? If yes, which of the following represents the maximum price you will pay for a one litre bottle of canola oil?"

Several alternative cutoff options are proffered for each of the four attributes. Options for the query on country of origin are: (1) My decision depends on the specific canola oil; (2) I only

[4] We compare a measure of education levels of the sample with that for Canadian population of 20 years age and over, in the nearest census year due to lack of national data on the education levels for the population 18 years and over in the study period.
[5] Regarding queries (2) and (3), definitions of food fortification and genetic modification/engineering are offered in the questionnaire.

purchase canola oils produced in Canada; (3) I only purchase canola oils produced in the U.S.; (4) I do not care. Regarding the query on food fortification, three options are proffered: (1) My decision depends on the specific food with fortified ingredients; (2) I am not willing to purchase any food with fortified ingredients; (3) I am indifferent towards foods with/without fortified ingredients. Options corresponding to the query on the GM attribute are: (1) My decision depends on the specific food with GM/GE ingredients; (2) I am not willing to purchase any food with GM/GE ingredients; and (3) I am indifferent towards foods with/without GM/GE ingredients. For the price attribute, respondents who indicated having a price cutoff were requested to choose one of the four proffered price ranges to indicate the maximum price they would pay. The applicability and presentation of the cutoff questions were initially assessed by a focus group of members of the public recruited in Edmonton. Initial analyses of data from two pre-tests of the revised survey gave a further means to assess the appropriateness of cutoffs before the implementation of the final Canada-wide survey and led to some revision of these before final implementation.

Table 5 reports the numbers and corresponding percentages of respondents who reported having attribute cutoffs. A large proportion of survey respondents, 336 out of 1,009, said that they only purchase canola oils produced in Canada. In view of previous studies of Canadians' attitudes, we did not find it surprising that almost 40% (38.95%) of respondents indicated that they are not willing to purchase food with GM ingredients. In general, it appears that respondents were generally willing to accept enhancement of food nutrients through fortification of ingredients—only 84 respondents indicated that they are not willing to purchase food with fortified ingredients. The price cutoffs chosen by respondents vary. Some 40% indicated that they do not have a maximum price for the purchase of a bottle of canola oil. Among those with price cutoffs, 11.6% said they are not willing to pay more than $2.49 for a one litre bottle of canola oil; 38.9% chose a maximum price in the range of $2.5 to $4.99; and 7.73% indicated their maximum willingness to pay to be a price in the range of $5 to $7.49.

5. Incorporating self-reported cutoffs into the modeling of consumers' choices of a functional food

There is growing interest in growth in the market for functional food. According to Agriculture and Agrifood Canada, such foods "are similar in appearance to, or may be, a conventional food that is consumed as part of a usual diet, and is demonstrated to have physiological benefits and/or reduce the risk of chronic disease beyond basic nutritional functions." (AAFC, 2009). Such foods have been pursued by fortification and may also be achieved by plant breeding, including through the application of modern agricultural biotechnology techniques. However, applying transgenic methods of biotechnology to food production is a controversial topic in society at large and is subject to regulation, although this tends to vary between different nations. This study examines Canadian consumers' preferences for canola oil products which vary in omega-3 content (which is increasingly recognized as important to health), and may be associated with genetic modification. However, a canola oil product with omega-3 content enhanced by genetic modification has not yet been developed or approved. As suggested by the summary of self-reported cutoff responses in Table 5, appreciable proportions of respondents reported having attribute cutoffs. We expect that taking these attribute constraints into consideration in modeling decision making will improve the model fit and explanation of choice behavior.

In section 3 above we outlined a utility model which allows for compensatory cutoffs in decision making (see Model (3)). Here we proceed to examine consumers' choices based on that model. We assume initially that respondents' self-reported cutoffs are exogenous to their choices. Dummy variables are created indicating whether there are violations of cutoffs. For example, if a respondent stated that he/she only purchases canola oils produced in Canada, a canola oil produced in the United States leads to a violation of the Canada-related cutoff for this respondent. Applying Model (3) to consumers' choices for canola oils, the utility function takes the form:

$$U_{ni} = \beta_1 \text{Nopurchase} + e_{ni}\,, \quad \text{i= "no purchase"}$$

$$U_{ni} = \text{(1-Nopurchase)}(\beta_2\,\text{Enhance} + \beta_3\,\text{Contain} + \beta_4\,\text{GM} + \beta_5\,\text{NonGM}$$

$$+\,\beta_6\,\text{Canada} + \beta_7\,\text{Price} + \beta_8\,\text{VCan} + \beta_9\,\text{VFort} + \beta_{10}\,\text{VGM} + \beta_{11}\,\text{VPrice1} \qquad (4)$$

$+\beta_{12}$ VPrice2+ β_{13} VPrice3)+ e_{ni} , i $\neq$ "no purchase"

where Nopurchase takes the value of 1 for the "no purchase" option, otherwise Nopurchase equals 0; Enhance takes the value of 1 if a canola oil is labeled "Enhanced omega-3" and is 0 otherwise; "Contain" equals 1 if a canola oil is labeled "Contains omega-3" and otherwise equals 0. The attribute of GM derivation is coded into two separate dummy variables, GM and NonGM, indicating the presence and absence of GM ingredients respectively; "No label" is the omitted level for this attribute. "Canada" equals 1 if a canola oil is produced in Canada, otherwise "Canada" equals 0; "U.S." is the omitted level of this attribute. Price denotes the price of a canola oil product; VCan is a dummy variable with a value of 1 if a violation of the cutoff of only purchasing Canadian oils occurs (a U.S. product is considered a violation of this cutoff), otherwise VCan equals 0. VFort and VGM are defined in a similar manner, with VFort indicating a violation of the fortification cutoff; based on the definitions and information given to respondents we define a canola oil with enhanced omega-3 as a violation of this cutoff. VGM denotes a violation of the GM cutoff; choice of a canola oil containing GM ingredients violates this cutoff. VPrice1, VPrice2 and VPrice3 are three dummy variables indicating violations of three different price cutoffs, with VPrice1 corresponding to a violation of the price cutoff at \$2.49/litre, VPrice2 at \$4.99/litre, and VPrice3 at \$7.49/litre; β s are parameters to be estimated; and e_{ni} represents an error term.

