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Improving nutrient content through genetic modification: Evidence from experimental auctions on consumer acceptance and willingness to pay for intragenic foods

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Improving nutrient content through genetic modification: Evidence from experimental auctions on consumer acceptance and willingness to pay for intragenic foods

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ABSTRACT

After more than a decade of experience in the global marketplace, genetically modified (GM) foods continue to be controversial. Early GM traits were obtained by transferring genes across species, largely from soil bacteria, and this *transgenic* nature is one dimension of consumer resistance. Recently, breakthroughs have occurred using *intragenic* bioengineering where genes are moved long distances within specie and without antibiotic markers. These new *intragenic* bioengineering methods offer the potential for new commercial crop varieties with traits of direct value to consumers (e.g., enhanced nutrition) without reliance on outside foreign genetic material.

To assess the potential market for new *intragenic* foods, a series of multiple-round random *n*th-price experimental auctions were conducted in the spring of 2007 on randomly chosen adult consumers with randomized food label and information treatments. Using the data collected through the experimental auctions, this dissertation assesses several issues including: (1) consumers' willingness to pay (WTP) for GM food products with and without enhanced antioxidant and vitamin C levels, (2) the impact of controversial and verifiable information on consumers' WTP, (3) the public good value of verifiable information about GM, (4) the welfare impact of alternative labeling policies for GM foods, and (5) the impact of outside-the-auction consumer held product inventories on bids in food experiments.

Results indicate that consumers are willing to pay significantly more for *intragenic* GM vegetables with enhanced nutrition than for a conventional product. This suggests that there is potential for new *intragenic* foods to find acceptance among consumers and that the food industry for the first time potentially has an incentive to voluntarily label GM foods as GM. The consumer welfare gains from labeling policies that differentiate *intragenic* and *transgenic* are quantified. However, the information available to consumers when making product purchase decisions is shown to have a significant impact on private valuations, thus potentially eroding demand for *intragenic* foods. Verifiable information from independent third-party organizations is shown to have value to consumers through enabling more informed product choices.

CHAPTER 1: GENERAL INTRODUCTION

1.1 Introduction

Since the introduction and deregulation of the first commercially available genetically modified (GM) crops in the mid-90s, many GM crops (e.g., canola, corn, cotton, and soybeans) have been rapidly adopted by producers, surpassing the one-billionth globally planted acre milestone in 2005. Commercial successes of GM during the past decade have been primarily in feed, fiber, and oil crops, but not in food crops with the exception of refined vegetable oils.[1]

Yet, despite the rapid expansion and worldwide market penetration of bioengineered field crops, the adoption of GM crop varieties has been slowed (or largely stalled in some countries) due in part to the staunch opposition of environmental groups and consumer advocacy groups over economic, environmental, and health concerns and general uncertainty about future outcomes (for reviews see Herdt, 2006; Van den Bergh and Holley, 2002). This contentious debate over genetic modification encompasses a wide array of interested parties who have disseminated information into the public domain with positions on GM foods spanning the spectrum from "frankenfoods" to "foods to feed the world" (e.g., Lewis, 1992; Gates, 2000). Given uncertainty and the presence of private information by interested parties, it is questionable whether consumers can make fully informed decisions regarding GM foods due to the incomplete and asymmetric characterization of publicly available information. However, in this

[1] When raw plant oils from crops such as soybean, corn, cotton and canola are refined, the resulting product is a pure lipid or fat, and hence, the chemical content is exactly the same in oils made from GM and non-GM crops.

conflicted information environment, independent third-party information may have value to both consumers and producers and serve as a moderating force (Rousu et al., 2007).

The early GM crops were all transgenic, i.e., genes from a different organism (typically soil bacteria) were transferred into commercial crop varieties to introduce a trait of interest (e.g., herbicide tolerance or insect resistance). This transgenic nature of genetically modified organisms (GMOs) has been one dimension of consumer resistance to GM – raising biodiversity, environmental, ethical, and safety concerns – and has been a factor in the larger controversy surrounding GM. Because of continued opposition to transgenic GM crops and foods, a new line of biotech research has emerged to quickly transfer genes a long distance across the same species, i.e., intragenic GM technology. For example, a potato is very difficult to manipulate with conventional plant breeding methods, but biotech methods can be used to rapidly move genes from primate potato varieties to commercial varieties. Thereby genomic and metabolic pathway discoveries can be rapidly introduced into established commercial varieties to fast-track the breeding processes. Not only does this new GM technology not transfer foreign DNA, but it also does not use antibiotic markers to identify the location of inserted genes.[2] These are all proffered reasons by biotechnology companies for a low regulatory hurdle.

A second neoteric development tied to intragenic breakthroughs is a renewed interest by some bioengineering companies to develop GM food crops with "product-enhanced consumer attributes" (henceforth abbreviated PECA) or traits that directly benefit consumers. With the exception of the short-lived marketing attempts in the mid-

[2] For a more technical overview of intragenic versus transgenic engineering see Rommens et al. (2004).

90s of the "Flavr-Savr tomato" and a "high solids tomato" produced by Zeneca, commercially successful GM crops in the US have possessed input traits (traits that reduce either the cost of production or the variance in the cost of production to farmers), and hence, have only benefited consumers to the extent that they have lowered food prices.[3] With new intragenic GM techniques it is feasible to dramatically enhance product attributes in horticulture crops, such as antioxidant and vitamin content, thus developing new foods with attributes of direct value to consumers. Although it is possible to introduce these attributes using transgenic methods, new intragenic GM methods are promising because they only move genes within specie and not across species as in transgenic GM methods. Hence, intragenic GM horticultural crops are free of one of the major negative attributes that has hindered transgenic crops.

The emergence of intragenic engineering opens a new chapter in the scientific investigations of consumers' acceptance of GM foods. This is the first study to explore consumer and regulatory issues related to intragenic engineering. The central objective of this dissertation is to assess consumers' willingness to pay for food products that contain improved nutrient content through genetic modification. The new food products considered are fresh vegetables – russet potato, beefsteak tomato, and broccoli – developed using intragenic or transgenic engineering with or without enhanced levels of antioxidants and vitamin C. A set of unique food experiments were designed and conducted to gather information to assess consumers' willingness to pay for these new food products.

[3] This indirect value of genetic modification to consumers has been estimated to be quite sizable by Falck-Zepeda, Traxler, and Nelson (2000) and Moschini, Lapan, and Sobolevsky (2000).

To complement the primary aim of the dissertation in assessing consumer acceptance of GM foods with enhanced nutrition, a number of additional research questions are explored to further our understanding of the existing and potential market for transgenic and intragenic foods. While consumers' view of GM Free food products as being weakly superior to transgenic GM foods has been well documented, little research has addressed exactly what aspect of the production of GM food products results in this inferiority. Namely, *is the inferiority of transgenic GM due to the use of genetic techniques for producing a product that likely would not otherwise appear in nature, the utilization and presence of foreign genetic content, or a combination of both factors*? The answer to this question rests squarely on whether consumers place a different value on intragenic food products when compared to otherwise equivalent transgenic food products.

Furthermore, while past attempts in marketing GM food products with enhanced consumer attributes have been largely unsuccessful, *do consumers respond favorably to genetic modification that yields more readily understandable and quantifiable attributes that are desirable by consumers such as improved nutrition?*

As well, while there is voluminous information regarding the benefits and dangers of genetic modification, there is a relative void of information in the public domain, pro and con, regarding the differences between intragenics and transgenics. As the debate angles in this new direction, *what is the impact of diverging views and information on consumer valuations and what is the value of this new information to consumers?*

Finally, as new intragenic food products are introduced into the marketplace, regulators will be faced with the question of how these new products should be labeled.

Given consumers' preferences towards different types of genetic modification, *what are the welfare effects of alternative labeling policies for intragenic foods?*

This dissertation serves to address these and other questions critical to our understanding of the potential market for intragenic GM foods utilizing data collected from a unique set of experimental auctions designed to elicit consumers' willingness to pay (WTP) for fresh vegetables (broccoli, beefsteak tomatoes, and russet potatoes) produced through varying types of genetic modification. The experimental procedure, which is described in detail in chapter 2, is innovative in several regards. We incorporate and refine both standard experimental procedures (e.g., see Shogren et al., 1994; Lusk et al., 2001) and the advances of Rousu et al. (2007). First, we use adult consumers from two distinct geographic regions that were drawn from a random phone book sample. This ensures our results are not artifacts of a single geographic region. Second, we chose not to endow participants with products and have them bid to upgrade to another product (e.g., see Alfnes and Rickertsen, 2003). Using this method, session monitors have potentially induced significant "endowment effects" by emphasizing the personal gift nature of the in-kind transfer to them (e.g., Corrigan and Rousu, 2006a; Plott and Zeiler, 2007). Third, we use the *n*th-price auction mechanism (Shogren et al., 2001) which has been shown to be a demand revealing mechanism that better engages off-margin bidders (e.g., Fox, Hayes, and Shogren, 2002). Fourth, we randomize all food labels to eliminate sequencing effects. Finally, in many previous experiments where information is disseminated to participants (e.g., Lusk et al., 2004; Rousu et al., 2007), each "group" receives the same information treatment. In our experiment, we disseminate multiple information treatments within the same "group". This helps ensure that the treatment effect is not tainted by a "group effect".

The experimental auction bid price data, which is summarized in chapter 3, reveals several insights into consumers' valuations for fresh intragenic vegetables. Most notably, we find that consumers are willing to pay a premium for fresh intragenic vegetables with enhanced nutritional content over non-GM alternatives without enhanced nutrition. However, the premium is greatly affected by the information available to consumers when they are placing their bids.

While the unconditional analysis of bid prices presented in chapter 3 is suggestive of the impact of controversial information (pro- and anti-GM) and verifiable third-party information on consumers' WTP for different types of intragenic and transgenic foods, several potential confounding factors are not controlled for. In order to better isolate the impact of controversial and verifiable information on WTP, a Bayesian seemingly unrelated regression Tobit model is estimated in chapter 4. As is discussed in chapter 4, the utilized regression model simultaneously incorporates a number of relevant econometric features that are typically left unmodeled in studies of auction bid price data. Estimates from the econometric model further reveal the impact of information on consumers' WTP and suggests that the success of intragenic foods in the marketplace will be greatly affected by the flow and nature of information about the new technology injected into the public domain.

While the analysis of the bid price data in chapters 3 and 4 yields strong evidence on the impact of information, a critical question is what the actual value of this information is to consumers. Information is vital for consumers to be able to make optimal purchase decisions maximizing welfare. Under incomplete or asymmetric information, consumers may not, ex-post, make "correct" purchase decisions resulting in welfare losses. In chapter 5 a theoretical and empirical framework is developed to estimate the value of independent verifiable information to consumers. We find that the value of verifiable information is small. However, when viewed as a percentage of the product price and extrapolated to multiple products and multiple purchase occasions, the public good value of the information is significant. This indicates that independent organizations can not only serve a role informing the public about the benefits and risks of intragenic foods, but also help consumers increase their welfare through making informed product purchase decisions.

While the results of the experimental auction reveal that there is potential demand by consumers for intragenic foods, a key policy question for regulatory bodies is if and how these products should be labeled. Over the past decade one of the most controversial issues surrounding transgenic foods has been labeling. Interested parties, including the biotechnology industry, environmental groups, and domestic regulators, have supported conflicting labeling proposals. This dispute has lead internationally to disparate policies for labeling of GM foods. This labeling issue, which predominately has taken the form of a debate over mandatory versus voluntary labeling regimes, will be faced with an additional complication as intragenic foods attempt to enter the market. Namely, the primary question that regulators will face is: should producers be permitted to differentiate intragenic foods from otherwise equivalent transgenic foods? In chapter 6, the issue of labeling intragenic foods is considered. Specifically, a model is developed to assess consumer welfare under alternative mandatory and voluntary labeling regimes that do and do not permit differentiation of intragenic foods from transgenic alternatives. Empirical estimates reveal that policies that allow labeling of intragenic foods are welfare improving.

Finally, while the results presented in this dissertation exploit the unique richness of experimental auction data (i.e., auctions directly solicit WTP as opposed to choice experiments which indirectly solicit WTP through ex-post analysis of preference relationships), there are two potential drawbacks to auctions in general like those used in this dissertation (and other similar methods as well such as choice experiments and surveys) that have been largely overlooked in the literature. First, experiments are static by nature in that they solicit consumers' preferences at a single point in time (i.e. conditional on the consumers' "state" at that moment in time). Failure to recognize this feature, as is explored in chapter 7, can potentially lead to incorrect interpretation and inference when using experimental data. The second drawback of experiments is their arguably "artificial" nature. In the case of experimental auctions, while theoretically they are demand revealing incentive compatible mechanisms, they clearly do not perfectly mimic the standard markets in which consumers typically interact. This is certainly true of the laboratory style auctions conducted for this dissertation. In chapter 7, we test a specific, and previously unaddressed, aspect of experimental auctions: do consumers assess their willingness to pay and submit bids conditional on their non-monetary endowment arising through transactions outside of the auction? More simply put, ceteris paribus, do consumers who hold inventories of products obtained outside of the auction recognize this endowment and submit lower bids accordingly as standard economics theory predicts? The experimental auction data indicates that the answer is indeed yes.

This, from a practitioner's perspective, is a comforting result and further demonstrates that, even in the artificial market of a laboratory experimental auction, consumers behave as would be expected in a conventional market.

1.2 Dissertation Organization

The dissertation is organized as follows. In the following chapter, a description of the experimental auction procedures is provided. Chapter 3 contains a summary of the auction data as well as an unconditional analysis of bid prices. Chapter 4 develops a regression model - the Bayesian seemingly unrelated regression Tobit model - for conditional analysis of bid prices and the impact of controversial and verifiable information on consumers' product valuations. Chapter 5 extends the analysis of the impact of information on WTP for GM and non-GM foods to assess the value to consumers of verifiable third-party information on genetic modification. Chapter 6 develops a model to assess the welfare effects of alternative labeling regimes for intragenic foods. The model is calibrated using the experimental auction data. Chapter 7 evaluates a previously unanalyzed aspect of consumer decision making in the context of an experimental auction – the impact of outside inventories on bidding behavior. Finally, chapter 8 concludes the dissertation.

CHAPTER 2: DESIGN OF THE EXPERIMENTS

2.1 Introduction

To elicit consumers' willingness to pay for food products produced through different GM and non-GM methods, a series of experimental auctions were conducted in the spring of 2007.[4] The experiments integrated recognized experimental procedures (e.g., Shogren et al., 1994; Lusk et al., 2001; Alfnes and Rickertsen, 2003) and most closely followed the methodology of Rousu et al. (2007) with several improvements upon their procedures. Participants for the study were recruited by an independent survey agency from the general public. Using a random sample of adult consumers, as opposed to university students or personnel, is critical to ensure that the preference data collected through the auctions is representative of the US population. Experiments were conducted in two cities, Des Moines, Iowa and Harrisburg, Pennsylvania. Two geographically separated urban cities were chosen in order to prevent results from being driven based on preferences from individuals in one geographic area. A total of fourteen experimental sessions (eight in Des Moines and six in Harrisburg) were conducted consisting of between nine and seventeen participants each. Across the experiments, a total of 190 individuals participated in a four round auction with three commodities sold in each

[4] The direct financial consequence of consumers' decisions in experimental auctions is a distinct advantage over other commonly utilized methodologies (e.g., contingent valuation and surveys). Many studies (e.g., Brookshire and Coursey, 1987; Cummings, Harrison, and Rutstrom, 1995; List and Shogren, 1998) have shown that individuals' decisions in a hypothetical setting may not necessarily correspond to decisions with actual purchase commitments involving a monetary exchange. A recent study by Noussair, Robin, and Ruffieux (2004) compares hypothetical and non-hypothetical approaches specifically for eliciting consumers' attitudes towards GMOs. Their findings confirm the disconnect between the two approaches and provides strong evidence for using non-hypothetical methods such as experimental auctions.

round. This yielded a total of 2,280 observations (bids). In this chapter a description of the recruitment procedure, participant socio-demographics, and experimental protocol is provided.

2.2 Participant Recruitment[5]

The Center for Survey Statistics and Methodology (CSSM) was contracted to recruit participants for the experiments conducted in Des Moines, Iowa and Harrisburg, Pennsylvania. The sessions in Pennsylvania were conducted on March 24, 2007 in classrooms at the Harrisburg campus of Pennsylvania State University. Six total sessions were conducted at 9:00 am, 11:30 am, and 2:00 pm (two sessions were conducted simultaneously during each time slot). The sessions in Iowa were conducted on April 14, 2007 at the John and Mary Pappajohn Education Center (JMPEC) which is located in downtown Des Moines, Iowa. Eight total sessions were conducted at 8:30 am, 11:00 am, 1:30 pm, and 4:00pm (again, two sessions were conducted during each time slot).

Recruitment goals for CSSM were 196 total participants (190 participants completed the experimental sessions, six individuals short of the recruitment goal). To recruit participants, CSSM purchased telephone samples for Iowa and Pennsylvania from Survey Sampling, International. A total of 2,500 phone numbers were purchased in each state. The sample for Pennsylvania was drawn from a frame consisting of census tracts within a six mile radius of the experiment location. The sample for Iowa was drawn from a frame consisting of census tracts within a three mile radius of the experiment location.

[5] Some of the details on participant recruitment provided in this section are adapted from a final report provided to the author by Jan Larson of CSSM who managed the project's recruitment.

Both frames were comprised of approximately 18,000-19,000 phone numbers. Tables 2.1 and 2.2 provide details for frames and samples in Pennsylvania and Iowa.

Table 2.1 Pennsylvania Frame and Sample

Census Tract	County FIPS	Frame Size	Sample %	Sample Size
023700	42043	303	1.6%	39
023800	42043	858	4.5%	112
023900	42043	1038	5.4%	136
023600	42043	2067	10.8%	269
023500	42043	654	3.4%	85
024001	42043	1426	7.4%	186
020921	42133	839	4.4%	109
023400	42043	352	1.8%	46
022800	42043	1148	6.0%	150
020220	42133	630	3.3%	82
024103	42043	2941	15.3%	383
024400	42043	1239	6.4%	161
022700	42043	1974	10.3%	258
022900	42043	1528	8.0%	199
020910	42133	935	4.9%	122
023300	42043	743	3.9%	97
023000	42043	507	2.6%	66
TOTAL		**19,182**		**2,500**

Table 2.2 Iowa Frame and Sample

Census Tract	County FIPS	Frame Size	Sample %	Sample Size
005100	19153	468	2.6%	65
002700	19153	390	2.2%	54
002600	19153	211	1.2%	29
005000	19153	423	2.3%	59
004200	19153	384	2.1%	53
001200	19153	461	2.6%	64
004900	19153	337	1.9%	47
002900	19153	929	5.2%	129
003200	19153	710	3.9%	99
004800	19153	417	2.3%	58
002800	19153	629	3.5%	87
001100	19153	398	2.2%	55
005200	19153	475	2.6%	66
004300	19153	1334	7.4%	185
004100	19153	780	4.3%	108
001000	19153	840	4.7%	117
001700	19153	425	2.4%	59
004400	19153	712	4.0%	99
001500	19153	552	3.1%	76
004001	19153	537	3.0%	75
000701	19153	432	2.4%	60
003100	19153	407	2.3%	56
004002	19153	743	4.1%	104
000500	19153	864	4.8%	120
000902	19153	742	4.1%	103
004502	19153	582	3.2%	80
000300	19153	692	3.8%	96
003001	19153	518	2.9%	72
003002	19153	815	4.5%	113
000703	19153	804	4.5%	112
TOTAL		**18,011**		**2,500**

Telephone interviewing staff were trained in the project protocols by CSSM professional staff and utilized a fixed recruitment script. There are two important aspects of the phone recruitment protocol/script to note. First, to avoid potential recruitment/participation bias and to ensure that participants were not affected by possible pre-experiment information, during phone interviews recruiters did not provide any specific details regarding the nature of the project. Potential participants were only informed that it was a project on consumer attitudes towards common household products being conducted by Iowa State University and Pennsylvania State University. Second, while two individuals from the same household were permitted to attend the experiments, they were required to attend during the same experiment time slot and were assigned to different session rooms. This ensured that no potentially biasing information could be passed between household members. Details on recruitment telephone number attempts and dispositions are presented in table 2.3.

Table 2.3 Telephone Numbers Attempts and Dispositions

	Pennsylvania		**Iowa**	
Answering Machine.	860	36.60%	622	36.80%
No Answer	131	5.60%	120	7.10%
Not in Service	130	5.50%	152	9.00%
Agree	63	2.70%	85	5.00%
Refuse	873	37.10%	390	23.10%
Not 18-65	125	5.30%	162	9.60%
No adult home	72	3.10%	62	3.70%
Busy	73	3.10%	55	3.30%
Business/Fax/Other Non-HH	20	0.90%	19	1.10%
No English	5	0.20%	22	1.30%
TOTAL	2352	100.00%	1689	100.00%

2.3 Steps in the Experiment

In this section the steps of the experiments are described. The full packet of questions and information treatments provided to participants is reproduced in the dissertation appendix.[6]

Auction Step I

Upon arrival at the experiment site,[7] participants were alternately assigned to one of two concurrent sessions, and relatives were assigned to different sessions; each session consisted of 9-17 individuals and lasted approximately 90 minutes. They were asked to sign a consent form and were paid $45 dollars for their participation. Next, they were asked to complete a short questionnaire soliciting socio-demo-economic information and to answer a few questions about agricultural technologies.

Auction Step II

Participants were informed by the session leader that they would be engaging in an auction of food products. They were told that the auction would consist of four rounds

[6] The experimental packet presented in the dissertation appendix was used in the Iowa experiments. The packet is identical to that used in the Pennsylvania experiments with one exception. Three additional questions (questions 25, 26, and 27) were added to the post-experiment questionnaire in the Iowa experiments only. These three questions, which are further explored in chapter 7 of the dissertation, were inserted at the very end of the experiment questionnaire and would not have affected the preceding components of the experiment.

[7] Many experimental studies are now being conducted in settings that are more familiar to consumers (e.g., Lusk, Pruitt, and Norwood, 2006; Monchuck et al., 2007). We also considered the possibility of using an intercept sample in a grocery store in a "framed field experiment" (Harrison and List, 2004), but the length of the experiment prohibited that option.

of bidding, but only one round would be binding and it would be randomly chosen after all bids were submitted. This accomplishes two things. First, it reduces participants' concerns about exceeding their resources (the $45 dollars plus any cash they brought with them to the experiment). Second, it fixes the idea that they are bidding on only one unit of each of the auctioned commodities despite multiple bidding rounds. This eliminates potential demand effects associated with multiple purchases.

Auction Step III

Participants were provided with instructions and examples about the auction method utilized in the study: the *n*th-price auction (Shogren et al., 2001, Huffman et al., 2007). In this type of auction, all individuals who bid higher than the randomly selected "*n*th-price" win the auction and pay the *n*th-price for the commodity. For example, suppose that there are *k* bidders. Following the submission of bids, the session leader draws the "random *n*" from a uniform distribution between 2 and *k*. The "*n*th-price" would be the *n*th highest bid. The *n-1* individuals who submitted bids greater than the *n*th-price would win the auction and each would pay the *n*th-price for one unit of the auctioned commodity.

The *n*th-price auction has a key advantage over the more common Vickrey sealed bid second-price auction mechanism (Vickrey, 1962) in that it has been shown to better engage off-margin (i.e., low-value) bidders. Insincere bidding by low-value individuals may occur in Vickrey auctions because the consumer may perceive no realistic probability of winning the auction. Hence, low value-bidders may perceive that they can freely alter their bid away from their true private value without repercussion (see Miller and Plott, 1985; Franciosi et al., 1993). By combining elements of the Vickrey auction and the Becker-Degroot-Marschak (1964) random pricing mechanism,[8] the *n*th-price auction incorporates a random endogenously determined market clearing price. This feature of the *n*th-price mechanism has the advantage of yielding all participants (including off-margin bidders) a positive probability of winning the auction while maintaining the dominant strategy of bidding one's private value.

Auction Step IV

Participants engaged in a practice two round *n*th-price auction with candy, pens, and pencils to gain experience with the *n*th-price auction. After completion of the practice auction, any final questions regarding the mechanism were answered.

Auction Step V

Participants were randomly provided one of five information treatments. The information treatments included: [9]

1) *No Information* - as a control group.

2) *Industry (Pro-Biotech) Perspective* - a collection of mainly positive or optimistic statements and information on GM provided by a group of leading biotechnology companies.

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[8] The Becker-Degroot-Marshak (1964) mechanism is also demand revealing, but the random *n*th-price auction has been shown to be more accurate at revealing preferences in experiments, potentially due to the endogenous clearing price (e.g., Lusk and Rousu, 2007).

[9] Throughout this dissertation, the following terms will be used synonymously to refer to types of information: 1) industry, positive, and pro-biotech, 2) environmental, negative, and anti-biotech, and 3) verifiable, independent, and 3rd party.

3) *Environmental (Anti-Biotech) Perspective* - a collection of mainly negative statements and information on GM from leading environmental groups.

4) *Industry and Environmental Perspectives* - information statements 2 and 3.

5) *Industry, Environmental, and Third-Party (Verifiable Information) Perspectives* - this included statements 2 and 3 as well as an objective statement on GM approved by a third-party group consisting of a variety of individuals knowledgeable about GM foods, including scientists, professionals, religious leaders, and academics, none of whom has a financial stake in GM foods.

To ensure that the volume of information contained in the perspectives on GMOs was not overwhelming to participants, each perspective was limited to one 8 1/2"x11" sheet of paper and organized under five common headings: General Information, Scientific Impact, Human Impact, Financial Impact, and Environmental Impact. For information treatments consisting of more than one perspective, the order in which the pro-biotech and anti-biotech perspectives were presented was randomized. The verifiable perspective was always presented last. Reproductions of the information treatments provided to auction participants are provided in the dissertation appendix.

Auction Steps VI-IX

Each participant engaged in an auction consisting of four rounds of bidding. In each round, participants were asked to place bids on three dissimilar fresh products: one pound of broccoli, one pound of beefsteak tomatoes, and five pounds of russet potatoes. Three products were chosen to provide some variety and increase the proportion of useful information, i.e., non-zero bids. We judged that most participants would be willing to post a positive bid for at least two of the three products.

Products were presented in plain packaging similar to how they are found in a grocery store, and a simple label was affixed. In each bidding round, the three commodities with labels were revealed on a table in the front of the lab. In half of the sessions (3 in Harrisburg and 4 in Des Moines), the four food labels (one in each round) were: GM Free, Intragenic GM, Transgenic GM, and Plain Label.[10] See figure 2.1 for examples of these labels. In the other half of the sessions (seven total), the first three rounds of the auction[11] had products with food labels of either GM, Intragenic GM, or Transgenic GM, but they also presented additional information: "Enhanced levels of Antioxidants and Vitamin C". See figure 2.2 for examples of these labels.

