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Measuring U.S. Consumer Preferences for Genetically Modified Foods Using Choice Modeling Experiments: The Role of Price, Product Benefits and Technology

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Abstract:

Food biotechnology promises to deliver a wide range of enhanced consumer benefits. This study models consumer's willingness to trade-off the potential risks of GM foods with the possibility of extracting significant benefits. The results of the choice modeling experiments reflect how different attributes of price, product benefits, and technology influence consumer demand for genetically modified food products. The results suggest that direct health, environmental, and production related benefits have a positive effect on choice. The results also generally show that genetic modification is viewed negatively, with use of bacterium and animal based genetic modification being viewed more negatively than the use of plant based genetic modification.

Introduction

The commercial potential of biotechnology emerged as a new reality in the agricultural and food industries in the 1990s. The use of food biotechnology offers the promise of delivering foods with a wide range of enhanced consumer benefits. Despite their promise, genetically modified (GM) products have received mixed regulatory and consumer approval in the U.S. and elsewhere (Gaskell *et al.*, 1999; Hallman *et al*., 2002). Controversy exists about the possibility and extent of externality costs resulting from unanticipated health, and environmental impacts, as well as the moral and ethical acceptability of the use of biotechnology in the food system.

Billions of dollars are being expended on R&D to develop GM products with output traits that bring tangible consumer benefits. The potential benefits include longer shelf stability, enhanced sensory appeal, reduced allergenicity and nutritional or wellness attributes (Dunahay, 1999; Riley and Hoffman, 1999; Feldman *et al*., 2000). Another promising use of biotechnology is the potential to develop organisms that produce pharmaceuticals such as vaccines and hormones (Hallman *et al*., 2002). These distinct consumer benefits of the GM food products (which are not available in the non-GM products) are likely to be critically important for broad consumer acceptance of bioengineered foods (House *et al*., 2001). As GM food products with enhanced and functional attributes appear in the marketplace, consumers will be faced with the choice between GM products bringing tangible benefits (but may carry unknown risks) and the traditional non-GM products that do not provide distinct and tangible consumer benefits.

It is important that researchers contribute to the ongoing discourse over benefits and risks of biotechnology by providing scientifically credible information on how consumers value various food attributes, including process attributes such as genetic modification. This is especially true given that food consumption in the U.S. and other developed countries is driven by factors other than pure physiological needs. Majority of consumers in these countries want foods that are not only safe, but also promote good health and overall well being (Senauer, 2001). As Antle (1999) rightfully argues, the analysis of food consumption demand needs to go beyond its traditional setting to incorporate consumer characteristics as well as non-price attributes of foods such as nutritional content, safety and convenience attributes, how the product is produced, environmental impacts of production, the use of pesticides, irradiation and GM organisms.

This study contributes to the ongoing debate over food biotechnology by explicitly modeling how consumers trade-off the potential or perceived risks of GM foods with the possibility of extracting significant benefits from GM foods. Specifically, the marginal effects of, and relationships between specific product characteristics and consumer attributes on consumer acceptance of GM food products are estimated. Consumer choice of food attributes are analyzed within the choice-modeling framework (Louviere *et al*., 2000).

In particular, this study will analyze (i) how consumers value the attributes embodied in food products (e.g., technology of production, product benefit content); (ii) how consumer valuation of these attributes vary across product-types (whether it is consumed as a fresh product or it is a processed product or it is an animal-based product); and (iii) how the preference over product-attribute and product-type combinations are related to observed consumer characteristics (e.g., economic and demographic variables).

Empirical Model

Consumer preferences over food attributes are analyzed within the random utility discrete choice model framework (McFadden, 1978; Revelt and Train, 1997). Since market data from GM food products are not available, stated preferences (SP) choice modeling framework

(Louviere, 2000) is used. The Lancaster (1966a,b) model provides a natural framework within which consumers' food choice may be analyzed. In this model, consumers derive utility (U) from the attributes or characteristics (*z*), which are embodied in the products purchased:

$$U = U(z_1, z_2, \cdots, z_m) \text{ where } z_i = a_{ij} q_j \tag{1}$$

In the above equation, z_i is the amount of ith attribute obtained by consuming the jth product, a_{ij} is the amount of ith attribute per unit of the jth product, and q_j is the quantity of jth good consumed. Although Lancaster envisaged this relationship between goods and attributes as being objective, this model can also be used in a setting where consumers' subjective perception of the technology and attributes affect their consumption decisions. In the context of this study, these attributes include: production technologies (whether the product is genetically modified; for GM products, whether genetic modification involves plants or animals, whether there is gene transfer across plants and animals, etc.).