In this study, survey respondents were asked to choose among different canola oils in a series of choice tasks. Each choice task contains three alternatives: two canola oil products and a "no purchase" option. Let U_{ni} denote the level of utility individual n obtains from choosing oil i. By assuming the error term has a type I extreme value distribution, the logit choice probability of individual n choosing oil i (P_{ni}) takes the form:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_k e^{V_{nk}}} \qquad (5)$$

where V_{ni} represents the deterministic component of U_{ni} (equation (4)).

Table 6 compares the results of a standard conditional logit (CL) model with that of a CL model which allows for cutoff violations (we label this "CL model with penalties"). These models were estimated with maximum likelihood methods using NLOGIT Version 4 (Greene, 2007). As can be seen in Table 6, the analytic findings from these models are similar. A negative coefficient on Nopurchase suggests that consumers are averse to not purchasing a canola oil product. Omega-3 content in a canola oil is valued by consumers since the coefficients on both "Enhanced omega-3" and "Contains omega-3" are positive and significant. Findings related to the GM attribute are as expected: in general, consumers do not like a canola oil with GM ingredients and are willing to pay a premium for a canola oil labeled "NonGM" relative to one that is not labeled. We also find that Canadian consumers prefer canola oils produced in Canada to those produced in the U.S.

The CL model that includes utility penalties when cutoffs are violated, given in Table 6, is based on the assumption that some respondents may be willing to sacrifice a utility loss rather than eliminate an alternative when there is a cutoff violation associated with that alternative[6]. Consequently we expected the coefficients for the variables representing cutoff violations to be negative. As expected, the results of the CL model incorporating utility penalties suggest that violations of the cutoffs result in utility losses to decision makers. All the coefficients for the cutoff violation variables are negative and significant except for that on the variable of VPrice3, which denotes a violation of the price cutoff at $7.49. It seems likely that this may arise from the feature that the maximum price employed in the choice experiment is $7.50, which is very close to $7.49 and thus unlikely to be considered a real violation of this particular price cutoff. We observe that the coefficient on VGM has the largest absolute value, which indicates that the utility penalty associated with violating the GM cutoff is larger than that associated with violating any other cutoff.

[6] A total of 6054 choices are made. Of these, 1644 choices involve violating at least one attribute cutoff. Among these, the cutoff of only purchasing Canadian oil was violated 311 times; the fortification cutoff was violated 56 times; the no-GM cutoff was violated 99 times; the price cutoff at $2.49 was violated 399 times; the price cutoff at $4.99 was violated 555 times; the price cutoff at $7.49 was violated 53 times.

Comparison between the two CL models in Table 6 suggests that incorporating the cutoffs into the CL model does affect the model estimates. For example, the results from the CL model without penalties indicate that the presence of GM ingredients in a canola oil reduces utility by 0.829 units compared with a canola oil without an explicit “GM/NonGM” label. However, the results from the CL model with penalties finds that a “GM” label only reduces utility by 0.282 units, while violating the no-GM cutoff results in a utility penalty of 1.9321 units. Table 6 also shows that incorporating attribute cutoffs into the utility function significantly increased the model fit. The log likelihood statistic increased from -5145.132 to -4804.135, while the pseudo R^2 increased from 0.2139 to 0.2656. A likelihood ratio (LR) test of inclusion of the cutoff violation variables in the model clearly favors inclusion: the LR statistic is -2[-5145.132-(-4804.135)] = 681.994. This is much greater than the 1 percent critical value of 16.81(the number of degrees of freedom is 6), suggesting that the utility function without the cutoff violation variables be rejected.

There is a possibility that overestimation of cutoff effects on decision making may arise from not accounting for taste variation among the respondents (Swait, 2001). To assess this, we further test the model with compensatory attribute cutoffs by controlling for unobservable preference heterogeneity among the survey respondents. We conduct this test by estimating a random parameters logit (RPL) (or mixed logit (ML) model), which allows for preference heterogeneity across individuals (Hensher and Greene, 2003; Train, 2003). The RPL/ML probability of individual n choosing alternative i is:

$$P_{ni} = \int \left(\frac{e^{V_{ni}(\beta)}}{\sum_k e^{V_{nk}(\beta)}} \right) f(\beta) d\beta \qquad (6)$$

where $V_{ni}(\beta)$ is the deterministic component of U_{ni}; β is a vector of parameters; and $f(\beta)$ denotes a density function of parameters (Train, 2003).

Table 7 presents the results from estimating the model described by equation (6). We allow for heterogeneous consumer preferences for all the attributes when estimating the RPL model. The coefficients for the attributes are assumed to have a normal distribution. Since economic theory suggests that price has a negative impact on utility, we assume that negative prices exhibit a lognormal distribution. The statistics on the model fit suggest that the RPL model reported in Table 7 is superior to the CL models presented in Table 6. Both the log likelihood and pseudo R^2 increase when taste variations are considered in the model. However, comparison of the results reported in Tables 6 and 7 suggests that in general the findings are not highly sensitive to the model specification in that we identify the same pattern of consumer preference for all the attributes. Specifically, from the results in both tables, consumers value omega-3 content in a canola oil product. Overall, they dislike GM food and prefer a canola oil that contains no GM ingredients. These Canadian consumers also prefer canola oils produced in Canada to those produced in the U.S.