Figure 2.1 Examples of Auction Food Labels for Products Without Enhanced Consumer Attributes

Russet Potatoes (5 lb.)	Russet Potatoes (5 lb.) GM Free Product
Russet Potatoes (5 lb.) Intragenic GM Product	Russet Potatoes (5 lb.) Transgenic GM Product

[10] For each of the labels, the name of the product (e.g. Russet Potatoes) and the product weight was listed. The phrase "Plain label" is used to describe a label that only contains this information without any description of genetic modification that may or may not be present.

[11] The label treatment in the fourth round of these sessions was a plain label product. This alternative always appeared in the fourth round of the auction and does not affect bids in the earlier three rounds. Bidding data for this fourth bidding round is not used in this dissertation.

Figure 2.2 Examples of Auction Food Labels for Products With Enhanced Consumer Attributes

Russet Potatoes (5 lb.) Enhanced levels of Antioxidants and Vitamin C GM Product	Russet Potatoes (5 lb.) Enhanced levels of Antioxidants and Vitamin C Intragenic GM Product	Russet Potatoes (5 lb.) Enhanced levels of Antioxidants and Vitamin C Transgenic GM Product

All three products within a round of bidding had the same food label, and the order in which labels were presented was randomized across sessions. After a set of experimental products was revealed, participants were asked to come to the front of the room and view the products before writing down their three bids. These bids were then collected by the session monitor before proceeding to the next round of bidding.

Auction Step X

After completion of all bidding rounds, the binding round was drawn, bids were posted and ranked on a whiteboard in the front of the lab (no bids were posted prior to this point), the random *n* was drawn to determine the clearing price, and winners were identified. Participants completed a short exit questionnaire. Winners were told to go to an adjacent room to complete their purchases, exchanging money for goods.[12] Non-winners were told that they had completed the project and were free to leave.

[12] Given the incomplete regulatory status of the intragenic foods, we were unable to obtain the product-enhanced GM fresh vegetables to deliver to winners. As an alternative, winners were given plain-labeled food products, which is similar to procedures followed by others in similar circumstances, e.g., Alfnes and Rickertsen (2003) and Tonsor et al. (2005). Reception to the experiments was positive, and no complaints from participants were received.

2.4 Auction Participant Questionnaire Responses

The pre- and post-auction questionnaires completed during the experimental sessions solicited socio-econo-demographic information from the participants in addition to measures of participants' attitudes towards genetic modification. A summary of responses is provided in table 2.4. The sample is 68% female, the mean age is 44 years, mean education is 14.5 years, and mean household income is $51,000.

Only 11% of the participants consider themselves well or extremely well informed about GM while over 50% of the sample consider themselves not very or not at all informed about GM. Only 17% report an opinion of GM that is supportive or strongly supportive while 23% report an opinion of GM that is in opposition or strongly in opposition. Responses to these two questions reflect the general division over genetic modification and the great deal of uncertainty among consumers over the benefits and risks of these products despite more than a decade of GM cultivation.

While consumers may be divided and uncertain about GM, 63% did report that they often or always read food labels. This underscores the importance and potential impact of food labeling policies on demand for GM foods. Regarding lifestyle indicators, 23% report that they smoke, and 51% report exercising regularly. On a 1 to 10 scale, self-assessed healthiness of their diet receives a mean score of 6.7, and for self assessed physical health, the mean is 7.2.

Table 2.4 Summary Statistics for Auction Participants (N=190)

Variable	Variable Definition	Mean	Stdev
Gender	1 if female	0.68	0.47
Age	Participant's age	44.33	15.80
Income	Household income (in 1000s)	51.09	35.23
Education	Years of schooling completed	14.47	2.26
Married	1 if married	0.53	0.50
Household	Number of people in household	2.74	1.41
Race	1 if participant is white	0.85	0.36
Informed	1 if well or extremely well informed about GM	0.11	0.31
Opinion	1 if opinion towards GM is supportive	0.17	0.38
Read_Labels	1 if often or always read food labels	0.63	0.48
Envi_Mem	1 if member of environmental group	0.04	0.20
Farm	1 if previously/currently engaged in farming	0.04	0.21
Smoke	1 if smoke	0.23	0.42
Exercise	1 if exercise regularly	0.51	0.51
Health_Diet	Self assessed healthiness of diet (1-10 scale)	6.73	1.61
Health_Phys	Self assessed physical health (1-10 scale)	7.16	1.69

2.4.1 Who Do Consumers Trust for Information about Food

Since the emergence of genetically modified foods in world markets, information campaigns by interested parties have played a role in shaping consumer perceptions about the safety and health impacts of GM foods. Ultimately, through its impact on public perceptions, information has influenced GM regulatory decisions internationally. The predominant sources of information about food safety and healthiness, particularly with regards to GM, fall into three major categories: biotechnology companies, environmental groups, and government organizations. Groups in each of these general categories have disseminated differing perspectives and information on GM into the public domain. To assess who consumers trust for food information, part of the survey instrument completed by the 190 participants in the experiments asked respondents to rank different sources of information based upon who they most trust to provide information about (a) food safety and (b) the healthiness of food. The questions are reproduced below.[13]

Please rank the following three organizations in order of who you trust most to provide information regarding food safety (1 = Most trusted, 3 = Least trusted). ***Please use each number (1, 2, and 3) only once.***
____ *Leading Environmental groups (ex. Greenpeace and Friends of the Earth)*
____ *Leading Biotechnology Companies (ex. Monsanto and Syngenta)*
____ *Government organizations (ex. USDA and FDA)*

Please rank the following three organizations in order of who you trust most to provide information regarding the healthiness of food (1 = Most trusted, 3 = Least trusted). ***Please use each number (1, 2, and 3) only once.***
____ *Leading Environmental groups (ex. Greenpeace and Friends of the Earth)*
____ *Leading Biotechnology Companies (ex. Monsanto and Syngenta)*
____ *Government organizations (ex. USDA and FDA)*

Survey respondents were largely split between environmental groups and government organizations as their most trusted source for providing information about food safety (48% and 43% respectively). Only 9% stated that their most trusted source for food safety information is biotechnology companies. Mirroring these responses, respondents overwhelming listed biotechnologies as their least trusted source for food safety information (58%) and where divided between environmental groups and government organizations (18% and 24% respectively).

Rankings of sources for information about the healthiness of food largely match the rankings for food safety information. Government organizations were the most trusted source (46%), followed by environmental groups (45%), and then biotechnology companies (9%).

[13] The order in which these two questions were presented was randomized across surveys. As well, the order of the three ranking options was also randomized across surveys.

To assess the individual-specific factors that influence respondents' choice of most trusted information source, a multinomial logit model is estimated.[14] The multinomial logit model can be derived fundamentally from a random (indirect) utility model (RUM) framework. The utility individual *i* derives from alternative *j* is given by

(1) $$U_{ij} = \beta' x_{ij} + \varepsilon_{ij}, \quad j = 1,2,...,J \text{ ,}$$

where ε_{ij} is assumed to be *iid* extreme value. The individual chooses the alternative *j* that yields the greatest utility. Defining this choice as

(2) $$y_{ij} = \begin{cases} 1 & U_{ij} > U_{ik} \ \forall k \neq j \\ 0 & else \end{cases},$$

the probability of an individual *i* choosing alternative *j* can be shown to equal

(3) $$P_{ij} = \frac{\exp(\beta' x_{ij})}{\sum_{k=1}^{J} \exp(\beta' x_{ik})} .$$

Finally, the log-likelihood function can be expressed as

(4) $$LL(y \mid \beta, x) = \sum_{i=1}^{N} \sum_{j=1}^{J} y_{ij} \ln(P_{ij}) .$$

Given the simple form of the likelihood function for the multinomial logit and that it is globally concave for a linear indirect utility specification, maximum likelihood estimation is simple in practice.

Table 2.5 presents estimates of the model for both the food safety and food healthiness questions. In both models, the base choice is government organizations. Regressors in the models include a number of socio-demographic variables and responses

[14] Given that there is no variation in attributes across the choice alternatives the full information contained in the rankings cannot econometrically be exploited via alternative estimation methods (e.g., a ranked logit).

to two questions that asked respondents (a) how informed they are about genetic modification and (b) their opinion towards genetic modification.

Table 2.5 Estimates for Multinomial Logit Models of Who Consumers Trust Most for Food Information (N=190 per model)

	Food Safety Model		Food Health Model	
Variable	Envi	Bio	Envi	Bio
Age	0.011	0.035	0.009	0.011
	(.011)	(.024)	(.011)	(.018)
Gender	0.345	-0.702	0.513	-0.357
	(.37)	(.653)	(.377)	(.56)
Income	-0.004	0.135	-0.001	-0.014
	(.054)	(.119)	(.055)	(.089)
Education	0.113	0.307	0.071	0.205
	(.12)	(.233)	(.122)	(.196)
Health Diet	0.064	-0.002	0.049	-0.272
	(.107)	(.22)	(.11)	(.176)
Informed 1[a]	-1.084*	-1.018	-1.115*	0.929
	(.579)	(.974)	(.587)	(.81)
Informed 2[b]	-0.468	-1.061	-0.542	-0.181
	(.381)	(.694)	(.381)	(.646)
Opinion 1[c]	-0.398	-0.554	-0.337	-0.893
	(.514)	(.848)	(.536)	(.789)
Opinion 2[d]	1.027**	-0.680	1.085**	-0.181
	(.435)	(1.141)	(.437)	(.853)
Constant	-1.543	-1.796	-1.684	-0.252
	(1.108)	(1.093)	(1.134)	(1.685)
Log-likelihood		-158.48		-149.04
LR Statistic		26.19		31.70
p-value		0.095		0.024

[a] Denotes a response of being well or extremely well informed about GM
[b] Denotes a response of being not very or not at all informed about GM
[c] Denotes a response of being supportive or strongly supportive of GM
[d] Denotes a response of being opposed or strongly opposed to GM
(*), (**), and (***) denote variable significant at 10%, 5%, and 1% respectively

While both models are statistically significant at the 10% level, few explanatory variables are individually significant. None of the explanatory variables are able to significantly explain why some individuals have greater odds of trusting biotechnology companies over government organizations. As well, across all of the models and choice alternatives, none of the socio-demographic variables offer any statistically significant explanation for choices. However, for both models (food safety and food health information), individuals who consider themselves well or extremely well informed about genetic modification have a greater odds of trusting government organizations over environmental groups for food information. In contrast, individuals who oppose or strongly oppose genetic modification have a much greater odds of trusting environmental groups over government organizations.

2.4.2 Prior Opinions and Knowledge about Genetic Modification

Despite more than a decade of experience with genetically modified foods and a wealth of publicly injected information about the benefits and hazards of GMOs, consumer confusion about GM still persists. Two questions were included in the survey instrument to assess how knowledgeable individuals consider themselves about GM and their opinion towards GM.

Regarding genetically modified foods, how informed do you consider yourself?
1 = Extremely well informed
2 = Well informed
3 = Somewhat informed
4 = Not very informed
5 = Not informed at all

Which statement best describes your opinion towards genetically modified food?
1 = Strongly support
2 = Support
3 = Neutral
4 = Oppose
5 = Strongly oppose

Among the 190 survey respondents, only 11% consider themselves well or extremely well informed about GM. More individuals stated that they were not informed at all about GM (15%). As well, only 40% of respondents stated that they have a non-neutral opinion towards GM (17% supportive, 23% opposed, and 60% neutral). In this section we analyze survey responses to assess the impact of individual-specific factors affecting opinions towards and knowledge of GM. To account for the ordinal nature of response alternatives, ordered probit models are estimated.

The ordinal probit model can be motivated via a latent variable specification. Define the latent variable y_i^* as

$$y_i^* = \beta' x_i + \varepsilon_i . \tag{1}$$

An individual's response of category *k* is observed if the underlying latent continuous response occurs in the *k*-th interval where

$$y_i = \begin{cases} 0 & if \quad y_i^* \le 0 \\ 1 & if \quad 0 < y_i^* \le \mu_1 \\ 2 & if \quad \mu_1 < y_i^* \le \mu_2 \\ 3 & if \quad \mu_2 < y_i^* \le \mu_3 \\ 4 & if \quad \mu_3 < y_i^* \end{cases} , \tag{2}$$

and μ_1, μ_2, μ_3 denote unobserved threshold parameters. Assuming that the unobserved component of the latent variable is normally distributed, $\varepsilon_i \sim N(0,1)$, it follows that the probabilities for each observed ordinal response is

$$
\begin{aligned}
&\Pr[y_i = 0 \mid x_i] = \Phi(-\beta' x_i) \\
&\Pr[y_i = 1 \mid x_i] = \Phi(\mu_1 - \beta' x_i) - \Phi(-\beta' x_i) \\
(3) \qquad &\Pr[y_i = 2 \mid x_i] = \Phi(\mu_2 - \beta' x_i) - \Phi(\mu_1 - \beta' x_i)\,. \\
&\Pr[y_i = 3 \mid x_i] = \Phi(\mu_3 - \beta' x_i) - \Phi(\mu_2 - \beta' x_i) \\
&\Pr[y_i = 4 \mid x_i] = 1 - \Phi(\mu_3 - \beta' x_i)
\end{aligned}
$$

An ordered probit model was estimated for both the opinion and GM knowledge questions. To facilitate interpretation of coefficients, responses were ordered in the following manner:

Response	**Opinion Question**	**Informed Question**
0	Strongly Opposed	Not Informed at all
1	Opposed	Not Very Informed
2	Neutral	Somewhat Informed
3	Support	Well Informed
4	Strongly Support	Extremely Well Informed

Coefficient estimates for both models are presented in table 2.6. Marginal effects and predicted probabilities are presented in tables 2.7 and 2.8.

First, concentrating on the model of respondents' opinion of genetic modification, we see that, as would be expected, individuals who are members of environmental groups have a significantly higher probability of being opposed to GM. As well, individuals who consider themselves poorly informed about genetic modification have a greater probability of being opposed to GM. While not significant at the 10% level, individuals who are more informed about GM have a marginally positive opinion. This is an interesting result providing some evidence that in the absence of knowledge, consumers tend to take a negative outlook on GMOs.

Table 2.6 Estimates for Ordered Probit Models of Consumers' Opinion and Knowledge of GM (N=190 per model)

Model	Opinion of GM		Knowledge of GM	
	Coef	Std. Err.	Coef	Std. Err.
Age	-0.002	0.006	-0.004	0.006
Gender	0.000	0.192	0.284	0.183
Income	-0.031	0.028	-0.012	0.027
Education	-0.021	0.063	0.071	0.060
Health Diet	0.137**	0.057	0.021	0.054
Read Labels	0.077	0.089	0.122	0.085
Envi_Mem	-0.393***	0.118	0.017	0.111
Farm	-0.246	0.217	0.368*	0.208
Informed 1[a]	-0.595**	0.290	-	-
Informed 2[b]	0.287	0.194	-	-
Opinion 1[c]	-	-	-1.013***	0.238
Opinion 2[d]	-	-	-0.133	0.216
Constant	2.144	0.804	0.254	0.768
μ_1	0.675	0.149	0.410	0.117
μ_2	2.727	0.205	1.522	0.164
μ_3	3.659	0.249	2.807	0.195
Log-likelihood	-182.75		-228.93	
LR Statistic	30.27		32.12	
p-value	0.001		0.001	

[a] Denotes a response of being well or extremely well informed about GM
[b] Denotes a response of being not very or not at all informed about GM
[c] Denotes a response of being supportive or strongly supportive of GM
[d] Denotes a response of being opposed or strongly opposed to GM
(*), (**), and (***) denote variable significant at 10%, 5%, and 1% respectively

Table 2.7 Marginal Effects and Predicted Probabilities for Ordered Probit Model of Consumers' Opinion of GM

Informed Level	Not at All	Not Very	Somewhat	Well	Extremely
Age	0.000	0.000	0.000	0.000	0.000
Gender	0.000	0.000	0.000	0.000	0.000
Income	0.002	0.004	0.001	-0.006	-0.002
Education	0.002	0.003	0.001	-0.004	-0.001
Health Diet	-0.011	-0.018	-0.006	0.026	0.010
Read Labels	-0.006	-0.010	-0.004	0.015	0.005
Envi_Mem	0.031	0.052	0.018	-0.074	-0.028
Farm	0.020	0.033	0.011	-0.046	-0.017
Informed 1[a]	0.070	0.088	-0.035	-0.094	-0.028
Informed 2[b]	-0.024	-0.039	-0.011	0.053	0.020
Predicted Pr.	0.036	0.095	0.693	0.145	0.031

[a] Denotes a response of being well or extremely well informed about GM
[b] Denotes a response of being not very or not at all informed about GM

Table 2.8 Marginal Effects and Predicted Probabilities for Ordered Probit Model of Consumers' Knowledge of GM

Informed Level	Not at All	Not Very	Somewhat	Well	Extremely
Age	0.000	0.000	0.001	-0.001	-0.001
Gender	-0.028	-0.023	-0.061	0.053	0.059
Income	0.001	0.001	0.002	-0.002	-0.002
Education	-0.007	-0.006	-0.015	0.013	0.015
Health Diet	-0.002	-0.002	-0.004	0.004	0.004
Read Labels	-0.012	-0.010	-0.026	0.023	0.025
Envi_Mem	-0.002	-0.001	-0.004	0.003	0.004
Farm	-0.037	-0.030	-0.078	0.069	0.076
Opinion 1[c]	0.175	0.091	0.114	-0.241	-0.139
Opinion 2[d]	0.014	0.011	0.027	-0.026	-0.026
Predicted Pr.	0.048	0.057	0.339	0.430	0.126

[c] Denotes a response of being supportive or strongly supportive of GM
[d] Denotes a response of being opposed or strongly opposed to GM

For the model of respondents perceived level of knowledge about GM, two similar results are found. Individuals who are engaged in occupations related to farming have a significantly higher probability of considering themselves highly informed about genetic modification. As well, mirroring the result found in the previous model, individuals who have largely negative opinions of GM are more likely to consider themselves less informed about GM. This again reinforces the proposition that biotechnology companies have an opportunity to sway public opinion by raising consumer awareness of GM and reducing the still prevalent uncertainty about the technology.

CHAPTER 3: SUMMARY AND ANALYSIS OF BID PRICES

3.1 Introduction

In this chapter we present a first look and analysis of the bid price data obtained through the experimental auctions. Unconditional analysis of consumers' willingness to pay reveals several key results. We find that informed consumers are willing to pay a premium for intragenic fresh vegetables when compared to otherwise equivalent transgenic alternatives. As well, we find that consumers are willing to pay a premium for intragenic fresh vegetables with enhanced nutrition over conventional plain labeled alternatives. This is perhaps the most critical finding of real-world importance in that it indicates that intragenic foods with attributes of direct value to consumers such as enhanced nutritional content have the potential to find acceptance among consumers and offer a viable alternative in the market place to conventional products. Yet, as is abundantly clear in the subsequent presentation, information has a significant impact on relative bid prices. The bidding data indicates that in a conflicted information setting consumers may not consider that the additional benefit of enhanced nutrition sufficiently outweighs the perceived detractors of genetic modification.

It is important to note that while the unconditional analysis of relative bid prices presented in this chapter is suggestive of the potential for intragenic foods, the simple analytic methods employed in this chapter do not control for individual-specific attributes or the methodological features of the experiments. In chapter 4, conditional analysis via an econometric model that controls for these potentially confounding features is presented reaffirming the conclusions drawn in this chapter.

3.2 Summary of Bid Prices

In tables 3.1 and 3.2 participants' bids from the experimental auctions are summarized. Table 3.1 contains the mean and standard deviation of bids for products without product enhanced consumer attributes (PECA) broken down by information treatments. Table 3.2 presents similar results for products with enhanced consumer attributes. To better visualize the distribution of bid prices, figures 3.1 – 3.6 present the inverse CDF of bid prices for each of the auctioned commodities (i.e., the graphs show the percentage of individuals willing to pay a given price for a particular commodity).

Comparing across labeling treatments, it can be seen that in general for all information treatments the preference relation $GM\ Free \succeq Plain\ Label \succeq Transgenic\ GM$ holds for products without enhanced attributes, but the relationship between the Plain Label and Intragenic GM products is not consistent and varies across information treatments. For products with enhanced attributes, the preference relation $Intragenic\ GM \succeq Transgenic\ GM$ in general holds, but the relationship between GM and Intragenic GM fluctuates across information treatments. The absence of a consistent pattern in the relative willingness to pay between the Plain Label and Intragenic products without enhanced attributes and the GM and Intragenic GM products with enhanced attributes across the different information treatments is to be expected given the dichotomous views contained in these perspectives. The following section and chapter 4 will further explore the preference relations between the different labeling treatments for products with and without enhanced nutrition.

Table 3.1 Mean Bid Prices for Foods Without Enhanced Consumer Attributes

Broccoli (1 lb.)				Tomato (1 lb.)				Potato (5 lb.)			
Plain	GMF	Intra	Trans	Plain	GMF	Intra	Trans	Plain	GMF	Intra	Trans
All Treatments (N=92)											
1.28	1.46	1.42	1.20	1.38	1.52	1.36	1.18	2.16	2.34	2.16	2.00
(0.76)	(0.77)	(0.86)	(0.78)	(0.98)	(0.91)	(0.97)	(0.87)	(1.16)	(1.16)	(1.23)	(1.22)
No Information (N=17)											
1.38	1.69	1.54	1.37	1.39	1.47	1.35	1.25	1.99	2.36	2.03	2.07
(0.61)	(0.82)	(0.70)	(0.66)	(1.08)	(1.04)	(0.88)	(0.83)	(0.84)	(1.05)	(0.79)	(0.88)
Pro-biotech Information only (N=20)											
1.30	1.37	1.74	1.24	1.49	1.46	1.62	1.29	2.33	2.33	2.54	2.21
(0.90)	(0.71)	(0.83)	(0.83)	(1.16)	(0.88)	(1.01)	(1.06)	(1.22)	(1.15)	(0.99)	(1.23)
Anti-biotech Information only (N=17)											
1.21	1.60	1.07	1.14	1.24	1.67	0.95	0.98	2.19	2.71	1.84	1.81
(0.72)	(0.73)	(0.83)	(0.84)	(0.93)	(0.97)	(0.81)	(0.74)	(0.85)	(0.96)	(1.20)	(1.13)
Pro-biotech & Anti-biotech Information (N=21)											
1.45	1.58	1.56	1.22	1.48	1.73	1.60	1.25	2.34	2.43	2.45	2.18
(0.79)	(0.76)	(0.99)	(0.76)	(0.86)	(0.87)	(1.11)	(0.83)	(1.19)	(1.14)	(1.42)	(1.22)
Pro-biotech, Anti-biotech, and Verifiable Information (N=17)											
1.03	1.07	1.08	1.03	1.23	1.22	1.19	1.09	1.86	1.86	1.83	1.66
(0.73)	(0.76)	(0.78)	(0.84)	(0.93)	(0.82)	(0.87)	(0.88)	(1.56)	(1.42)	(1.51)	(1.59)

Note: Standard deviation in parenthesis

Table 3.2 Mean Bid Prices for Foods With Enhanced Consumer Attributes

Broccoli (1 lb.)			Tomato (1 lb.)			Potato (5 lb.)		
GM	Intra	Trans	GM	Intra	Trans	GM	Intra	Trans
All Treatments (N=98)								
1.51	1.67	1.45	1.42	1.76	1.41	2.45	2.61	2.27
(1.01)	(1.14)	(1.01)	(0.86)	(1.26)	(0.97)	(1.76)	(1.84)	(1.96)
No Information (N=20)								
1.91	1.86	1.83	1.65	1.95	1.73	3.18	3.20	3.23
(1.54)	(1.16)	(1.28)	(1.23)	(1.34)	(1.32)	(3.06)	(2.73)	(3.40)
Pro-biotech Information only (N=18)								
1.63	2.52	1.79	1.81	2.64	1.90	2.73	3.49	2.65
(0.65)	(1.20)	(0.68)	(0.70)	(0.94)	(0.68)	(1.00)	(1.89)	(1.35)
Anti-biotech Information only (N=18)								
1.25	1.07	1.06	1.23	1.10	0.98	2.12	1.92	1.71
(0.82)	(0.89)	(0.89)	(0.69)	(0.66)	(0.63)	(1.46)	(1.34)	(1.37)
Pro-biotech & Anti-biotech Information (N=20)								
1.67	1.84	1.63	1.36	1.74	1.43	2.54	2.64	2.34
(0.87)	(1.15)	(1.04)	(0.67)	(1.32)	(1.04)	(1.14)	(1.45)	(1.24)
Pro-biotech, Anti-biotech, and Verifiable Information (N=22)								
1.10	1.16	0.97	1.11	1.44	1.05	1.74	1.90	1.48
(0.77)	(0.70)	(0.74)	(0.75)	(1.38)	(0.72)	(0.98)	(0.87)	(0.97)