Assuming that each available choice is one configuration of M product attributes, each of which has multiple levels. Different levels of the M product attributes yield a total of N choices from which the consumer makes his/her choice. The consumers' utility from the choice of alternative j is given by:

$$U_j = V_j + \varepsilon_j = \sum_m \beta_m z_{mj} + \varepsilon_j \tag{2}$$

where U_j is the latent utility associated with choice j, V_j is the explainable part of latent utility that depends on the chosen product attributes (z_{mj}), and ε_j is the random component of utility associated with choice j. The consumer chooses alternative j if $U_j > U_r$ ($j \neq r$). Therefore, the probability that the consumer chooses the option j (which is indicated by $y_i = j$) is given by:

$$P(y_i = j) = P(U_j \succ U_r) \quad \text{for } \forall\ r \neq j. \tag{3}$$

The model is implemented by making assumption about the distribution ε_j. Assuming that ε_j are iid with type-I extreme value (Gumbel) distribution, the probability that the consumer chooses option j is given by (McFadden, 1973):

$$P(y_i = j) = \exp\left(\sum_m \beta_m z_{mj}\right) \Big/ \sum_j \exp\left(\sum_m \beta_m z_{mj}\right) \tag{4}$$

Which leads to the standard conditional logit model. However, the above model suffers from the well-known and restrictive *Independence from Irrelevant Alternatives (IIA)* property and, therefore, is unable to incorporate preference heterogeneity across consumers. To address this problem, consumer preferences are modeled using the random parameter logit model(the mixed logit model). In this framework, it is assumed that β_{ij} (β_j associated with consumer i) is random across individual consumers whose distribution can be specified as follows:

$$\beta_{ij} = \bar{\beta}_j + \sum_k \theta_{kj} x_{ik} + \sigma_k u_{ik} \tag{5}$$

Where u_{ik} is normally distributed with correlation matrix **R**, σ_k is the standard deviation of the distribution, $\bar{\beta}_j + \sum \theta_{kj} x_{ik}$ is the mean of the distribution that depend on x_{ik} representing person-specific (observable) characteristics (age, gender, etc.), and u_{ik} are random errors that capture unobservable and excluded consumer attributes. In this formulation, $\bar{\beta}_j$ reflects the *average taste* (preference) of all consumers for choice j and $\sum \theta_{kj} x_{ik}$ denotes the variation (or deviation) of individual preference that depends on observable consumer characteristics. The constant term can be portioned into alternative specific constants (ASC) that are unique to each alternative that are considered in the choice sets. ASC captures the influence on choice of unobserved attributes relative to the specific alternative.

Substituting equation (5) in equation (2), the random utility function can be written as:

$$U_{ij} = \sum_m \bar{\beta}_m z_{im} + \sum_m \sum_k \theta_{km} x_{ik} z_{im} + \sum_m z_{im} \sigma_k u_{ik} \tag{6}$$

In this model, the mean utility is $\sum \bar{\beta}_m z_{im}$ which depends only on product attributes (z_{ij}) and, thus it is a product specific component that does not depend on consumer characteristics. On the other hand, heterogeneity in preferences depends on the interaction between product attributes and consumer characteristics. The parameters of the model are estimated using the Maximum Likelihood (ML) estimator.

Application of Choice Modeling to the U.S GM Food Market

The targeted sample frame for the survey was the non-institutional U.S. adult civilians aged 18 years or older selected from more than 97 million telephone households in the contiguous 48 United States, using random proportional probability dialing. A total of 1,201 interviews were completed between February 27,2003 and April 1,2003.The CATI program guided a random but balanced selection process to ensure that representative numbers of males and females were interviewed. U.S. Census Bureau population estimates determined the distribution necessary for proportionate geographic coverage.

The sampling design accounts for the possibility that people who answer the telephone immediately are different from those who are rarely at home. To maximize generalizability, a 12-call design with attempts to contact an elusive individual was made at different times and days throughout the week. Interviewers left a voice mail message on the second, fifth and ninth attempt, explaining the study and the purpose for calling. The CATI software maintained callback appointments and prompted the interviewers to leave an answering-machine message when necessary. Many of the telephone numbers originally selected as part of the sampling frame were excluded as non-residential or non-working numbers. Only 38%of the phone numbers selected at random yielded completed interviews. However, calls to 56%of the working residential numbers resulted in completed interviews. Moreover, 65%of those who were available and eligible to participate agreed to complete the study. These response rates did not significantly differ between the two versions of the questionnaire. The 1,201 completed interviews yield a sampling error rate of ±3%[1]. Questions asked in a split-ballot[2] format yielded a sampling error rate of ±4%. Once the data were obtained, they were weighted to ensure their representativeness, using race, ethnicity and education variables as weighting factors.