Regarding the attribute cutoffs, we find that consumers suffer a utility loss when they violate their self-reported attribute cutoffs and that this holds even after we consider unobservable preference heterogeneity across individuals in the model. As suggested by the estimates of the CL model with utility penalties in Table 6, the results of the RPL model also indicate that a violation of the no-GM cutoff results in the largest utility penalty. A possible explanation for this is that individuals consider the GM attribute to be a more important factor than the other attributes in their decision making, so they suffer more from violating the cutoff associated with this attribute. However, whether a utility penalty increases with the level of importance of an attribute remains an interesting topic to be further investigated in future studies. The findings on the price cutoffs change slightly when unobservable preference heterogeneity is considered. The estimates of the CL model suggest that there is a utility penalty associated with violating the price cutoff at $2.49, whereas the RPL model indicates that the violation of that price cutoff variable (VPrice1) had no impact on utility. Both the CL model and the RPL model indicated no evidence that a violation of the highest price cutoff ($7.49), affects an individual’s utility level. However, as noted above, the highest price level that appeared in the choice experiment is $7.50, very close to the price cutoff at $7.49, suggesting that inclusion in the model of a price cutoff at $7.49 is redundant. Since both the CL model and the RPL model suggest that violation of the price cutoff at $7.49 has no impact on utility, we consider only two price cutoffs in the following analyses, one at the level of $2.49 and the other at the level of $4.99.

6. Modeling consumer behavior under predicted cutoffs

Endogeneity associated with attribute cutoffs has been discussed in several studies (Klein and Bither, 1987; Huber and Klein, 1991; Swait, 2001). It has been found that cutoffs are influenced by numbers of factors, such as an individual's knowledge of the attributes (Huber and Klein, 1991) and the choice context (Swait, 2001). In this section, we relax the assumption that the respondents' self-reported cutoffs are exogenous to their choices. A common approach to solving the problem of endogeneity is to use instrumental variables (IV) in model estimation. We create instruments for respondents' self-reported cutoffs by predicting cutoffs based on respondents' demographic characteristics. In modeling choices we then replace the self-reported cutoffs with predicted cutoffs.

6.1. Linking cutoffs to demographic characteristics using a binary logit model

Respondents' demographic characteristics are exogenous variables. One possibility to address the problem of endogeneity of the self-reported cutoffs is to predict cutoffs based on individuals' demographic characteristics. However, the feasibility of this approach depends on how much explanatory power an individual's demographic characteristics has on his/her self-stated cutoffs. In this section we try to understand the relationships between respondents' self-reported cutoffs and their demographic characteristics.

Four types of cutoffs are identified by respondents in the survey, corresponding to each of the four attributes employed in the choice tasks (see Table 5). About one third of the respondents indicated that they would only purchase canola oils produced in Canada; 8% of the respondents indicated that they would not purchase food with fortified ingredients; almost 40% of the respondents identified that they were not willing to purchase a canola oil with GM ingredients; and the majority of the respondents indicate that they would pay no more than one of the specified prices for a bottle of canola oil. Since these are all discrete cutoffs, respondents' answers to each of the cutoff questions can be grouped into the two categories of having a cutoff and not having a cutoff. Thus it is appropriate to use a binary indicator to show whether or not an individual has a cutoff for a particular attribute. This indicator has two values, 0 and 1, with 1 indicating that the individual has a cutoff and 0 indicating no cutoff. The creation of a binary indicator for each of the attribute cutoffs allows us to link individuals' self-reported cutoffs to their demographic characteristics using a binary logit model.

In a binary logit model, the dependent variable (Y) is a binary variable, taking a value of either 1 or 0. Let y* be an unobservable variable and y*= $X'\alpha + \varepsilon$, where X represents the factors influencing y* and α is a vector of parameters. We cannot observe y* directly; what we see is Y=1 if y*>0, otherwise Y=0. Assuming that ε has a logistic distribution:

$$\text{Prob}\left(Y = 1 \middle| X\right) = \frac{e^{X'\alpha}}{1 + e^{X'\alpha}} \qquad (7)$$

We define Y=1 if a respondent reports having a cutoff and Y=0 if a respondent has no reported cutoff. We then examine how the respondents' demographic characteristics affect their answers to each of the cutoff questions respectively based on equation (7). The definitions of the variables used in the binary logit models are presented in Appendix 1 and the results are presented in Tables 8a and 8b.

Table 8a reports the results from estimating three binary logit models. Model (1) examines how demographic variables affect the probability that an individual only purchases canola oils produced in Canada. In this context we are not primarily interested in the magnitude of the influence that a demographic variable has on the probability of only purchasing Canadian oils and consequently do not present the marginal effects of the demographic variables in the table. According to the results of Model (1), the older people are, the more likely they are only to purchase Canadian oils. Compared with respondents from other regions in Canada, respondents that reside in Quebec are less likely to have a cutoff only to purchase Canadian oils, while respondents that reside in the Prairie provinces are more likely not to consider purchase of canola oils produced outside of Canada. We also find that urban residents are less likely only to purchase Canadian oils.

