Market Segmentation within Contingent Valuation [1]

by

Kristine M. Grimsrud and Ron C. Mittelhammer[2]

University of Guelph and Washington State University

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Abstract

A finite probability mixture model is combined with a contingent valuation model to analyze the existence of differential market segments in a hypothetical market. The approach has at least two principle benefits. First, the model is capable of identifying market segments within the hypothetical market. Second, the model can be used to estimate WTP/WTA within each segment. The model is illustrated using a data set collected on consumer response to genetically modified foods in Norway.

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[2] Kristine Grimsrud is an assistant professor in the Department of Agricultural Economics and Business, University of Guelph, Canada, and Ron Mittelhammer is a Professor in the Department of Agricultural and Resource Economics and in the Department of Statistics, Washington State University, USA. Contact e-mail: grimsrud@uoguelph.ca .

1. Introduction

With most resources there are conflicts between interest groups and a thorough understanding of the structure of the behavior of the market for the resource is essential for meaningful policy analysis and decision-making. Marketing literature provides a plethora of empirical methods for identifying and characterizing groups of agents with opposing preferences in markets based on purchasing behavior (see Wedel and Kamakura, 1998). These and other methods to model heterogeneous preferences are increasingly being applied in agricultural and resource economics problems.

Some heterogeneous preference models attempt to identify the existence of market segments. Market segments in such statistical models are characterized by individuals with “fairly homogenous” preferences, where, “fairly homogenous” implies statistically that any variation in preferences among individuals within sub-populations/segments can be assumed to be statistically insignificant in so far as observed behavior is concerned, while preferences, and associated behavior, across different sub-populations/segments are assumed statistically different.

We utilize market segmentation techniques in the context of contingent valuation (CV). The CV method has become an important tool in environmental economics as well as in marketing in order to evaluate hypothetical markets (see, e.g. Loureiro, McCluskey and Mittelhammer (2001)). In dichotomous choice CV, each respondent is asked whether or not he/she would be willing to accept a hypothetical welfare change, e.g. improvement in some environmental quality, together with a hypothetical bid amount of money that they would have to pay to secure this welfare change. The estimated average willingness to pay (WTP) is the price for which the average consumer would have a 50/50 chance of accepting or refusing the welfare change (Hanemann, Loomis and Kanninen, 1991). Estimates generated in CV often provide inputs to arguments in environmental policy decisions. Covariates of the WTP function such as demographic information are often used to describe markets based on the aggregate sample. However, such an aggregate description will produce a crude description of a market, and the need to fine-tune contingent valuation models to recognize heterogeneity of preferences has been recognized in literature.

Finite mixture models can be used to fit data sampled from populations where one suspects that there is an inherent structure such as that produced by the existence of market segments (Wedel and Kamakura, 1998). Because the membership of an observation to 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 of the individual groups or market segments (Wedel and Kamakura, 1998). In other words, in latent-class mixture models one attempts to simultaneously organize observations into component distributions (market segments), and characterize each component density function along with the relationship (differences) between components.

The method we propose allows one to discover market segments for non-market goods; estimate the willingness to pay function for each segment and characterize market segments in terms of relative size of the market and relevant explanatory variables. We will first discuss the methodology in general and then we will demonstrate it for the case of genetically modified (GM) bread in Norway.

Some of the most popular heterogeneous preference models in the natural resource economics literature are random (varying) parameters logit/probit models and mixture models. These models allow parameter values to vary with every observation (see e.g. Layton & Brown, 2000). Finite mixture models are also being applied (see e.g. Boxall and Adamowicz, 1999). These models have a finite number of support points, i.e., observations that are statistically similar are grouped into a certain finite number of groups.

We extend the work on CV models that allow for the possibility of heterogeneous preferences by using a latent class finite mixture model. Our model has two components: 1) A within market segment component using a CV framework and 2) a statistical model describing variation across segments.

2. Methodology

The probability density function for a mixture distribution is generally of the form (Titterington, Smith and Makov, 1985):

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

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, and $G_{\pi}(\boldsymbol{\theta})$ denotes the probability measure over Θ defined by $\boldsymbol{\pi}$ (Titterington, Smith and Makov, 1985). Assume that the market for the good has *S* market segments, *s* =0,1, 2,…*S*, where *S* is unobservable but can be identified statistically.