During the telephone survey interviews, respondents who reported consuming corn flakes, bananas or ground beef at least occasionally (1199 respondents) were asked if they would be interested in further participating in a mail survey. Of the 1199 potential respondents, 661 (55.1%) agreed to respond to the mail questionnaire in exchange for nominal compensation of $5. Of the 661 who agreed, 409 (61.9%) returned completed surveys distributed as follows: banana: 137, cornflakes: 128; and ground beef 144.

The mail survey consisted of three parts; with part one eliciting consumers' stated preference for the GM foods, part 2 focused on willingness to consume genetically modified food products, while part 3 covered trust questions on institutions associated with biotechnology. Instructions at the front page included; a presentation of a choice set example with directions to respondents in making a selection, a brief description of the GM technologies; and the accompanying cover letter explaining survey purpose.

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[1] *The sampling error is the difference between the population percentage and its estimate. The sampling error associated with a nationwide sample of 1,200 people is approximately ±3 percent with a 95 percent confidence interval. This means that if 50 percent of the sample gave a particular response, the entire US adult population will be between 47 percent and 53 percent, 95 out of 100 times. This should be kept in mind when comparing smaller groups within the sample or when comparing surveys with different sample sizes, as sampling error is greater for smaller samples.*

[2] *To limit the length of the survey and minimize fatigue on the part of respondents, two versions of the survey were created and given to two identically drawn split samples.*

Some questions from the telephone interviews were repeated in the mail survey to act as breakers stopping potential response patterns and fatigue. On the other hand, these questions were used to test whether the responses changed in any way due to learning process that would occur by taking the mail survey. The Choice modeling questions were pretested with suggestions to put "Price", "Product Benefit", and "Technology" as row headings and "Survey Instructions" at the top of the page.

The execution and planning of the choice modeling part of the survey was a stepwise process, with the experimental design for the choice modeling first being subjected to several lengthy discussions by various groups, comprising of life and social scientists. The step facilitated decisions on the appropriateness of products that may appeal to the larger public, with potential and likely attributes and plausible genetic modification technologies through which the products could be delivered. The following principles guided consideration of the range and scope of products, technologies and benefits to be covered:

(1). **Products**; cover plant and animal food products, these products could be either whole (fresh) or processed; or animal based (2) **Benefits**; broadly incorporate benefits that either impact consumer’s health, have some type of consumer benefit, or provides a "societal" benefit. (3) **Technologies**; incorporate a wide range of existing and potential technologies such as plant or animal based genes or micro-organisms (bacterium); (4) within and cross product analysis; and (5) keep the matrix of technology, price, and benefit combinations plausible.

The group discussions and consultations yielded a proposal to offer specific product/benefits and generalized technology (i.e., genes from a different plant, genes from a different animal, gene from the same plant/animal that have been modified to emphasize a given attribute. Although there was expressed need to carry out cross product and/or within product analysis, it was only feasible and more enriching to carry out a within product analysis. The cross product analysis was viewed to be unnecessarily complex yielding no meaningful analysis. Additionally, it was argued that some of the combinations in the design matrix might lead to illogical permutations. Moreover, even if the categories of benefits were held constant (input trait, health benefit, non-health consumer benefit, etc.), the analysis was also likely to be confounded by interaction effects between the specific benefit and the specific product, making across-product analysis difficult.

Admittedly, the decision to carry out a within product analysis was considered optimal in yielding differences in the marginal effects on consumer preference due to various (specific) benefits and technology combinations within a specific product. Thus, making product specific analysis more attractive (even if the products/benefits analyzed may not be of interest to any specific company). The analysis will involve examination of potential industry products in very specific details. Secondly, there is potential gain of value, as respondents are able to relate to specific product characteristics based on carefully thought out responses. For example, corn flakes with longer shelf life versus corn flakes that stays crispy in milk longer or a banana that does not often/bruise as quickly

A fraction factorial experiment design was used to create a balanced and efficient design matrix for a number of choice sets using the ***SAS Macros***. Each of the three products is characterized by a four level three (factor) i.e., technology, benefit and price. The experimental design for banana, ground beef and cornflakes were run concurrently in a same survey yielding 48 choice sets. After elimination of dominated choices, 40 choice sets remained. Three of the alternatives (options) in each choice set were all variants of a GM product (i.e. A, B, and C), the fourth alternative (D) was the status quo (a conventional product), which was constant and common to all choice sets across the products. The 40 choice sets were split into 4 subsets, with each respondent randomly allocated one set of 10 questions to complete (a process refereed to as blocking).