The results of Model (2) suggest that male respondents are more likely to have a cutoff for fortified ingredients in a food product; respondents with higher levels of education (a university degree and above) tend to dislike fortified ingredients in a food product; and urban respondents are less likely to have a cutoff for fortified ingredients. Model (3) examines how demographic characteristics influence the probability that a respondent has a cutoff for GM ingredients in a food product. We find that male respondents and urban residents are less likely to have a cutoff for GM food while residents of Quebec and those with more education (a university degree and above) are more likely to have a cutoff for GM food.

The maximum prices indicated by respondents to be acceptable for the purchase of a bottle of canola oil vary from \$2.49/litre to \$7.49/litre. As discussed above, only two price cutoffs, at the levels of \$2.49 and \$4.99, have impacts on utility. Therefore, we creat two binary variables representing the two relevant levels of price cutoffs at \$2.49 and \$4.99. The results for Models (4)-(5), presented in Table 8b, investigate how demographic variables influence the probability that a respondent has a price cutoff at \$2.49/litre and \$4.99/litre respectively. In general, we find that, except for income levels, socio-economic and demographic variables tend to have limited impacts on the price cutoffs. As can be seen in Table 8b, the coefficients on income in Models (4) and (5) are negative and significant, suggesting that the respondents with more income are less likely to specify price cutoffs at \$2.49/litre or \$4.99/litre.

6.2. Incorporating predicted cutoffs into the utility function

The results in Tables 8a and 8b suggest that demographic characteristics do influence the probability that an individual has a cutoff for an attribute. Thus it should be possible to predict cutoffs based on respondents' demographic characteristics and to use the predicted cutoffs as the instruments for the self-reported cutoffs. In this section, we construct two sets of instruments for the self-reported attribute cutoffs based on the respondents' demographic characteristics and the estimated binary logit models, and compare the results from different models estimated under self-reported cutoffs and predicted cutoffs.

The first set of instruments consist of the predicted probabilities of having a cutoff. These predicted probabilities can be used as instruments for the self-reported cutoffs if we assume that the respondents who are more likely to have a cutoff for an attribute suffer a larger utility penalty when a violation of a cutoff occurs. Given a respondent's demographic information and the estimated binary logit models, we can calculate the probability that a respondent has a cutoff for a particular attribute. For example, the probability that a respondent has a cutoff for the GM attribute can be calculated by substituting the respondent's demographic information and the parameters in Model (3) (Table 8a) into equation (7), where X represents the demographic variables and α represents the parameters. We then incorporate the predicted probabilities of having a cutoff into equation (5) and estimate a CL model. The results for these CL models are presented in Table 9 (labelled as Model (2), whereas Model (1) in Table 9, included for purposes of comparison, is a CL model in which attribute cutoffs are as reported by the respondents themselves. The cutoff violation variables in Model (2) include: VCana, denoting the violation associated with the cutoff of only purchasing Canadian oils; VForta, denoting the violation of the fortification cutoff; VGMa, indicating the violation of the GM cutoff; and VPrice1a and VPrice2a, indicating the violations of the price cutoffs at \$2.49 and \$4.99 respectively. For purposes of further comparison, two RPL models are also estimated and reported, in Table 10, with one (Model (4) employing the respondents' self-reported cutoffs and the other (Model (5) employing the predicted probabilities of having a cutoff as instruments for the self-reported cutoffs.

The results of Model (2) in Table 9 and Model (5) in Table 10 show that consumers are averse to not purchasing a canola oil product. They value omega-3 content in canola oils and prefer canola oils produced in Canada to those produced in the U.S. These findings are consistent with those from the models which employed self-reported cutoffs, i.e. Model (1) in Table 9 and Model (4) in Table 10. However, the findings on the cutoff violation variables have changed as a result of using the predicted probabilities as instruments for the self-reported cutoffs. Both Model (2) and Model (5) suggest that consumers' utility is penalized for violating the cutoff of only purchasing Canadian oils and the no-GM cutoff. However, violations of the fortification cutoff were found to have no impact on utility. The latter finding contradicts those from Model (1) and Model (4), which indicate utility penalties associated with violating the fortification cutoff. This discrepancy suggests that the results from a model which assumes the cutoffs to be exogenous may be misleading. In other words, endogeneity in Models (1) and (4) appears to be generating some bias in these estimates.

Regarding the impacts of violating the price cutoffs, Model (2) (Table 9) indicates that consumers were penalized on utility for violating the price cutoff at \$2.49 but there was no utility penalty associated with violating the price cutoff at $4.99. Model (5) in Table 10, however, indicates no penalty for violating the price cutoff at $2.49 but suggests that violating the price cutoff at $4.99 has a significant and positive effect on utility. Thus, in general, the results on the price cutoffs are not stable across models. These unexpected findings from Model (5) may be caused by the instruments used for the self-reported price cutoffs at $2.49 and $4.99. The instruments for these two price cutoffs could be correlated since these were predicted based on respondents' demographic and socioeconomic information and income has a significant negative impact on having a price cutoff at both $2.49 and $4.99. Considering that the predicted probabilities of having price cutoffs at $2.49 and $4.99 might be correlated, we dropped the cutoff violation variable associated with the price cutoff at $4.99 (VPrice2a) and re-estimated the CL model and the RPL model. These results are presented in Tables 11 and 12. The CL model presented in Table 11 suggests that there is a penalty associated with violating the price cutoff at $2.49 while the RPL model (Table 12) found no evidence of penalizing the violations of a price cutoff.