Note: Standard deviation in parenthesis

Figure 3.1 Inverse CDF of Bid Prices for Broccoli Without PECA

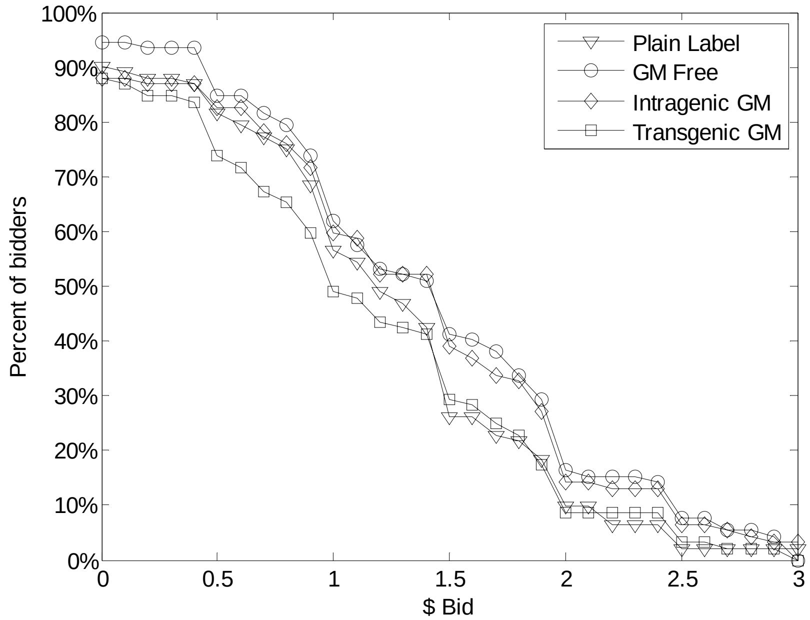


Figure 3.2 Inverse CDF of Bid Prices for Tomato Without PECA

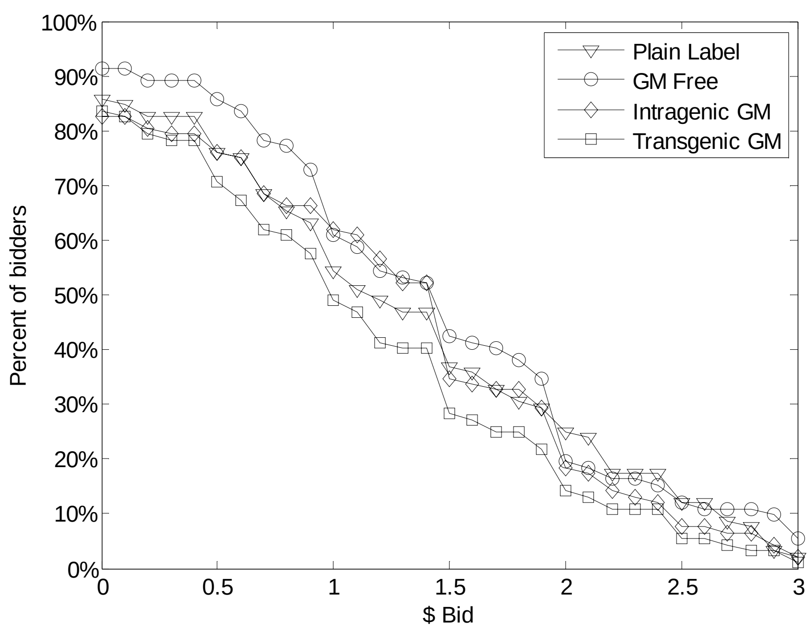


Figure 3.3 Inverse CDF of Bid Prices for Potato Without PECA

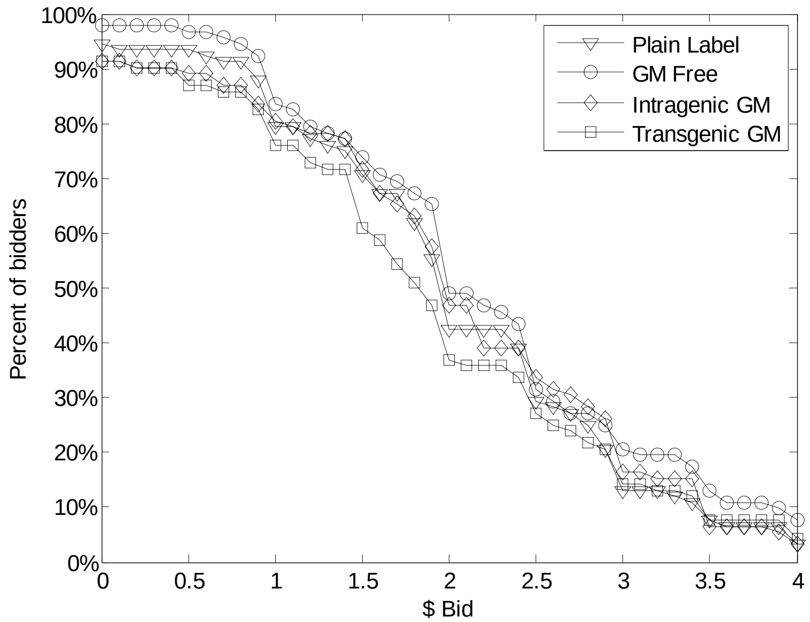


Figure 3.4 Inverse CDF of Bid Prices for Broccoli With PECA

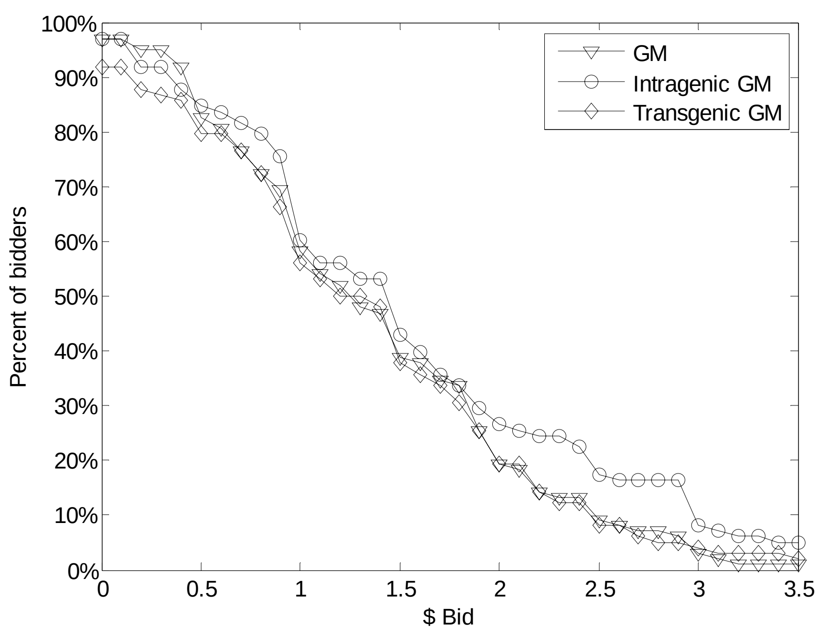


Figure 3.5 Inverse CDF of Bid Prices for Tomato With PECA

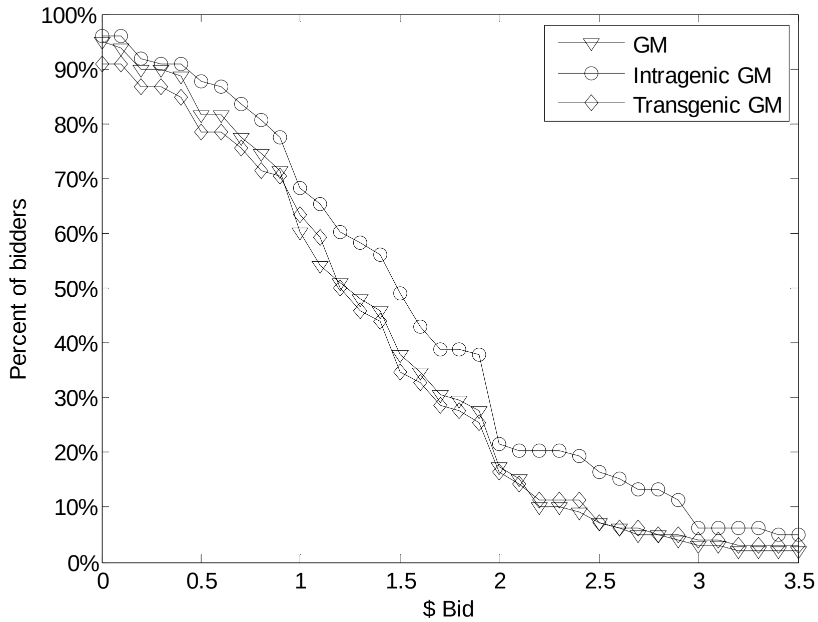
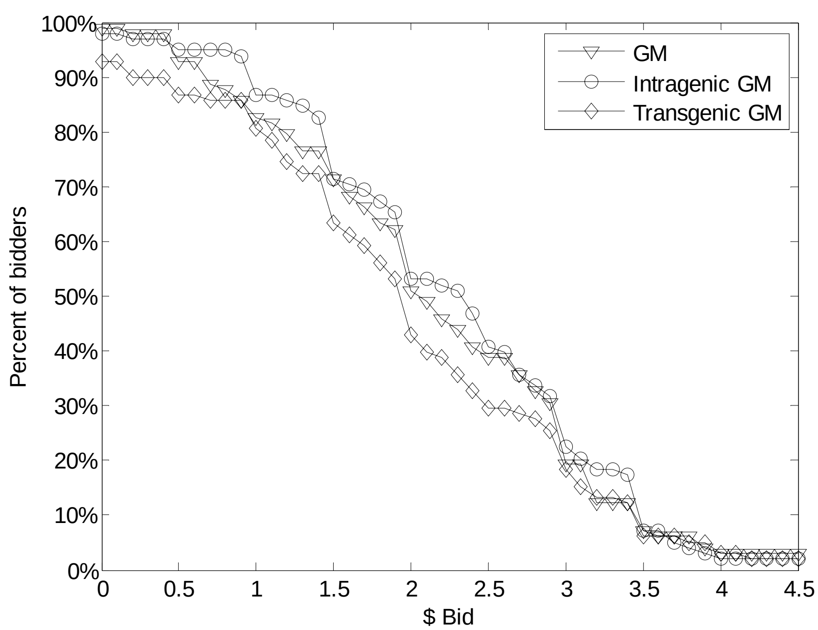


Figure 3.6 Inverse CDF of Bid Prices for Potato With PECA



3.3 Unconditional Analysis of Bid Prices

Tables 3.3, 3.4, and 3.5 present differences in mean bid prices across a selection of different labels. Table 3.3 is a comparison between bid prices for GM Free vs. Intragenic GM and GM Free vs. Transgenic GM labeled products, all without product enhanced consumer attributes (PECA). Under all information treatments consumers are willing to pay a premium for GM Free over Transgenic GM labeled products. Average premiums across all information treatments are \$0.26 per pound of broccoli, \$0.34 per pound of tomatoes, and \$0.34 per five pound of potatoes, all statistically different from zero. The premiums participants are willing to pay for GM Free over Intragenic GM labeled products are in general smaller, or even negative (e.g., under the pro-biotechnology treatment). Averaging across all information treatments, the premium ranges from \$0.05 per pound of broccoli to \$0.18 per five pounds of potatoes, but are not statistically different from zero. Participants receiving anti-biotech information are willing to pay the greatest premium for GM Free labeled products.

Table 3.3 Difference in Mean Bid Prices for Foods Without PECA

	GM Free w/o PECA vs. Intragenic w/o PECA			GM Free w/o PECA vs. Transgenic w/o PECA		
Info Treatment	Broccoli	Tomato	Potato	Broccoli	Tomato	Potato
ALL	$0.05	$0.15	$0.18	$0.26**	$0.34**	$0.34**
No info	$0.15	$0.12	$0.33	$0.32	$0.22	$0.29
Pro	$-0.36	$-0.16	$-0.21	$0.13	$0.17	$0.13
Anti	$0.53**	$0.72**	$0.87**	$0.46**	$0.69**	$0.90**
Pro & Anti	$0.01	$0.13	$-0.01	$0.36	$0.49*	$0.25
Pro,Anti,& Ver	$-0.01	$0.02	$0.03	$0.03	$0.13	$0.20

(*) and (**) denote variable significant at 10% and 5% respectively

The first part of table 3.4 compares average bid prices for Intragenic GM labeled products with and without PECA. Across all three commodities the differences are positive—consumers value enhanced antioxidants and vitamin C. Pooling all information treatments, the mean WTP differences are positive, significantly different from zero, and range from $0.26 per pound of broccoli to $0.45 per five pounds of potato. Premiums are the greatest under the pro-biotech treatment and least under the anti-biotech treatment.

The second part of table 3.4 provides evidence on the mean difference in bid prices for Transgenic GM labeled products with and without PECA. Here the differences are smaller and in the case of anti-biotech information and the pro, anti and third-party information treatments, the differences are slightly negative but not significantly different from zero. Combined, these results show that consumers do value enhanced nutrition in fresh vegetables, but are willing to pay a greater premium when these traits are obtained through intragenics instead of transgenics.

Table 3.4 Difference in Mean Bid Prices for Foods With and Without PECA

	Intragenic w/ PECA vs. Intragenic w/o PECA			Transgenic w/ PECA vs. Transgenic w/o PECA		
Info Treatment	Broccoli	Tomato	Potato	Broccoli	Tomato	Potato
ALL	$0.26*	$0.40**	$0.45**	$0.25*	$0.23*	$0.27
No info	$0.32	$0.60	$1.17*	$0.46	$0.48	$1.16
Pro	$0.78**	$1.02**	$0.95*	$0.55**	$0.61**	$0.44
Anti	$0.00	$0.14	$0.08	$-0.08	$-0.01	$-0.10
Pro & Anti	$0.27	$0.14	$0.19	$0.41	$0.18	$0.16
Pro,Anti,& Ver	$0.09	$0.25	$0.06	$-0.06	$-0.04	$-0.18

(*) and (**) denote variable significant at 10% and 5% respectively

Finally, the first part of table 3.5 compares average bid prices for Intragenic GM labeled products with PECA versus Plain Label products without PECA. Across all information treatments, except for the anti-biotechnology perspective, consumers are willing to pay a premium for the Intragenic GM labeled products with PECA with average values ranging from \$0.38 per pound of tomato to \$0.45 per five pounds of potato.

The second part of table 3.5 is a comparison between Transgenic GM labeled products with PECA versus Plain Label products without PECA. Here the magnitudes of the differences are smaller, not significantly different from zero, and negative in the conflicted information setting with anti-, pro-, and verifiable-information. Hence, table 3.5 provides additional evidence on the positive value placed by consumers on nutrition derived through intragenics.

Table 3.5 Difference in Mean Bid Prices for Foods With PECA and Plain Label Foods Without PECA

	Intragenic w/ PECA vs. Plain Label w/o PECA			Transgenic w/ PECA vs. Plain Label w/o PECA		
Info Treatment	Broccoli	Tomato	Potato	Broccoli	Tomato	Potato
ALL	$0.39**	$0.38**	$0.45**	$0.17	$0.03	$0.11
No info	$0.48	$0.56	$1.21*	$0.45	$0.34	$1.24
Pro	$1.22**	$1.15**	$1.16**	$0.49*	$0.41	$0.32
Anti	$-0.14	$-0.14	$-0.27	$-0.15	$-0.26	$-0.48
Pro & Anti	$0.39	$0.26	$0.30	$0.18	$-0.05	$0.00
Pro,Anti,& Ver	$0.13	$0.21	$0.04	$-0.06	$-0.18	$-0.38

(*) and (**) denote variable significant at 10% and 5% respectively

3.4 A Note on Zero Bids

Experimental auctions have become a common mechanism for eliciting willingness to pay (WTP) due to their non-hypothetical, incentive compatible, and demand revealing nature. From a practitioner's perspective, one of the drawbacks of experimental auctions for value elicitation is the presence of bids of zero by some individuals. Bids of zero are problematic for two primary reasons. First, depending upon the application, zero bids may simply be unusable because in certain contexts they provide no information to the researcher regarding demand, and hence reduce the experiment's useable sample size.[15] Second, zero bids present an additional, but minor, hurdle for econometric analysis of auction data. Since auctions typically restrict bids to the non-negative interval, zero bids are typically interpreted as reflecting censoring of latent demand by consumers with a negative WTP for the commodity (i.e. these consumers would prefer to be net sellers of the commodity and net purchasers of the numeraire). The Tobit model and related variants have been used in the literature for econometric analysis of auction bids in order to avoid the well-known bias in estimates that arises when censoring is present in the data, but not modeled.

While negative WTP for a commodity is consistent with standard demand theory and its manifestation as bids censored at zero can be easily managed econometrically, no study has addressed the question of whether bids of zero are an artifact of negative latent

[15] For example, consider a standard endow-and-upgrade auction where consumers are endowed with a product X and asked to bid to upgrade to a superior product X with some desirable attribute Y (e.g., upgrade from an apple to an organic apple). If the consumer does not value product X, they may bid zero for the upgrade even though they value the attribute Y. Hence, no preference information for attribute Y is revealed. This is why many studies engage in pre-screening to ensure that consumers value the product X.

WTP or simply a failure of the auction to engage some consumers in truthfully revealing their positive demand. While this is seemingly an innocuous question, its answer is critical to ensure that researchers are employing the correct regression model for analysis of auction data and that the auction mechanism is properly eliciting demand. If zero bids do not represent a censoring problem, but merely a failure of the auction to engage some consumers to truthfully reveal their positive WTP, a censored regression model is no longer appropriate and will yield biased estimates. Furthermore, if the "failure to engage" is not at random, but systematic along some individual-specific characteristics, a two-stage sample selection model would be appropriate.

This note provides evidence on the consistency of zero bids using bidding data from a random sample of adult consumers. Participants engaged in a multi-round random *n*th-price auction of fresh produce (broccoli, russet potatoes, and beefsteak tomatoes) carrying Plain label[16] and Genetically Modified (GM) Free labels. To test whether zero and positive bids are consistent with participants' underlying preferences, several additional pieces of information were solicited. In particular, participants were asked to report whether they eat or purchase fresh potatoes, tomatoes, and broccoli.

We would expect that consumers who historically eat or purchase the vegetables have a true WTP for GM Free (and likely Plain label) vegetables that is positive. Hence, these individuals should likely submit positive bids if the experimental auction appropriately elicits their demand. Conversely, individuals who do not eat or purchase the vegetables at market prices should be more likely, but not necessarily, to have a

[16] "Plain label" denotes a product that carried a label listing only the product name and weight with no reference to GM that may or may not be present.

negative WTP. Hence, this set of bidders should be the most likely to submit zero bids if the experimental auction properly engages them to truthfully reveal their preferences. If these expectations are not met, this would give rise to the supposition that zero bidders are simply unengaged in the auction and not truthfully revealing their demand.

3.4.1 Data and Analysis

Fifty-seven individuals submitted bids for the three GM Free vegetables and the three Plain label vegetables for a total of 342 bids. Of the 171 bids for GM Free vegetables, 8.8% were zero. Among those individuals bidding zero, 66.6% reported that they do not purchase and eat the commodity regularly. Among individuals who submitted positive bids, only 25% reported the same. Of the 171 bids for Plain label vegetables, 12.3% of bids were zero. Among those individuals bidding zero, 70% reported that they do not purchase and eat the commodity regularly. Among individuals who submitted positive bids, only 23.3% reported the same. For individuals who reported that they do purchase and eat the commodities, only 5.7% and 4.1% bid zero for Plain label and GM Free respectively. While, for non purchasers or eaters, 71.4% and 79.6% bid zero for Plain label and GM Free vegetables respectively.

As a whole, the incidence of zero bids conditional on purchase and eating habits indicates that the experimental auction is properly eliciting demand. Individuals who do not purchase or eat the vegetables are much more likely to submit a zero bid while a very small percentage of their counterparts do so. To further evaluate the consistency of zero bids while controlling for other potential confounding factors, two Probit models are estimated using bids for GM Free and Plain label broccoli, tomato, and potato. In each regression, the dependent variable is a dummy constructed from bids prices and is equal to 1 if the participant submitted a positive bid and 0 if the participant submitted a zero bid. Dependent variables include socio-demographic variables and information treatment dummies to potentially capture individual-level characteristics that affect the likelihood of submitting a zero bid. Given the nature of the commodities up for auction, we would not expect these consumer-specific attributes to have strong explanatory power for zero bids. Additionally, a dummy variable "Eat & Purchase" is constructed taking a value of 1 if the participant indicated that they regularly purchase and eat the vegetable up for auction.[17] If the auction is properly eliciting demand, we would except that this variable would have strong explanatory power for the occurrence of zero bids.

Table 3.6 provides estimates of the Probit models for GM Free and Plain Label products. In both regressions, none of the socio-demographic variables or information treatment variables are significant at the 10% level. The coefficient for the dummy variable indicating that participants eat and purchase the product is negative and significant at the 5% level in both regressions (p-values 0.016 and 0.011 respectively). This indicates that individuals who eat and purchase the commodities are significantly less likely to bid zero. A likelihood ratio test for both GM Free and Plain label bids fails to reject a constrained model consisting only of the Purchase & Eat dummy variable in favor of the full unconstrained model.

[17] Note that responses to purchasing and eating are nearly identical.

Table 3.6 Estimates for Probit Models of Zero Bids

	GM Free Bids		Plain Label Bids	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Pro	0.093	0.658	0.251	0.590
Anti	0.153	0.591	0.154	0.562
Pro & Anti	-0.700	0.772	-0.774	0.814
Pro,Anti,Ver	0.609	0.685	0.948	0.629
Income	-0.006	0.006	-0.006	0.006
Informed	0.419	0.613	0.259	0.625
Age	-0.001	0.014	-0.004	0.013
Opinion	0.422	0.519	0.134	0.548
Gender	-0.215	0.549	0.110	0.536
Education	0.119	0.110	0.248	0.109
Read Labels	0.628	0.552	0.094	0.480
Smoke	0.120	0.536	0.054	0.539
Exercise	0.054	0.471	-0.069	0.446
Health_Diet	-0.123	0.143	-0.120	0.132
Purch & Eat	-0.820**	0.342	-0.814**	0.319
Constant	-2.070**	1.835	-3.637**	1.844
Log-likelihood		-41.20		-48.57
LR Statistic		19.25		30.24
Constrained log-likelihood[a]		-45.66		-56.12
Constrained LR Statistic[a]		10.33		15.15

(*) and (**) denote variable significant at 10% and 5% respectively
[a] Constrained model of only the "Purch & Eat" dummy variable and a constant.

3.4.2 Concluding Remarks

The conditional and unconditional analyses of zero bids presented in this note yield a comforting result for researchers who employ experimental auctions for demand solicitation. The analysis suggests that experimental auctions are properly eliciting preferences and that zero bids are not an artifact of either a systematic or random failure of the experimental auction to induce bidders to truthfully reveal their demand. As well, given this result, further support is provided for the widespread practice of using censored demand models (e.g., a Tobit model) to account for zero bids when analyzing auction bid price data.

CHAPTER 4: CONDITIONAL ANALYSIS OF BID PRICES

4.1 Introduction

Although the data and unconditional analysis presented in the previous chapter are suggestive of the impact of information on the valuation of various types of genetic modification, it is necessary to undertake a more rigorous analysis of bid prices in order to identify label and information effects. In this chapter, a multivariate regression model is constructed for this task.

Before deriving the econometric model, it is beneficial to summarize several of the pertinent econometric issues that need to be addressed in modeling bid prices. The first issue, which is common to all analyses of multiple round auctions, is whether it is appropriate to assume that bid prices by an individual in two different rounds are uncorrelated. While this is a common assumption in the experimental economics literature, it is a questionable assumption. First, it requires that unmodeled individual factors affecting bid prices in one round are uncorrelated with bid prices in other rounds. Second, ignoring potential correlation across rounds of bidding for a given individual reduces the efficiency of the estimators. While individual effects can be easily included in standard single and system of equation models, they have the drawback of restricting correlation across different rounds (or labels) to have a common term. While for some experiments this may be a fair assumption, given the potential diversity of relative preferences for our experimental products, a general error specification is a more natural starting place for estimation. Hence, a seemingly unrelated regression (SUR) model (Zellner 1962) is selected to account for correlation across rounds of bidding.

A second important issue affecting the choice of modeling approach is the common dilemma in experimental auctions of bid prices of zero. A zero bid for a product presents a censoring problem, i.e., bids were restricted to the non-negative interval. In our sample, across all of the experimental sessions, less than 8% of bids were equal to zero. In the case of single equation models, censoring can be easily managed (e.g., a Tobit model). In the case of a system of equations with censoring, there are a number of classical estimation techniques that have been proposed, but they suffer from a variety of econometric issues and diminished tractability, particularly for systems with larger numbers of equations and cross-equation correlation (e.g., a SUR Tobit model). Difficulty in estimating the SUR Tobit model arises because multiple integrals are required for maximum likelihood estimation, hence requiring simulation algorithms (e.g., Huang, Sloan and Adamache, 1987, Meng and Rubin, 1996, and Huang 1999). An alternative, which is selected for this study, is to estimate the model via Bayesian techniques with data augmentation. In a Bayesian framework, appealing to well established data augmentation techniques (e.g., Albert and Chib 1993), the complication of multiple integrals in the SUR Tobit model is alleviated and replaced with a straightforward Gibbs sampler that is fast to estimate and easily scaled to larger order systems.

Hence, in order to address simultaneously these three relevant econometric issues, Huang's (2001) model is adapted and extended to develop a Bayesian SUR Tobit model of individual bid prices.

4.2 Econometric Model

Let y_{ij} denote the bid price by an individual $i = 1,2,...,N$ for a food product with label $j = 1,2,...,J$ ($J = 4$ for the auctions without PECA and $J = 3$ for the auctions with PECA). The latent WTP of the i^{th} individual for the food product under label j can be expressed as

(1) $y_{ij}^{*} = x_{ij}^{'}\beta_j + \varepsilon_{ij}$, $i = 1,2,...,N$, $j = 1,2,...,J$,

where

(2) $$y_{ij} = \begin{cases} y_{ij}^{*} \; if \;\; y_{ij}^{*} > 0 \\ 0 \;\; if \;\; y_{ij}^{*} \leq 0 \end{cases},$$

and y_{ij} is the observed bid price, y_{ij}^{*} is the latent bid price, and $\varepsilon_i = (\varepsilon_{i1},...,\varepsilon_{iJ})' \overset{iid}{\sim} N(0,\Omega)$. For individual i, we can express a system of equations, one equation for each label $j = 1,2,...,J$, as

(3) $$\begin{bmatrix} y_{i1}^{*} \\ y_{i2}^{*} \\ \vdots \\ y_{iJ}^{*} \end{bmatrix} = \begin{bmatrix} x_{i1}^{'} & 0 & \cdots & 0 \\ 0 & x_{i2}^{'} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & x_{iJ}^{'} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_J \end{bmatrix} + \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \vdots \\ \varepsilon_{iJ} \end{bmatrix}.$$

In stacked notation, for each individual i we can express the system of WTP equations as $y_i^{*} = x_i\beta + \varepsilon_i$, $i = 1,2,...,N$, where $y_i^{*} = (y_{i1}^{*},...,y_{iJ}^{*})'$ is a $Jx1$ vector, $x_i = diag(x_{i1}^{'},...,x_{iJ}^{'})$ is a Jxk matrix, and $\beta = (\beta_1^{'},...,\beta_J^{'})'$ is a $Jkx1$ vector. Finally, stacking over all N individuals we have a complete system of equations $y^{*} = X\beta + \varepsilon.$

Treating latent bid prices as additional model parameters (e.g., Albert and Chib 1993), it follows that the augmented posterior is proportional to

(4) $$p(\beta,\Omega,y^* \mid y) \propto p(y \mid y^*,\beta,\Omega)p(y^* \mid \beta,\Omega)p(\beta,\Omega),$$

where the conditional for y is directly predicted by the latent bid price

(5) $$p(y \mid y^*,\beta,\Omega) = \prod_{i=1}^{N}\prod_{j=1}^{J}\left\{I(y_{ij}^* > 0)I(y_{ij} = y_{ij}^*) + I(y_{ij}^* \leq 0)I(y_{ij} = 0)\right\},$$

and the conditional for y^* is proportional to

(6) $$p(y^* \mid \beta,\Omega) \propto \prod_{i=1}^{N}\left\{|\Omega|^{-N/2}\exp\left[-\frac{1}{2}\sum_{i=1}^{N}(y_i^* - x_i\beta)'\Omega^{-1}(y_i^* - x_i\beta)\right]\right\}.$$

Assuming independent priors of the form

(7) $$\begin{gathered}\beta \sim N(\beta_0,V_\beta)\\ \Omega^{-1} \sim W(a_\varepsilon,V_\varepsilon),\end{gathered}$$

where N and W denote the multivariate normal and Wishart distributions respectively, the conditional posterior distribution for β and Ω^{-1} are given by standard results:

(8) $$\beta \mid \Omega^{-1}, y \sim N(D_\beta d_\beta, D_\beta),$$

where

(9) $$\begin{aligned}D_\beta &= \left(X'(\Omega^{-1}\otimes I_N)X + V_\beta^{-1}\right)^{-1}\\ d_\beta &= X'(\Omega^{-1}\otimes I_N)y + V_\beta^{-1}\beta_0,\end{aligned}$$

and

(10) $$\Omega^{-1} \mid \beta, y \sim W\left(N + a_\varepsilon, \left[V_\varepsilon^{-1} + \sum_{i=1}^{N}(y_i - X_i\beta)(y_i - X_i\beta)'\right]^{-1}\right).$$

The posterior conditional for latent bids is a multivariate truncated normal and given by

(11) $$y_{ij}^* \mid \beta,\Omega^{-1} \sim TN_{[-\infty,0]}\left(\mu_{j|-j},\omega_{j|-j}^2\right) \quad \forall ij\ s.t.\ y_{ij} = 0,$$

where

$$\text{(12)} \qquad \begin{aligned} \mu_{j|-j} &= \mu_j + \Omega'_{j-j}\Omega^{-1}_{-j-j}(y^{*'}_{-j} - \mu_{-j}) \\ \omega^2_{j|-j} &= \omega^2_{jj} - \Omega'_{j-j}\Omega^{-1}_{-j-j}\Omega'_{j-j}, \end{aligned}$$

$\mu = X_i\beta$, μ_j is the j^{th} row element of μ and μ_{-j} is obtained by deleting the j^{th} row element of μ. The matrix Ω_{-j-j} is derived from Ω by eliminating the j^{th} column and row, Ω_{j-j} is the vector derived from the j^{th} column of Ω by removing the j^{th} row term.

