A Mixture Model of Consumers' Intended Purchase Decisions for Genetically Modified Foods

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Abstract

A finite probability mixture model is used to analyze the existence of multiple market segments for a pre-market good. The approach has at least two principal benefits. First, the model is capable of identifying likely market segments and their differentiating characteristics. Second, the model can be used to estimate the discount different consumer groups require to purchase the good. The model is illustrated using stated preference survey data collected on consumer responses to the potential introduction in Norway of bread made with genetically modified wheat.

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1. Introduction

As trade and technologies develop, and goods increasingly cross cultural boundaries, consumer preferences for types of production processes, rather than just the functionality of the good, are a topic of considerable economic interest. While trade organizations, such as the WTO, argue that regardless of production process, goods with otherwise the same quality characteristics must be considered equivalent in the market, there is considerable empirical evidence that *perceived* ethical dimensions of a production process are an embedded attribute of the good (Frank 2006). Production processes perceived as somehow morally or ecologically superior by consumers may reap a price premium, while production processes perceived as somehow inferior may require a discount. Examples of production processes that consumers may consider superior are fair trade products (Loureiro and Lotade, 2005), organic products (Maguire, Owens and Simon, 2004; Loureiro, McCluskey, Mittelhammer, 2001), and products produced with animal welfare standards (Bennett, 1996). Examples that consumers might perceive as inferior include beef produced using growth hormones (Lusk, Roosen and Fox, 2003), milk produced with recombinant bovine somatotropin (rBST) (Dhar and Foltz, 2005) and genetically modified (GM) foods (McCluskey *et al*. 2003, Grimsrud *et al*., 2004). For example, the skepticism of the Norwegian population toward gene technology is considerable (Grimsrud *et al*., 2004), and has been treated as a largely homogenous phenomenon. The emphasis has been on comparing Norway to other countries (see e.g. McCluskey, Grimsrud and Wahl, 2006). Surveys comparable to the Eurobarometer surveys indicate that the percentage of people who think that gene technology would make society better off minus the percentage of people who think it would make things worse was a negative 32 percent for Norway as opposed to a positive 9 for the EU overall (Lund, Hviid-Nielsen, and Kalgraff-Skjåk, 2000). McCluskey *et al*. (2003) and Grimsrud *et al*. (2004) found that large discounts were required for consumers to purchase pre-market GM foods in Norway. But average discount estimates may obscure underlying differential discounts required to induce purchasing within multiple market segments.

The economics and marketing literature provides various methods for identifying and characterizing groups of consumers with opposing preferences (e.g., Wedel and Kamakura, 1998). Methods used to model heterogeneous preferences include random (varying) parameters logit/probit models and continuous mixture models. These models allow parameter values to vary with every observation (see e.g. Layton and Brown, 2000). Finite mixture models are also being applied (e.g. Boxall and Adamowicz, 2002). To investigate market segmentation, this paper uses a latent class mixture model in the context of stated preferences for a pre-market GM food product. A standard tool for generating survey data on stated preferences is the contingent valuation (CV) method, where willingness to pay (or be paid) responses are elicited for changes in a non-market goods. Valuation questions can either be open-ended, or discrete, such as the commonly applied dichotomous choice where respondents accept or reject a payment amount that is varied across the sample (Boyle, 2003). Cameron and James (1987) demonstrated that the dichotomous choice (DC) format also is a valuable tool for marketing applications. For a pre-market good that simply differs in terms of production processes, the valuation question can be stated as offering a premium/discount for the pre-market good in comparison to the existing substitute.

2. Latent Class Mixture Model Methodology

Finite mixture models can be used to analyze data sampled from populations where one suspects that there is an inherent segmental structure (Wedel and Kamakura, 1998). Because the membership of an observation to a certain market segment generally is unobservable, a *latent class* version of a finite mixture model is appropriate (Agresti, 2002). Latent-class finite mixture models assume that observations in a sample are "mixed" in unknown proportions. The goal in estimation is generally to "unmix" the sample and identify the explicit stochastic structure governing the unique behavior of each market segment (Wedel and Kamakura, 1998). Latent-class mixture models attempt to simultaneously organize observations into component distributions (market segments) and characterize each component density function along with the relationship (differences) between components.