An interesting feature of the results from Models (2) and (5) is that the coefficient on GM is not significant, but the coefficient on VGMa, which denotes a violation of the no-GM cutoff, has a large negative value and is statistically significant. These results suggest that the presence of GM ingredients in a canola oil product has no impact on the utility of those who are not concerned about GM food. However, violating the no-GM cutoff results in a large utility loss for those who are concerned about GM food. The finding that the presence of GM ingredients in a food product has no impact on utility is unexpected and contradictory to the results from Models (1) and (4). This may be due to the estimation method: when we instrument the self-reported cutoff for the GM attribute with the predicted probabilities of having a no-GM cutoff, we change the cutoff variable from a binary variable to a continuous variable. The self-reported cutoff is described as having a cutoff for GM ingredients or not having a cutoff, while the predicted probabilities are the probabilities that respondents have a cutoff for the GM attribute. Employing the self-reported cutoffs, the model only punishes those who reported having a cutoff for the GM attribute when a violation occurs. However, using predicted probabilities as instruments, all the respondents for whom predicted probabilities are greater than 0 suffer a utility loss when a violation occurs. It is likely that the negative impact of the GM attribute on utility is also captured by the utility penalty variable (VGMa).

As mentioned earlier in this section, in using the predicted cutoff probabilities as the instruments for the self-reported cutoffs, we assume that respondents who are more likely to have a cutoff for an attribute suffer a larger utility penalty when a violation of a cutoff occurs. However, it could be the case that a utility penalty may not occur until the probability of having a cutoff surpasses a specific threshold. In other words, a violation of a cutoff may have no impact on respondents with a predicted probability of having a cutoff under a particular threshold, say of 50%, but may cause a large utility loss for those respondents with a predicted probability even slightly above that threshold. To explore this, we constructed a second set of instruments for the self-reported cutoffs which allow a utility penalty to take effect only when the predicted probability surpasses a threshold.

Given information on socioeconomic and demographic characteristics of respondents and the estimated functions between the respondents' self-reported cutoffs and these characteristics, we can predict whether a respondent has a cutoff for an attribute. These predicted cutoffs can be used as the alternative instruments for the self-reported cutoffs. We initially adopted a threshold value of probability of 0.5 in predicting cutoffs so that if a respondent has a predicted probability greater than 0.5 of having a cutoff for an attribute, the model predicts that this respondent has a cutoff for that attribute. Otherwise, the model predicts that this respondent does not have a cutoff for the attribute. However, a probability level of 0.5 may not be an appropriate threshold value if the dependent variable in a binary logit model consists of either too many 0s or too many 1s. In this study, we identify that only 8.33% of the survey respondents have a self-reported cutoff for fortified ingredients in food and only 11.6% have a price cutoff at $2.49 (see Table 5). As a result, it is not possible for the model to predict any respondent to have a fortification cutoff or a price cutoff at $2.49 if we set the threshold value at 0.5. Consequently, we adjusted the threshold value to 0.2 in predicting whether a respondent has a cutoff for fortified ingredients or for a price over $2.49.

We proceed to estimate a CL model (Model (3) in Table 9) based on the predictions of whether a respondent has a cutoff for an attribute instead of using respondents' self-reported cutoffs[7]. The variables indicating the cutoff violations in Model (3) were adjusted accordingly. VCanb has a value of 1 if a respondent violates his/her predicted (not self-reported) cutoff of only purchasing Canadian oils; otherwise VCanb has a value of 0; VFortb, VGMb, VPrice1b and VPrice2b were defined in a similar manner, taking the value of 1 if a violation occurs based on the predicted cutoffs; otherwise these variables equal 0. As is the general case from the previous estimations, the results of Model (3) suggest that respondents do not like GM food and are willing to pay more for canola oils labelled as "Contains omega-3," "Enhanced omega-3" and "Produced in Canada". Regarding the cutoff violation variables, from Model (3), violating the cutoff of only purchasing Canadian oils and the no-GM cutoff results in utility penalties. However, the magnitude of the utility penalties suggested by Model (3) are much smaller than suggested by Models (1) (Table 9) and (4) (Table 10), which are based on the respondents' self-reported cutoffs. We find no evidence that violating the fortification cutoff and the price cutoffs resulted in utility losses based on the results of Model (3).

7. Conclusions

In this study, we incorporate attribute cutoffs into the modeling of consumers' choices for functional canola oil which may be associated with genetic modification. We find empirical evidence that consumers tend to use attribute cutoffs in their decision making regarding stated purchases of a food product. Even so, our results show that some respondents do not adhere to their self-stated cutoffs but take a utility penalty rather than eliminate an alternative when a violation occurs. The results of both CL models and RPL models suggest that incorporating attribute cutoffs into the compensatory utility function significantly improved the model fit over ignoring cutoffs.

By linking respondents' self-stated cutoffs to their demographic characteristics, we find evidence that respondents' demographic characteristics explain some of the cutoff level selected for some attributes. In general, we find that demographic variables have less impact on price cutoffs than on cutoffs associated with the other attributes. We examine the potential

[7] A corresponding RPL model was also estimated, but this did not converge and therefore is not reported.

endogeneity problem of cutoffs by predicting cutoffs based on the respondents' demographic characteristics. Our results suggest that using predicted cutoffs as the instruments for the self-reported cutoffs affected some of the parameter estimates, relative to the model without instruments. In general, our results for cutoffs relating to the purchase of Canadian oils only and the no-GM cutoff are stable across the different models estimated. Model estimates that incorporate self-reported cutoffs and those that incorporate predicted cutoffs all suggest that violations of the cutoff of purchasing Canadian oil only and the no-GM cutoff result in utility penalties to consumers. However, the magnitude of the utility penalty associated with violating these two cutoffs is influenced by whether the self-reported cutoffs or the predicted cutoffs are employed in the model. In contrast, findings related to the fortification cutoff and the price cutoffs are not consistent between models using self-reported cutoffs and those using predicted cutoffs. Although the models employing the self-reported cutoffs suggest that there is a utility loss associated with violating the fortification cutoff, we found no evidence of utility penalties associated with violating the fortification cutoff when we estimated the model using predicted cutoffs. In this context we note that relatively few respondents actually indicated a fortification cutoff. Findings on the violations of price cutoffs also vary among models. One interesting feature of these is that the results from CL models based on both self-reported cutoffs and predicted cutoffs seem to suggest that violations of the lower price cutoff lead to more consistent evidence of utility loss. This may be due to respondents that report a lower price cutoff being particularly concerned about price, so that violating a price cutoff is more likely to result in their having a utility loss.