Iteratively sampling from the posterior conditionals for β, Ω^{-1}, and y^* yields a set of draws from the joint posterior density.

4.3 Regression Estimates

Several different specifications of the Bayesian SUR Tobit model developed in the previous section are estimated for both the cases of with and without PECA. In all models, the prior probability density functions for unknown parameters are specified so that they are slightly informative to allow the sample information to be the main determinant of the parameters in the posterior probability density function. Following the tradition of Bayesian econometrics, results are presented for the posterior mean (or regression coefficients) of key parameters and their standard deviations and posterior probability of the estimated parameter being greater than zero (e.g., Koop, Poirier, and Tobias, 2007). The tables presented in section 4.5 include posterior estimates for models of each individual commodity (e.g., broccoli without PECA, tomato with PECA, etc.). As well, to concentrate the results, two models (one for products without PECA and one for products with PECA) are estimated where the model is further stacked over the three commodities (broccoli, tomatoes, and potatoes) and commodity specific effects are included. Tables of marginal effects (abbreviated henceforth M.E.) are also presented. Additionally, to aid in evaluating the relative impact on WTP of different labeling treatments, posterior estimates of bid differences are also included.[18] In all of the models, assumed values of key parameters of the priors were chosen to impose minimal structure: $\beta_0 = 0$, $V_\beta = (10e4)I_J$, $a_\varepsilon = J * k$, and $V_\varepsilon = (10e4)I_J$. A total of 10,000 draws from the Gibbs sampler were used following a 1,000 iterate burn-in. Given the volume of different model specifications and estimates presented in this chapter, in the subsequent discussion the more compact specification of the stacked models for with and without PECA are considered.

Table 4.1 presents estimates of the stacked Bayesian SUR Tobit model for products without PECA. The signs of the estimated posterior means of the information treatment dummy variables fall in line with expectations. Individuals who receive anti-biotech information are willing to pay a premium for the GM Free label (M.E. \$0.054) and discount both Intragenic GM and Transgenic GM foods (M.E. \$-0.120 and \$-0.228 respectively).[19] For individuals who receive only pro-biotech information, the situation is reversed with higher WTP for Intragenic GM and Transgenic GM (M.E. \$0.120 and \$0.082 respectively) and lower WTP for the GM Free (M.E. \$-0.066).

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[18] Some readers may find this form of estimate presentation easier to digest, particularly since relative impacts on WTP of different factors are of key interest. However, please note that some care is needed in interpreting the impact of the information treatments on relative WTP since models were estimated with the dummy variable for the “no information” treatment omitted.

[19] Note that the excluded information treatment is the one where no information is disseminated to participants.

Individuals who receive the package of pro- and anti-biotech information treatments have greater WTP for all four types of labels. However, the impact on relative WTP for Intragenic GM vs. GM Free and Transgenic GM vs. GM Free labels is less than when pro-biotech information is received in isolation. This indicates that, in combination, the anti-biotech information dampens the augmenting impact on WTP of pro-biotech information for GM labels relative to the GM Free. WTP for all four labels by individuals who received the combined pro, anti, and third party perspectives is reduced. While the marginal impact is similar for each of the four labels, the largest reduction occurs for the GM Free label.

Turning to the demographic variables, we can see that individuals who are older, of white ethnicity, have larger households, and have higher household incomes are willing to pay more for products under each of the four labels. For individuals who are members of an environmental group the posterior mean for each label is negative and, as expected, the marginal decrease in WTP is most pronounced for the Transgenic GM and least for the GM Free label (M.E. $-0.592 and $-0.174 respectively).

The results for the opinion variables present an interesting picture. Individuals who typically read food labels have lower WTP for all four labels, but the marginal effect is most pronounced for the Intragenic and Transgenic GM labels. Individuals who are more informed about GM coming into the experiments are willing to pay more than their counterparts for, in particular, Transgenic GM and Plain Label foods. However, the posterior mean across the four labeling treatments for individuals with a positive opinion of GM coming into the experiments is close to zero. This indicates that the provided information treatments in part confounded prior opinions towards GM.

The results for the health proxies are mixed. While the signs of the posterior means for smoking, regular exercise, and highly rated physical and diet healthiness are consistent across the four food labels, there is little variation in the magnitude of the marginal effect across the different products. While a priori one might expect that those individuals who are healthier would be willing to pay a higher premium for the GM Free (and maybe the Intragenic GM) than for Transgenic GM, the data cannot support this conclusion.

Finally, the results show a significant first round bidding effect – i.e., participants bid relatively more in the first round for some labels – and these coefficients have high posterior probabilities of being positive.[20] Our results also show that bid prices to a varying degree are significantly correlated across labels. For example, the estimated correlation between bid prices for Plain and Intragenic GM labels is 0.51 and between Plain and Transgenic GM labels is 0.31. Despite the greater modeling burden, the variability in correlation across different labels supports the more general SUR error specification.

Table 4.10 presents results for the stacked econometric model of bid prices for the three commodities under the three label treatments with PECA. The posterior mean is positive across all three labels for individuals receiving the pro-biotech information treatment with the greatest relative increase for the Intragenic GM label.[21] Individuals

[20] Alternative dummy specifications to capture potential round order effects were considered. Tests revealed that bids in the first round were affected by the type of label presented, but no significant order effect arose in subsequent bidding rounds (e.g., round 2 versus round 3).

[21] Again, note that the excluded information treatment is the one where no information is disseminated to participants.

who receive anti-biotech information have reduced WTP for all three labels. In combination, individuals receiving both the pro- and anti-biotech information have a lower WTP for the GM and Transgenic GM labels, but higher for the Intragenic GM. This indicates that these two perspectives in combination largely counterbalance each other in terms of their impact on valuations, but the positive impact on WTP for Intragenic GM marginally still holds. Finally, when verifiable information is injected, valuations for all three products are lower, indicating that verifiable information bolsters the negative impact of anti-biotech information on WTP for GM food products with enhanced consumer attributes.

Turning to the demographic variables, individuals who are environmental group members, have experience in farming, are white, and have higher household incomes have lower WTP for all three GM labels. Consumers who are older or have larger households have a higher WTP. Consistent with the results for products without PECA, individuals who were informed about GM before the experiments or typically read food labels are willing to pay more under each of the three labels. Interestingly, individuals with a favorable prior opinion towards GM are willing to pay more for both the GM and Transgenic GM labels, but the posterior is flat and centered at zero for the Intragenic GM. This indicates that prior perceptions toward GM did not carry over into valuations of Intragenic GM foods with enhanced nutrition.

As in the estimates for products without PECA, the signs of the posterior estimates for health variables do not present a clear relation between "healthiness" and WTP for foods with enhanced nutrition obtained through genetic modification.

Individuals who regularly exercise, have higher self-assessed physical healthiness, or smoke are willing to pay more under each of the three labels, while those with self-assessed healthier diets are willing to pay less.

Finally, as in the case of products without PECA, there was a significant first round label effect and correlation in bid prices across labels. The correlation coefficients across the different labels is approximately 0.5, which is large and consistent with the cross-label correlations in bid prices for products without PECA.

4.4 Concluding Remarks

While the controversy over the balance between the benefits and hazards of genetically modified foods continues to unfold in the arenas of global politics and public information campaigns, the advancements in intragenic bioengineering present a new piece to the puzzle. Overall, we find in our experiments that consumers do value enhanced nutrition attributes (antioxidants and vitamin C) obtained through genetic modification. But, consumers are more accepting of foods with PECA obtained through intragenics compared to transgenics. Most notably, we find that a significant share of consumers is willing to pay more for intragenic foods with enhanced nutrition compared to conventional products. This opens the door for voluntary private sector labeling of GM foods with PECA.

These results pose a dilemma for individuals and groups that have historically taken a position of staunch opposition to GM. While intragenics may present a more palatable form of bioengineering compared to transgenics, our laboratory experiments indicate that there is the potential for an even greater crowding out of non-GM foods.

Although our findings present a mildly positive picture for the potential of intragenics to obtain a foothold in the food market, they also suggest that information injected into the public domain will continue to play an important role in determining consumer acceptance. Our findings reveal that the information available to consumers when making purchase decisions has a significant effect on relative valuations for GM and conventional products. While pro-biotechnology information disseminated by agribusiness in isolation has significant positive effects on consumer valuations for GM foods, this effect is reduced when anti-biotechnology information is simultaneously injected into the market.

Finally, the refinements of the experimental procedures and the econometric methods employed in this study advance the frontier of food experiments research. This study has sought to minimize and control for a number of factors that may bias bid elicitation and reduce the usefulness of research on consumer acceptance of foods as reflected in WTP analysis.

4.5 Tables

Given the volume of tables presented in this section, below is a brief description of the corresponding specification of the Bayesian SUR Tobit model that was estimated.

- Table 4.1– Stacked bid prices for all products (broccoli, tomato, and potato) without PECA.
- Table 4.2 –Bid prices for broccoli without PECA.
- Table 4.3 –Bid prices for tomato without PECA.

- Table 4.4 –Bid prices for potato without PECA.
- Table 4.5 –Bid price differences (relative to GM Free) for stacked model of products without PECA.
- Table 4.6 –Bid price differences (relative to GM Free) for broccoli without PECA.
- Table 4.7 –Bid price differences (relative to GM Free) for tomato without PECA.
- Table 4.8 –Bid price differences (relative to GM Free) for potato without PECA.
- Table 4.9 – Marginal effects for stacked model products without PECA.
- Table 4.10– Stacked bid prices for all products (broccoli, tomato, and potato) of products with PECA.
- Table 4.11 –Bid prices for broccoli with PECA.
- Table 4.12 –Bid prices for tomato with PECA.
- Table 4.13 –Bid prices for potato with PECA.
- Table 4.14 –Bid price differences (relative to GM) for stacked model with PECA.
- Table 4.15 –Bid price differences (relative to GM) for broccoli with PECA.
- Table 4.16 –Bid price differences (relative to GM) for tomato with PECA.
- Table 4.17 –Bid price differences (relative to GM) for potato with PECA.
- Table 4.18 – Marginal effects for stacked model products with PECA.

Table 4.1 Bayesian Estimates of Bid Price Equations for All Products Without PECA (N=92, Obs=1104)

Dep Var	$Y^{Plain\ Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Information Dummy Omitted)											
Pro	0.116	0.185	0.74	-0.140	0.187	0.23	0.284	0.195	0.93	0.105	0.183	0.79
Anti	-0.119	0.209	0.28	0.191	0.212	0.82	-0.171	0.219	0.21	-0.257	0.207	0.11
Pro & Anti	0.252	0.169	0.93	0.212	0.170	0.89	0.369	0.180	0.98	0.112	0.169	0.75
Pro,Anti,Ver	-0.108	0.195	0.29	-0.243	0.197	0.11	-0.013	0.205	0.53	-0.112	0.194	0.28
	Demographic Variables											
Gender	-0.130	0.146	0.19	-0.067	0.146	0.33	0.058	0.153	0.65	-0.228	0.145	0.06
Race	0.432	0.176	0.99	0.240	0.179	0.91	0.292	0.183	0.95	0.239	0.173	0.92
Age	0.021	0.004	1.00	0.019	0.004	1.00	0.017	0.004	1.00	0.016	0.004	1.00
Income	0.004	0.002	0.98	0.005	0.002	1.00	0.005	0.002	0.99	0.005	0.002	1.00
Educ	-0.004	0.020	0.42	-0.010	0.021	0.32	0.028	0.022	0.90	0.028	0.020	0.92
Married	-0.137	0.131	0.14	-0.071	0.131	0.30	-0.180	0.136	0.09	-0.159	0.130	0.11
Household	0.139	0.045	1.00	0.178	0.045	1.00	0.095	0.047	0.98	0.086	0.044	0.98
Iowa	-0.182	0.118	0.06	-0.169	0.121	0.08	-0.115	0.125	0.17	0.127	0.118	0.86
Farm	0.014	0.138	0.54	0.105	0.139	0.78	0.095	0.144	0.75	0.131	0.137	0.83
Envi_Mem	-0.495	0.313	0.06	-0.250	0.318	0.22	-0.315	0.328	0.17	-0.628	0.310	0.02
	Opinion Variables											
Informed	0.392	0.213	0.97	0.236	0.214	0.86	0.025	0.220	0.54	0.263	0.212	0.89
Opinion	-0.046	0.160	0.39	0.055	0.162	0.63	0.064	0.166	0.65	-0.114	0.159	0.24
Read_Labels	-0.289	0.154	0.03	-0.091	0.153	0.28	-0.183	0.155	0.12	-0.436	0.148	0.00

Table 4.1 (Continued)

Dep Var	$Y^{Plain\,Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
						Health Variables						
Smoke	0.381	0.147	1.00	0.437	0.149	1.00	0.274	0.152	0.96	0.262	0.145	0.97
Exercise	0.043	0.140	0.63	0.105	0.141	0.78	0.386	0.146	1.00	0.162	0.138	0.88
Health_Diet	0.055	0.047	0.88	0.075	0.047	0.95	-0.016	0.048	0.37	0.071	0.046	0.94
Health_Phys	-0.047	0.041	0.13	-0.053	0.041	0.10	-0.052	0.043	0.11	-0.080	0.041	0.03
Round 1 Label	0.115	0.066	0.96	0.148	0.082	0.97	0.282	0.095	1.00	0.218	0.061	1.00

Inter-Round Correlation Coefficients

$\rho_{Plain,GMF}$	$\rho_{Plain,Intra}$	$\rho_{Plain,Trans}$	$\rho_{GMF,Intra}$	$\rho_{GMF,Trans}$	$\rho_{Intra,Trans}$
0.46	0.51	0.31	0.51	0.13	0.24

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.2 Bayesian Estimates of Bid Price Equations for Broccoli Without PECA (N=92, Obs=1104)

Dep Var	$Y^{Plain\,Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Information Dummy Omitted)											
Pro	-0.096	0.403	0.40	-0.394	0.202	0.03	-0.067	0.493	0.45	-0.232	0.321	0.22
Anti	-0.224	0.458	0.30	-0.084	0.229	0.35	-0.915	0.634	0.06	-0.334	0.363	0.16
Pro & Anti	0.165	0.339	0.69	-0.011	0.191	0.48	0.120	0.417	0.62	-0.175	0.277	0.25
Pro,Anti,Ver	-0.550	0.447	0.10	-0.550	0.226	0.01	-0.660	0.556	0.10	-0.444	0.352	0.09
	Demographic Variables											
Gender	-0.152	0.320	0.32	-0.076	0.163	0.32	0.009	0.391	0.53	-0.484	0.295	0.03
Race	0.137	0.421	0.64	0.076	0.203	0.65	-0.423	0.527	0.19	-0.273	0.340	0.20
Age	0.025	0.011	0.99	0.016	0.005	1.00	0.018	0.013	0.93	0.013	0.009	0.94
Income	0.008	0.004	0.98	0.006	0.002	1.00	0.013	0.006	1.00	0.009	0.004	1.00
Educ	-0.068	0.064	0.13	-0.055	0.034	0.05	-0.059	0.081	0.22	-0.088	0.057	0.04
Married	-0.043	0.275	0.42	-0.123	0.145	0.19	0.089	0.348	0.59	-0.031	0.230	0.43
Household	0.053	0.132	0.67	0.142	0.060	0.99	-0.094	0.180	0.31	-0.075	0.109	0.24
Iowa	-0.292	0.260	0.12	-0.048	0.131	0.35	-0.257	0.313	0.19	0.198	0.208	0.85
Farm	-0.312	0.349	0.18	-0.031	0.158	0.43	-0.577	0.495	0.09	-0.244	0.261	0.16
Envi_Mem	-0.334	0.585	0.27	-0.009	0.330	0.49	-0.406	0.722	0.28	-0.341	0.463	0.22
	Opinion Variables											
Informed	0.655	0.443	0.94	0.264	0.235	0.88	0.379	0.629	0.74	0.246	0.381	0.77
Opinion	-0.097	0.338	0.39	0.052	0.171	0.62	-0.107	0.416	0.41	-0.106	0.265	0.34
Read_Labels	-0.156	0.333	0.31	-0.129	0.170	0.22	-0.370	0.419	0.17	-0.397	0.261	0.06

Table 4.2 (Continued)

Dep Var	$Y^{Plain\,Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Health Variables											
Smoke	0.466	0.317	0.94	0.289	0.164	0.96	-0.084	0.440	0.46	-0.092	0.275	0.38
Exercise	-0.011	0.276	0.49	0.104	0.150	0.76	0.316	0.337	0.85	0.080	0.222	0.65
Health_Diet	0.079	0.095	0.80	0.062	0.051	0.88	-0.012	0.113	0.45	0.095	0.078	0.90
Health_Phys	-0.045	0.079	0.29	-0.019	0.045	0.35	-0.051	0.099	0.30	-0.081	0.068	0.10
Round 1 Label	0.029	0.209	0.59	0.126	0.188	0.74	0.408	0.319	0.91	0.326	0.165	0.98

Inter-Round Correlation Coefficients

$\rho_{Plain,GMF}$	$\rho_{Plain,Intra}$	$\rho_{Plain,Trans}$	$\rho_{GMF,Intra}$	$\rho_{GMF,Trans}$	$\rho_{Intra,Trans}$
0.60	0.41	0.53	0.43	0.23	0.36

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.3 Bayesian Estimates of Bid Price Equations for Tomato Without PECA (N=92, Obs=368)

Dep Var	$Y^{Plain\ Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Information Dummy Omitted)											
Pro	0.157	0.707	0.59	-0.078	0.232	0.37	0.235	0.458	0.72	0.320	0.430	0.78
Anti	-0.444	0.831	0.29	0.041	0.264	0.56	-0.434	0.527	0.19	-0.139	0.472	0.36
Pro & Anti	0.331	0.647	0.70	0.193	0.223	0.81	0.412	0.429	0.85	0.137	0.415	0.63
Pro,Anti,Ver	-0.460	0.774	0.27	-0.381	0.256	0.07	-0.188	0.505	0.35	0.026	0.483	0.52
	Demographic Variables											
Gender	-0.166	0.579	0.39	0.195	0.189	0.85	0.371	0.387	0.84	-0.304	0.351	0.18
Race	0.263	0.742	0.64	0.201	0.233	0.81	0.688	0.526	0.92	0.881	0.558	0.96
Age	0.024	0.016	0.94	0.011	0.006	0.98	0.010	0.010	0.84	0.016	0.011	0.94
Income	0.009	0.007	0.90	0.003	0.003	0.87	0.007	0.005	0.94	0.011	0.005	1.00
Educ	-0.366	0.126	0.00	-0.107	0.039	0.00	-0.108	0.075	0.06	-0.069	0.070	0.15
Married	0.649	0.542	0.89	0.179	0.173	0.85	0.216	0.369	0.73	0.027	0.343	0.53
Household	-0.380	0.244	0.05	-0.018	0.069	0.40	-0.150	0.160	0.16	-0.023	0.136	0.43
Iowa	-0.761	0.470	0.05	-0.335	0.149	0.01	-0.288	0.305	0.15	0.317	0.316	0.85
Farm	-0.480	0.548	0.19	0.111	0.179	0.73	0.054	0.363	0.57	-0.017	0.341	0.50
Envi_Mem	0.227	0.989	0.59	0.080	0.385	0.59	-0.088	0.667	0.44	-0.527	0.615	0.18
	Opinion Variables											
Informed	0.756	0.740	0.86	0.125	0.268	0.68	-0.050	0.522	0.47	0.571	0.472	0.90
Opinion	0.128	0.588	0.58	0.144	0.198	0.77	0.238	0.371	0.75	-0.007	0.342	0.49
Read_Labels	-0.461	0.514	0.18	-0.088	0.192	0.32	-0.268	0.344	0.20	-0.504	0.324	0.06

Table 4.3 (Continued)

Dep Var	$Y^{Plain\,Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
						Health Variables						
Smoke	0.790	0.511	0.95	0.405	0.188	0.98	0.245	0.343	0.78	0.441	0.329	0.92
Exercise	0.405	0.505	0.79	-0.108	0.176	0.27	0.380	0.321	0.89	0.133	0.311	0.67
Health_Diet	0.203	0.176	0.88	0.155	0.058	1.00	0.119	0.119	0.85	0.126	0.109	0.88
Health_Phys	-0.204	0.150	0.08	-0.142	0.053	0.00	-0.230	0.104	0.01	-0.229	0.098	0.01
Round 1 Label	-0.320	0.403	0.21	-0.008	0.216	0.47	0.345	0.356	0.85	0.264	0.260	0.85

Inter-Round Correlation Coefficients

$\rho_{Plain,GMF}$	$\rho_{Plain,Intra}$	$\rho_{Plain,Trans}$	$\rho_{GMF,Intra}$	$\rho_{GMF,Trans}$	$\rho_{Intra,Trans}$
0.55	0.32	0.61	0.52	0.25	0.25

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.4 Bayesian Estimates of Bid Price Equations for Potato Without PECA (N=92, Obs=368)

Dep Var	$Y^{Plain\ Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Information Dummy Omitted)											
Pro	0.570	0.354	0.95	-0.002	0.298	0.49	0.432	0.450	0.84	0.233	0.456	0.70
Anti	0.335	0.396	0.80	0.473	0.335	0.93	-0.531	0.592	0.18	-0.215	0.516	0.32
Pro & Anti	0.425	0.333	0.90	0.233	0.286	0.80	0.460	0.433	0.86	0.186	0.434	0.68
Pro,Anti,Ver	-0.130	0.418	0.39	-0.184	0.341	0.29	-0.185	0.564	0.38	-0.573	0.590	0.15
	Demographic Variables											
Gender	-0.867	0.319	0.00	-0.457	0.238	0.03	-0.203	0.414	0.31	-0.875	0.428	0.01
Race	0.334	0.385	0.81	0.084	0.299	0.61	0.659	0.574	0.89	0.074	0.518	0.56
Age	0.029	0.009	1.00	0.019	0.007	1.00	0.015	0.011	0.93	0.019	0.011	0.95
Income	0.010	0.004	1.00	0.010	0.003	1.00	0.015	0.006	1.00	0.014	0.005	1.00
Educ	-0.007	0.059	0.45	0.002	0.050	0.51	0.021	0.079	0.62	0.003	0.079	0.52
Married	-0.067	0.264	0.39	-0.088	0.218	0.34	-0.348	0.335	0.14	-0.219	0.347	0.25
Household	0.175	0.118	0.93	0.250	0.089	1.00	0.004	0.158	0.54	0.068	0.155	0.69
Iowa	-0.189	0.239	0.21	-0.308	0.194	0.05	-0.097	0.338	0.36	0.194	0.337	0.71
Farm	-0.291	0.294	0.15	0.024	0.230	0.54	-0.641	0.459	0.06	0.000	0.380	0.51
Envi_Mem	-1.175	0.581	0.02	-0.703	0.499	0.08	-0.918	0.756	0.11	-0.990	0.746	0.09
	Opinion Variables											
Informed	0.629	0.410	0.94	0.371	0.342	0.86	0.310	0.612	0.71	0.138	0.617	0.61
Opinion	-0.374	0.339	0.13	-0.087	0.255	0.37	-0.192	0.421	0.32	-0.557	0.443	0.09
Read_Labels	-0.135	0.313	0.33	-0.061	0.253	0.40	-0.426	0.395	0.13	-0.495	0.393	0.10

Table 4.4 (Continued)

Dep Var	$Y^{Plain\,Label}$			$Y^{GM\ Free}$			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
						Health Variables						
Smoke	0.345	0.289	0.89	0.483	0.245	0.98	-0.057	0.398	0.46	0.134	0.421	0.65
Exercise	0.005	0.274	0.52	0.226	0.232	0.84	0.533	0.349	0.94	0.287	0.363	0.80
Health_Diet	-0.135	0.096	0.08	-0.030	0.075	0.34	-0.098	0.120	0.20	-0.115	0.121	0.16
Health_Phys	-0.012	0.078	0.44	-0.045	0.066	0.25	-0.030	0.103	0.38	-0.069	0.103	0.24
Round 1 Label	0.248	0.203	0.90	0.242	0.234	0.86	0.238	0.312	0.80	0.251	0.228	0.88

Inter-Round Correlation Coefficients

$\rho_{Plain,GMF}$	$\rho_{Plain,Intra}$	$\rho_{Plain,Trans}$	$\rho_{GMF,Intra}$	$\rho_{GMF,Trans}$	$\rho_{Intra,Trans}$
0.49	0.56	0.25	0.31	0.18	0.25

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.5 Bayesian Estimates of Differences of Bid Price Equations for Products Without PECA (N=92, Obs=828)

