South Korean Public Preferences for Genetically Modified Foods: A Random-Parameter Model

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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. It estimates the marginal effects and relationships between product characteristics and consumer attributes on acceptance of GM foods for South Korea.

Public perception and acceptance of biotechnology use in the production of food is a controversial subject in the U.S and elsewhere, especially in the European Union. The proponents of biotechnology highlight the potentials benefits to society via reduction of hunger, prevention of malnutrition, cure of diseases, and promotion of health and quality of life. Opponents often view its use as an unnecessary interference with nature that has unknown and potentially disastrous interactions with human genetics and natural ecosystems. Hoban (1998) reported broad support among consumers for biotechnology use in the production of food.

Research dollars are being expended on R&D to develop GM products with output traits that bring tangible consumer benefits. These potential benefits include longer shelf stability, enhanced sensory appeal, reduced allergenicity, and enhanced nutritional or wellness attributes (Dunahay 1999; Riley and Hoffman 1999; Feldman, Morris, and Hoisington 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 GM food products (which are not available in the non-GM products) are likely to be critically important for broad consumer acceptance of bio-engineered 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 that bring tangible benefits (but may be carrying unknown risks) and the traditional non-GM products that do not provide these distinct benefits.

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It is important that researchers contribute to the ongoing debate over the 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 majority of the developed countries is driven by factors other than pure physiological needs. A majority of consumers in these countries want foods that are not only safe but that 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, how the product is produced, environmental impacts of production, the use of pesticides, irradiation, and GM.

This study contributes to the ongoing discourse over food biotechnology by explicitly modeling how South Korean consumers trade-off potential or perceived risks of GM foods with potential benefits from GM foods. Specifically, marginal effects of, and relationships between specific product characteristics and consumer attributes on consumer acceptance of GM foods are estimated. Consumer choice of food attributes will be analyzed within the choice-modeling framework (Louviere, Hensher, and Swait 2000). The modeling approach follows Ben-Akiva et al. (2002), which integrates the random-utility discrete-choice model (Train 2002) and the latent-variable model

This study analyzes consumers' valuation of attributes embodied in GM food products (e.g., technology of production, product benefit content), how consumer valuation of these attributes varies across product-types (fresh product, processed product, or animal-based product), and how the preference over product-attribute and product-type combinations are related to observed consumer characteristics (e.g., economic and demographic variables). Various parameters of consumer demand such as demand elasticities with respect to various product attributes are obtained. The analysis also decomposes effects of genetic modification on consumer choice by product type and measures the relationship between consumer characteristics and preferences for product attributes.

Empirical Model

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. The consumers' utility from the choice of alternative j is given by

1) $U_j = V_j + \varepsilon_j = \sum_m \beta_m z_{mj} + \varepsilon_j$,

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

2) $P(y_i = j) = P(U_j \quad U_r)$ for $\forall\ r \neq j$.

The model is implemented by making assumptions 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)

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

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 is therefore unable to incorporate preference heterogeneity across consumers. To address this problem, we model consumer preference using the random-parameter 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

4) $\beta_{ij} = \bar{\beta}_j + \sum_k \theta_{kj} x_{ik} + \sigma_k u_{ik}$,

where u_{ik} is normally distributed with correlation matrix **R**, σ_k is the standard deviation of the distribution, $\bar{\beta}_j + \sum_k \theta_{kj} x_{ik}$ is the mean of the distribution that depends 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 $\sum_k \theta_{kj} x_{ik}$ denotes the variation (or deviation) of individual preference that depends on observable consumer characteristics. The constant term *b* can be portioned into alternative specific constants (ASCs) that are unique to each alternative considered in the choice sets. ASCs capture the influence on choice of unobserved attributes relative to the specific alternative.

Substituting equation in equation , the random utility function can be written as

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

In this model, the mean utility is $\sum_m \bar{\beta}_m z_{im}$, which depends only on product attributes (z_{ij}) and, thus it is a product specific component that is independent of 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 South Korea Food Market

The data used in this study was collected in April–May 2003 during a survey carried out in South Korea. The Food Policy Institute at Rutgers University developed the survey questionnaire that was later used in South Korea. The Korean survey in many instances had identical questions similar to those for the U.S. survey on the same subject carried out from February to April, 2003. Most of the questions in the two surveys were similar with modifications made considering cultural differences. The Korean Biosafety Clearing House (KBCH) commissioned Gallup Korea to conduct national face-to-face interviews. A target sample was obtained through proportionate random sampling based on population by region. The survey group included adults from across South Korea ranging in age from 20 to 59 years.