It is a concern that attribute cutoffs are not exogenous to choices, but are jointly determined with choices. If individual's demographic characteristics are exogenous variables to choices, predicting cutoffs based on respondents' demographic characteristics provides a way to investigate this concern about endogeneity. However, there are some drawbacks in pursuing this approach. First, there may be problems if respondents' demographic characteristics affect both their cutoffs and their choices. Consequently, predicting cutoffs based on demographic characteristics may cause a problem of identification between cutoffs and demographics. Further, our work suggests that demographic characteristics have limited predictive power on the cutoffs. Thus the instruments based on demographic characteristics could be weak. However, it remains a challenge to find good instruments for attribute cutoffs. Nevertheless, this study provides some evidence that self reported cutoffs may be endogenous and that researchers should consider using approaches that account for the potential endogeneity.

In this study we examine the problem of endogeneity associated with self-reported attribute cutoffs by predicting cutoffs based on respondents' demographic characteristics. However, it is possible that the use and violation of attribute cutoffs by respondents are also affected by choice contexts, such as the specific choice questions that respondents encounter. Future study may extend the current model by incorporating information on the specific choice questions encountered by individual respondents. Moreover, in this study we assume that cutoffs are fixed over time. Previous literature suggests that decision makers learn from their decision making and tend to adjust cutoffs when they have more information about their choice tasks (Klein and Bither, 1987; Huber and Klein, 1991). Future studies may also consider extensions to the current model by allowing for adjustments in cutoffs over time.

Acknowledgements

The authors gratefully acknowledge funding support for this research from Genome Canada and Genome Alberta. Travel funding support from the Consumer and Market Demand Agricultural Network, which is funded by Agriculture and Agri-Food Canada and hosted by the Department of Rural Economy at the University of Alberta, is also acknowledged.

Table 1 Attributes, attribute levels and the definitions of the attributes and levels used in the experiment on stated choices of canola oils

Attribute	Attribute level [a]	Definition [b]
Omega-3 content	Contains Omega-3	Any regular canola oil has some level of omega-3 fatty acids. Manufacturers may choose to state this on the label as "contains omega-3 fatty acids".
	Enhanced Omega-3	While ordinary canola oil has a certain level of omega-3 fatty acids, the type and level of omega-3 fatty acids in canola oil can be increased and enhanced through genetically modifying/engineering (GM/GE) canola plants. Enhanced omega-3 fatty acids can also be achieved without the use of GM/GE by fortification.
	No label indicated	
GM ingredients	Contains GM/GE	GM/GE is a modern agricultural biotechnology which involves the transfer of genetic material from one organism to another. Through GM/GE, it is easier to introduce new traits without changing other traits in the plant or animal. GM/GE also makes it possible to introduce traits from other species, something not possible with traditional breeding methods.
	No GM/GE	
	No label indicated	
Country of origin	Product of Canada	This means that the canola oil is Canadian grown and processed.
	Product of US	This means that the canola oil is imported from the US where it was grown and processed.
Price	$2.50/litre $5.00/litre $7.50/litre	

[a] This column indicates product labels used in the choice experiment.

[b] This column gives the definitions of the attributes and their levels.

Table 2 Distributions of age of the study sample (2009) and the Canadian population (2006), expressed in percentages

Age group	Sample (18+)	Population (18+)
24 and below	0.06	0.12
25-34	0.15	0.16
35-44	0.21	0.19
45-54	0.22	0.20
55-64	0.17	0.15
65 and over	0.19	0.18

Source of Canadian Population data: Statistics Canada, 2006 Census (a)

Table 3 Distributions of education levels for the study sample (2009) and the Canadian population (2006), expressed in percentages

	Sample	Population (20+)
Some High School or less	6.94	15.66
High School Graduate	26.86	22.7
Some College or Technical School	25.27	13.29
College or Technical School Graduate	9.32	20.28
Some University	14.57	5.38
University degree and above	17.05	22.68

Source of Population data: Statistics Canada, 2006 Census (b)

Table 4 Regional distributions of population of the study sample (2009) and the Canadian population (2006), expressed in percentages

	Sample	Population
Alberta	10.7	10.41
British Columbia	12.49	13.01
Manitoba	5.15	3.63
New Brunswick	3.47	2.31
Newfoundland and Labrador	0.5	1.6
Nova Scotia	1.98	2.89
Ontario	33.6	38.47
Quebec	27.75	23.87
Saskatchewan	4.36	3.06

Source of Population data: Statistics Canada, 2006 Census (c)

Table 5 Numbers and percentages of respondents reporting cutoffs (sample size: 1009)

Cutoff Statements	Numbers of respondents with cutoffs	%
I only purchase canola oil produced in Canada	336	33.3
I am not willing to purchase any food with fortified ingredients	84	8.33
I am not willing to purchase any food with genetically modified ingredients	387	38.35
My maximum price for 1 litre bottle of canola oil is $2.49 or less	117	11.6
My maximum price for 1 litre bottle of canola oil is $2.5~$4.99	393	38.95
My maximum price for 1 litre bottle of canola oil is $5~$7.49	78	7.73