A description of the permutations of levels of each of the attributes is detailed below:

Technologies: For a plant based product (banana and cornflakes), technology alternatives were: (1) a plant genetically modified by simply removing or altering one of its own DNA; (2) a plant genetically modified by using DNA from another plant; (3) a plant genetically modified by using DNA from an animal; and (4) a plant genetically modified by using DNA from a microorganism (e.g., bacterium, virus, etc) relative to traditional or conventional technology. In the case of the animal product (ground beef), the technology alternatives were: (1) cows fed on GM feed; (2) cattle genetically modified by simply manipulating one of its own DNA; (3) a cow genetically modified by using DNA from a microorganism (e.g., bacterium, virus, etc); 4) cattle genetically modified using DNA from another animal; and (5) cattle genetically modified by using DNA from a plant relative to traditional or conventional technology.

Benefits: The plant-based products' alternatives were: (1) reduced pesticide use in production (an environmental benefit that lowers risk of pesticide residue in fresh produce); (2) enhanced shelf-life for products consumed fresh or enhanced chemical properties that help processing; (3) enhanced level of a nutrient (e.g., antioxidants, added compounds or nutrients that are believed to prevent disease); and (4) enhanced level of a nutrient that has medicinal value (e.g., a chemical that works as a remedy for arthritis type inflammation). In addition, reduced antibiotics use in the livestock production was also considered, as the direct health benefits remained similar across the food products. All benefits were analyzed relative to no benefit.

Price: The following price offers were considered: (1) a 10% discount; (2) a 10% premium; (3) a

5% premium; (4) a 5% discount, all price changes are relative to the current price (status quo).

Results

The random parameter logit model results are presented in Tables 1-3 for each of the three products analyzed, while tables 4, 5 and 6 present random attributes correlations, elasticities and the marginal willingness to pay for the non-marketable attributes of benefit and technology, along with the corresponding 95% confidence intervals. The estimated mean for price and both the estimated mean and standard deviations of the random attributes are reported. The model was estimated with simulated maximum likelihood using the Halton draws with 300 replications. Estimation was done using Nlogit 3.0 (2002). The results show that sign for the price variable across the three products is correct and significant, consistent with a priori expectations. The price has a negative effect on choice with the increase in price being associated with decreased demand (a negative impact on utility). The standard deviations of all the random attributes across the three products are highly significant implying heterogeneity in preferences across the consumers.

Although the returned surveys yielded 4090 choice sets across the three products, only 2090 of these choice sets are used for analysis (i.e., banana: 1010; cornflakes: 980; and ground beef: 920). Of these respondents, 29 % are lexicographic; i.e., those respondents who would not chose A, B, & C regardless of the attributes contained in the other food alternatives. Inclusion of lexicographic responses will not be amenable to choice modeling since any attempt to analyze these choices on the basis of attribute levels (the basic premise of choice modeling) would produce biased estimates. Consequently, the analysis is based on 2910 choice sets spread across the three food products (i.e., 71 % of those respondents who chose A, B, C, & D). Several models were tried and in the process eliminated those yielding singular matrices. For example, in the case of cornflakes and banana, the inclusion of both own and plant technologies yielded singular matrices.

Most of the product benefits have positive effect on choice across the three products. The exception is antioxidants in the banana and added nutrients for stronger teeth and bones in ground that were insignificant. The significant and positive product benefits have a welfare improving effect on A GM food choice. The negative coefficients on technology imply that moving from the conventional technology to a GM product (reduces the probability of the GM alternatives being selected) with overall reduction in a consumer's utility. Conversely, a positive coefficient on a technology leads to an increase of utility. When ground beef product was a product of cows fed on GM corn and the banana was modified using its own genes, technology serves to enhance consumer utility. Genetic modification involving animal genes, Bacterium, and plant genes has a negative effect on choice (i.e., reduces the probability of the GM alternative being selected).

Results on consumer's mean willingness to pay are presented in table 6; the results show the monetary values of the attributes given a unit change in price. The values were estimated by evaluating the ratio of the attribute coefficient to the coefficient of the monetary variable to produce partworths. Ceteris paribus, implicit prices are marginal rates of substitution between the attribute of interest (technology and benefit) and the monetary attribute. A partworth should normally be represented by an absolute currency figure, in this study the payment vehicle was the percent change in price. Accordingly, the numbers generated are also in percentage terms (% change in price will reflect in percent terms the willingness to pay). The positive values imply changes that are beneficial (i.e., a respondent is willing to pay a positive amount for an increase of the positive attribute) while negative values imply reduction in utility (i.e., respondents require compensation which may be in form of a price discount for a unit increase in this attribute and therefore the value may measure of willingness to accept (WTA)).