When adapting the general mixture model in (1) to market segmentation in a CV context, we are interested in finding estimates for the differing willingness to pay 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 the within segment behavior, and the π_s - component indicates the probability that a consumer belongs to a segment. The likelihood function proposed in the subsequent discussion is a mixture of logistic distributions, while other combinations are possible.

We begin with describing our formulation of the within-segment part of the likelihood function, $f(\mathbf{x} \mid \boldsymbol{\theta}_s)$. The within-segment part of the model follows a random utility framework (Hanemann, Loomis and Kanninen, 1991). The most commonly used bidding methods are single-bounded and double-bounded dichotomous choice. The single-bounded model approach recovers the bid amount as a threshold by asking only one dichotomous choice question. If using a single bounded CV model, we have that:

(2) Pr("No" to Bid)= $P(WTP < B_i) = G(B_i \mid \theta_s)$

(3) Pr("Yes" to Bid)= $P(WTP \geq B_i) = 1 - G(B_i \mid \theta_s)$

where $G(B_i;\theta_s)$ is some cumulative probability distribution function, often taken to be the logistic distribution function. The response-choices for the bid B_i are a "yes" or a "no". Denote these choices by *j*=1,2, respectively.

In double-bounded CV models, respondents are first asked if they accept an initial bid and, conditional on the reply to the initial bid, a follow-up bid is offered. In a WTP context, if the reply to the initial bid B_i is a "No", then the follow-up bid would be a lower bid B^D that the respondent then could accept or reject. Opposite, if the reply to the initial bid is a "Yes", then the follow-up bid would be a higher bid B_i^U that the respondent may accept or reject. Usually, the ultimate bid amount for each respondent together with relevant covariates are used to estimate the probability of accepting the bid. Double bounded contingent valuation models are popular because they have been found to produce more efficient willingness to pay/willingness to accept (WTP/WTA) estimates than single bounded models (Hanemann, Loomis and Kanninen, 1991), but are also criticized for being biased because the response to the follow-up question may be dependent on the initial question (Hanemann, Loomis and Kanninen, 1999). If a double-bounded model is used, the choice probabilities are (Hanemann, Loomis and Kanninen, 1991)

(4) $\Pr(\text{"No" then "No"}) = P(WTP < B_i^D \text{ and } B_i) = G(B_i^D \mid \theta_s)$

(5) $\Pr(\text{"No" then "Yes"}) = P(B_i^D \leq WTP < B_i) = G(B_i \mid \theta_s) - G(B_i^D \mid \theta_s)$

(6) $\Pr(\text{"Yes" then "No"}) = P(B_i \leq WTP < B_i^U) = G(B_i^U \mid \theta_s) - G(B_i \mid \theta_s)$

(7) $\Pr(\text{"Yes" then "Yes"}) = P(B_i \text{ and } B_i^U \leq WTP) = 1 - G(B_i^U \mid \theta_s)$

For the respondent, there are now four choices, "no, no", "no, yes", "yes, no," and "yes, yes". Denote these response choices by $j = 1, 2, 3, 4$ respectively. The main conceptual difference between the single- and the double-bounded models are that there are $J = 2$ response-choices or partitions of the intervals of willingness to pay for the single-bounded, and $J = 4$ for the double-bounded case.

In general, let the probability of consumer i choosing j, conditional on belonging to segment s, be denoted as $P_i(j \mid s)$. In our mixture model, we use the following representation of the probability density function within a segment:

$$(8) \qquad f(\mathbf{x} \mid \boldsymbol{\theta}_s) = \prod_{j=1}^{J} P_i(j \mid s)^{I_i(j)}$$

where J is the total number of choices, i.e., $J = 2$ for a single bounded model, $J = 4$ for the double-bounded model. The indicator function $I_i(j)$ is defined over $j \in \{1,\ldots J\}$ to equal one if the individual i chooses j and is equal to zero otherwise.