The sampling error was ±3.1 percent, with a statistical significance confidence level of 95 percent. Interviewers attended an orientation covering the survey method, contents, and exercise in an effort to minimize non-sampling error. Control over the interviewers was exercised by distributing and collecting questionnaires each day. Interviewers approached subjects, briefly describing the study, and asked them to participate. The data was weighted using demographic variables, just as the U.S data set (with exception of race/ethnicity) using the Korean National Census. Respondents were given a pen (worth US$2) for answering the questionnaire. In total, 1054 complete surveys were collected. Besides the choice-modeling questions, the survey collected information on public awareness and perceptions of food and food biotechnology and willingness to accept and approve GM foods. Information was also collected on socioeconomic and value attributes of the consumers. In addition, the survey elicited respondents' views about scientists and companies involved in biotechnology research as well as their confidence in the government's ability to protect the public interest.

To carry out the choice-modeling analysis, the sample was trisected, with 343 respondents answering questions on bananas, a fresh plant product; another 359 respondents answered questions on tofu, a processed plant product; and the remaining 352 respondents answering questions on pork, an animal product. During the interviews respondents were asked to state their preferences for the three products (banana, tofu, and pork). The products were chosen on grounds of familiarity to the Korean consumer and also to allow for comparisons with the U.S survey on a similar subject. The choice-modeling questions were pretested at Rutgers with suggestions to put "*Price*," "*Product Benefit*," and "*Technology"* as row headings and "Survey Instructions" at the top of the page. Additionally, for the Korean survey, ground beef and cornflakes were replaced with pork and tofu, respectively.

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 of life and social scientists. This 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 will be delivered. The following principles guided consideration of the range and scope of products, technologies, and benefits to be covered:

- Products—covers plant and animal food products. These products could be either whole (fresh) or processed plant products, or animal-based.
- Benefits—broadly incorporates benefits that either impact consumer's health, have some type of consumer benefit, or provide a "societal" benefit.
- Technologies—incorporates a wide range of existing and potential technologies such as plant- or animal-based genes or micro-organisms (bacterium).
- Within- and cross-product analysis.
- 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 the need to carry out cross-product and/or within-product analysis was expressed, 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 involves examination of potential industry products in very specific details. Secondly, there is a potential gain of value as respondents are able to relate to specific product characteristics based on carefully thought-out responses.

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 (factors) i.e., technology, benefit, and price. The experimental design on each of the banana, pork, and tofu products yielded 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).

Results

The random-parameter logit model results are presented in Tables 1–3. The mean price and both the mean and standard deviations of the random

Table 1. Parameter Estimates: The Mixed Logit Model: Banana (Normally Distributed Random Parameters).

Variable		Coefficient	Std error	t-ratio
PRICE		-0.1245	0.0295357	-4.22***
Grown using Less chemicals and pesticides	Mean Coefficient	1.0420	0.121579	8.57***
	Std Dev of the Coefficient	0.4126	0.188441	2.19**
Added antioxidants to promote heart health	Mean Coefficient	1.4397	0.141585	10.17***
	Std Dev of the Coefficient	0.8576	0.175849	4.88***
Added compounds to prevent arthritis and joint pains	Mean Coefficient	1.0159	0.161907	6.27***
	Std Dev of the Coefficient	0.9674	0.192903	5.01***
Genetic modification using genes from a Bacterium	Mean Coefficient	-1.0764	0.609574	-1.77*
	Std Dev of the Coefficient	2.3154	0.259581	8.92***
Genetic modification using Banana's Own Genes	Mean Coefficient	0.0935	0.604709	0.15
	Std Dev of the Coefficient	2.2072	0.232494	9.49***
Genetic modification using genes from a different Plant	Mean Coefficient	-0.6535	0.598628	-1.09
	Std Dev of the Coefficient	2.2620	0.28723	7.88***
Genetic modification using genes from a different animal	Mean Coefficient	-1.5714	0.633643	-2.48***
	Std Dev of the Coefficient	2.6350	0.325678	8.09***
Model statistics				
Log Likelihood	-2172.98			
Restricted Log Likelihood	-2758.73			
Chi Square	1171.49			
DF	39			

*** (α=. 01), ** (α=. 05) and * (α=. 10).

attributes are reported for each product. Table 4 also presents results on the marginal willingness to pay for the non-marketable attributes of benefit and technology along with the corresponding 95%-confidence intervals. 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 the price sign across the three products was correct and significant, which met a priori expectations. The price had a negative effect on choice, with an increase in price being associated with decreased demand (negatively affecting utility). The standard deviations of all the random attributes across the three products were highly significant, suggesting heterogeneous preferences across the consumers.

Although 1040 surveys were returned, only 563 (54%) were analyzable, providing 5630 choice sets (1990 banana 1990, 2010 tofu, 1620 pork) across the three products. The remaining 477 respondents (46%) did not chose A, B, & C regardless of the attributes contained in those food alternatives, and so were excluded from the analysis. Inclusion of lexicographic responses is not 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. The model estimates are based on the 5630 choice sets spread across the three food

Table 2. Parameter Estimates: The Mixed Logit Model: Tofu (Normally Distributed Random Parameters).