The probability density function for a finite mixture distribution can be represented in general form as (Titterington, Smith and Makov, 1985):

$$p(\mathbf{x} \mid \boldsymbol{\psi}) = \sum_{s=1}^{S} \pi_s f(\mathbf{x} \mid \boldsymbol{\theta}_s) = \int_{\Theta} f(\mathbf{x} \mid \boldsymbol{\theta}) dG_{\pi}(\boldsymbol{\theta}) \tag{1}$$

where $\boldsymbol{\psi} = \{\boldsymbol{\theta}, \boldsymbol{\pi}\}$, $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_S\} \in \Theta$, $\boldsymbol{\pi} = (\pi_1, ..., \pi_S)$ define a probability distribution over Θ, $f(\mathbf{x} \mid \boldsymbol{\theta})$ denotes a generic member of a parametric family of probability densities, $G_{\pi}(\boldsymbol{\theta})$ denotes the probability measure over Θ defined by $\boldsymbol{\pi}$ (Titterington, Smith and Makov, 1985), and it is assumed that there are S market segments, s =0,1, 2,…S, where S is generally unobservable. The appropriate number of segments is most often chosen by evaluating goodness-of-fit statistics (such as the Pearson statistic, likelihood-ratio, and the Cressie-Read statistic (see e.g. Eid, Langeheine and Diener, 2003)) over a number of values of S as well as the Bayesian Information Criterion (Gupta and Chintagunta, 1994) and the Akaike Information Criterion (Eid, Langeheine and Diener, 2003).

When adapting the general mixture model (1) to market segmentation for pre-market goods using commonly applied dichotomous choice CV methods, one is interested in finding the probability of purchase for various price-levels within each segment, as well as in characterizing each segment. In (1), the $f(\mathbf{x} \mid \boldsymbol{\theta}_s)$ component of the likelihood function describes within-segment behavior, and the π_s component indicates the probability of belonging to a segment.

Our formulation of the within-segment part of the likelihood function, $f(\mathbf{x} \mid \boldsymbol{\theta}_s)$, follows a random utility framework (Hanemann, Loomis and Kanninen, 1991). Two commonly used elicitation formats in CV studies are single-bounded and double-bounded DC (Boyle, 2003). The single-bounded model approach recovers an estimate of the underlying value of the good (e.g., willingness to pay) by asking each respondent a single DC question, where the price of the pre-market good, B_i, is varied randomly across the sample. For example, the consumer may be asked to respond either Yes or No to the question of whether she would be willing to purchase the pre-market good at a price B_i. When using a single bounded model, the within market segment behavior is described by:

$$\Pr(\text{No}) = P(V_i^* < B_i) = G(B_i \mid \boldsymbol{\theta}_s) \tag{2}$$

$$\Pr(\text{Yes}) = P(V_i^* \geq B_i) = 1 - G(B_i \mid \boldsymbol{\theta}_s) \tag{3}$$

where $G(B_i;\theta_s)$ is some cumulative probability distribution function (e.g., the logistic distribution function) and V_i^* is individual *i*'s latent value for the pre-market good.

The double-bounded model has four response choices. Respondents are first asked whether they would be willing to purchase the good at an initial price B_i, and conditional on the reply a follow-up question with a different price is asked. If the reply to the initial price B_i is a No, then the follow-up question asks whether they would purchase the good at a discounted price, B_i^D, compared to initial price B_i. In the opposite case, if the initial price for the good is accepted (Yes response), then the follow-up question asks whether they are willing to purchase the good at a price that includes a premium, B_i^P, compared to the initial price, B_i. Response choices to the follow-up questions are Yes or No. As a result the response choices of the double-bounded model are: No-No, No-Yes, Yes-No, and Yes-Yes. The within market segment behavior is described by:

$$\Pr(\text{No-No}) = P(V_i^* < B_i^D \text{ and } \mathrm{B}_i) = G(B_i^D \mid \theta_s) \tag{4}$$

$$\Pr(\text{No-Yes}) = P(B_i^D \le V_i^* < B_i) = G(B_i \mid \theta_s) - G(B_i^D \mid \theta_s) \tag{5}$$

$$\Pr(\text{Yes-No}) = P(B_i \le V_i^* < B_i^U) = G(B_i^U \mid \theta_s) - G(B_i \mid \theta_s) \tag{6}$$

$$\Pr(\text{Yes-Yes}) = P(B_i \text{ and } \mathrm{B}_i^U \le V_i^*) = 1 - G(B_i^U \mid \theta_s)\ . \tag{7}$$

The individual response choice and price information is used in estimating the probability of purchasing the pre-market good at a range of prices. Double-bounded models have sometimes been found to produce more efficient estimates than single bounded models (Hanemann, Loomis and Kanninen, 1991), but are also criticized for introducing potential bias in cases where responses to the follow-up question may be dependent on the initial question (Hanemann, Loomis and Kanninen, 1999; Boyle, 2003).