Covariates are often included in CV models along with the ultimate bid information. In the context of market segmentation, covariates affecting the choice of product such as quality characteristics of the product/good could be included, but other configurations are possible. For the i th respondent, let the vector containing the ultimate bid and product attributes of the good in question be denoted $\mathbf{x}_{i.}$ Let the corresponding vector of parameters to be estimated be denoted $\boldsymbol{\theta}_s$. If the WTP function is linear and $G(\mathbf{x}_{i.} \mid \boldsymbol{\theta}_s)$ is a logistic distribution function, then

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

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

Needless to say, consumers participating in a survey may give the same response based on differing reasoning. Wegner (1999) proposed to classify responses in the lowest willingness-to-pay category into two groups: Those truly indifferent and those with a bid even less than the lowest bid offered in the survey. From the point of view of modeling market segments, the same response to a bid offered may be better explained by different sets of variables causing the willingness to pay function to be a mixture of several distributions. Including this component may improve the understanding of a respondent's behavior with respect to the bids offered.

The actual mixture of these distributions in relation to the responses to the contingent valuation bids are estimated in the segmentation component. Following Gupta and Chintagunta (1994), we endow π_s with a parametric structure. That is, we specify the segmentation probabilities as $\pi_s(\boldsymbol{\gamma}_s \mid \mathbf{z})$, where $\boldsymbol{\gamma}_s$ is a parameter vector and $\mathbf{z}$ is data, which in this case may be information related to attitudes and/or sociodemographic information. Let $\pi_s(\boldsymbol{\gamma}_s \mid \mathbf{z}) = P(s)$ be an unordered multinomial logit model (see e.g. Gupta and Chintagunta, 1994) representing the market segmentation component, and let the unobservable latent variable Y_i^*, where $Y_i^* = \mathbf{z}_{i.}\boldsymbol{\gamma}_s + \varepsilon_i$, represent an index that can be used to indicate to which market segments an observation belongs. Then the probability that consumer *i* belongs to market segment *s* is

$$(10) \qquad P_i(s) = P(Y_i^* = s) = F_{is}(\mathbf{z}_{i.}\boldsymbol{\gamma}_s) = \frac{\exp(\mathbf{z}_{i.}\boldsymbol{\gamma}_s^*)}{1+\sum_{s=2}^{S}\exp(\mathbf{z}_{i.}\boldsymbol{\gamma}_s^*)} \text{ for } s \geq 2$$

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

and for parameter identification purposes, $\boldsymbol{\gamma}_s^* = \boldsymbol{\gamma}_s - \boldsymbol{\gamma}_1$. Now that we have both the CV component and the market segmentation component in place, we can derive the likelihood function.

The probability that a consumer chooses option *j* in the valuation survey and belongs to market segment *s* is:

(11) $$P_i(j \cap s) = P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_i(j)}$$

The total probability of an individual making choice *j* and belonging to any of the segments in the market *S* is

(12) $$P_i(j \cap s \in \{1,\ldots,S\}) = \sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i(j \mid s)^{I_i(j)}$$

Based on (12), the likelihood function can be expressed as

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

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

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

Estimates of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ can be obtained by maximizing (14). We now present an example of how a finite mixture model could be applied to a contingent valuation data set.

3. Example: GM-foods in Norway

In this section we investigate the existence of market-segments in the market for bread baked with genetically modified wheat (GM-bread) in Norway. The skepticism of the general Norwegian population toward gene technology is considerable. Surveys comparable to the Eurobarometer surveys from 1993, 1996 and 1999 indicate that the percentage of people who think that gene technology would make society better 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 EU in (Lund, Hviid-Nielsen, and Kalgraff-Skjåk 2000). Results of these surveys also indicate that there are no significant differences between Norway and the EU in general regarding cognitive knowledge about biotechnology in general. In addition, Gruner *et al.* (2000) found that consumers in Norway acknowledge the benefits of genetic modification such as improved taste, functional benefits, and environmental benefits, but that these benefits generally do not compensate for the negative associations such as uncertainty, unnatural, diseases/ deformities, loss of species and ecological imbalance. The degree of genetic modification was important to consumers in Norway. For example, use of genetically modified organisms as part of the production process is more acceptable than if the genetically modified organism would be present in the final product (Gruner *et al*., 2000).