Dep Var	$Y^{GMF} - Y^{Plain\ Label}$			$Y^{GMF} - Y^{Intragenic}$			$Y^{GMF} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.255	0.103	0.01	-0.422	0.135	0.00	-0.137	0.131	0.14
Anti	0.309	0.116	1.00	0.364	0.150	0.99	0.448	0.145	1.00
Pro & Anti	-0.042	0.095	0.33	-0.161	0.122	0.09	0.097	0.117	0.80
Pro,Anti,Ver	-0.135	0.110	0.11	-0.255	0.140	0.03	-0.132	0.137	0.17
	Demographic Variables								
Gender	0.063	0.081	0.78	-0.126	0.104	0.11	0.164	0.102	0.95
Race	-0.189	0.100	0.03	-0.053	0.128	0.34	0.002	0.126	0.51
Age	-0.002	0.002	0.14	0.001	0.003	0.69	0.003	0.003	0.87
Income	0.001	0.001	0.88	0.001	0.001	0.67	0.000	0.001	0.50
Educ	-0.006	0.012	0.32	-0.038	0.015	0.00	-0.038	0.014	0.00
Married	0.068	0.074	0.82	0.108	0.095	0.87	0.089	0.094	0.83
Household	0.039	0.025	0.94	0.082	0.032	1.00	0.091	0.031	1.00
Iowa	0.012	0.066	0.57	-0.053	0.084	0.26	-0.296	0.081	0.00
Farm	0.093	0.079	0.88	0.009	0.098	0.54	-0.027	0.096	0.39
Envi_Mem	0.250	0.172	0.93	0.063	0.221	0.61	0.384	0.214	0.96
	Opinion Variables								
Informed	-0.154	0.122	0.10	0.213	0.154	0.92	-0.023	0.153	0.45
Opinion	0.099	0.087	0.87	-0.010	0.112	0.46	0.166	0.110	0.94
Read_Labels	0.198	0.086	0.99	0.096	0.108	0.81	0.346	0.105	1.00
	Health Variables								
Smoke	0.053	0.082	0.74	0.160	0.106	0.94	0.172	0.103	0.96
Exercise	0.062	0.077	0.78	-0.282	0.098	0.00	-0.057	0.097	0.28
Health_Diet	0.021	0.026	0.79	0.090	0.034	1.00	0.003	0.033	0.54
Health_Phys	-0.006	0.023	0.40	0.000	0.029	0.50	0.027	0.029	0.83
Round 1 Label	0.035	0.111	0.62	-0.136	0.126	0.14	-0.067	0.104	0.26

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.6 Bayesian Estimates of Differences of Bid Price Equations for Broccoli Without PECA (N=92, Obs=828)

Dep Var	$Y^{GMF} - Y^{Plain\ Label}$			$Y^{GMF} - Y^{Intragenic}$			$Y^{GMF} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.298	0.326	0.17	-0.328	0.419	0.19	-0.162	0.264	0.25
Anti	0.139	0.369	0.66	0.830	0.559	0.96	0.250	0.301	0.82
Pro & Anti	-0.176	0.255	0.24	-0.131	0.335	0.33	0.164	0.217	0.79
Pro,Anti,Ver	0.000	0.363	0.48	0.110	0.473	0.57	-0.106	0.291	0.32
	Demographic Variables								
Gender	0.075	0.252	0.60	-0.085	0.328	0.36	0.408	0.254	0.97
Race	-0.061	0.348	0.42	0.499	0.455	0.89	0.349	0.290	0.91
Age	-0.010	0.010	0.15	-0.002	0.011	0.47	0.003	0.008	0.71
Income	-0.002	0.004	0.30	-0.007	0.006	0.08	-0.003	0.004	0.20
Educ	0.014	0.050	0.59	0.004	0.068	0.48	0.033	0.049	0.75
Married	-0.080	0.217	0.36	-0.212	0.295	0.22	-0.092	0.194	0.31
Household	0.089	0.111	0.81	0.236	0.161	0.96	0.216	0.096	0.99
Iowa	0.244	0.207	0.90	0.208	0.263	0.81	-0.247	0.171	0.06
Farm	0.280	0.295	0.84	0.545	0.445	0.93	0.213	0.221	0.86
Envi_Mem	0.325	0.430	0.79	0.397	0.586	0.77	0.332	0.365	0.83
	Opinion Variables								
Informed	-0.391	0.347	0.12	-0.115	0.552	0.43	0.018	0.323	0.51
Opinion	0.150	0.270	0.72	0.160	0.352	0.68	0.159	0.220	0.78
Read_Labels	0.027	0.268	0.54	0.241	0.361	0.76	0.268	0.217	0.90
	Health Variables								
Smoke	-0.177	0.257	0.24	0.373	0.389	0.85	0.381	0.240	0.97
Exercise	0.114	0.213	0.72	-0.212	0.279	0.20	0.024	0.179	0.57
Health_Diet	-0.017	0.073	0.41	0.074	0.093	0.81	-0.034	0.064	0.30
Health_Phys	0.026	0.058	0.68	0.032	0.080	0.66	0.062	0.056	0.89
Round 1 Label	0.097	0.267	0.63	-0.283	0.379	0.21	-0.200	0.264	0.21

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.7 Bayesian Estimates of Differences of Bid Price Equations for Tomato Without PECA (N=92, Obs=828)

Dep Var	$Y^{GMF} - Y^{Plain\ Label}$			$Y^{GMF} - Y^{Intragenic}$			$Y^{GMF} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.235	0.611	0.34	-0.313	0.387	0.19	-0.398	0.369	0.13
Anti	0.484	0.730	0.76	0.475	0.444	0.87	0.180	0.398	0.69
Pro & Anti	-0.138	0.552	0.41	-0.220	0.359	0.27	0.055	0.358	0.58
Pro,Anti,Ver	0.079	0.669	0.55	-0.193	0.422	0.30	-0.407	0.416	0.15
	Demographic Variables								
Gender	0.362	0.503	0.77	-0.176	0.331	0.29	0.499	0.308	0.96
Race	-0.062	0.649	0.47	-0.487	0.461	0.12	-0.680	0.516	0.08
Age	-0.013	0.013	0.16	0.002	0.009	0.57	-0.004	0.009	0.32
Income	-0.006	0.006	0.15	-0.004	0.004	0.16	-0.008	0.005	0.01
Educ	0.259	0.111	0.99	0.001	0.062	0.49	-0.038	0.060	0.24
Married	-0.470	0.480	0.16	-0.037	0.325	0.47	0.152	0.302	0.71
Household	0.362	0.221	0.96	0.132	0.143	0.84	0.005	0.119	0.51
Iowa	0.427	0.411	0.86	-0.047	0.260	0.41	-0.652	0.285	0.01
Farm	0.591	0.476	0.90	0.057	0.311	0.56	0.128	0.301	0.66
Envi_Mem	-0.148	0.786	0.43	0.168	0.525	0.64	0.606	0.499	0.89
	Opinion Variables								
Informed	-0.631	0.607	0.14	0.175	0.433	0.66	-0.446	0.402	0.12
Opinion	0.016	0.501	0.53	-0.094	0.306	0.38	0.151	0.287	0.72
Read_Labels	0.374	0.421	0.82	0.181	0.275	0.76	0.416	0.270	0.94
	Health Variables								
Smoke	-0.385	0.425	0.17	0.160	0.287	0.73	-0.036	0.285	0.46
Exercise	-0.513	0.423	0.10	-0.489	0.262	0.03	-0.241	0.264	0.16
Health_Diet	-0.048	0.152	0.38	0.036	0.101	0.66	0.029	0.093	0.63
Health_Phys	0.062	0.126	0.69	0.088	0.087	0.86	0.087	0.084	0.86
Round 1 Label	0.313	0.465	0.75	-0.353	0.432	0.20	-0.272	0.365	0.21

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.8 Bayesian Estimates of Differences of Bid Price Equations for Potato Without PECA (N=92, Obs=828)

Dep Var	$Y^{GMF} - Y^{Plain\ Label}$			$Y^{GMF} - Y^{Intragenic}$			$Y^{GMF} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.572	0.258	0.01	-0.434	0.359	0.10	-0.235	0.369	0.25
Anti	0.138	0.274	0.70	1.004	0.504	0.98	0.688	0.415	0.95
Pro & Anti	-0.192	0.227	0.20	-0.227	0.338	0.23	0.047	0.345	0.56
Pro,Anti,Ver	-0.055	0.329	0.43	0.001	0.484	0.47	0.389	0.499	0.79
	Demographic Variables								
Gender	0.410	0.246	0.96	-0.254	0.349	0.21	0.418	0.364	0.89
Race	-0.249	0.297	0.19	-0.575	0.504	0.11	0.011	0.438	0.52
Age	-0.010	0.007	0.06	0.004	0.009	0.68	0.000	0.010	0.51
Income	0.000	0.003	0.52	-0.005	0.005	0.13	-0.005	0.005	0.16
Educ	0.008	0.041	0.58	-0.020	0.064	0.36	-0.001	0.066	0.48
Married	-0.022	0.188	0.46	0.259	0.271	0.85	0.130	0.285	0.69
Household	0.075	0.091	0.80	0.246	0.135	0.98	0.182	0.136	0.92
Iowa	-0.120	0.170	0.23	-0.211	0.283	0.22	-0.502	0.292	0.03
Farm	0.315	0.219	0.93	0.665	0.407	0.97	0.024	0.325	0.52
Envi_Mem	0.472	0.388	0.89	0.216	0.597	0.64	0.287	0.596	0.70
	Opinion Variables								
Informed	-0.258	0.287	0.18	0.061	0.526	0.55	0.233	0.540	0.66
Opinion	0.288	0.254	0.88	0.105	0.342	0.62	0.470	0.384	0.91
Read_Labels	0.074	0.253	0.62	0.365	0.322	0.88	0.434	0.327	0.91
	Health Variables								
Smoke	0.138	0.209	0.75	0.539	0.329	0.96	0.349	0.373	0.84
Exercise	0.221	0.214	0.85	-0.306	0.283	0.13	-0.061	0.305	0.43
Health_Diet	0.105	0.075	0.92	0.068	0.099	0.76	0.085	0.100	0.81
Health_Phys	-0.033	0.054	0.27	-0.015	0.082	0.42	0.024	0.085	0.61
Round 1 Label	-0.006	0.295	0.48	0.005	0.400	0.49	-0.009	0.352	0.49

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.9 Marginal Effects of Explanatory Variables on Bid Prices for Products Without PECA (N=92,Obs=1104)

Dep Var	$Y^{No\ Label}$		$Y^{GM\ Free}$		$Y^{Intragenic}$		$Y^{Transgenic}$	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
	Information Treatment Dummy Variables (No Info Dummy Omitted)							
Pro	0.048	0.090	-0.066	0.090	0.120	0.084	0.082	0.132
Anti	-0.084	0.132	0.054	0.066	-0.120	0.150	-0.228	0.198
Pro & Anti	0.108	0.072	0.066	0.054	0.156	0.072	0.060	0.108
Pro,Anti,ver	-0.072	0.120	-0.120	0.114	-0.006	0.114	-0.102	0.156
	Demographic Variables							
Gender	-0.060	0.066	-0.018	0.054	0.036	0.090	-0.132	0.084
Race	0.330	0.174	0.120	0.102	0.204	0.150	0.210	0.168
Age	0.012	0.000	0.006	0.000	0.006	0.000	0.012	0.000
Income	0.000	0.000	0.000	0.000	0.000	0.000	0.006	0.000
Educ	0.000	0.012	-0.006	0.006	0.012	0.012	0.018	0.012
Married	-0.072	0.072	-0.024	0.048	-0.096	0.078	-0.108	0.090
Household	0.060	0.024	0.060	0.018	0.048	0.024	0.054	0.030
Iowa	-0.090	0.060	-0.060	0.042	-0.060	0.066	0.090	0.090
Farm	0.000	0.072	0.030	0.048	0.042	0.072	0.078	0.084
Envi_Mem	-0.474	0.390	-0.174	0.222	-0.288	0.324	-0.592	0.522
	Opinion Variables							
Informed	0.138	0.066	0.060	0.060	-0.006	0.120	0.132	0.108
Opinion	-0.036	0.090	0.012	0.060	0.024	0.084	-0.096	0.132
Read_Labels	-0.138	0.078	-0.030	0.054	-0.090	0.078	-0.270	0.096
	Health Variables							
Smoke	0.150	0.054	0.120	0.042	0.120	0.060	0.150	0.078
Exercise	0.024	0.072	0.036	0.054	0.198	0.084	0.108	0.096
Health_Diet	0.024	0.024	0.024	0.018	-0.006	0.024	0.042	0.030
Health_Phys	-0.024	0.018	-0.018	0.012	-0.024	0.024	-0.048	0.024
Round 1 Label	0.054	0.030	0.048	0.030	0.114	0.036	0.138	0.036

Mean and Stdev denote the posterior mean $E(\cdot \mid y)$ and posterior standard deviation $Std(\cdot \mid y)$.

Table 4.10 Bayesian Estimates of Bid Price Equations for Products With PECA (N=98,Obs=882)

Dep Var	Y^{GM}			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	0.198	0.256	0.78	0.982	0.267	1.00	0.479	0.341	0.93
Anti	-0.109	0.266	0.34	-0.478	0.279	0.05	-0.387	0.355	0.13
Pro & Anti	-0.085	0.258	0.36	0.152	0.270	0.72	-0.250	0.349	0.24
Pro,Anti,Ver	-0.718	0.243	0.00	-0.566	0.256	0.01	-0.506	0.325	0.06
	Demographic Variables								
Gender	-0.045	0.164	0.39	0.224	0.173	0.91	0.252	0.220	0.87
Race	-0.419	0.232	0.03	-0.488	0.243	0.02	-0.476	0.305	0.06
Age	0.023	0.006	1.00	0.016	0.006	0.99	0.017	0.008	0.98
Income	-0.008	0.003	0.01	-0.008	0.003	0.01	-0.012	0.004	0.00
Educ	-0.022	0.035	0.27	0.073	0.036	0.98	-0.001	0.048	0.50
Married	-0.072	0.199	0.35	-0.413	0.207	0.03	0.021	0.264	0.53
Household	0.265	0.062	1.00	0.215	0.065	1.00	0.156	0.083	0.97
Iowa	-0.170	0.161	0.14	-0.265	0.170	0.06	0.352	0.224	0.95
Farm	-0.473	0.206	0.01	-0.518	0.221	0.01	-0.298	0.282	0.14
Envi_Mem	-0.323	0.419	0.22	-0.458	0.445	0.15	-0.213	0.562	0.35
	Opinion Variables								
Informed	0.169	0.291	0.72	0.178	0.304	0.72	0.284	0.380	0.77
Opinion	0.448	0.262	0.95	-0.025	0.282	0.46	0.804	0.348	0.99
Read_Labels	0.483	0.184	1.00	0.348	0.194	0.97	0.068	0.249	0.60
	Health Variables								
Smoke	0.308	0.189	0.94	0.201	0.200	0.84	0.154	0.244	0.73
Exercise	0.146	0.164	0.81	0.551	0.176	1.00	0.408	0.224	0.97
Health_Diet	-0.046	0.074	0.27	-0.134	0.078	0.05	-0.112	0.098	0.13
Health_Phys	0.179	0.074	0.99	0.132	0.079	0.95	0.171	0.100	0.96
Round 1 Label	-0.210	0.110	0.02	0.342	0.138	1.00	0.626	0.159	1.00
	Inter-Round Correlation Coefficients								
	$\rho_{GM,Intra}$			$\rho_{GM,Trans}$			$\rho_{Intra,Trans}$		
	0.49			0.46			0.54		

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.11 Bayesian Estimates of Bid Price Equations for Broccoli With PECA (N=98,Obs=294)

Dep Var	Y^{GM}			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.026	0.272	0.46	0.936	0.280	1.00	0.460	0.388	0.88
Anti	-0.162	0.284	0.28	-0.462	0.297	0.06	-0.235	0.403	0.28
Pro & Anti	0.012	0.269	0.51	0.259	0.279	0.82	0.008	0.386	0.51
Pro,Anti,Ver	-0.814	0.256	0.00	-0.687	0.259	0.00	-0.559	0.362	0.06
	Demographic Variables								
Gender	-0.054	0.173	0.38	0.159	0.181	0.81	0.278	0.242	0.88
Race	-0.564	0.241	0.01	-0.523	0.251	0.02	-0.373	0.340	0.13
Age	0.012	0.007	0.96	0.002	0.007	0.63	0.008	0.010	0.81
Income	-0.003	0.003	0.19	-0.003	0.003	0.20	-0.006	0.005	0.08
Educ	-0.098	0.045	0.01	-0.041	0.047	0.19	-0.081	0.064	0.10
Married	-0.079	0.204	0.35	-0.307	0.213	0.07	0.016	0.284	0.52
Household	0.089	0.074	0.89	0.020	0.076	0.61	0.057	0.106	0.71
Iowa	-0.114	0.166	0.24	-0.081	0.170	0.32	0.348	0.241	0.93
Farm	-0.288	0.217	0.09	-0.315	0.232	0.09	-0.244	0.321	0.22
Envi_Mem	-0.281	0.444	0.26	-0.227	0.465	0.31	0.034	0.608	0.52
	Opinion Variables								
Informed	0.172	0.297	0.72	0.375	0.317	0.88	0.476	0.415	0.88
Opinion	0.253	0.275	0.82	-0.296	0.290	0.15	0.401	0.381	0.86
Read_Labels	0.450	0.195	0.99	0.359	0.202	0.96	0.149	0.270	0.71
	Health Variables								
Smoke	0.304	0.210	0.93	0.019	0.219	0.54	0.139	0.286	0.69
Exercise	0.211	0.170	0.89	0.559	0.181	1.00	0.481	0.245	0.98
Health_Diet	-0.043	0.078	0.29	-0.095	0.080	0.12	-0.083	0.107	0.21
Health_Phys	0.013	0.079	0.56	-0.040	0.084	0.31	0.003	0.109	0.50
Round 1 Label	-0.136	0.118	0.12	0.302	0.134	0.99	0.485	0.177	1.00
	Inter-Round Correlation Coefficients								
	$\rho_{GM,Intra}$			$\rho_{GM,Trans}$			$\rho_{Intra,Trans}$		
	0.55			0.58			0.58		

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.12 Bayesian Estimates of Bid Price Equations for Tomato With PECA (N=98,Obs=294)

Dep Var	Y^{GM}			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	0.205	0.217	0.83	0.921	0.318	1.00	0.875	0.405	0.99
Anti	-0.101	0.224	0.33	-0.352	0.329	0.14	-0.078	0.411	0.42
Pro & Anti	-0.324	0.218	0.07	-0.039	0.315	0.45	0.108	0.397	0.60
Pro,Anti,Ver	-0.512	0.207	0.01	-0.446	0.299	0.07	-0.069	0.380	0.42
	Demographic Variables								
Gender	-0.212	0.138	0.06	0.019	0.198	0.54	0.117	0.250	0.68
Race	-0.448	0.194	0.01	-0.719	0.287	0.01	-0.511	0.349	0.07
Age	0.017	0.005	1.00	0.017	0.008	0.99	0.021	0.010	0.98
Income	-0.002	0.003	0.17	-0.003	0.004	0.20	-0.010	0.005	0.02
Educ	-0.110	0.036	0.00	-0.093	0.052	0.04	-0.104	0.065	0.05
Married	0.064	0.164	0.65	-0.183	0.240	0.22	0.053	0.292	0.57
Household	0.086	0.058	0.93	0.067	0.083	0.79	0.073	0.103	0.77
Iowa	-0.051	0.133	0.35	-0.424	0.190	0.01	0.239	0.239	0.84
Farm	-0.382	0.174	0.01	-0.434	0.255	0.04	-0.515	0.323	0.05
Envi_Mem	-0.509	0.358	0.08	-0.824	0.520	0.06	-0.503	0.625	0.21
	Opinion Variables								
Informed	0.081	0.244	0.63	0.100	0.357	0.61	0.115	0.419	0.61
Opinion	0.253	0.222	0.87	-0.022	0.324	0.48	0.626	0.389	0.95
Read_Labels	0.258	0.159	0.95	0.304	0.229	0.91	-0.020	0.279	0.47
	Health Variables								
Smoke	-0.036	0.171	0.42	-0.015	0.247	0.47	-0.253	0.296	0.19
Exercise	-0.155	0.136	0.13	0.098	0.200	0.69	0.331	0.247	0.91
Health_Diet	-0.125	0.062	0.02	-0.175	0.090	0.03	-0.159	0.111	0.08
Health_Phys	0.177	0.063	1.00	0.094	0.092	0.85	0.128	0.112	0.88
Round 1 Label	-0.254	0.102	0.00	0.254	0.174	0.93	0.464	0.182	0.99
	Inter-Round Correlation Coefficients								
	$\rho_{GM,Intra}$			$\rho_{GM,Trans}$			$\rho_{Intra,Trans}$		
	0.51			0.58			0.41		

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.13 Bayesian Estimates of Bid Price Equations for Potato With PECA (N=98,Obs=294)

Dep Var	Y^{GM}			$Y^{Intragenic}$			$Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Dummy Variables (No Info. Dummy Omitted)								
Pro	-0.235	0.428	0.29	0.554	0.471	0.88	0.130	0.686	0.58
Anti	-0.487	0.447	0.14	-0.853	0.500	0.04	-0.746	0.708	0.14
Pro & Anti	-0.471	0.423	0.13	-0.264	0.468	0.29	-0.643	0.690	0.18
Pro,Anti,Ver	-1.397	0.406	0.00	-1.179	0.447	0.01	-0.988	0.647	0.06
	Demographic Variables								
Gender	0.220	0.273	0.79	0.412	0.307	0.91	0.629	0.446	0.92
Race	-0.525	0.381	0.08	-0.758	0.427	0.04	-0.498	0.620	0.21
Age	0.008	0.011	0.78	0.000	0.012	0.51	0.007	0.016	0.66
Income	-0.009	0.005	0.04	-0.006	0.006	0.16	-0.015	0.008	0.04
Educ	-0.132	0.070	0.03	-0.009	0.080	0.46	-0.060	0.112	0.29
Married	0.144	0.323	0.67	-0.371	0.359	0.15	0.091	0.506	0.56
Household	0.219	0.115	0.97	0.096	0.127	0.78	0.144	0.186	0.78
Iowa	-0.377	0.261	0.08	-0.361	0.288	0.11	0.411	0.436	0.83
Farm	-0.450	0.342	0.09	-0.435	0.382	0.13	-0.596	0.585	0.15
Envi_Mem	-0.099	0.718	0.45	-0.300	0.792	0.35	-0.071	1.117	0.47
	Opinion Variables								
Informed	0.432	0.484	0.81	0.226	0.541	0.67	0.461	0.747	0.74
Opinion	0.814	0.439	0.97	0.226	0.487	0.68	1.431	0.685	0.98
Read_Labels	0.562	0.311	0.96	0.343	0.348	0.84	-0.140	0.493	0.40
	Health Variables								
Smoke	-0.036	0.333	0.46	-0.254	0.373	0.25	-0.073	0.508	0.44
Exercise	0.192	0.270	0.76	0.880	0.307	1.00	0.683	0.435	0.94
Health_Diet	-0.084	0.123	0.24	-0.297	0.135	0.01	-0.252	0.190	0.09
Health_Phys	0.094	0.126	0.77	0.048	0.139	0.64	0.138	0.195	0.77
Round 1 Label	-0.201	0.181	0.13	0.352	0.228	0.94	0.873	0.331	0.99
	Inter-Round Correlation Coefficients								
	$\rho_{GM,Intra}$			$\rho_{GM,Trans}$			$\rho_{Intra,Trans}$		
	0.45			0.46			0.59		

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.14 Bayesian Estimates of Differences of Bid Price Equations for Products With PECA (N=98,Obs=588)

Dep Var	$Y^{GM} - Y^{Intragenic}$			$Y^{GM} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Variables					
Pro	-0.786	0.183	0.00	-0.282	0.226	0.10
Anti	0.365	0.202	0.97	0.279	0.244	0.88
Pro & Anti	-0.237	0.183	0.10	0.171	0.234	0.77
Pro,Anti,Ver	-0.150	0.173	0.19	-0.211	0.213	0.16
	Demographic Variables					
Gender	-0.268	0.119	0.01	-0.293	0.147	0.02
Race	0.066	0.163	0.66	0.056	0.195	0.62
Age	0.007	0.005	0.93	0.006	0.006	0.85
Income	-0.001	0.002	0.39	0.004	0.003	0.94
Educ	-0.094	0.026	0.00	-0.020	0.034	0.27
Married	0.337	0.134	0.99	-0.096	0.170	0.28
Household	0.050	0.044	0.87	0.109	0.054	0.98
Iowa	0.096	0.111	0.80	-0.517	0.147	0.00
Farm	0.044	0.145	0.62	-0.171	0.186	0.18
Envi_Mem	0.133	0.295	0.68	-0.096	0.356	0.39
	Opinion Variables					
Informed	-0.010	0.204	0.48	-0.118	0.239	0.31
Opinion	0.474	0.186	1.00	-0.355	0.223	0.06
Read_Labels	0.128	0.134	0.83	0.404	0.167	0.99
	Health Variables					
Smoke	0.107	0.134	0.79	0.156	0.157	0.84
Exercise	-0.402	0.119	0.00	-0.257	0.147	0.04
Health_Diet	0.087	0.053	0.95	0.066	0.063	0.85
Health_Phys	0.046	0.053	0.80	0.006	0.063	0.54
Round 1 Label	-0.550	0.207	0.00	-0.839	0.233	0.00

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.15 Bayesian Estimates of Differences of Bid Price Equations for Broccoli With PECA (N=98,Obs=588)

Dep Var	$Y^{GM} - Y^{Intragenic}$			$Y^{GM} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Variables					
Pro	-0.962	0.201	0.00	-0.485	0.284	0.04
Anti	0.300	0.220	0.92	0.073	0.295	0.61
Pro & Anti	-0.247	0.200	0.11	0.004	0.281	0.51
Pro,Anti,Ver	-0.127	0.187	0.24	-0.255	0.262	0.16
	Demographic Variables					
Gender	-0.213	0.128	0.05	-0.332	0.174	0.03
Race	-0.041	0.173	0.41	-0.191	0.241	0.21
Age	0.010	0.005	0.97	0.004	0.007	0.71
Income	0.000	0.002	0.53	0.003	0.003	0.85
Educ	-0.057	0.035	0.05	-0.017	0.047	0.35
Married	0.228	0.145	0.94	-0.095	0.198	0.31
Household	0.069	0.053	0.90	0.032	0.077	0.66
Iowa	-0.034	0.116	0.38	-0.462	0.170	0.00
Farm	0.028	0.158	0.57	-0.043	0.236	0.41
Envi_Mem	-0.054	0.313	0.43	-0.315	0.412	0.21
	Opinion Variables					
Informed	-0.203	0.213	0.17	-0.304	0.278	0.13
Opinion	0.549	0.195	1.00	-0.148	0.262	0.28
Read_Labels	0.091	0.143	0.74	0.300	0.192	0.94
	Health Variables					
Smoke	0.284	0.153	0.97	0.165	0.194	0.81
Exercise	-0.348	0.125	0.00	-0.271	0.175	0.06
Health_Diet	0.052	0.058	0.82	0.040	0.074	0.71
Health_Phys	0.053	0.059	0.82	0.010	0.074	0.56
Round 1 Label	-0.438	0.208	0.01	-0.621	0.246	0.01