Let the probability of consumer *i* choosing response j*,* conditional on belonging to market segment *s,* be $P_i(j \mid s)$ so that the probability density function within a segment s is defined as:

$$f(x \mid \boldsymbol{\theta}_s) = \prod_{j=1}^{J} P_i(j \mid \boldsymbol{\theta}_s)^{I_j(x)},\ x = 1,\ldots,J \tag{8}$$

where *J* is the total number of response choices (e.g., $J = 2$ for a single bounded model, with j = $1 \Rightarrow No$ and j = 2 $\Rightarrow Yes$, or $J = 4$ for the double-bounded model, with j = 1,2,3, or 4 referring to No-No, No-Yes, Yes-No, or Yes-Yes, respectively), and $\sum_{j=1}^{J} P_i(j \mid \boldsymbol{\theta}_s) = 1$. The indicator function $I_j(x)$ is equal to 1 if the response is $x = j$ and equal to 0 otherwise. For respondent i, let $\mathbf{x}_{i.}$ be a row vector containing the price as well as other factors affecting the decision to purchase the good, with the corresponding vector of estimable parameters being $\boldsymbol{\theta}_s$. Assuming a linear index model in which the willingness to purchase a good depends on price and the other explanatory factors through $\mathbf{x}_{i.}\boldsymbol{\theta}_s$, and assuming the probability of making a purchase at this price can be modeled using a logistic distribution function, the within-market segment model (4)-(8) can be completed by specifying the cumulative probability distribution:

$$G(\mathbf{x}_{i.} \mid \boldsymbol{\theta}_s) = \frac{\exp(\mathbf{x}_{i.}\boldsymbol{\theta}_s)}{1 + \exp(\mathbf{x}_{i.}\boldsymbol{\theta}_s)} \qquad \text{for } s = 1,\ldots,S\ . \tag{9}$$

Note without loss of generality that it is necessary to normalize the parameter vector for one of the segments to zero for identification purposes.

We endow the segmentation probabilities with a parametric structure as in Gupta and Chintagunta (1994). Assuming a linear index structure, the segmentation probabilities π_s may be modeled by an unordered multinomial logit specification so that the probability that consumer *i* belongs to market segment *s* is:

$$P_i(s) = \frac{\exp(\mathbf{z}_{i.}\boldsymbol{\gamma}_s^*)}{1+\sum_{s=2}^{S}\exp(\mathbf{z}_{i.}\boldsymbol{\gamma}_s^*)} \tag{10}$$

where for parameter identification purposes, $\boldsymbol{\gamma}_s^* = \boldsymbol{\gamma}_s - \boldsymbol{\gamma}_1$, so that $\boldsymbol{\gamma}_1^* = 0$, and $\mathbf{z}$ represents data pertaining to the consumer (e.g., cognitive and sociodemographic information).

The models for the within market-segment consumer-behavior and the across market segmentation component are used jointly to define the likelihood function. The probability that consumer *i* chooses responses $x = j \in \{1,...,J\}$ and belongs to market segment *s* is:

$$P_i(x \cap s) = P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_j(x)} \,. \tag{11}$$

The total probability of an individual choosing a response $x = j \in \{1,...,J\}$ and belonging to any of the segments in the market *S* is:

$$\sum_{s=1}^{S} P_i(x \cap s) = \sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_j(x)} \,. \tag{12}$$

Based on (12), the likelihood function across all sample observations can be expressed as:

$$L(\boldsymbol{\theta}, \boldsymbol{\gamma} \mid \mathbf{x}, \mathbf{z}) = \prod_{i=1}^{n}\sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_j(x)} \,, \tag{13}$$

where *n* denotes the sample size. The log likelihood function is then:

$$LL(\boldsymbol{\theta}, \boldsymbol{\gamma} \mid \mathbf{x}, \mathbf{z}) = \sum_{i=1}^{n} \ln\left(\sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_j(x)}\right). \tag{14}$$

Estimates of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ can be obtained by maximizing (14) for a given *S* and the size of each market segment can be calculated by allocating each observation to the segment it belongs to with the highest probability (Gupta and Chintagunta, 1994).