Variable		Coefficient	Std error	t-ratio
PRICE		-0.1008	0.0330	-3.05***
Grown using Less chemicals and pesticides	Mean Coefficient	1.2883	0.5481	2.35***
	Std Dev of the Coefficient	2.3540	0.2344	10.04***
Added antioxidants to promote heart health	Mean Coefficient	1.6379	0.5614	2.92***
	Std Dev of the Coefficient	2.6867	0.2544	10.56***
Added compounds to increase energy	Mean Coefficient	1.1455	0.5368	2.13**
	Std Dev of the Coefficient	2.0746	0.2291	9.06**
Stays fresher longer than conventional tofu		1.0377	0.5502	1.89*
		2.4255	0.2696	9.00***
Genetic modification using genes from a Bacterium	Mean Coefficient	-1.0854	0.1890	-5.74***
	Std Dev of the Coefficient	1.7431	0.2075	8.40***
Genetic modification using genes from a different Plant	Mean Coefficient	-1.0708	0.1617	-6.62***
	Std Dev of the Coefficient	1.4974	0.2324	6.44**
Genetic modification using genes from an Animal	Mean Coefficient	-1.8392	0.2296	-8.01***
	Std Dev of the Coefficient	2.3804	0.2913	8.17***
Model statistics				
Log Likelihood	-2265.46			
Restricted Log Likelihood	-2786.45			
Chi Square	1041.98			
DF	39			

*** (α=. 01), ** (α=. 05) and * (α=. 10).

products (i.e., the 54% of those respondents who chose A, B, C, & D).

In the case of benefits and technologies, growing GM banana and soybeans that use less chemicals/pesticides was positive and significant at the 1% level, making environmental benefits a desirable attribute. Direct health benefits derived from bananas and tofu—i.e., added antioxidants for heart health and added compounds to prevent arthritis and joint pains—were also positive and significant. The benefits of compounds added to increase energy, as well as to increase shelf life, was positive and significant for tofu. In the case of pork, pigs requiring fewer antibiotics, meat with added nutrients to promote stronger teeth and bones, and meat with added antioxidants to promote hearth health were positive and significant. Most of the technologies for banana and pork products were not statistically significant except for genetic modification involving pigs' own genes, genetic modification using bacterium, and

Table 3. Parameter Estimates: The Mixed Logit Model: Pork (Normally Distributed Random Parameters).

Variable		Coefficient.	Std error	t-ratio
PRICE		-0.1229	0.0389	-3.16***
Pigs produced using Fewer Antibiotics	Mean Coefficient	1.3440	0.6957	1.93**
	Std Dev of the Coefficient	1.5643	0.2665	5.87***
Added Nutrients to promote stronger teeth and bones	Mean Coefficient	1.6877	0.7178	2.35***
	Std Dev of the Coefficient	1.7136	0.2380	7.20***
Added antioxidants to promote heart health	Mean Coefficient	2.9942	0.8571	3.49***
	Std Dev of the Coefficient	1.9103	0.2435	7.84***
Genetic modification using genes from a Bacterium	Mean Coefficient	-2.0318	0.9437	-2.15***
	Std Dev of the Coefficient	3.1891	0.4066	7.84***
Genetic modification using pig's Own Genes	Mean Coefficient	0.0089	0.8077	0.01
	Std Dev of the Coefficient	2.8461	0.3543	8.03***
Genetic modification using genes from a different Plant	Mean Coefficient	-13.9368	22.6220	-0.62
	Std Dev of the Coefficient	18.5287	20.2993	0.91
Genetic modification using genes from an Animal	Mean Coefficient	-1.1163	0.9662	-1.16
	Std Dev of the Coefficient	3.1179	0.4123	7.56***
Pig fed on genetically modified corn	Mean Coefficient	-0.9635	0.9145	-1.05
	Std Dev of the Coefficient	3.0662	0.3808	8.05***
Model statistics				
Log Likelihood	-1712.97			
Restricted Log Likelihood	-2259.66			
Chi Square	1093.38			
DF	52			

*** (α=. 01), ** (α=. 05) and * (α=. 10).

Table 4. 95% Confidence Intervals for Range of Willingness to Pay for the Normally Distributed Random Attributes.