Grimsrud, McCluskey, Loureiro, and Wahl (2002) found that the WTA discount for GM-bread compared to conventional bread was about 47% foods. We use their data in our analysis. The data was collected in a Norwegian grocery store, in January 2002. The grocery stored is located in the Oslo-region of Norway, which is the most populated part of Norway and one of the Norwegian centers of economic activity. The survey data was collected with in-person interviews and respondents were selected randomly with the criterion that the interviewer was to solicit every third customer who came into the survey area. The turndown rate was approximately 5%.

In total, 400 consumers were surveyed, producing 381 complete observations. The majority of respondents are primary food shoppers for the household (82%) and female (69%). The average age of respondents is 41.6 years, which is close to the average age of 44 years for the general population of Norway in 1998. The discount offered for GM bread compared to the conventional bread was set at one of the following levels: 5%, 10%, 25%, 40%, and 50%. Each level of discount was used for one fifth of the surveys. The assignment of discount was random to the respondent.

The survey had three choices for each respondent; a "Yes", a "No" followed by a "Yes", and a "No" followed by a "No". These choices were associated with the following probabilities:

(16) Pr("Yes")= $P(WTA < B_i^0) = G(B_i^0 \mid \boldsymbol{\theta})$

(17) Pr("No" then "Yes")= $P(B_i^0 \leq WTA < B_i^D) = G(B_i^D \mid \boldsymbol{\theta}) - G(B_i^0 \mid \boldsymbol{\theta})$

(18) Pr("No" then "No")= $P(WTA \geq B^D{}_i) = 1 - G(B_i^D ; \boldsymbol{\theta})$

where $G(B_i \mid \boldsymbol{\theta})$ is the logistic distribution function, B_i^0 denotes the initial bid which represented a zero (no) discount, and B_i^D denotes the discounted bid. The choices in (16)-(18) will be indexed j=1,2,3, respectively.

Following the framework developed in earlier sections, the probability of a consumer accepting or rejecting a bid is conditioned on belonging to a specific market segment s as

(19) $P_i(j = 1 \mid s) = G(B_i^0 ; \boldsymbol{\theta}_s)$

(20) $P_i(j = 2 \mid s) = G(B_i^D ; \boldsymbol{\theta}_s) - G(B_i^0 ; \boldsymbol{\theta}_s)$

(21) $P_i(j = 3 \mid s) = 1 - G(B_i^D ; \boldsymbol{\theta}_s)$.

where $G(B_i ; \boldsymbol{\theta})$ is defined in (9). Equations (19)-(21) represent the contingent valuation component of the model.

Cognitive variables (opinions, beliefs, knowledge) have been found to greatly influence U.S. consumers preferences for GM-products, and as many as 30% of consumers based their purchasing decision on GM content (Baker and Burnham, 2001).

Baker and Burnham (2001) also find that socioeconomic variables are not as important for explaining preferences for GM foods. We use the socioeconomic variables to explain the market segmentation component and cognitive variables to explain the willingness to accept.

The variables included to explain the bid are

(22) $\mathbf{x}_i = [Intercept \quad Bid_i \quad KnowGMO_i]$

where Bid_i is the ultimate bid and $KnowGMO_i$ indicate the self-reported level of knowledge about gene technology. Self reported knowledge comes from several sources such as education, media and organizations and is originally measured on an integer scale from 1 to 5, where 5 is the highest level of knowledge. In the analysis the variable is used in a dichotomous fashion, indicating lower (≤ 3) or higher (≥ 4) knowledge. If the self-reported knowledge is based on information from organizations or media that have argued against GMO's, this is expected to affect the discount needed to accept GM bread. The variables included in the market segmentation component of the model are

(23) $\mathbf{z}_i = [Intercept \quad Gender_i \quad Age_i \quad Education_i]$,

where *Education* is the level of formal education, *Age* is measured in years, and *Gender* = 1 if the respondent is a male, and is zero otherwise. Summary statistics for the included variables are presented in Table 1.