In the case of bananas, positively associated attributes are that of using less pesticides and chemicals to grow bananas, and increased banana shelf life (i.e. a banana that stays riper longer and reduces bruising). Respondents are willing to pay about 3% to obtain such benefits. However, if the banana product is a result of genetic modification via plant, animal or bacterium genes, the respondents need to be compensated to accept it. The results show that more compensation is required to induce acceptance of processes involving animal, bacterium and plant genes (22% and 9 %, and 5%, respectively). Conversely, if the GM banana was a result of own gene transfer, consumers are willing to pay 3% more for the product. The results also show that respondents rank technology from least to more acceptable (i.e., moving from a small to a larger negative and vice-versa). They rank genetic modification via own genes, followed by plant, with bacterium and animal, at the bottom. Given the normality assumption, at the same price, about 32-35% of the respondents would have placed a negative valuation of less pesticide use, added antioxidants and a banana that ripens longer. Unlike the banana benefits, respondents largely placed negative valuation on technologies, ranging from 63-84 %.

Similar to banana, respondents valued positively all the cornflakes benefits. The benefits are: less chemicals/pesticides in corn production, added antioxidants to reduce aging, added compounds for increased energy. However, given the normal distribution assumption, about 18 to 40% of the respondents could have valued these benefits negatively. Results indicate that respondents are willing to pay between 5% and 19% more to get such direct health or gain environmentally via less pesticides and chemicals. Unlike benefits, all the respondents largely placed a negative valuation on technologies ranging from 47-81%. As a result, if the cornflakes are genetically modified using plant, bacterium and animal genes, consumers need to be compensated by about 10% to 37% more to accept the cornflakes.

For ground beef, with the exception of added compounds for stronger teeth and bones which is insignificant, consumers are willing to pay 2% to obtain the benefits of less antibiotics in cow production and 3% for antioxidants to slow down the aging process. In contrast, consumers require a compensation to accept ground beef, a product of genetically modified cow via animal or bacterium genes (20% and 13%, respectively). However, if the ground beef was a product of a cow fed on GM corn, consumers are willing to pay 6% more. With the normality assumption, at the same price, about 52-62% of the respondents placed a positive valuation on fewer antibiotics and antioxidants. On the other hand, fairly few compared to cornflakes and banana placed a positive coefficient on technology ranging from 19-60%.

Table 5 presents results on elasticity estimates. Own price elasticities for the cornflakes and ground beef products have almost similar magnitudes. The elasticities are inelastic (below 0.20); the exception is banana (a fresh plant product) with own price elasticity approximately (0.30). The results may imply that a fresh plant product may be more responsive to price changes than processed (i.e., cornflakes) or meat products (i.e., ground beef). The cross price elasticities are smaller in magnitudes compared to own price elasticities across all the three products. The similarities in elasticities for alternatives A, B, and C within a product may reflect similarity of the product options (variation of some GM technology), compared to the non-GM (traditional or conventional product). The differences stem from variation on benefits and technologies combinations. The correlation matrix for the random parameters presented in table 4 show possible tradeoffs made by respondents. Any individual choosing a commodity bundle comprised of (technology*benefit*price) in an option may choose to combine a positive with negative valued attribute.

Conclusions

The study results show that the use of choice modeling experiments provides a way of valuing non-monetary attributes associated with consumption of GM food products and a way of identifying consumer preferences. The products analyzed in the present study are: banana (a fresh plant product), cornflakes (a processed plant product), and ground beef (a meat product). The results indicate how different attributes of price, product benefits, and technology influence consumer demand for genetically modified food products. The results demonstrate how a consumer makes tradeoffs between the product attributes.

The results suggest that across the products, direct health, environmental and production related benefits have a positive effect on choice. Also, the results generally show that genetic modification is viewed negatively. However, through the choice modeling experiments, respondents viewed own and plant based genetic modification less negatively than the use of bacterium and animal based genetic modification. These results may suggest that attitudes may be somehow more promising for GM processes involving own or plant based gene technology. Respondents' willingness to pay for benefits embedded in the products suggests that there is potential for GM foods in the market.

Understanding the values consumers place on individual attributes can provide insights for the food industry in tailoring targeted marketing product strategies in line with changing consumer demands. The study results may also provide information to policy makers on which direction to go in terms of genetic modification; i.e., what is viable and acceptable. A limitation of this study is that three products are not representative of all other foods items. Obviously, different products are capable of delivering different set of valuation of attributes with differing acceptance results. Ethical and socioeconomic variables have also not been included in these experiments. Besides tangible attributes (benefits and technology), attitudinal variables if included in the choice models may also add to model robustness. Therefore, future work should explore possibilities of including such variables.

References

Antle, J. 1999. The New Economics of Agriculture. *AJAE*, 81:993-1010.