3. Example: Bread Made with GM Wheat in Norway

For this analysis, we use the survey sample data described in Grimsrud *et al*. (2004). The data was collected using in-person interviews in 2002 in a Norwegian grocery store in the Oslo-region. In total, 400 consumers were randomly surveyed, producing 381 complete observations. The majority of respondents are primary food shoppers for the household (82%) and female (69%). Prior to the valuation questions, respondents were told that GM wheat with no added benefits in terms of attributes and functionality (e.g. improved taste, added vitamin contents, increased shelf-life) had been developed at a University research lab, in the US. Then, bread made of this GM wheat was presented as being potentially introduced in Norway.

The CV or stated preference elicitation procedure utilized was a hybrid of the single and double-bounded approaches, and begins by offering the pre-market GM-food product at the same price as the conventional product. Consumers were asked: "Would you be willing to purchase bread that contains flour from this wheat at the same price as bread without genetically modified wheat flour?" If the offer is refused, the bread was offered at a percentage discount: "Are you willing to purchase this bread if it was offered at an X% lower price than the bread without genetically modified wheat?" If the consumer was willing to purchase the good at the same price as the conventional food product then a follow-up question with a price premium was not asked. This is because the GM bread was described as not conveying any additional benefits to the consumer. Thus, with this modified double-bounded elicitation procedure there were three response choices *j* as follows: (1) a Yes, (2) a No followed by a Yes (No-Yes), (3) and a No followed by a No (No-No). The chosen price discount offered for GM bread compared to conventional bread was randomly chosen among 5%, 10%, 25%, 40%, or 50%.

In contrast to most dichotomous choice CV studies that use absolute dollar amounts in their valuation questions, we use percentage discounts. The advantage of percentage discounts is that they can be generalized (e.g., across regional variations in expected price), and are a valid measure of price reduction regardless of the price category of bread that the consumer commonly purchases. They are also relatively simple to respond to. Since only actual shoppers participated in the survey and because of the heavy bread consumption in Norway, it is expected that respondents were familiar with bread prices, as well as commonly used percentage discounts.

Given that three response choices, indexed as j = 1, 2, 3, were utilized in this study, and following the framework developed in the preceding section, the probability of a consumer accepting or rejecting a price offer, conditioned on belonging to a specific market segment *s,* is:

$$P_i(j=1\,|\,s) = G(B_i^{\,0};\boldsymbol{\theta}_s) \tag{15}$$

$$P_i(j=2\,|\,s) = G(B_i^{\,D};\boldsymbol{\theta}_s) - G(B_i^{\,0};\boldsymbol{\theta}_s) \tag{16}$$

$$P_i(j=3\,|\,s) = 1 - G(B_i^{\,D};\boldsymbol{\theta}_s)\,. \tag{17}$$

In the application, the specification of $G(B_i;\boldsymbol{\theta})$ is expanded to take into account other explanatory factors, as indicated previously, and thus the distribution is defined as in (9). Equations (15)-(17) represent the within market-segment consumer-behavior component of the model.

Regarding the other explanatory factors, we use socioeconomic variables to explain the market segmentation component, and cognitive variables (Baker and Burnham, 2001) to explain the intended purchase decision. Variables for explaining the probability of purchasing GM bread include: $\mathbf{x}_{i.} = [Intercept \quad Discount_i \quad KnowGMO_i]$ where $Discount_i$ is the last percentage discount offered to the respondent, and $KnowGMO_i$ indicates self-reported level of knowledge about biotechnology. Self -reported knowledge about biotechnology originates from several sources such as education, media and organizations and is presented here as a binary variable (i.e., 1 = higher knowledge or 0 = lower knowledge). Variables included in the market segmentation component include $\mathbf{z}_{i.} = [Intercept \quad Female_i \quad Age_i \quad Education_i]$ where *Education* is the level of formal education, *Age* is measured in years, and *Female* equals 1 if the respondent is a female, and is 0 otherwise. Summary statistics are presented in Table 1.