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.16 Bayesian Estimates of Differences of Bid Price Equations for Tomato With PECA (N=98,Obs=588)

Dep Var	$Y^{GM} - Y^{Intragenic}$			$Y^{GM} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Variables					
Pro	-0.716	0.246	0.00	-0.670	0.308	0.01
Anti	0.251	0.254	0.84	-0.023	0.310	0.47
Pro & Anti	-0.285	0.243	0.12	-0.433	0.298	0.07
Pro,Anti,Ver	-0.066	0.233	0.39	-0.443	0.287	0.06
	Demographic Variables					
Gender	-0.231	0.153	0.06	-0.329	0.187	0.04
Race	0.271	0.219	0.89	0.062	0.258	0.59
Age	0.000	0.006	0.50	-0.004	0.008	0.30
Income	0.001	0.003	0.61	0.007	0.004	0.98
Educ	-0.017	0.040	0.33	-0.006	0.049	0.45
Married	0.246	0.183	0.91	0.011	0.213	0.53
Household	0.019	0.065	0.61	0.013	0.078	0.57
Iowa	0.373	0.146	0.99	-0.290	0.179	0.05
Farm	0.052	0.196	0.60	0.132	0.246	0.70
Envi_Mem	0.315	0.401	0.78	-0.005	0.447	0.49
	Opinion Variables					
Informed	-0.020	0.270	0.46	-0.034	0.301	0.46
Opinion	0.275	0.251	0.86	-0.373	0.284	0.09
Read_Labels	-0.046	0.175	0.39	0.278	0.206	0.92
	Health Variables					
Smoke	-0.022	0.188	0.46	0.216	0.214	0.85
Exercise	-0.253	0.154	0.05	-0.487	0.185	0.00
Health_Diet	0.049	0.070	0.76	0.034	0.082	0.66
Health_Phys	0.083	0.071	0.88	0.049	0.081	0.74
Round 1 Label	-0.507	0.224	0.01	-0.718	0.240	0.00

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.17 Bayesian Estimates of Differences of Bid Price Equations for Potato With PECA (N=98,Obs=588)

Dep Var	$Y^{GM} - Y^{Intragenic}$			$Y^{GM} - Y^{Transgenic}$		
	Mean	Stdev	Pr	Mean	Stdev	Pr
	Information Treatment Variables					
Pro	-0.789	0.292	0.00	-0.364	0.464	0.21
Anti	0.367	0.317	0.88	0.260	0.475	0.71
Pro & Anti	-0.207	0.294	0.24	0.171	0.472	0.64
Pro,Anti,Ver	-0.218	0.279	0.22	-0.409	0.433	0.17
	Demographic Variables					
Gender	-0.191	0.193	0.16	-0.409	0.302	0.08
Race	0.233	0.271	0.80	-0.027	0.420	0.48
Age	0.008	0.007	0.85	0.001	0.011	0.54
Income	-0.003	0.004	0.19	0.006	0.006	0.84
Educ	-0.123	0.052	0.01	-0.073	0.075	0.16
Married	0.516	0.225	0.99	0.054	0.335	0.56
Household	0.123	0.079	0.94	0.074	0.129	0.73
Iowa	-0.015	0.184	0.47	-0.787	0.298	0.00
Farm	-0.015	0.249	0.48	0.147	0.427	0.64
Envi_Mem	0.201	0.495	0.65	-0.028	0.733	0.47
	Opinion Variables					
Informed	0.206	0.336	0.73	-0.029	0.477	0.48
Opinion	0.588	0.307	0.97	-0.618	0.458	0.09
Read_Labels	0.219	0.218	0.84	0.701	0.330	0.98
	Health Variables					
Smoke	0.218	0.231	0.83	0.037	0.324	0.55
Exercise	-0.687	0.203	0.00	-0.491	0.302	0.05
Health_Diet	0.213	0.085	0.99	0.168	0.121	0.92
Health_Phys	0.046	0.087	0.71	-0.044	0.125	0.36
Round 1 Label	-0.553	0.345	0.05	-1.074	0.449	0.01

Mean, Stdev, and Pr respectively denote the posterior mean $E(\cdot \mid y)$, posterior standard deviation $Std(\cdot \mid y)$, and posterior probability of being greater than zero $\Pr(\cdot > 0 \mid y)$.

Table 4.18 Marginal Effects of Explanatory Variables on Bid Prices for Products With PECA (N=98,Obs=882)

Dep Var	Y^{GM}		$Y^{Intragenic}$		$Y^{Transgenic}$	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
	Information Treatment Variables (No Info Omitted)					
Pro	0.040	0.056	0.140	0.034	0.136	0.094
Anti	-0.034	0.072	-0.122	0.080	-0.142	0.132
Pro & Anti	-0.026	0.068	0.026	0.050	-0.092	0.122
Pro,Anti,Ver	-0.226	0.092	-0.142	0.074	-0.182	0.122
	Demographic Variables					
Gender	-0.010	0.040	0.048	0.038	0.084	0.074
Race	-0.086	0.046	-0.080	0.038	-0.138	0.084
Age	0.008	0.002	0.004	0.002	0.010	0.004
Income	-0.002	0.000	-0.002	0.000	-0.006	0.002
Educ	-0.006	0.012	0.020	0.010	-0.002	0.026
Married	-0.018	0.050	-0.082	0.042	0.008	0.086
Household	0.082	0.022	0.058	0.020	0.082	0.044
Iowa	-0.042	0.040	-0.052	0.034	0.118	0.076
Farm	-0.140	0.070	-0.128	0.064	-0.106	0.100
Envi_Mem	-0.118	0.146	-0.140	0.144	-0.098	0.202
	Opinion Variables					
Informed	0.030	0.066	0.026	0.056	0.078	0.112
Opinion	0.088	0.048	-0.012	0.060	0.216	0.084
Read_Labels	0.132	0.056	0.076	0.046	0.024	0.082
	Health Variables					
Smoke	0.068	0.040	0.036	0.038	0.046	0.076
Exercise	0.038	0.042	0.116	0.042	0.136	0.076
Health_Diet	-0.014	0.024	-0.036	0.022	-0.060	0.054
Health_Phys	0.056	0.024	0.036	0.022	0.092	0.056
Round 1 Label	-0.054	0.030	0.064	0.026	0.188	0.048

Mean and Stdev denote the posterior mean $E(\cdot \mid y)$ and posterior standard deviation $Std(\cdot \mid y)$.

CHAPTER 5: THE VALUE OF VERIFIABLE INFORMATION

5.1 Introduction

While in the previous chapter it was shown that information has an impact on both absolute and relative valuations of food products produced through different bioengineering methods, these results alone are not sufficient to assess the welfare impact or "value" of information to consumers. The seminal paper by Foster and Just (1989) asserts that information has value to consumers if, from an ex-post perspective, the information has an impact on purchasing behavior. In the following section a simple methodology in the spirit of Foster and Just is developed for estimating the value of information in the context of a market with close substitutes.

5.2 Theoretical Model

Consider a market with $n = 1,2,\ldots,N$ consumers who may consume at most one unit of one product from a selection of three alternatives A, B, and C. Let P^A, P^B, and P^C denote the respective prices of the three products. Let I_n denote the information set consumer n possesses prior to making his or her purchase decision. In this simple market, consumers choose the product (or none) that maximizes consumer surplus

(13) $$S_n = \max\left\{\left(WTP^A_{n,I_n} - P^A\right),\left(WTP^B_{n,I_n} - P^B\right),\left(WTP^C_{n,I_n} - P^C\right),0\right\}.$$

Now consider the same scenario, but suppose the consumer receives new information and is operating under a different information set $I_n^{'}$. Surplus under the new information set is

(14) $$S_n^{'} = \max\left\{\left(WTP^A_{n,I_n^{'}} - P^A\right),\left(WTP^B_{n,I_n^{'}} - P^B\right),\left(WTP^C_{n,I_n^{'}} - P^C\right),0\right\}.$$

Using these two equations, we can express the "direct" change in consumer surplus resulting from the different sets of information as

(15) $\Delta S_n = S_n^{'} - S_n$.

The problem with this as a measure of the value of information, as argued by Foster and Just, is that it leads to the paradox of "blissful ignorance" in that by solely comparing welfare under different "information states", information may have a negative impact on welfare (i.e. the consumer may be better off without the new information). Hence, Foster and Just argue that welfare measures should be assessed under the new information state only. Their proposed measure, the cost of ignorance (COI), compares welfare of informed and uniformed purchases measured in terms of the informed state.[22] Let $Z_{I_n} = \{A, B, C, 0\}$ denote the product that for consumer n yields the highest surplus under information set I_n. Then, from an ex-post perspective, the "indirect" impact of information is

(16) $\Delta \widetilde{S}_n = \left(WTP_{n,I_n^{'}}^{Z_{I_n}} - P^{Z_{I_n}} \right) - S_n$,

where $WTP_{n,I_n^{'}}^{Z_{I_n}}$ denotes WTP under information set $I_n^{'}$ for the product the individual would have purchased under the previous information set I_n. Finally, the welfare impact of information, the COI, is given by

(17) $COI_n = \Delta S_n - \Delta \widetilde{S}_n = S_n^{'} - \left(WTP_{n,I_n^{'}}^{Z_{I_n}} - P^{Z_{I_n}} \right)$.

[22] An incomplete list of studies utilizing the COI or a related variant for analysis of information within the context of food products include Hu, Veeman, and Adamowicz (2005), Mazzocchi, Stefani, and Henson (2004), Teisl and Roe (1998), and Teisl, Bockstael, and Levy (2001).

Within the context of the considered market, it can be seen that information has value to consumers iff the information leads to a change in the product purchased.

5.3 Empirical Model

To estimate the value of information using the described methodology, several values are required including WTP before and after receipt of information and market prices. In the conducted experimental auctions, participants' WTP was only obtained after receiving information treatments. To proceed, in lieu of making restrictive assumptions,[23] the regression model derived in the previous section is used to generate WTP forecasts. This permits controlling for confounding factors that affect WTP other than the information treatment. More explicitly, suppose one seeks to estimate the value of information i. For those individuals with information set I where $i \in I$, a forecast is generated of their WTP under the information set $I\neg i$. As well, for those individuals who received information set $I\neg i$, a forecast of their WTP under information set I is generated. Using these forecasts (denoted by $\wedge$), the direct change in surplus from information i for those individuals who received information treatments I or $I\neg i$ can be expressed as

$$(18)\quad \begin{aligned} \Delta S_{n,I,I\neg i} &= S_{n,I} - \hat{S}_{n,I\neg i} = \max\left\{\left\{WTP^{Z}_{n,I} - P^{Z}\right\}_{Z=A,B,C}, 0\right\} - \max\left\{\left\{W\hat{T}P^{Z}_{n,I\neg i} - P^{Z}\right\}_{Z=A,B,C}, 0\right\} \\ \Delta S_{n,I\neg i,I} &= \hat{S}_{n,I} - S_{n,I\neg i} = \max\left\{\left\{W\hat{T}P^{Z}_{n,I} - P^{Z}\right\}_{Z=A,B,C}, 0\right\} - \max\left\{\left\{WTP^{Z}_{n,I\neg i} - P^{Z}\right\}_{Z=A,B,C}, 0\right\} \end{aligned}$$

The indirect impact of information on consumer surplus for an individual who received treatment I and $I\neg i$ are

[23] For example, one could assume that participants who receive an information treatment have relative preferences that are uniformly distributed across the subset of individuals who did not receive the information treatment.

$$\text{(19)}\qquad \begin{aligned} \Delta\widetilde{S}_{n,I,I\neg i} &= \left(WTP_{n,I}^{\hat{Z}_{n,I\neg i}} - P^{\hat{Z}_{n,I\neg i}}\right) - \hat{S}_{n,I\neg i} \\ \Delta\widetilde{S}_{n,I\neg i,I} &= \left(W\hat{T}P_{n,I}^{Z_{n,I\neg i}} - P^{Z_{n,I\neg i}}\right) - S_{n,I\neg i}, \end{aligned}$$

where $\hat{Z}_{n,I\neg i}$ denotes the forecasted product that would have yielded individual n the greatest surplus under information set $I\neg i$ and $Z_{n,I\neg i}$ denotes the observed product that yielded the greatest surplus under information set $I\neg i$.

Putting the two pieces together, we can express the value of information for each type of individual as

$$\text{(20)}\qquad \begin{aligned} COI_{n,I,I\neg i} &= \Delta S_{n,I,I\neg i} - \Delta\widetilde{S}_{n,I,I\neg i} = S_{n,I} - \left(WTP_{n,I}^{\hat{Z}_{n,I\neg i}} - P^{\hat{Z}_{n,I\neg i}}\right) \\ COI_{n,I\neg i,I} &= \Delta S_{n,I\neg i,I} - \Delta\widetilde{S}_{n,I\neg i,I} = \hat{S}_{n,I} - \left(W\hat{T}P_{n,I}^{Z_{n,I\neg i}} - P^{Z_{n,I\neg i}}\right) \end{aligned}$$

Finally, we can express the estimated average value of information i per individual per product as

$$\text{(21)}\qquad COI_i = \frac{1}{N_I + N_{I\neg i}}\left(\sum_{n=1}^{N_I} COI_{n,I,I\neg i} + \sum_{n=1}^{N_{I\neg i}} COI_{n,I\neg i,I}\right),$$

where N_I and $N_{I\neg i}$ denote the number of individuals in the sample who received treatments I and $I\neg i$ respectively.

For estimating the value of information, three different market scenarios are considered. Scenario 1 is a market with GM Free, intragenic, and Plain Label products, scenario 2 is a market with GM Free, intragenic, and transgenic products, and scenario 3 is a market with GM, intragenic, and transgenic products all with enhanced consumer attributes. For each market scenario, we consider the value of verifiable information in a conflicted information setting (i.e., $I = \{\text{Pro, Anti, Ver}\}$ and $i = \text{Ver}\}$). Market prices for the products are assumed to be the average bid by participants in the experimental auctions (see the bid summary tables in chapter 3 for specific values).

5.4 Value of Information Estimates

Tables 5.1-5.3 present for each scenario the following: (1) the percentage of individuals who switch to purchasing a different product after receipt of the verifiable information, (2) the value of verifiable information (COI measure) for those individuals who switch purchases, and (3) the total value of verifiable information across all individuals (switchers and non-switchers).

From table 5.1 we can see that under market scenario 1 a small number of consumers (11.2% for broccoli, 17.6% for tomato, and 11.8% for potato) switch products from receipt of the verifiable information treatment. The value of the verifiable information (COI measure) to the switching set of consumers is small, ranging from eight to eleven cents. Across all consumers, the public value of the verifiable information is slightly less than one-percent of the average valuation of the product.

Table 5.1 Value of Verifiable Information: Scenario 1

Product	Percent Switch[a]	Switcher Value[b]	Total Value[c]
Broccoli	11.2%	$0.094	$0.011
Tomato	17.6%	$0.079	$0.013
Potato	11.8%	$0.110	$0.013

[a] Percentage of individuals who purchase a different product after receiving the information.
[b] The value of information (COI) for individuals who switch products.
[c] The value of information (COI) across all individuals (switchers and non-switchers).

Under product scenario 2 (table 5.2), which models a market with both intragenic and transgenic alternatives in addition to a GM Free product, verifiable information has a greater impact on purchase decisions and has a greater public good value. The percentage of switching consumers (17.1% for broccoli, 22.4% for tomato, and 14.5% for potato) and the public value of the verifiable information ($0.023 for broccoli, $0.04 for tomato, and $0.024 for potato) is larger for each of the three commodities compared to scenario 1.

Table 5.2 Value of Verifiable Information: Scenario 2

Product	Percent Switch[a]	Switcher Value[b]	Total Value[c]
Broccoli	17.1%	$0.133	$0.023
Tomato	22.4%	$0.180	$0.040
Potato	14.5%	$0.163	$0.024

[a] Percentage of individuals who purchase a different product after receiving the information.
[b] The value of information (COI) for individuals who switch products.
[c] The value of information (COI) across all individuals (switchers and non-switchers).

Finally, under scenario 3 (table 5.3), which considers a market with three different GM alternatives with enhanced consumer attributes, we find that verifiable information yields the lowest benefit to all consumers. While for individuals that switch products the value of the verifiable information is between ten and thirteen cents (i.e., between 4 and 7 percent of the product price), the total percentage of switchers is low.

Table 5.3 Value of Verifiable Information: Scenario 3

Product	Percent Switch[a]	Switcher Value[b]	Total Value[c]
Broccoli	8.48%	$0.101	$0.009
Tomato	10.6%	$0.113	$0.012
Potato	9.09%	$0.130	$0.012

[a] Percentage of individuals who purchase a different product after receiving the information.
[b] The value of information (COI) for individuals who switch products.
[c] The value of information (COI) across all individuals (switchers and non-switchers).

Overall, the simulation estimates presented in this chapter indicate that while verifiable information has value to consumers through enabling informed product choices, the percentage of benefiting consumers is relatively small (less than 22.4% across all products and all scenarios). Hence, the per-individual, per-product, per-purchase occasion value of the information is low. However, if the value of verifiable information is viewed in the context of a repeated choice setting (e.g., annual purchases) and considered across multiple products (i.e., all fresh produce instead of a single vegetable), the benefit grows substantially. For example, consider a population of consumers who makes bi-monthly purchases of each of the three commodities considered in scenario 2. Per individual, on an annual basis, the value of verifiable information is $2.26. When this individual value of verifiable information is extrapolated to the adult U.S. population (approximately 228 million in 2009), the total public value of verifiable information is roughly 500 million dollars annually. Hence, when viewed at the population level, it is evident that there are significant potential welfare gains by consumers from information campaigns by credible 3rd-party organizations.

CHAPTER 6: ESTIMATES OF THE WELFARE IMPACT OF INTRAGENIC AND TRANSGENIC GM LABELING POLICIES

6.1 Introduction

Since the commercialization of the first genetically modified foods, a diverse set of interested parties including environmental groups, biotechnology companies, and government and health organizations have disseminated to the public and policymakers conflicting information on the benefits and risks of GM. A central issue in the larger debate between critics and advocates of GM has been if and how GM foods should be labeled. Given that genetic modification is a product attribute not directly observable by consumers pre- or post-purchase/consumption, a market with GM and non-GM products will result in a pooled equilibrium ala Akerlof's (1970) lemons model with too great a proportion of the weakly inferior GM product. In markets characterized by this form of information asymmetry, labeling requirements and credible certification schemes can alleviate the undesirable welfare properties of the lemons market.

While there are numerous potential labeling policies that facilitate informed GM product purchases by consumers (for discussions see Caswell, 1998 and 2000; Sheldon, 2001), globally two divergent policies have primarily been implemented. Countries including the EU, Australia, and Japan have adopted a "mandatory" labeling policy that requires all GM foods to be clearly labeled as such. In the United States and Canada (among other countries), a "voluntary" labeling policy has been adopted where producers in most circumstances may label their products as GM on a voluntary basis. From a welfare perspective, the optimal choice of labeling policy by a governmental regulatory body depends in part upon the balance between compliance and labeling costs and consumer preferences towards genetically engineered foods. Several analyses, including Berwald, Carter, and Gruere (2006), Crespi and Marette (2003), Kirchhoff and Zago (2001), and Lapan and Moschini (2004), have considered the implications resulting from the imposition of these two disparate labeling policies in a variety of contexts.

While the contentious debate over labeling policies for GM foods continues, a new feature is beginning to be introduced. To date, all commercially available GM food products have relied upon "transgenic" engineering techniques in which genes from a different organism (typically soil bacteria) are transferred into a commercial crop variety in order to yield a new product with a desired trait. Yet, a new line of research has emerged around so-called "intragenic" engineering techniques in which genes from an alternative variety of the same species are transferred into a commercial crop variety. These new intragenic engineering techniques have the potential for genomic and metabolic pathway discoveries to be rapidly introduced into established commercial varieties to fast-track the breeding processes without introducing foreign DNA or antibiotic markers and to deliver new varieties that were previously impossible through conventional cross-breeding techniques. For a more technical overview of intragenic versus transgenic engineering see Rommens et al. (2004).

While consumers' view of non-GM as being weakly superior to GM has been well documented, little research has addressed exactly what aspect of the production of GM food products results in this inferiority. Namely, is it the use of genetic techniques for producing a product that would otherwise not appear in nature, the presence of foreign genetic content, or a combination of both factors? The answer to this question manifests in whether consumers place a different value on intragenic foods when compared to otherwise equivalent transgenic foods (i.e., to what extent is intragenics weakly/strictly superior to transgenics). Furthermore, if consumers do have non-equivalent preferences towards intragenic and transgenic food products, the debate over mandatory versus voluntary labeling policies is augmented with a new question: is it socially optimal to impose a labeling regime that differentiates between intragenic and transgenic GM?

This chapter serves to address these questions, but takes a distinctly different approach from previous works studying the provision of quality in agriculture markets. In this chapter a model is developed where GM Free, intragenic GM, transgenic GM, and generically labeled GM foods are modeled as "vertically differentiated" goods ala Mussa and Rosen (1978). In the model, consumers differ with respect to two taste parameters - dislike for genetic modification and dislike for foreign genetic content - as opposed to the typical assumption of a single taste parameter.[24] In models of vertically differentiated goods, the typical approach for arriving at a tractable solution is to assume that consumer tastes are uniformly distributed along some interval.[25,26] While this assumption may be appropriate in some contexts, this is highly questionable when considering tastes

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[24] The author is unaware of previous studies addressing the provision of quality in agricultural markets where consumers in a vertically differentiated product setup are modeled using more than one continuously distributed taste parameter.

[25] An exhaustive list of papers utilizing the assumption of uniformly distributed consumers within a vertically differentiated product model is extensive. A sampling of relevant papers addressing product quality or labeling include: Berwald, Carter, and Gruere (2006), Crespi and Marette (2003), Giannakas (2002), Giannakas and Fulton (2002), Hamilton and Zilberman (2006), Hollander, Monier-Dilhan, and Ossard (1999), Moschini, Bulut, and Cembalo (2005), Scarpa (1998), Stivers (2003), and Valletti (2000).

[26] A notable exception is Lapan and Moschini (2007) where the assumption of uniformly distributed consumer tastes is only used in order to derive unambiguous comparative statics. The authors show analytically that the reduced modeling burden from assuming uniform tastes does not come without a cost.

involving GM foods because, by construction, uniformity implies that the fraction of individuals who are indifferent between GM Free and GM alternatives is relatively minor.

This chapter strives to move in the opposite direction away from an emphasis on tractability towards a more realistic characterization of consumer preferences. To that end, the actual distributions of consumers' taste preferences are estimated using data from a unique series of multiple-round random *n*th-price experimental auctions with randomly chosen adult consumers in two geographically separated cities. In addition to randomized labeling treatments, biased and verifiable information on GM are injected into the experiment. Using the estimated taste distributions and numerical methods it is possible to derive and evaluate a set of complex welfare functions under mandatory/voluntary labeling policies with/without labeling of intragenic and transgenic products. Finally, these welfare estimates are compared to those found under the typical assumption in the literature of uniformly distributed consumer tastes.

The chapter is organized as follows. In the following section a model with a vertically differentiated market structure for GM food products is developed. Section 6.3 derives consumer surplus functions under different government policies. Section 6.4 provides a brief overview of the conducted experimental auctions. Section 6.5 develops and estimates a model of consumer taste distributions. Section 6.6 evaluates welfare under different government labeling policies under the assumption of uniformly distributed tastes and using the distributions estimated in section 6.5. Finally, section 6.7 concludes the chapter.

6.2 Model of the Market for GM Foods

In this section a theoretical model of the market for genetically modified food products is developed. Firms are assumed to be able to produce three different products: GM Free (GMF), Intragenic GM (IGM), and Transgenic (TGM) with marginal costs C^{GMF}, C^{IGM}, C^{TGM} (where $C^{GMF} > C^{IGM} > C^{TGM} > 0$) respectively.[27] Firms act competitively. Depending upon the imposed government policy, food products may bear one of the following labels: *GM Free, Intragenic GM*, *Transgenic GM*, or *GM* (note, the generic *GM* label arises when intragenic/transgenic is not allowed to be included on the label).

6.2.1 Compliance Costs

Depending upon the government labeling policy imposed on the market, producers incur a number of compliance costs related to "identity preservation" activities (e.g. segregation, testing, and labeling costs). We assume that compliance costs per unit of production (if they are incurred under the considered government policy) are t^{IGM}, t^{TGM}, and t^{GMF} for intragenic, transgenic, and GM Free products respectively (where $t^{GMF} \geq t^{TGM} \geq t^{IGM} \geq 0$).[28] While intragenic foods may face lower compliance costs compared to transgenic foods, it is assumed that $C^{IGM} + t^{IGM} > C^{TGM} + t^{TGM}$, else transgenic foods would completely exit the market.

[27] Implicitly in this specification it is assumed that a product cannot be intragenically and transgenically modified. Relaxing this assumption is trivial, and would only modify the later described assumed setup for compliance costs.

[28] The assumed compliance cost relationship $t^{TGM} \geq t^{IGM}$ reflects speculation that intragenic foods may face a lower regulatory hurdle.

6.2.2 Government Labeling Policies

This chapter considers four alternative labeling policies. *Mandatory Policy 1*, which corresponds to a modified[29] version of the current policy of the EU (among other nations), mandates that all GM products must be labeled as GM. No labeling of intragenic or transgenic is allowed. Hence, the only GM product produced will be transgenic since $C^{IGM} + t^{IGM} > C^{TGM} + t^{TGM}$. Under this policy, GM Free products incur a compliance cost of t^{GMF} and transgenic products incur a compliance cost of t^{TGM}. Under *Mandatory Policy 2*, again all products must be labeled, but now labeling of intragenic GM and transgenic GM is permitted. Compliance costs for GM Free, intragenic GM, and transgenic GM are t^{GMF}, t^{IGM}, and t^{TGM} respectively. Under *Voluntary Policy 1*, which corresponds to a modified version of the current policy in the US (among other nations), only products that seek the GM Free label incur a compliance cost of t^{GMF}. No labeling of intragenic or transgenic is allowed. Hence no intragenic products will be produced.[30] Finally, under *Voluntary Policy 2*, only products seeking the GM Free or intragenic GM labels incur compliance costs of t^{GMF} and t^{IGM} respectively. In the perfectly competitive setting, equilibrium prices under each policy are given by table 6.1.

---

[29] This policy is "modified" because no current governmental policy considers intragenic content since these products have not yet reached the market.

[30] Note that since $C^{GMF} > C^{IGM} > C^{TGM}$, no producer would produce GM Free products and attempt to sell them under the inferior label.