Adamowicz, W., Boxall, P., Williams, M. and Louviere, J. J. 1998. “Stated Preference approaches for measuring passive use values: Choice experiments and contingent valuation.” *American Journal of Agricultural economics,* Vol. 80, 64-75.

Burton, M., Rigby, D., Young, T, and James, S. (2001). Consumer Attitudes to Genetically Modified Organisms in Food in the U.K. *European Review of Agricultural Economics*, 28, 479-498.

Burton, M., and Pearse. D. (2002). **“**Consumer Attitudes Towards Genetic Modification, Functional Foods, and Microorganisms: A Choice Modeling Experiment for Beer.” *AgBioforum*, 5(20): 51-58.

Dunahay, T. “Testing May Facilitate Marketing of Value-Enhanced Crops” *Agricultural Outlook,* March 1999:24-25.

Feldman, M. P., Morris, M. L. and Hoisington, D. “Genetically Modified Organisms: Why All the Controversy?” *Choices* (First Quarter): 2000: 8-12.

Gaskell, G., Bauer, M.W., Durant, J. and Allum, N. C. “Worlds Apart? The Reception of Genetically Modified Foods in Europe and the U.S.”, *Science*, Vol. 285, 1999:384-387.

Hallman, W. K., Adelaja, A. O., Schilling, B. J. and Lang, J. (2002). *Public Perceptions of Genetically Modified Foods: Americans Know Not What They Eat*. Publication No. RR-0302-001, Food Policy Institute, Rutgers University.

House, L., B. Morrow, J. Lusk, and M. Moore. 2001. Modeling Consumer Acceptance and Willingness to Pay for Genetically Modified Foods in the U.S. and the European Union. Paper presented at the International Food and Agribusiness Symposium, Sydney.

Hoban, T. “Trends in consumer attitudes about agricultural biotechnology.” *AgBioforum*, 11 (1998): 3-7.

Lancaster, K. J. “A New Approach to Consumer Theory.” *Journal of Political Economy.* 74. (1966a): 132-157.

Lancaster, K. J. “Change and Innovation in the Technology of Consumption.” *Amer. Econ. Rev.* 56(1966b): 14-23.

Louviere, J., Hensher, D. and Swait, J. 2000. *Stated Choice Methods: Analysis and Application*. Cambridge, University Press.

Mendenhall, C. 2000. "Estimates of WTP Premium for Non-GMO Foods-A survey 's paper presented to the 4th international conference on the economics of Agricultural Biotechnology." Ravello, Italy, Aug 24-28: International consortium on Agricultural Biotechnology.

McFadden, D. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." in P. Zarembka, (ed), Frontiers in Econometrics, New York: Academic Press.

McFadden, D. 1978. "Modeling the choice of residential location, in A. Karlqvist, L. Lundqvist, F. Snickars and J. Weibull, eds., "Spatial Interaction Theory and Planning Models," North Holland, Amsterdam, pp 75-96.

Moon, W., and Balasubramanian, S. (2001). "A Multi-attribute Model of Public Acceptance of Genetically Modified Organism", Paper Presented at the AAEA Meetings, August 5-8, Chicago.

Revelt, D. and K. Train (1998), "Mixed Logit with repeated choices," Review of Economics and Statistics 80:647-657.

Riley, P. and L. Hoffman. 1999. Value-Enhanced Crops: Biotechnology's Next Stage. *Ag. Outlook* (March Issue): 18-23.

Senauer, B. 2001. The Food Consumer in the 21st Century: New Research Perspectives. Paper presented at the 71st EAAE Seminar: The Food Consumer in the 21st Century, April 18-20, Zaragoza, Spain.

Train, K. 2002. *Discrete Choice Methods with Simulation*, Cambridge University Press.

Wolf, Mcgarry and Domegan, C. 2000. "A comparison of consumer attitudes towards genetically modified food in Europe and United States: A case study over time." Paper presented to the 4th international conference on the economics of Agricultural Biotechnology." Ravello, Italy, Aug 24-28: International consortium on Agricultural Biotechnology.

Table 1: Parameter Estimates: The Mixed Logit Model: Banana (normally distributed random parameters)