Table 6 Results of conditional logit (CL) models with/without utility penalties

	CL model without penalties		CL model with penalties	
Attribute	Coefficient	Standard error	Coefficient	Standard error
Nopurchase	-2.0037***	0.069	-2.414***	0.0787
Enhance	0.3922***	0.0492	0.4732***	0.0525
Contain	0.43***	0.0513	0.4706***	0.0537
GM	-0.829***	0.0513	-0.282***	0.0588
NonGM	0.2709***	0.0479	0.3039***	0.0496
Canada	0.6574***	0.0385	0.3967***	0.0451
Price	-0.4548***	0.0115	-0.4367***	0.0134
VCan			-1.0224***	0.0759
VFort			-0.5797***	0.1473
VGM			-1.9321***	0.1083
VPrice1			-0.735***	0.0935
VPrice2			-0.5641***	0.0683
VPrice3			0.0864	0.1654
Log likelihood	-5145.132		-4804.135	
Pseudo R^2	0.2139		0.2656	

*** denotes a significance level of 1%.

Table 7 Results of a random parameters logit (RPL) model with attribute cutoffs

Attribute	Coefficient	Standard error
Random parameter in utility functions		
Nopurchase	-4.0262***	0.131
Enhance	0.701***	0.0816
Contain	0.6588***	0.0748
GM	-0.6368***	0.1357
NonGM	0.4479***	0.0726
Canada	0.6003***	0.0791
Nsprice [a]	0.6967***	0.0376
Nonrandom parameters in utility functions		
VCan	-1.5961***	0.1118
VFort	-0.7175***	0.23
VGM	-3.2318***	0.2511
VPrice1	-0.324	0.2736
VPrice2	-0.5093***	0.1074
VPrice3	0.0007	0.2468
Derived standard deviation of parameter distributions		
Sd-Nopurchase	1.3413***	0.1329
Sd-Enhance	0.9841***	0.1126
Sd-Contain	0.7106***	0.1372
Sd-GM	2.046***	0.1529
Sd-NonGM	0.5452***	0.1612
Sd-Canada	1.1753***	0.0904
Sd-Nsprice	0.4373***	0.0275
Log likelihood	-4369.062	
Pseudo R^2	0.329	

***indicates a significance level of 1%.

[a] : Nsprice denotes negative normalized prices.

Table 8a Impacts of demographic variables on respondents' answers to different cutoff questions

	Model (1)-Canadian oils only		Model (2)-No fortified ingredients		Model (3)-No GM ingredients	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Constant	-2.3506***	0.3394	-2.9627***	0.553	-0.38	0.3076
Male	0.1984	0.145	0.763***	0.2455	-0.3627***	0.1392
Age	0.0365***	0.005	0.0096	0.0083	0.0049	0.0046
QC	-0.4213**	0.1784	0.2338	0.2803	0.5574***	0.1601
Pra	0.4851***	0.1768	-0.1616	0.3408	-0.2927	0.1804
Univ	-0.0388	0.1611	0.8468***	0.2533	0.3218**	0.1494
Incm [a]	0.0004	0.0026	-0.0028	0.0044	-0.0021	0.0025
Urban	-0.328**	0.1645	-0.6683**	0.2632	-0.343**	0.1591
Log likelihood	-602.7724		-271.2302		-650.672	
Pseudo R^2	0.06		0.06		0.03	

***,** represents significance levels of 1% and 5% respectively.

[a] The coefficients and standard errors presented in this row are 1000 times the estimated coefficients and standard errors.

Table 8b Impacts of demographic variables on respondents' price cutoffs

	Model (4)-Price cutoff at $2.49		Model (5)-Price cutoff at $4.99	
	Coefficient	Standard error	Coefficient	Standard error
Constant	-1.3294***	0.445	0.1844	0.3016
Male	0.4703**	0.2033	-0.1219	0.1351
Age	0.0025	0.0068	-0.007	0.0045
QC	-0.2196	0.2561	0.3252**	0.1602
Pra	0.056	0.2563	0.0311	0.1719
Univ	0.0182	0.2324	-0.1362	0.1492
Incm [a]	-0.0131***	0.0038	-0.0048**	0.0025
Urban	-0.2984	0.2295	-0.0079	0.1585
Log likelihood	-352.6311		-668.8105	
Pseudo R^2	0.03		0.01	

***,** represent significance levels of 1% and 5% respectively.

[a] The estimated coefficient and standard error on income are very small due to the scale effect (the values of income are very large relative to the values of other variables). The presented coefficient and standard error on income are 1000 times the estimated coefficient and standard error.

Table 9 Results of conditional logit (CL) models incorporating self-reported and predicted cutoffs

	Model (1)		Model (2)		Model (3)	
Attribute	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Nopurchase	-2.409***	0.0781	-2.5287***	0.1373	-2.057***	0.0708
Enhance	0.473***	0.0525	0.3373***	0.0746	0.3945***	0.0498
Contain	0.4705***	0.0537	0.4347***	0.0516	0.4284***	0.0514
GM	-0.2823***	0.0588	0.2311	0.1713	-0.7655***	0.0533
NonGM	0.3044***	0.0496	0.2687***	0.0481	0.2679***	0.048
Canada	0.3969***	0.0451	0.2978***	0.0927	0.6149***	0.0404
Price	-0.4349***	0.013	-0.4344***	0.0216	-0.4556***	0.0116
VCan	-1.0222***	0.0759				
VFort	-0.5798***	0.1473				
VGM	-1.9321***	0.1083				
VPrice1	-0.7381***	0.0933				
VPrice2	-0.5699***	0.0674				
VCana			-1.113***	0.2564		
VForta			0.6393	0.6733		
VGMa			-2.8117***	0.4385		
VPrice1a			-1.6464**	0.6996		
VPrice2a			-0.2565	0.2036		
VCanb					-0.3765***	0.1018
VFortb					-0.1615	0.2027
VGMb					-0.6111***	0.1393
VPrice1b					0.0002	0.1422
VPrice2b					-0.0546	0.2307
Log likelihood	-4804.27		-5110.538		-5127.355	
Pseudo R^2	0.2657		0.2189		0.2163	