4. Results and Discussion

Estimation results are reported in Table 2. The segment *s* willingness to purchase GM-bread was modeled as a function of $\mathbf{x\theta}_s = \alpha_s + \rho_s B + \theta_s^* knowGMO$ and the percentage discount needed for each market segment can be calculated as $B_s = -\left(\tilde{\alpha}_s + \overline{knowGMO}\tilde{\boldsymbol{\theta}}_s^* / \tilde{\rho}_s\right)$ where $\tilde{\alpha}, \tilde{\rho}, \tilde{\boldsymbol{\theta}}_s$ are estimated parameters and $\overline{knowGMO}$ is the sample average level of knowledge of biotechnology. Our results show evidence of two highly distinct market segments for GM-bread. We find that one of the two estimated market segments for GM-bread requires a discount of 123% when explanatory variables are evaluated at their mean levels, and purchase probabilities are at median levels, which in effect means that such consumers consider it an impossibility to purchase GM-bread under the current circumstances. This segment is large, representing 92.5 % of the sample respondents. A second smaller segment (about 7.5%) essentially needs no discount (a discount of 1.3%), with consumers seemingly indifferent between the GM and non-GM product. These segment sizes were calculated assuming the highest segment-probability for each individual as denoting their segment. If, alternatively, segment sizes are calculated as the average segment-probabilities across all observations for each segment, $\frac{1}{n}\sum_{i=1}^{n} \tilde{P}_i(s)$, $s = 1,2$, the largest segment decreases to 81% and the smallest segment increases to 19%. The parameters of the willingness to purchase function in both segments are positive, implying that a higher discount increases the probability of purchase. The segment that requires the lowest (almost no) discount is most sensitive to the level of discount, because consumers in this segment are not concerned with consuming GM-bread. In both segments increased self-reported knowledge of biotechnology in food production reduced the probability of purchasing GM-bread.

The probability of membership in the segments can be significantly explained by socio-demographic variables. We find that the segment with the lowest (almost no) discount needed is typically characterized by respondents that are male, have a higher formal education, and have a lower age. The segment requiring the highest discount in order to purchase GM bread is characterized in precisely the opposite way, with respondents being female, having lower levels of formal education and having a higher age. Using a Wald test, the hypothesis that the parameters of the conditional-on-segment choice probability models were identical across the segments was tested. Given the model specification, this test amounted to a test of linear equality restrictions on the segmentation parameters of the model, namely, $\mathrm{H_o} : \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2$. The Wald statistic for this test was 7.68, with a probability value of .05 from a Chi-square distribution with three degrees of freedom. Thus, for this application, results show that there is evidence of two sharply distinct segments, where one requires a high discount and the other needs an essentially negligible discount to encourage purchases of GM bread.

In conclusion, with increasing attention on consumer preferences for types of production processes used, rather than just functionality of a given good, it is important to not treat these ethical, moral or ecological dimensions in a homogenous fashion. To facilitate such distinctions, this paper uses a finite mixture model in combination with stated preference survey data to analyze the existence of multiple market segments in the intended purchasing decisions of Norwegian consumers for a GM food product. We emphasize that the mixture model generalizes to a wide range of applications for intended purchasing behavior, and may be particularly useful for goods where ethical, moral or ecologically production processes may matter in understanding heterogeneous consumer preferences.

References

Agresti, A. (2002) *Categorical Data Analysis*. Hoboken, NJ:, John Wiley & Sons, Inc.

Baker, G.A. and T.A. Burnham (2001) "Consumer response to genetically modified foods: market segment analysis and implications for producers and policy makers" *Journal of Agricultural and Resource Economics* **26**, 387-403.

Bennett, R. M. (1996) "People's Willingness to Pay for Farm Animal Welfare" *Animal Welfare* **5**, 3-11.

Boxall, P.C., and W.L. Adamowicz (2002) "Understanding Heterogeneous Preferences in Random Utility Models: A Latent Class Approach" *Environmental and Resource Economics* **23**, 421-446.

Boyle, K. (2003) "Contingent Valuation in Practice" in *A Primer on Nonmarket Valuation* in P. Champ, K. Boyle, and T. Brown, Eds., Boston, MA: Kluwer Academic Press, 99-169.

Cameron, T.A., and M.D. James (1987) "Estimating Willingness to Pay from Survey Data: An Alternative Pre-Test-Market Evaluation Procedure" *Journal of Marketing Research* **24**, 389-95.

Dhar, T., and J. D. Foltz (2005) "Milk by Any Other Name…Consumer Benefits from Labeled Milk" *American Journal of Agricultural Economics* **87**. 214-228.

Eid, M., R. Langheine and E. Diener (2003) "Comparing Typological Structures across Cultures by Multigroup Latent Class Analysis" *Journal of Cross-Cultural Psychology* **34**, 195-210.

Frank, J. (2006) "Process attributes of goods, ethical considerations and implications for animal products" *Ecological Economics* **58**, 538-547.

Grimsrud, K.M., M.L. Loureiro, J.J. McCluskey, and T.I. Wahl (2004) "Consumer Attitudes to Genetically Modified Food in Norway" *Journal of Agricultural Economics* **55**, 75-90.

Gupta, S. and P.K. Chintagunta (1994) "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models" *Journal of Marketing Research* **31**, 128-36.