Table 6.1 Product Prices Under Different Government Policies

	P^{GMF}	P^{IGM}	P^{TGM}	P^{GM}
Mandatory Policy 1	$C^{GMF} + t^{GMF}$	-	-	$C^{TGM} + t^{TGM}$
Mandatory Policy 2	$C^{GMF} + t^{GMF}$	$C^{IGM} + t^{IGM}$	$C^{TGM} + t^{TGM}$	-
Voluntary Policy 1	$C^{GMF} + t^{GMF}$	-	-	C^{TGM}
Voluntary Policy 2	$C^{GMF} + t^{GMF}$	$C^{IGM} + t^{IGM}$	C^{TGM}	-

6.2.3 Consumers

The impetus for labeling of food products derives from consumers' preferences towards GM food products. As previously discussed, it is assumed that the preference ordering GM Free $\succeq$ intragenic GM $\succeq$ transgenic GM holds across consumers. Consumer preferences are modeled using a vertically differentiated demand structure. Typically in a model of this nature, consumers are differentiated according to a single "taste parameter". In order to address the market at hand, it is necessary to partition the taste parameter into two components. Let θ^{GM} denote a consumer's type with regards to "dislike" for genetic modification and let θ^{F} denote a consumer's type with regards to "dislike" for foreign genetic content in food. The first type parameter, θ^{GM}, applies to preferences for both intragenic GM and transgenic GM products since both involve some form of "unnatural" genetic production methods. The second type parameter, θ^{F}, applies only for the transgenic GM product since it is the only product that is produced with the additional negative attribute of containing foreign genetic material. This specification of consumer types allows for differentiating the two components that make up "dislike" for transgenic food products. Without loss of generality, consumer types are normalized to the unit interval, $\theta^{GM}, \theta^{F} \in [0,1]$.

Consumers are assumed to purchase at most one unit of one type of product depending upon those available under the imposed regulatory policy. The indirect utility for a consumer of type $\{\theta^{GM}, \theta^{F}\}$ is

$$
(1) \qquad \begin{aligned}
U^{GMF} &= U - P^{GMF} \\
U^{IGM} &= U - P^{IGM} - \alpha\theta^{GM} \\
U^{TGM} &= U - P^{TGM} - \alpha\theta^{GM} - \delta\theta^{F} \\
U^{GM} &= U - P^{GM} - \alpha\theta^{GM} - \gamma\delta\theta^{F}
\end{aligned}
$$

where U denotes the fixed utility from consuming a food product, P denotes price, α and δ are non-negative intensity parameters, and $\gamma \in [0,1]$ is a parameter capturing consumers' expectation that a generically labeled GM product is transgenic.[31]

6.3 Welfare

In this section, consumer surplus functions under policies allowing and not allowing labeling of intragenic GM and transgenic GM are setup, but not explicitly solved. Due to the complexity of modeling two taste parameters with generic distributions, the explicit solution is quite lengthy, intractable, and uninformative. In a later section, where the distributions of θ^{GM} and θ^{F} are empirically estimated using data collected through experimental auctions, it is feasible to numerically solve for welfare under different government policies. Before solving for the consumer surplus functions it

[31] Technically, under full information of labeling policies consumers should infer that a generically labeled GM product is in fact a transgenic product (i.e. $\gamma = 1$). However, this is a source of contention and a feature of the argument by GM opponents for mandatory labeling. To keep the model as general as possible and to facilitate later discussion this expectation parameter is included throughout the derivations. Later analysis is considered under both the full information setting in which $\gamma = 1$ and a partial information setting where $\gamma \in [0,1)$.

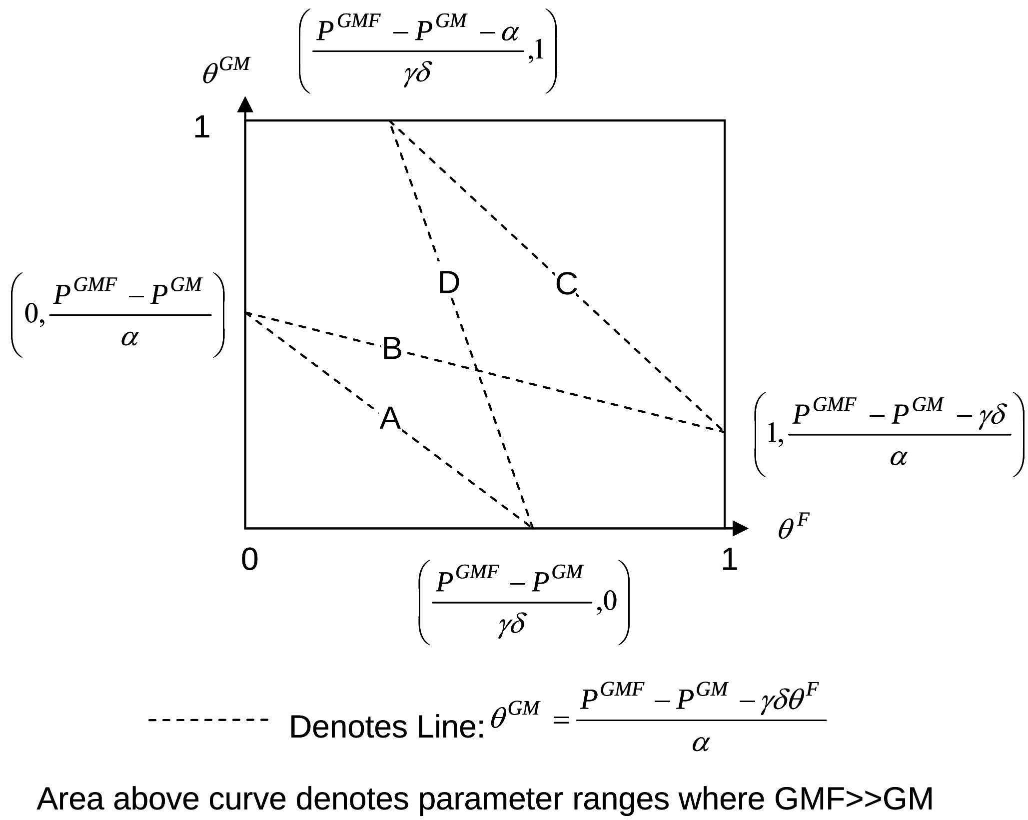
is necessary to specify notationally the taste parameter distributions. Let $k^{GM}\left(\theta^{GM}\right)$ and $k^{F}\left(\theta^{F}\right)$ denote the probability distribution functions and $K^{GM}\left(\theta^{GM}\right)$ and $K^{F}\left(\theta^{F}\right)$ denote the cumulative distribution functions.[32]

6.3.1 Welfare when Labeling of Intragenic GM and Transgenic GM is Not Allowed

In this section, welfare is considered under *Mandatory Policy 1* and *Voluntary Policy 1* where labeling of intragenic GM and transgenic GM is not allowed. Given the specification of consumer preferences, the GM Free product will be strictly preferred if $\alpha\theta^{GM} + \gamma\delta\theta^{F} > P^{GMF} - P^{GM}$ and vice versa for the GM product. Given this preference structure, the ranges of θ^{GM} and θ^{F} under which the GM Free product (or GM product) are strictly preferred is not uniquely defined. Figure 6.1 provides a graphical representation of the four possible cases that may arise. The area above each line represents the set $\left\{\theta^{GM}, \theta^{F}\right\}$ under which the GM Free product is strictly preferred and below the line is where the GM product is strictly preferred.

[32] In an earlier version of this paper, a joint distribution function for θ^{GM} and θ^{F} was considered in order to incorporate possible correlation between these two parameters. However, the experimental auction data used to calculate these parameters revealed less correlation than expected. Hence the previous joint distribution approach was abandoned in favor of a relatively simpler independent specification.

Figure 6.1 Bounds of Integration for Consumer Surplus Under Mandatory and Voluntary Policies 1



For the four possible cases, the conditions under which they may occur can be characterized by

$$
(2)\qquad
\begin{aligned}
&Case\,A: P^{GMF}-P^{GM}\le\alpha \;\; and \;\; P^{GMF}-P^{GM}\le\gamma\delta\\
&Case\,B: P^{GMF}-P^{GM}\le\alpha \;\; and \;\; P^{GMF}-P^{GM}\ge\gamma\delta\\
&Case\,C: P^{GMF}-P^{GM}\ge\alpha \;\; and \;\; P^{GMF}-P^{GM}\ge\gamma\delta\\
&Case\,D: P^{GMF}-P^{GM}\ge\alpha \;\; and \;\; P^{GMF}-P^{GM}\le\gamma\delta
\end{aligned}
$$

Through a bit of algebra, the consumer surplus functions under each of the four possible cases can be expressed as:

$$
(3)\quad
\begin{aligned}
CS^{GMF} &= \int_{\max\{0,H\}}^{\min\{J,1\}} \int_{G}^{1} \{\bullet^{GMF}\}\, d\theta^{GM}\, d\theta^{F} + \int_{\min\{J,1\}}^{1} \int_{0}^{1} \{\bullet^{GMF}\}\, d\theta^{GM}\, d\theta^{F} \\
CS^{GM} &= \int_{\max\{0,H\}}^{\min\{J,1\}} \int_{G}^{1} \{\bullet^{GM}\}\, d\theta^{GM}\, d\theta^{F} + \int_{0}^{\max\{0,H\}} \int_{0}^{1} \{\bullet^{GM}\}\, d\theta^{GM}\, d\theta^{F}
\end{aligned}
$$

where $\bullet^{GMF} = U^{GMF} k^{GM}(\theta^{GM}) k^{F}(\theta^{F})$, $\bullet^{GM} = U^{GM} k^{GM}(\theta^{GM}) k^{F}(\theta^{F})$, $G = \frac{1}{\alpha}(P^{GMF} - P^{GM} - \gamma\delta\theta^{F})$,

$H = \frac{1}{\gamma\delta}(P^{GMF} - P^{GM} - \alpha)$, and $J = \frac{1}{\gamma\delta}(P^{GMF} - P^{GM})$.

As is evident from these consumer surplus functions, given the general specification of the model there is little intuition to be gained. As well, it can be seen that in order to solve for an explicit solution would require a distributional assumption over tastes that the CDF is twice integrable with a closed form, severely restricting the class of distributions which could be utilized.

6.3.2 Welfare when Labeling of Intragenic GM and Transgenic GM is Allowed

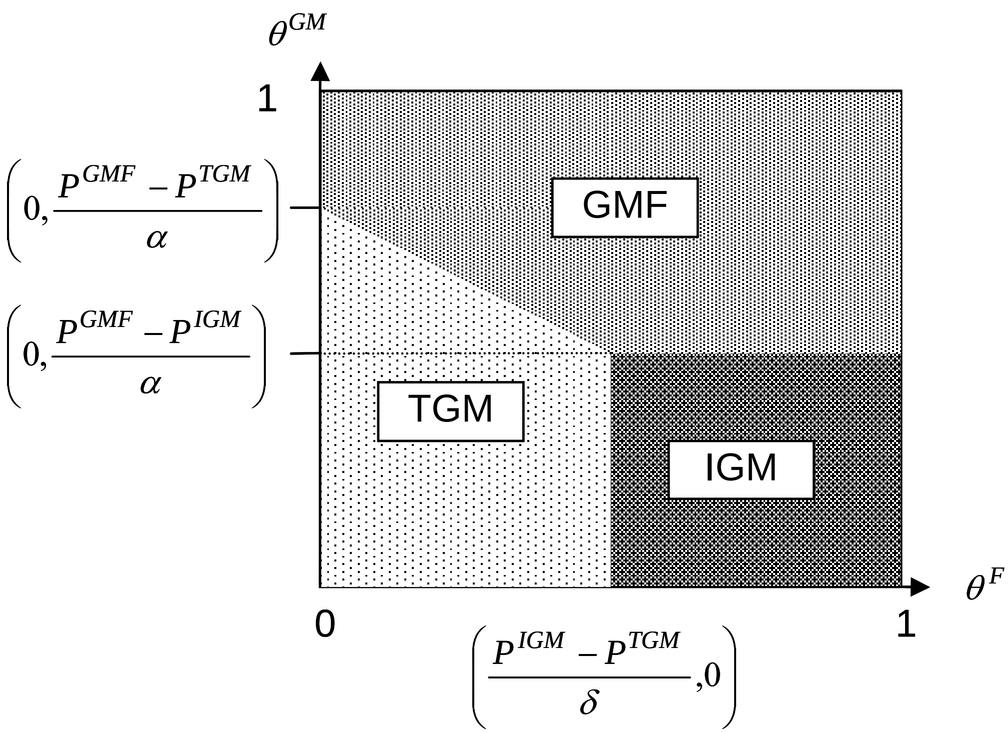
In this section, welfare is considered under *Mandatory Policy 2* and *Voluntary Policy 2* where labeling of intragenic GM and transgenic GM is allowed. Given the specification of consumer preferences, the following are the sufficient conditions on the taste parameters for each product to be strictly preferred.

$$
(4)\quad
\begin{aligned}
&GMF: \theta^{GM} > \frac{P^{GMF} - P^{IGM}}{\alpha} && \textit{and} \quad \alpha\theta^{GM} + \delta\theta^{F} > P^{GMF} - P^{TGM} \\
&IGM: \theta^{GM} < \frac{P^{GMF} - P^{IGM}}{\alpha} && \textit{and} \quad \theta^{F} > \frac{P^{IGM} - P^{TGM}}{\delta} \\
&TGM: \alpha\theta^{GM} + \delta\theta^{F} < P^{GMF} - P^{TGM} && \textit{and} \quad \theta^{F} < \frac{P^{IGM} - P^{TGM}}{\delta}
\end{aligned}
$$

To this point, given the assumed competitive market setting, the only assumption built-up for prices is $P^{GMF} > P^{IGM} > P^{TGM}$. Without further restrictions, the ranges of θ^{GM} and

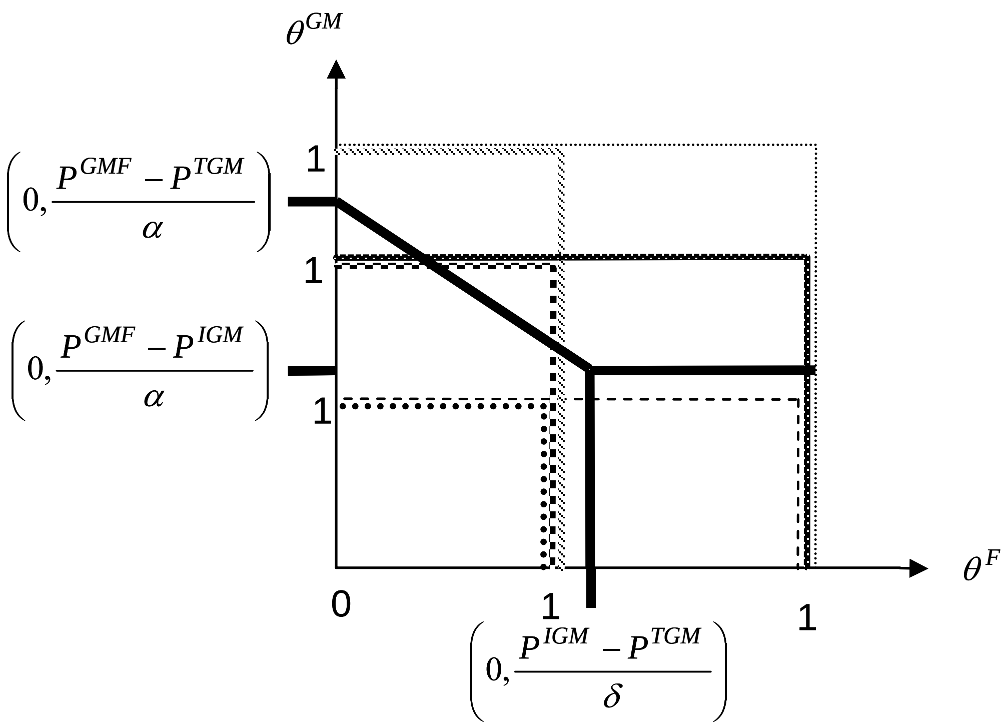
θ^F under which each product is strictly preferred are not characterized by a single set of conditions. This significantly increases the complexity at hand, but allows for more generality. To illustrate, figure 6.2 provides a graphical representation of the sets of $\{\theta^{GM}, \theta^F\}$ under which each product is strictly preferred assuming that $\frac{P^{GMF} - P^{TGM}}{\alpha} < 1$ and $\frac{P^{IGM} - P^{TGM}}{\delta} < 1$.

Figure 6.2 Bounds of Integration for Consumer Surplus Under Mandatory and Voluntary Policies 2 Assuming $\left(P^{GMF} - P^{TGM}\right)/\alpha < 1$ **and** $\left(P^{IGM} - P^{TGM}\right)/\delta < 1$



Without placing price or parameter restrictions six feasible cases may occur. Figure 6.3 presents each of the possible cases. In this graph, depending upon the parameters, the point at which the preference lines "cut the axis at 1" changes.

Figure 6.3 Bounds of Integration for Consumer Surplus Under Mandatory and Voluntary Policies 2



While the presence of six possible cases increases the complexity in deriving expressions for consumer surplus, they can be expressed as

$$CS^{GMF} = \int_{\max\{R,X\}}^{\max\{R,X,\min\{1,Q\}\}} \int_{L}^{1} \{\bullet^{GMF}\} d\theta^{GM} d\theta^{F} + \int_{\min\{Q,1\}}^{1} \int_{0}^{1} \{\bullet^{GMF}\} d\theta^{GM} d\theta^{F}$$

(5) $$CS^{IGM} = \int_{0}^{\min\{1,X\}} \int_{\min\{1,Y\}}^{1} \{\bullet^{IGM}\} d\theta^{GM} d\theta^{F}$$

$$CS^{TGM} = \int_{0}^{\min\{1,\max\{R,X\}\}} \int_{0}^{\min\{1,Y\}} \{\bullet^{TGM}\} d\theta^{GM} d\theta^{F} + \int_{\min\{1,\max\{R,X\}\}}^{\min\{1,Q\}} \int_{0}^{L} \{\bullet^{TGM}\} d\theta^{GM} d\theta^{F}$$

where $\bullet^{GMF} = U^{GMF} k^{GM}(\theta^{GM}) k^{F}(\theta^{F})$, $\bullet^{IGM} = U^{IGM} k^{GM}(\theta^{GM}) k^{F}(\theta^{F})$,

$\bullet^{TGM} = U^{TGM} k^{GM}(\theta^{GM}) k^{F}(\theta^{F})$, $L = \dfrac{P^{GMF} - P^{TGM} - \alpha\theta^{GM}}{\delta}$, $Q = \dfrac{P^{GMF} - P^{TGM}}{\alpha}$,

$R = \dfrac{P^{GMF} - P^{TGM} - \delta}{\alpha}$, $X = \dfrac{P^{GMF} - P^{IGM}}{\alpha}$ and $Y = \dfrac{P^{IGM} - P^{TGM}}{\delta}$.

Again, as in the case of the welfare functions under policies without labeling of intragenic GM and transgenic GM, tractability is certainly not present in this model design. Even under the assumption of uniform distributions, as opposed to the utilized generic setup, little intuition is to be gained due to the dual taste parameters. But, as will be shown in later sections, the generality of the presented market design yields a much richer characterization of the welfare impact of different government labeling policies.

6.4 Empirical Model

Utilizing the bids from the experimental auctions, it is possible to estimate the distribution of the taste parameters θ^{GM} and θ^{F}. Let $B_i^{L,f}$ denote the bid by an individual $i = 1,2,...,I$ for a food product $f \in \{Broccoli, Tomato, Potato\}$ with label

$\ell \in \{GMF, IGM, TGM, GM\}$.[33] Using these conventions and following from the theoretical model, consumer utility can be restated as

$$\begin{aligned} U_i^{GMF,f} &= U_i^f - P^{GMF,f} \\ U_i^{IGM,f} &= U_i^f - P^{IGM,f} - \alpha^f \theta_i^{GM,f} \\ U_i^{TGM,f} &= U_i^f - P^{TGM,f} - \alpha^f \theta_i^{GM,f} - \delta^f \theta_i^{F,f} \\ U_i^{GM,f} &= U_i^f - P^{GM,f} - \alpha^f \theta_i^{GM,f} - \gamma_i^f \delta^f \theta_i^{F,f}. \end{aligned} \tag{6}$$

In the experimental auction, consumers were not faced with a choice based upon market prices, but instead submitted bids for what they are willing to pay for a product. The utilized auction mechanism, the *n*th-price auction, is incentive compatible meaning that an individual's optimal strategy is to submit a bid for a product equal to their willingness to pay (i.e. the price at which they would be indifferent between consuming the product or not). Given the specification of preferences, the bid submitted by an individual is the price at which purchase would yield a utility equal to zero. Thus we can express utility in terms of bids as

$$\begin{aligned} B_i^{GMF,f} &= U_i^f \\ B_i^{IGM,f} &= U_i^f - \alpha^f \theta_i^{GM,f} \\ B_i^{TGM,f} &= U_i^f - \alpha^f \theta_i^{GM,f} - \delta^f \theta_i^{F,f} \\ B_i^{GM,f} &= U_i^f - \alpha^f \theta_i^{GM,f} - \gamma_i^f \delta^f \theta_i^{F,f}. \end{aligned} \tag{7}$$

Rearranging these expressions we can solve for the relationship between bids and taste parameters

[33] In the series of experimental auctions used for this chapter, participants did not bid on products labeled as GM (instead they were faced with a plain label case). The absence of this information prevents explicit calculation of the expectation parameter γ at the individual level. In a second set of similar but modified experimental auctions also conducted in 2007, consumers did bid on products with a GM label. Using this data, an average value of γ across individuals was calculated and found to be equal to approximately 0.68. While this estimate is not as robust as the estimates for θ^{GM} and θ^{F} it is evidence that consumers are not characterized by the full information case ($\gamma = 1$).

$$(8)\qquad \begin{aligned} \theta_i^{GM,f} &= \frac{1}{\alpha^f}\left(B_i^{GMF,f} - B_i^{IGM,f}\right) \\ \theta_i^{F,f} &= \frac{1}{\delta^f}\left(B_i^{IGM,f} - B_i^{TGM,f}\right) \\ \gamma_i^f &= \frac{1}{\delta^f \theta_i^{F,f}}\left(B_i^{IGM,f} - B_i^{GM,f}\right). \end{aligned}$$

As can be seen in the above expression, given the information available from the experimental auction it is not possible to individually identify α^f, δ^f, γ_i^f, $\theta_i^{GM,f}$, and $\theta_i^{F,f}$. But, given the generic space over which $\theta_i^{GM,f}$ and $\theta_i^{F,f}$ are defined, if we assume these parameters are constrained to the unit interval $[0,1]$ it must hold that

$$(9)\qquad \begin{aligned} \alpha^f &\geq \max_i\left\{B_i^{GMF,f} - B_i^{IGM,f}\right\} \\ \delta^f &\geq \max_i\left\{B_i^{IGM,f} - B_i^{TGM,f}\right\} \end{aligned}$$

in order to ensure that tastes are properly mapped to the dollar space. Thus, while we cannot explicitly solve for the parameters α^f and δ^f, we can place a lower bound on their values, which, as will be shown, is sufficient and revealing for subsequent analysis.[34]

Finally, while given the data available it is possible to consider each food product f separately, to simplify the analysis and concentrate the results reducing potential noise across products, consumer types are averaged across the three products ($\overline{\theta}_i^{GM} = \frac{1}{3}\sum_f \theta_i^{GM,f}$

[34] Please note that clearly, given the information contained in bid differences, we could simply reformulate the model by combining intensity and type parameters into a single variable (for example $\tilde{\theta}_i^{GM,f} \equiv \alpha^f \theta_i^{GM,f} = B_i^{GMF,f} - B_i^{IGM,f}$) thereby dropping the normalization of consumer types to the unit interval. We purposely choose not to in order to keep our model consistent with the structure typically used in theoretical and empirical applications and to facilitate comparisons.

and $\overline{\theta}_i^F = \frac{1}{3}\sum_f \theta_i^{F,f}$).[35] This yields a composite calculation of each consumer's aversion to genetic modification and foreign genetic content.

6.4.1 *Distribution of Taste Parameters*

In both the theoretical and empirical models it was assumed that $\overline{\theta}_i^{GM}, \overline{\theta}_i^F \in [0,1]$, but no assumption was made regarding the specific distribution governing these parameters. Given the data provided by the experimental auction, we can actually estimate the governing distributions, but we require a distributional form to fit. One potential flexible form candidate would be the beta distribution which can characterize a wide variety of potential forms, but suffers from not having a closed form CDF. An alternative, but less frequently utilized distribution which mimics the beta distribution but with a closed form PDF and CDF, is the Kumaraswamy distribution. The PDF for the Kumaraswamy distribution is $f = abx^{a-1}(1-x^a)^{b-1}$ and the CDF is $F = 1-(1-x^a)^b$ where $a, b > 0$.

One of the drawbacks of the Kumaraswamy distribution (and similarly the beta distribution) is that it, by construction, has zero probability at the endpoints 0 and 1 ($f(0) = f(1) = 0$). Hence, while the distribution is flexible over the internal interval (0,1) it does not allow for potential masses of individuals at 0 or 1. This is highly unsatisfactory in that it does not allow for individuals to have preferences such that products are weakly superior (i.e. it forces strict superiority). To remedy this shortcoming, a piecewise

[35] Conducted sensitivity analysis showed that averaging across types did not qualitatively change the results of the model and had a minor impact on quantitative estimates.

distribution is defined. Let $\Psi = \{GM, F\}$, 0_Ψ denote the fraction of individuals with $\overline{\theta}_i^\Psi = 0$, and 1_Ψ denote the fraction of individuals with $\overline{\theta}_i^\Psi = 1$. Define the piecewise Kumaraswamy CDF as

$$(10) \qquad K^\Psi\left(\overline{\theta}_i^\Psi\right) = \begin{cases} K^\Psi\left(\overline{\theta}_i^\Psi = 0\right) = 0_\Psi \\ K^\Psi\left(0 < \overline{\theta}_i^\Psi < 0\right) = (1 - 0_\Psi - 1_\Psi) F^\Psi\left(\overline{\theta}_i^\Psi\right) \\ K^\Psi\left(\overline{\theta}_i^\Psi = 1\right) = 1_\Psi \end{cases}$$

where $F^\Psi\left(\overline{\theta}_i^\Psi\right)$ denotes the standard Kumaraswamy CDF. With this piecewise modified version of the Kumaraswamy distribution we have an extremely flexible distribution over the interval (0,1) that will allow for nontrivial positive masses at the endpoints.