***,** represent significance levels of 1% and 5% respectively.

Table 10 Results of random parameters logit (RPL) models under self-reported and predicted cutoffs

	Model (4)		Model (5)	
Attribute	Coefficient	Std. error	Coefficient	Std. error
Random parameter in utility functions				
Nopurchase	-4.0637***	0.1306	-4.6777***	0.2957
Enhance	0.7041***	0.0833	0.5373***	0.1251
Contain	0.6759***	0.0749	0.6421***	0.0749
GM	-0.6349***	0.1345	0.2288	0.4391
NonGM	0.4414***	0.0741	0.4647***	0.0757
Canada	0.5603***	0.0778	0.4255***	0.1555
Nsprice [a]	0.7072***	0.0364	0.8658***	0.0526
Nonrandom parameters in utility functions				
VCan	-1.6573***	0.1126		
VFort	-0.7421***	0.2401		
VGM	-3.2705***	0.2536		
VPrice1	-0.2523	0.2779		
VPrice2	-0.5176***	0.1062		
VCana			-2.1755***	0.4213
VForta			0.7793	1.185
VGMa			-5.3391***	1.109
VPrice1a			-0.6277	2.0683
VPrice2a			0.7321**	0.339
Derived standard deviations of parameter distributions				
Sd-Nopurchase	1.382***	0.1355	1.61***	0.143
Sd-Enhance	1.0526***	0.1127	1.0035***	0.1282
Sd-Contain	0.6454***	0.1285	0.618***	0.1355
Sd-GM	2.0105***	0.1468	2.4183***	0.1785
Sd-NonGM	0.6021***	0.1497	0.6131***	0.1608
Sd-Canada	1.211***	0.0909	1.3424***	0.1007
Sd-Nsprice	0.4422***	0.0269	0.4148***	0.0255
Log likelihood	-4367.073		-4536.515	
Pseudo R^2	0.329		0.3386	

*** and ** indicate significance levels of 1% and 5% respectively.

[a] : Nsprice denotes negative normalized prices.

Table 11 Results of a conditional logit (CL) model including only one price cutoff

	CL model with penalties	
Attribute	Coefficient	Standard error
Nopurchase	-2.5751***	0.1323
Enhance	0.3364***	0.0746
Contain	0.4337***	0.0515
GM	0.2335	0.1712
NonGM	0.2689***	0.0481
Canada	0.3017***	0.0925
Price	-0.4575***	0.0115
VCana	-1.104***	0.256
VForta	0.6517	0.6734
VGMa	-2.88223***	0.438
VPrice1a	-1.689**	0.6983
Log likelihood	-5111.332	
Pseudo R^2	0.2188	

***,** represent significance levels of 1% and 5% respectively.

Table 12 Results of a random parameters logit (RPL) model including only one price cutoff

Attribute	Coefficient	Standard error
Random parameter in utility functions		
Nopurchase	-4.4886***	0.2813
Enhance	0.5518***	0.1235
Contain	0.6436***	0.0743
GM	0.0793	0.4517
NonGM	0.4552***	0.0755
Canada	0.4147***	0.1579
Nsprice [a]	0.7801***	0.0325
Nonrandom parameters in utility functions		
VCana	-2.1714***	0.4246
VForta	0.7461	1.1782
VGMa	-5.1094***	1.1364
VPrice1a	-0.7103	1.999
Derived standard deviation of parameter distributions		
Sd-Nopurchase	1.6177***	0.141
Sd-Enhance	0.9661***	0.1245
Sd-Contain	0.5878***	0.1472
Sd-GM	2.4664***	0.1794
Sd-NonGM	0.6325***	0.131
Sd-Canada	1.382***	0.0931
Sd-Nsprice	0.4205***	0.0267
Log likelihood	-4532.448	
Pseudo R^2	0.3431	

*** indicates a significance level of 1%.

[a] : Nsprice denotes negative normalized prices.

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Appendix Table 1 Definitions of the variables presented in the binary logit models

Variables [a]	Definitions
Y1	Y1=1 if a respondent is only willing to purchase Canadian oils; otherwise Y1=0
Y2	Y2=1 if a respondent is not willing to purchase food with fortified ingredients; otherwise Y2=0
Y3	Y3=1 if a respondent is not willing to purchase food with GM ingredients; otherwise Y3=0
Y4	Y4=1 if a respondent has a maximum price for a bottle of canola oil at $2.49; otherwise Y4=0
Y5	Y5=1 if a respondent has a maximum price for a bottle of canola oil at $4.99; otherwise Y5=0
Gender	Male=1; female=0
Age	the actual age of a respondent
Region of residency	QC=1 if Quebec, Pra=1 if the Prairie provinces; 0 if other regions
Education	Univ=1 if a university degree and above; 0 otherwise
Income	Incm=the actual annual income of a household
Urban	Urban=1 if a respondent resides in an urban area; otherwise urban=0

[a] Y1-Y5 denote the dependent variables of Models (1)-(5) in Tables 8a and 8b respectively.