4. Estimation Results

The estimation results are reported in table 2. For a willingness to accept discount function of $WTA = \mathbf{x}\boldsymbol{\theta}_s = \alpha + \rho B + \mathbf{x}\boldsymbol{\theta}^*$, the discount needed for each segment is calculated as

$$B_s = -\frac{\tilde{\alpha}_s + \bar{\mathbf{x}}\tilde{\boldsymbol{\theta}}_s^*}{\tilde{\rho}_s} \tag{24}$$

where $\tilde{\alpha}_s, \tilde{\rho}_s, \tilde{\boldsymbol{\theta}}_s$ are estimated parameters. From this calculation, we find that one of the market segments for GM-bread need a discount of 129% 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 as large as 81 %. This is consistent with the expressed skepticism toward GMO reported in the literature. On the other hand, a second smaller segment practically needs no discount (0.013%), with consumers in this segment seeming not to be overly concerned with purchasing a genetically modified food product. The size of this segment is 19%. The parameters of the bid in both segments are positive which means that in both segments more 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 GMO knowledge reduced the probability of purchasing GM-bread. A reason for is that self-reported knowledge may be drawn from many sources, many of which are not favorable to GM-foods.

The probability of membership in the segments is explained by sociodemographic variables. We find that the segment with the lowest (almost no) discount needed is characterized by being male, people with higher formal education, and people of lower age. On the other hand, the segment requiring the highest discount in order to purchase

GMO bread is characterized by being female, people with lower levels of formal education and people of higher age.

The significance of the difference in behavior between the two segments was tested statistically using a Wald test. The specific hypothesis tested was that the parameters of the conditional-on-segment choice probability models were identical across the segments. Given the model specification described above, this test amounted to a test of three linear equality restrictions on the parameters of the model, namely, $H_o : \theta_1 = \theta_2$. The Wald statistic for this test was calculated to be 7.68, which is associated with a probability value of .05 for a Chi-square distribution with three degrees of freedom. Thus, there is notable statistical support for the notion that different market segments exist in the market of GMO bread in this Norwegian market, characterized by differential purchasing behavior.

The results presented in this paper are preliminary and do not preclude the possibility that more than two market segments might exist in this market. Research is ongoing to investigate the number of segments that exist, as well as to investigate the robustness of the results to different assumptions relating to the distributional assumptions underlying the choice models.

Concluding Remarks

We proposed a finite probability mixture model in combination with a contingent valuation model to analyze the existence of differential market segments for characterizing the purchasing decisions of consumers. This approach has at least two principle benefits. First, the model is capable of identifying market segments within the hypothetical market. Second, the model can be used to estimate WTP/WTA within each segment.

We illustrate the application of the model using a data set collected on consumer response to genetically modified foods in Norway. Based on our estimation results, we found evidence of separate socio-economic consumer-groups with differing willingness to accept GM-bread. Variables used to separate socio-economic groups include gender, formal education, and age. Within each segment, the willingness to pay function included an explanatory variable relating specifically to knowledge relating to the product in question as well as the level of discount available for the product. For this application we chose an explanatory variable representing the self-reported level of knowledge about GMOs. Other variables relating to the product itself could have been included

Preliminary results show that there is evidence of two segments, where one needs a high discount and one only need a very low discount to encourage purchases of GM-bread. The estimates were polar in the sense that one segment would not want to buy GM-bread at any price, while the other hardly needed any discount at all to purchase the GM product. The segment that needed a very high discount was characterized by being a women, and people of lower formal education and of higher age. The segment that needed the lesser (almost no) discount was characterized by being male, and people with higher formal education and of lower age.

Table 1: Summary Statistics Variables from the Survey

Variable	**Description**	**Descriptive Statistics**
Age	Age of the consumer	Mean: 41.6 years St. Dev : 12.9 years
Gender	0 if female, 1 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 knowledgeable about biotechnology 1= Know a lot, know something 0 = Know little	Mean: 0.61

Table 2. Estimation Results for 2 Segment Model

	Variables	Estimate	Z-value
Segment 1	*Intercept*	-0.9494	-3.5211
	Bid	0.9954	2.4525
	KnowGMO	-0.4496	-1.4006
Segment 2	*Intercept*	0.0686	0.1317
	Bid	19.9409	1.7383
	KnowGMO	-0.5351	-0.6611
Segmentation Variables	*Intercept*	1.1016	0.8117
	Gender	1.4622	2.5831
	Education	0.3963	1.2066
	Age	-0.1135	-1.8480

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