Variable		Coefficient	Standard error	t-ratio
PRICE		-0.3015	0.0729	-4.14***
Grown using Less chemicals and pesticides	Mean Coefficient	1.0126	0.3368	3.01***
	Standard Deviation of the Coefficient	2.2515	0.3038	7.41***
Added antioxidants to promote heart health	Mean Coefficient	0.3389	0.2440	1.39
	Standard Deviation of the Coefficient	0.8448	0.3183	2.65***
Stays Riper longer and reduces bruises	Mean Coefficient	1.0047	0.3321	3.03***
	Standard Deviation of the Coefficient	2.8289	0.2622	10.79***
Genetic modification using genes from a Bacterium	Mean Coefficient	-2.7741	0.4421	-6.28***
	Standard Deviation of the Coefficient	3.5244	0.3397	10.37***
Genetic modification using genes from a different Plant	Mean Coefficient	-1.4090	0.3842	-3.67***
	Standard Deviation of the Coefficient	3.1778	0.3150	10.09***
Genetic modification using genes from an Animal	Mean Coefficient	-6.4853	1.1986	-5.41***
	Standard Deviation of the Coefficient	5.3876	0.7027	7.67***
Genetic modification using Banana's Own Genes	Mean Coefficient	0.7768	0.3799	2.04***
	Standard Deviation of the Coefficient	2.7196	0.3625	7.50***
Model statistics				
Log Likelihood	-970.7503			
Restricted Log Likelihood	-1386.294			
Chi Square	831.09			
DF	39			
*** α=. 01, **α=. 05** and α=. 10				

Table 2: Parameter Estimates: The Mixed Logit Model: Cornflakes (normally distributed random parameters)

Variable		Coefficient	Standard error	t-ratio
PRICE		-0.0981	0.0598	-1.64*
Grown using Less chemicals and pesticides	Mean Coefficient	1.6244	0.2728	5.95***
	Standard Deviation of the Coefficient	2.3308	0.3972	5.87***
Added antioxidants to promote heart health	Mean Coefficient	1.8444	0.3711	4.97***
	Standard Deviation of the Coefficient	2.1333	0.3289	6.49***
Added compounds to increase energy	Mean Coefficient	0.4466	0.2684	1.66*
	Standard Deviation of the Coefficient	2.1022	0.3058	6.87***
Genetic modification using genes from a Bacterium	Mean Coefficient	-2.7659	0.4537	-6.10***
	Standard Deviation of the Coefficient	2.9581	0.5456	5.42***
Genetic modification using corn's Own Genes	Mean Coefficient	-0.0145	0.4310	-0.03
	Standard Deviation of the Coefficient	3.2600	0.4180	7.80***
Genetic modification using genes from an Animal	Mean Coefficient	-3.5868	0.5885	-6.09***
	Standard Deviation of the Coefficient	3.6173	0.5871	6.16***
Genetic modification using genes from a different Plant	Mean Coefficient	-0.9932	0.4351	-2.28***
	Standard Deviation of the Coefficient	3.4445	0.4443	7.75***
Model statistics				
Log Likelihood	-964.76			
Restricted Log Likelihood	-1358.57			
Chi Square	787.62			
DF	39			
*** α=. 01, **α=. 05** and α=. 10				

Table 3: Parameter Estimates: The Mixed Logit Model: Ground Beef (normally distributed random parameters)

Variable		Coefficient	Standard error	t-ratio
PRICE		-0.1791	0.0887	-2.02***
Cows produced using Fewer Antibiotics	Mean Coefficient	0.5511	0.3349	1.65*
	Standard Deviation of the Coefficient	2.2874	0.4331	5.28***
Added Nutrients to promote stronger teeth and bones	Mean Coefficient	0.2991	0.3918	0.76
	Standard Deviation of the Coefficient	2.1852	0.4263	5.13***
Added antioxidants to promote heart health	Mean Coefficient	1.2814	0.4358	2.94***
	Standard Deviation of the Coefficient	3.0544	0.4954	6.17***
Genetic modification using genes from a Bacterium	Mean Coefficient	-2.2940	0.8465	-2.71***
	Standard Deviation of the Coefficient	4.2144	0.5994	7.03***
Genetic modification using genes from a different Plant	Mean Coefficient	-0.1332	1.2307	-0.11
	Standard Deviation of the Coefficient	4.4187	1.2117	3.65***
Genetic modification using genes from an Animal	Mean Coefficient	-3.6445	1.1704	-3.11***
	Standard Deviation of the Coefficient	4.3354	0.8945	4.85***
Genetic modification using Cow's Own Genes	Mean Coefficient	-0.7217	0.6097	-1.18
	Standard Deviation of the Coefficient	3.8259	0.4884	7.83***
Cow fed on genetically modified corn	Mean Coefficient	1.0496	0.5482	1.91**
	Standard Deviation of the Coefficient	2.7662	0.4386	6.31***
Model statistics				
Log Likelihood	-904.16			
Restricted Log Likelihood	-1275.39			
Chi Square	742.47			
DF	46			
*** α=. 01, **α=. 05** and α=. 10				

Table 4: Correlation matrix for random variables (Banana, Cornflakes & Ground Beef)