Hanemann, M., J. Loomis, and B.J. Kanninen (1991) "Statistical Efficiency of Double-Bounded Dichotomous Choice Contingent Valuation" *American Journal of Agricultural Economics* **73**, 1255-63.

Hanemann, W.M., J. Loomis and B.J. Kanninen (1999) "The Statistical Analysis of Discrete Response CV Data" in *Valuing Environmental Preferences* by I.J. Bateman and K.G. Willis, Eds., New York, NY: Oxford University Press, 302-442.

Layton, D. and G. Brown (2000) "Heterogeneous Preferences Regarding Global Climate Change" *The Review of Economics and Statistics* **82**, 616-624.

Loureiro, M., and J. Lotade (2005) "Do Fair Trade and Eco-labels in Coffee Wake up the Consumer Conscience?" *Ecological Economics* **53**, 129-38.

Loureiro, M.L., J.J. McCluskey and R.C. Mittelhammer (2001) "Assessing Consumer Preferences for Organic, Eco-labeled, and Regular Apples" *Journal of Agricultural and Resource Economics*. **26**, 404-16.

Lusk, J.L., J. Roosen, J.A. Fox (2003) "Demand for Beef from Cattle Administered Growth Hormones or Fed Genetically Modified Corn: A Comparison of Consumers in France, Germany, the United Kingdom, and the United States" *American Journal of Agricultural Economics* **85**, 16-29.

Lund, M., T. Hviid Nielsen and K. Kalgraff Skjåk (2000) "Norwegian attitudes to biotechnology." Norsk Samfunnsvitenskapelig Datatjeneste (NSD) report no. 118., Bergen, Norway.

Maguire, K.B., N. Owens, N.B. Simon (2004) "The Price Premium for Organic Babyfood: A Hedonic Analysis" *Journal of Agricultural and Resource Economics* **29**, 32-49.

McCluskey, J.J., K.M. Grimsrud, H. Ouchi, and T.I. Wahl (2003) "Consumer Response to Genetically Modified Food Products in Japan" *Agricultural and Resource Economics Review* **32**, 222-31.

McCluskey, J.J., K.M. Grimsrud, and T.I. Wahl (2006) "Comparisons of Consumer Responses to Genetically Modified Foods in Asia, North America, and Europe," in *Economics of Regulation of Agricultural Biotechnologies* by R. E. Just, J. Alston, and D. Zilberman, (Eds.), New York, NY: Springer/Kluwer Academic Publishers.

Titterington, D.M., A.F.M. Smith, and U.E. Makov (1985) "*Statistical Analysis of Finite Mixture Distributions.*" Chichester: John Wiley & Sons, Ltd.

Wedel, M., and W.A. Kamakura (1998) "*Market Segmentation: Conceptual and Methodological Foundations.*" Norwell, MA: Kluwer Academic Publishers.

Table 1: Survey Variable Descriptions and Descriptive Statistics

Variable	Description	Descriptive Statistics
Age	Age of consumer in years	Mean: 41.6 St. Dev : 12.9
Female	1 if female, 0 if male	69.3 % females 30.8 % males
Education	compulsory school HS diploma 2-3 year college 4-5 year degree Adv./Prof. degree refuse	15.5 % 29.3 % 32.1 % 20.1 % 2.3 % 0.5 %
	0=compulsory school, HS diploma, refuse 1=2-3, 4-5 year college, Adv./Prof. degree	
Income	1 = < 150 NOK 2 = 150-300,000 NOK 3 = 300-450,000 NOK 4 = 450-600,000 NOK 5 = 600-750,000 NOK 6 = 750-900,000 NOK 7= > 900,000 NOK	3.6 % 19.5 % 23.6 % 27.7 % 13.2 % 6.9 % 5.6 %
KnowGMO	Self-reported knowledge about biotechnology 1= Know a lot, know something 0 = Know little	Mean: 0.61

Table 2: Estimation Results for Two-Segment Model

	Variables	Estimate	z-value
	Intercept	-0.9494	-3.5211
Segment 1	*Discount*	0.9954	2.4525
	KnowGMO	-0.4496	-1.4006
	Intercept	0.0686	0.1317
Segment 2	*Discount*	19.9409	1.7383
	KnowGMO	-0.5351	-0.6611
	Intercept	2.5638	1.8015
Segmentation	*Female*	-1.4622	-2.5831
Variables	*Education*	0.3963	1.2066
	Age	-0.1135	-1.8480