Lower bound (Limit)				Mean	St. dev.			Upper bound (limit)	
Banana	%							%	
Less chemicals and pesticides	0	1.74	5.05	8.37	3.31	11.68	15.00	95	***
Added antioxidants	4	-2.21	4.68	11.56	6.89	18.45	25.34	91	***
Added compounds	13	-7.38	0.39	8.16	7.77	15.93	23.70	82	***
Bacterium	63	-45.83	-27.24	-8.64	18.59	9.95	28.54	32	***
Own Genes	46	-34.70	-16.97	0.75	17.73	18.48	36.20	49	
Plant Genes	57	-41.58	-23.41	-5.25	18.17	12.92	31.08	38	
Animal genes	68	-54.94	-33.78	-12.62	21.16	8.54	29.70	27	***
Lower bound (Limit)				Mean	St. dev.			Upper bound (limit)	
Tofu	%							%	
Less pesticides	29	-33.93	-10.57	12.78	23.36	36.14	59.49	66	***
Antioxidants	27	-37.06	-10.41	16.25	26.66	42.91	69.57	68	***
Added compounds for energy	29	-29.80	-9.22	11.37	20.58	31.95	52.53	66	***
Stays fresher longer	33	-37.84	-13.77	10.30	24.07	34.36	58.43	62	**
Bacterium	69	-45.36	-28.06	-10.77	17.29	6.53	23.82	26	**
Plant genes	72	-40.34	-25.48	-10.62	14.86	4.23	19.09	23	***
Animal genes	74	-65.48	-41.87	-18.25	23.62	5.37	28.99	21	***
Lower bound (Limit)				Mean	St. dev.			Upper bound (limit)	
Pork	%							%	
Few antibiotics	18	-14.52	-1.79	10.93	12.72	23.66	36.38	77	**
Compounds for stronger teeth and bones	14	-14.15	-0.21	13.73	13.94	27.67	41.60	81	***
Added antioxidants	6	-6.72	8.82	24.35	15.54	39.89	55.43	89	***
Bacterium	73	-414.78	-264.07	-113.36	150.71	37.35	188.06	22	***
Own genes	60	-59.80	-34.44	-9.08	25.36	16.28	41.64	35	
Plant genes	69	-68.41	-42.47	-16.53	25.94	9.41	35.35	26	
Animal genes	47	-46.23	-23.08	0.07	23.15	23.22	46.37	48	
Fed on genetically modified corn	58	-57.72	-32.78	-7.84	24.94	17.10	42.04	37	

*** (α=. 01), ** (α=. 05) and * (α=. 10).

genetic modification involving genes from a different animal. All the technologies—i.e., genetic modification involving genes from a different animal or different plant, and genetic modification using a bacterium—were negative and significant in the case of tofu.

The significant and positive product benefits had a welfare-improving effect on a GM food choice. The negative coefficients on technology imply that moving from 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. Animal genes, bacterium, and in some cases plant genes had a negative effect on choice.

Results of consumer's willingness to pay are presented in Table 4; the results show the monetary values of 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 percentage change in price; accordingly, the numbers generated are also in percentage terms (% change in price will reflect the willingness to pay in percentage terms). 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), and 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).

In the case of bananas, the attributes of using less pesticides and chemicals to grow bananas, added antioxidants to promote heart health (a direct human benefit), and a banana with added compounds to fight arthritis and joint pains were valued positively. The respondents were willing to pay between 8% and 12% more than the current price to obtain such benefits. Conversely, in case of technology respondents required a compensation of 9% and 12 %, respectively, to accept a banana genetically modified by either bacterium or animal genes. Given the normality assumption for attributes, at the same price, 82–95% of the respondents placed a positive valuation on the three banana benefits made possible by genetic modification. On the other hand, about 63–68% of the respondents placed a negative valuation on a banana genetically modified using bacterium and animal genes.

Similar to bananas, all four tofu benefits were valued positively by respondents. The benefits were less pesticides, added antioxidants, added compounds, and increased shelf life. Assuming normally distributed attributes, the results show about 25 to 30% of the respondents could have valued these benefits negatively. In the case of pork, more respondents placed a positive valuation for the benefits of added compounds for stronger teeth and bones, reduced use of antibiotics in pork production, and added antioxidants for heart health (77–89%). Less than 20% of the respondents valued the three benefits negatively. A majority of respondents valued genetic modification involving bacterium negatively.

Conclusions

The study results show that choice-modeling experiments provide a way of valuing non-monetary attributes associated with consumption of GM food products while providing a more precise way of identifying consumer preferences. The products analyzed were bananas (a fresh plant product), tofu (a processed plant product), and pork (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 consumers make tradeoffs between the product attributes.

The results suggest that across products, direct health, environmental, and production benefits have a positive effect on choice. In general, genetic modification is viewed negatively. However, respondents were able to rank the GM processes, with own and plant-based genetic modification more readily acceptable than genetic modification involving bacterium and animal genes. 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 will 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 proceed 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; different products are capable of delivering different set of valuation of attributes with differing acceptance results. Ethical and socioeconomic variables have not been included in these experiments; besides tangible attributes (benefits and technology), attitudinal variables may add to model robustness. Therefore, future work should explore possibilities of including such variables.

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