Bananas	Less chemicals and pesticides	Added antioxidants	Stays Riper longer	Bacterium	Plant Genes	Animal genes	Own Genes
Less chemicals and pesticides	1	0.46	0.5	-0.63	-0.64	-0.63	-0.49
Added antioxidants		1	-0.39	0.33	0.34	0.33	0.06
Stays Riper longer			1	0.69	-0.71	-0.78	-0.28
Bacterium					0.94	0.95	0.57
Plant Genes					1	0.9	0.6
Animal genes						1	0.68
Own Genes							1

Cornflakes	Less pesticides	Added Antioxidants	Added compounds for energy	Bacterium	Own genes	Animal genes	Plant genes
Less pesticides	1	0.33	0.57	-0.92	-0.87	-0.91	-0.86
Antioxidants		1	-0.26	-0.56	-0.37	-0.4	-0.41
Added compounds for energy			1	-0.34	-0.47	-0.57	-0.5
Bacterium				1	0.74	0.82	0.69
Own genes					1	0.75	0.95
Animal genes						1	0.82
Plant genes							1

Ground Beef	Few Antibiotics	Compounds for Stronger teeth	Added antioxidants	Bacterium	Plant genes	Animal genes	Own genes	Fed on GM corn
Few antibiotics	1	-0.49	-0.67	0.79	0.73	0.74	0.64	0.62
Compounds for stronger teeth and bones		1	0.93	-0.43	-0.52	-0.18	-0.25	-0.09
Added antioxidants			1	-0.73	-0.7	-0.44	-0.52	-0.39
Bacterium				1	0.74	0.8	0.78	0.72
Plant genes					1	0.41	0.4	0.5
Animal genes						1	0.69	0.6
Own genes							1	0.82
Fed on genetically modified corn								1

Table 5: Estimated marginal utility increase/decrease given 1 % change in Price

Banana	**k=1**	**k=2**	**k=3**	**k=4**
j=1	-0.360	0.124	0.13	0.104
j=2	0.107	-0.373	0.1	0.092
j=3	0.136	0.118	-0.358	0.105
j=4	0.227	0.209	0.22	-0.628
Cornflakes	**k=1**	**k=2**	**k=3**	**k=4**
j=1	**-0.131**	0.043	0.04	0.035
j=2	0.041	**-0.139**	0.036	0.033
j=3	0.054	0.051	**-0.121**	0.04
j=4	0.071	0.072	0.072	**-0.226**
Ground Beef	**k=1**	**k=2**	**k=3**	**k=4**
j=1	**-0.206**	0.062	0.055	0.047
j=2	0.065	**-0.202**	0.054	0.051
j=3	0.072	0.065	**-0.182**	0.057
j=4	0.122	0.124	0.12	**-0.323**

Note: k is attribute (price), k=1,4(-10,-5, +10+5% changes in prices), j=1,2,..4) i.e. of a, b, c, d (choice alternatives)

Table 6. Range of Willingness to Pay and 95% confidence intervals: Normally Distributed Random Attributes

	% Respondents valuing attribute negatively	Lower Bound	Mean WTP	Upper Bound	% Respondents Valuing attribute positively	
			Banana			
Less chemicals and pesticides	32	-11.58	**3.36**	18.29	63	***
Added antioxidants	34	-4.48	**1.12**	6.73	61	
Stays Riper longer	35	-15.43	**3.33**	22.10	60	***
Bacterium	74	-32.58	**-9.20**	14.18	21	***
Plant Genes	63	-25.75	**-4.67**	16.41	32	***
Animal genes	84	-57.25	**-21.51**	14.23	11	***
Own Genes	72	-15.46	**2.58**	20.62	23	***
			Cornflakes			
Less pesticides	24	-30.96	**16.56**	64.07	71	***
Antioxidants	18	-24.69	**18.80**	62.28	77	***
Added compounds for energy	40	-38.30	**4.55**	47.40	55	*
Bacterium	79	-88.49	**-28.19**	32.11	16	***
Own genes	48	-66.60	**-0.15**	66.30	47	
Animal genes	81	-110.29	**-36.56**	37.18	14	***
Plant genes	47	-80.34	**-10.12**	60.09	38	***
			Ground Beef			
Few antibiotics	39	-22.47	**3.08**	28.62	56	*
Compounds for stronger teeth and bones	43	-22.74	**1.67**	26.08	52	
Added antioxidants	33	-26.96	**7.16**	41.27	62	***
Bacterium	66	-59.88	**-12.81**	34.26	29	***
Plant genes	49	-50.09	**-0.74**	48.61	46	
Animal genes	76	-68.77	**-20.35**	28.07	19	***
Own genes	54	-46.76	**-4.03**	38.70	41	
Fed on genetically modified corn	35	-25.03	**5.86**	36.76	60	**