6.4.2 Estimates of Taste Parameter Distributions

For estimating the distribution of individuals with $0 < \overline{\theta}_i^\Psi < 1$ the likelihood function is

$$(11) \qquad L = \max_{a^\Psi, b^\Psi > 0} \left\{ \prod_{i\{0 < \overline{\theta}_i^\Psi < 1\}} a^\Psi b^\Psi \left(\overline{\theta}_i^\Psi\right)^{a^\Psi - 1} \left(1 - \left(\overline{\theta}_i^\Psi\right)^{a^\Psi}\right)^{b^\Psi - 1} \right\}.$$

Since there is no closed form solution to the likelihood function, the parameters a^Ψ and b^Ψ are estimated using numerical simulations. Table 6.2 presents the estimated parameters of the piecewise defined Kumaraswamy distribution for participants receiving different information treatments ("All" denotes all participants and all information treatments).

Table 6.2 Parameter Estimates of Piecewise Kumaraswamy Distribution

	0_{GM}	a^{GM}	b^{GM}	0_{F}	a^{F}	b^{F}
ALL	0.51	0.75	1.13	0.51	0.80	2.82
No Info	0.53	1.01	1.40	0.59	0.90	5.40
Pro-Biotech	0.70	1.50	15.20	0.45	1.12	2.27
Anti-Biotech	0.29	0.98	0.82	0.65	0.66	2.07
Pro & Anti	0.42	0.58	0.88	0.29	0.81	1.31
Pro, Anti, & Ver.	0.59	1.08	2.48	0.65	1.30	6.90

As can be seen from table 6.2, for each information treatment a significant percentage of individuals are of type $\overline{\theta}^{GM} = 0$ or $\overline{\theta}^{F} = 0$ meaning that these individuals are indifferent between GM Free and the intragenic or transgenic alternatives. This is the first clear indication that by assuming uniformly distributed tastes the impact of GM on utility is overstated. To gain a clearer picture of the estimated taste distributions, figure 6.4 presents the estimated PDFs over the interval $0 < \overline{\theta}_i^{\Psi} < 1$ and figure 6.5 presents the estimated CDFs over the interval $0 \leq \overline{\theta}_i^{\Psi} \leq 1$.

From figures 6.4 and 6.5 it is clear that a uniform distribution does not appropriately characterize individuals' tastes for either genetic modification or foreign genetic content. A uniform distribution drastically overestimates the fraction of individuals of non-zero type as well as the percentage of individuals of higher order types (i.e. types approaching one). This arises even though the parameter α used for estimating these distributions is potentially less than the "true" α that characterizes the population.[36] These results raise the question as to whether previous analyses addressing the impact of

[36] Note that from the derivation of the taste parameters that $\overline{\theta}^{GM}$ and $\overline{\theta}^{F}$ are monotonically decreasing in α.

labeling (or other quality market applications) are potentially significantly overestimating the impact of consumer types on welfare.

Figure 6.4 Estimates of Kumaraswamy PDF for $0 < \overline{\theta}_i^{\Psi} < 1$

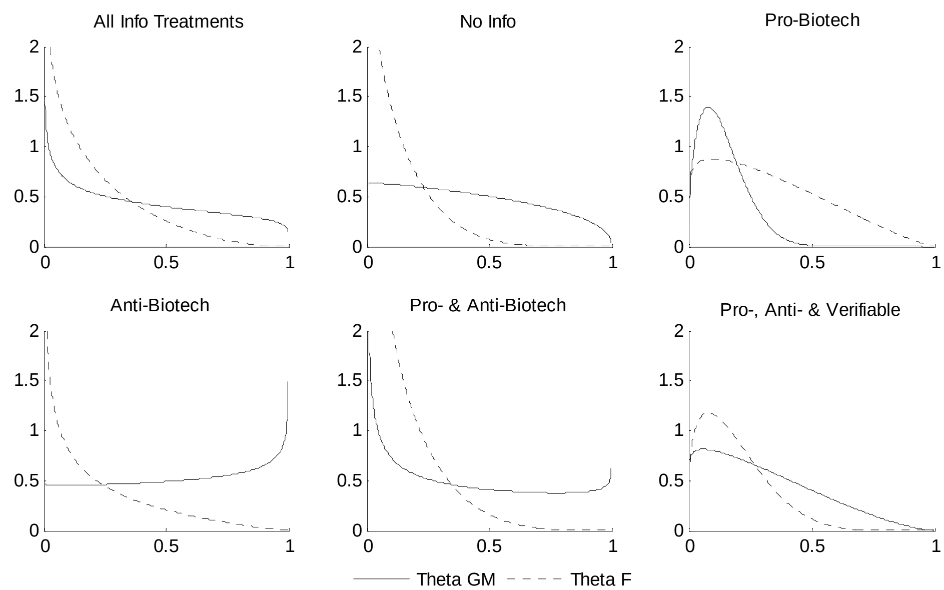
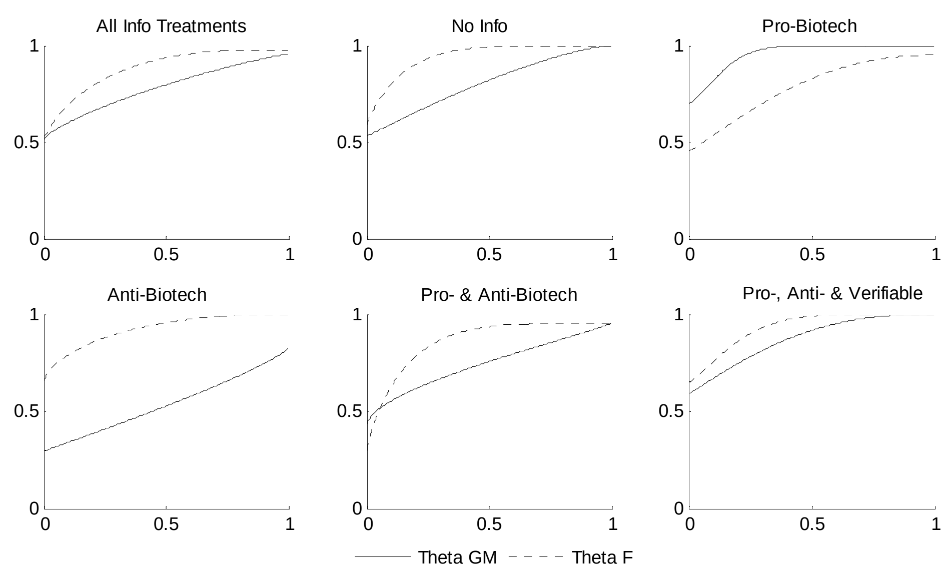


Figure 6.5 Estimates of Kumaraswamy CDF for $0 \le \overline{\theta}_i^{\Psi} \le 1$



Comparing across information treatments, we can see that both dislike for genetic modification of food and foreign genetic content in food play a role in the weakly inferior nature of intragenic and transgenic food products. Neither attribute can be characterized as being the dominant factor. We see that consumers do view intragenic food products differently and weakly superior to transgenic food products. The effect of the information treatments on the fraction of individuals with $\bar{\theta}^{GM} = 0$ or $\bar{\theta}^{F} = 0$ falls in line with expectations. Seventeen percent more individuals who received the *pro-biotech perspective* are of type $\bar{\theta}^{GM} = 0$ as compared to those receiving the *no information treatment*. As well, the distribution of those with $\bar{\theta}^{GM} > 0$ is more heavily massed towards zero. For those receiving the *anti-biotech perspective* the result is reversed, with 14% fewer individuals being of type $\bar{\theta}^{GM} = 0$ and the distribution being more heavily weighted towards one over the range $\bar{\theta}^{GM} > 0$. An interesting, but not unexpected result arises for the distribution of $\bar{\theta}^{F}$ by those individuals who received the *pro-biotech perspective*. The fraction of those individuals with $\bar{\theta}^{F} = 0$ is actually 14% less than the *no information treatment* and the estimated distribution is fairly diffuse over the unit interval. While seeming surprising, since the *pro-biotech* and the *verifiable information perspectives* were the only information treatments that contained specifics regarding intragenic and transgenic processes, it is apparent that the emphasis on foreign genetic material increased participants' concerns regarding this content.

Finally, when comparing the distributions of the *pro- and anti-biotech perspectives* with and without *verifiable information* we can see that the 3rd party information has an augmenting effect on the fraction of individuals that have $\overline{\theta}^{GM} = 0$ or $\overline{\theta}^{F} = 0$ (17% and 36% respectively). This implies that the *verifiable information* acts to dampen the effect of the *anti-biotech perspective*.

6.5 Welfare Estimates

Using the estimated distributions from the empirical model and experimental auction data, it is now possible to evaluate welfare under the four considered government labeling policies. Since the welfare functions are largely intractable and the assumed piecewise Kumaraswamy distribution does not have a closed form single or double integral over the CDF, it is necessary to evaluate welfare using numerical methods. To estimate welfare under each government policy, the consumer surplus functions detailed in the model section are evaluated via numerical integration using an adaptive Simpson quadrature algorithm.

For brevity, results are presented using parameter estimates across all of the information treatments (i.e. the entire auction sample), but the accompanying discussion relates the alternative information treatments with the presented results. Figure 6.6 compares welfare between policies that do and do not allow for labeling of intragenic products (i.e. *mandatory or voluntary policy 2 vs. mandatory or voluntary 1*). Here, the price of the transgenic GM product is normalized to one and the relative prices of the intragenic GM and GM Free products are considered over the intervals [1,1.2] and [1,1.4] respectively.[37] Figure 6.7 compares welfare between voluntary and mandatory policies that do not allow labeling of intragenic foods (*voluntary policy 1 vs. mandatory policy 1*). Here, the production cost of the transgenic GM product is normalized to one and the transgenic compliance cost (t^{GM}) and price of the GM Free are considered over the intervals [0,0.05] and [1,1.4] respectively. Finally, figure 6.8 compares welfare under *voluntary policy 2* using the empirically estimated taste distributions with those that arise under the assumption of uniformly distributed tastes. All results in the figures are presented as a percentage difference in aggregate welfare under the considered policies and distributional assumptions and estimated assuming full consumer information ($\gamma = 1$).

As can be seen by figure 6.6, there are small welfare gains under mandatory and voluntary policies with the introduction of intragenic labeling. These welfare gains are substantial only when the production and compliance costs for the intragenic product are nearly equivalent to the transgenic, but 25% (or more) lower than for the GM Free. Only then is the price differential sufficiently great to induce a large percentage of consumers to switch to the intragenic product and yield large welfare gains. For example, if the price of the intragenic product is 5% greater than for the transgenic product and 25% less than the GM Free there is approximately a 5% increase in welfare. The welfare gains from introducing intragenic labeling is lower than one might potentially expect (or find under the assumption of uniform tastes) because the experimental auction revealed that a significant percentage of individuals are indifferent between the GM Free and GM

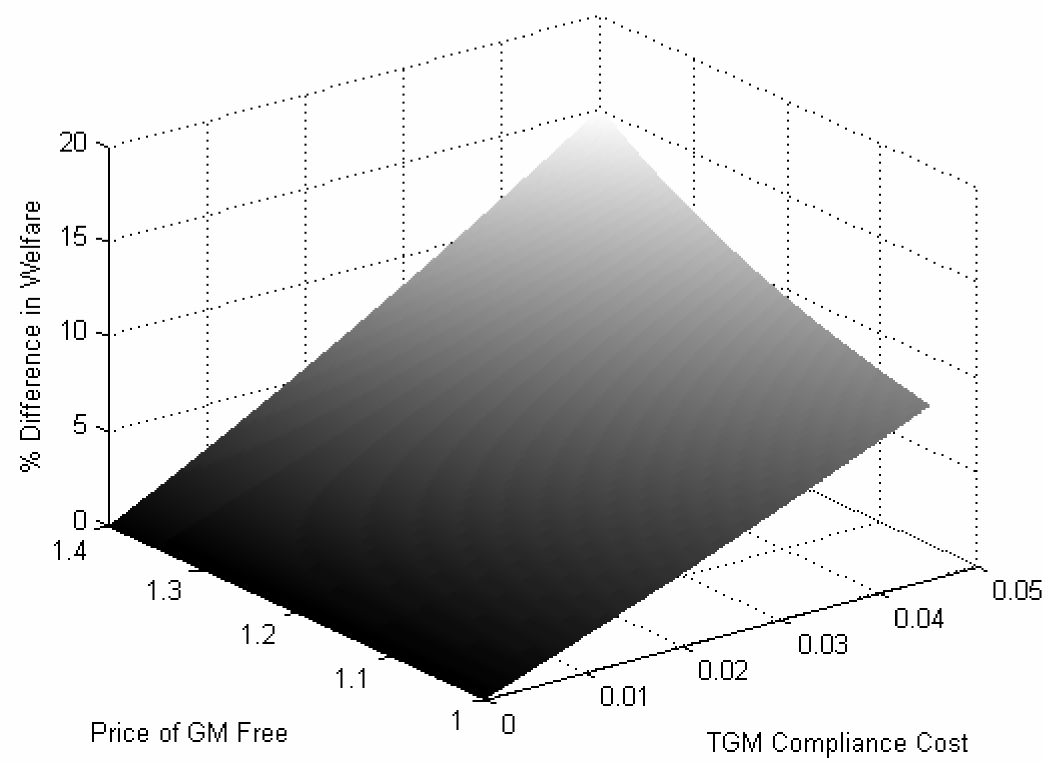
[37] Prices are considered over reasonable ranges since price data does not exist for intragenic products.

alternatives. Under information treatments that increase aversion to foreign genetic content in food the difference in welfare between the two policies increases.

Figure 6.6 Welfare With Vs. Without Labeling of Intragenic Products

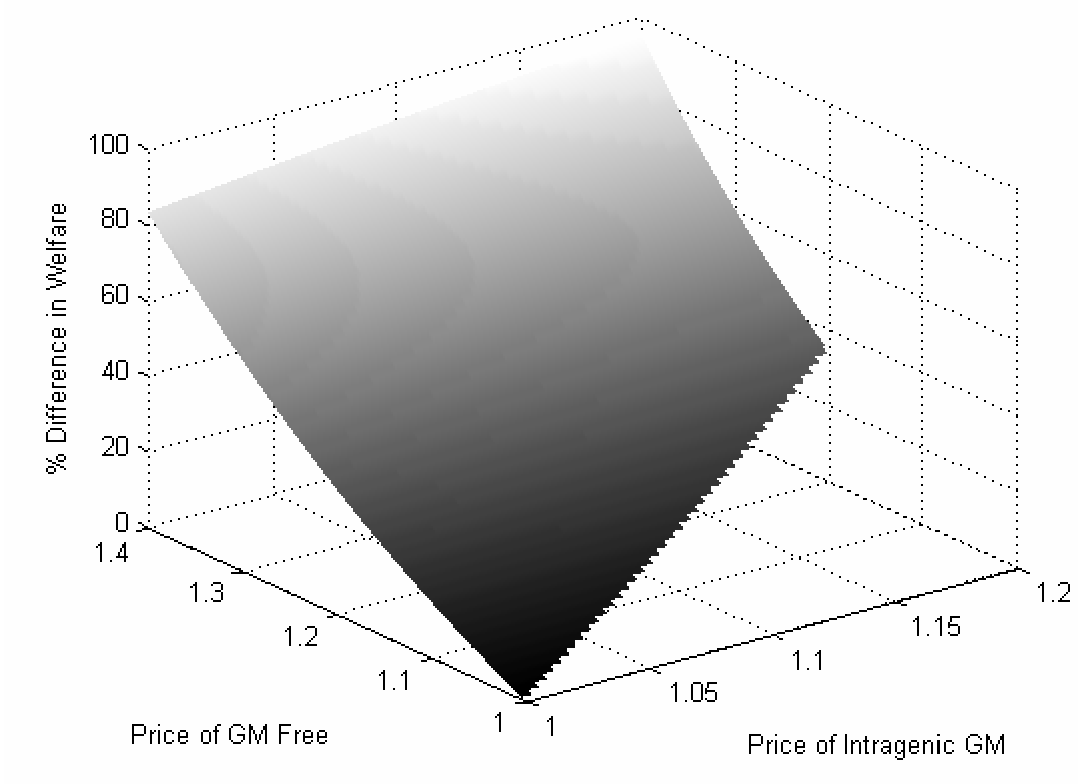
Comparing voluntary and mandatory policies that do not allow labeling of intragenic foods (figure 6.7) we find that, depending upon the cost for transgenic products to comply with a mandatory policy, that there is small difference in welfare. For example, if the compliance cost is $0.02 for the transgenic product (i.e. 2% of the production cost) a voluntary policy translates into a welfare gain of over 3% when compared to a mandatory policy. The welfare gain under a voluntary policy is monotonically increasing in the price of the GM Free product and the transgenic compliance cost. Under information treatments that reduce aversion to the transgenic product the welfare gains are even larger. For brevity, results comparing mandatory and voluntary policies that do allow labeling of intragenic foods are not shown, but the welfare differences are very similar to those shown in figure 6.7.

Figure 6.7 Welfare Under Voluntary Policy 1 Vs. Mandatory Policy 1



Comparing welfare under the estimated distributions with the typical literature assumption of uniformly distributed tastes, figure 6.8, it can be seen that uniformity drastically under estimates welfare because it fails to appropriately model the significant fraction of individuals who are indifferent between the alternatives and the skewed characterizing distribution of consumers. Similar results are found under different labeling policies. Under information treatments where the share of type zero consumers increases or the distribution of tastes is massed towards zero, the mischaracterization of welfare under uniformity is greater.

Figure 6.8 Welfare Under Voluntary Policy 2: Estimated Distribution Vs. Uniform Distribution



Finally, while all of the results presented here assume full consumer information regarding the type of genetic modification used in the production of a generically labeled GM food product ($\gamma = 1$), relaxing this assumption (i.e. $\gamma < 1$) has an interesting effect in that it actually increases welfare under policies without labeling of intragenic and transgenic products (*mandatory* and *voluntary policies 1*). Given the model setup, welfare from consumption of GM products is monotonically increasing in γ. This is an interesting case where ignorance or misinformation increases welfare.

6.6 Concluding Remarks

As new intragenic biotechnology engineering techniques improve and these products begin to enter worldwide food markets, the GM labeling and compliance policies of governments internationally will be forced to adapt. In this paper a model of consumer demand for GM Free, Intragenic GM, and Transgenic GM food products is developed where consumers are characterized based upon two distinct taste parameters. Using experimental auction bid-price data the distribution of consumer tastes is estimated in order facilitate an analysis of consumer welfare under alternative labeling regimes. Additionally, by injecting biased and verifiable information into the experimental auctions allows evaluation of the shifts in the distributions of tastes resulting from these new perspectives. The estimated distributions of consumer tastes unequivocally reveal that a uniform distribution fails to properly characterize consumers. The welfare estimates clearly show that policies that differentiate between intragenic and transgenic food products yield greater aggregate welfare for consumers. Furthermore, it is shown that a voluntary policy is superior from a welfare perspective to a comparable mandatory policy.

Finally, the results of this paper show that while assuming uniformly distributed consumer tastes may not qualitatively change models of demand for quality, this assumption is clearly inappropriate for empirical endeavors. At a minimum, if tractability is of concern, the presented results suggest that it would be prudent to model consumers utilizing a piecewise uniform distribution, as opposed to a standard uniform distribution, allowing for a significant mass of individuals to be indifferent between products of different qualities.

CHAPTER 7: DEMAND CURVE EFFECTS IN EXPERIMENTAL AUCTIONS: THE EFFECT OF HOLDING PRE-EXPERIMENT INVENTORIES

7.1 Introduction

Experimental auctions have become an increasingly common mechanism for eliciting consumers' willingness to pay (WTP). In part, the increased prominence of experimental auctions derives from their theoretically demand revealing properties. That is, unlike a hypothetical survey, participants have a dominant strategy to truthfully reveal their preferences through their bids. Comparisons between value estimates from experimental auctions have shown this is indeed the case (e.g., see Fox et al., 1998; List, 2001).

While experimental auctions are demand revealing in theory, there has been much attention in the literature focusing on the “proper” design of auctions. There has been discussion regarding whether participants should bid on products in repeated rounds with posted prices (e.g., List and Shogren, 1999; Corrigan and Rousu, 2006b), the effect of endowing participants with products (e.g., Corrigan and Rousu, 2006a), and the impact of laboratory versus market environments (e.g., Lusk and Fox, 2003).

Across studies, one area where most experimental auction methods are consistent is in dealing with potential substitution or negatively sloped demand-curve effects. These effects occur when participants' bids are affected through the potential of obtaining multiple units of a product during the auction. Researchers usually prevent this possibility by having only one round of bidding (on one unit of a commodity) in the auction serve as the "binding" round where participants can win products (e.g., Dickinson and Bailey, 2002; Alfnes and Rickertsen, 2003; Rousu et al. 2007).

Although researchers have been careful to control for demand curve effects within experimental auction, they have ignored the potential effects on bids of inventories that participants may hold of products similar to those up for auction. As previously mentioned, a demand-revealing auction theoretically elicits a consumers' reservation price for a product. If bidders may at most win a single unit of the product, then their bids reflect their reservation price for a single unit. But, the fact that bidding is on only a single unit does not yield the researcher any information as to whether consumers are in fact bidding on their 1st or nth (n>1) unit of the product. This arises because it is possible that they currently posses the product through a previous transaction unrelated to the auction. Hence, to the researcher it is unknown whether bids reflect reservation prices for the 1st or nth unit of the product.

Omitting inventories presents problems in the standard design and analysis of experimental auction data.[38] First, if bids by otherwise equivalent individuals with and without inventories are the same, experimental auctions may not properly access willingness to pay or demand. Namely, it would raise the question of whether consumers fully consider their monetary and non-monetary endowments in the somewhat “artificial” market environment of the experimental auction. Conversely, if consumers with and without units of the product do in fact bid differently as theory dictates, this can present a

[38] Please note that while this chapter in particular considers the impact of quantity owned in the context of experimental auctions, the implications extend beyond auctions. Other mechanisms commonly used to elicit preferences or valuations (e.g. stated choice experiments) will potentially be affected by the same issue.

problem for previous studies in that bids are compared from individuals at different points on their demand curves. In addition, if a researcher does not know where an individual bidding in an auction is on his demand curve, it is not possible to distinguish preferences from demand curve effects. For example, an individual who submits a small bid for a product could either have low preferences for the product or high preferences for the product, but with quantity already owned. As illustrated in the next section, this has implications for the interpretation and application of auction data, particularly when considering non-durable commodities that are purchased on a repeated basis.

In this chapter, we examine the impact of outside inventories on WTP in a random nth-price auction with fresh broccoli, tomatoes, and potatoes as commodities. After completing the rounds of bidding, participants were asked if they currently have any of the auctioned products at home. Since the auctioned vegetables have a short shelf-life, we propose that individuals with inventory would have lower bids conditional on properly controlling for other confounding factors. Regression analysis indicates that there is a significant inventory or "quantity owned effect". This result has important implications for the design of experimental auctions where the target is elicitation and analysis of willingness to pay.

The chapter is outlined as follows. The next section provides a simple model of bidding when pre-experiment outside inventories are held. Section 7.3 describes the auction procedures. Section 7.4 summarizes bids by individuals with and without quantity owned. Section 7.5 presents estimates of a fixed-effects regression model. Finally, the chapter is concluded.

7.2 Model of Auction Bids

To illustrate how product inventories can affect consumers' bids in an experimental auction we present a simple model of product demand and bidding behavior. Consider a representative consumer with a per unit of time monetary budget of Y (e.g., a weekly food budget) to be allocated over a choice set of $N+1$ goods denoted by $\{z,\mathbf{x}\}$ where z is a scalar and x is a vector of N goods. Let market prices for the goods be denoted w and p respectively. At the time of the auction, the consumer may potentially hold inventories of some of the products in their resource set (i.e. products that have been purchased but not consumed/depleted during the time period). For simplicity of exposition, we consider an individual who (potentially) holds inventories only of good z and denote the quantity already owned as $\bar{z}$ (where $\bar{z} \geq 0$). We assume that there is no resale market for these inventories (or equivalently that the transaction cost for resale is sufficiently high). As well, we assume that a unit of a similar good that is purchased in an experimental auction is a perfect substitute for a corresponding unit in inventory. Given the choice set of goods, market prices, product inventory, and resource constraints, the representative consumer solves a utility maximization problem whose dual representation is the following expenditure minimization problem:

(1) $$e(w,p,U) = \min wz + px, \quad s.t. \;\; U(z+\bar{z},x) \geq U, \quad z,x \geq 0 .$$

Immediately from the optimization specification we see that if the consumer holds inventories ($\bar{z} > 0$), the expenditure minimization problem departs slightly from the classic textbook representation. Here, z represents the net demand for the good (i.e. the quantity of additional units the consumer would purchase, $\bar{z}$ is the quantity already owned, and the sum $z+\bar{z}$ is total demand (i.e., the aggregate quantity that would be consumed over an appropriate time interval). For each commodity optimization yields compensated demand functions, $z+\bar{z}=h(w,p,U)$ and $x=h(w,p,U)$, and inverse compensated demand functions (or "WTP curves"), $w=\pi(z+\bar{z},p,U)$ and $p=\pi(x,w,U)$. The expression $\pi(z+\bar{z},p,U)$ represents the price the consumer is willing to pay for the $(z+\bar{z})$'th unit.

Now, appealing to the compensating variation measure, we are able to express the consumer's WTP for an additional unit of good z. Assuming that the consumer engages in a fully demand revealing incentive compatible auction, they should submit a bid equal to the maximum amount of money such that they would be indifferent between winning the auction or not. This amount is simply equal to the area under the inverse compensated demand function arising from the change in quantity. Assuming that the consumer is bidding on a single unit of commodity z, their auction bid is

(2) $$Bid_z = \int_0^1 \pi(z+\bar{z},p,U)dz\ .$$

The bid expression shows that product inventories can have an impact on bid levels. Specifically, as would be expected, given that π is a non-increasing function in quantity, it follows that the bid level is non-increasing in inventory $\bar{z}$. Hence, we would expect bids by an individual with inventory who is otherwise identical to an individual without inventory to be smaller.

While from the preceding model it is clear that units held in inventory can decrease a consumer's bid-price in an auction, from a researcher's perspective the question remains: is this a concern? The answer depends upon the target of the inquiry and the nature of the goods being considered. For durable goods that are infrequently replaced, consumers' bid-prices conditional on inventories represents their willingness to pay for an additional unit in both the near and more distant future. This is likely the target value a researcher studying these types of goods is seeking, and hence, assuming bidders do in fact consider their inventories when bidding, should receive appropriate bid data.

However, for studies involving non-durable goods that degrade and are characterized by repeated replenishment (e.g., food items that spoil), bids will reflect current conditions, not the near future where inventories are consumed and potentially replaced (e.g., after the refrigerator is depleted and the consumer returns to the supermarket). Using bids without considering the impact of inventories prohibits appropriate analysis of arguably the primary target of such studies, behavior in the next purchase scenario when inventory is depleted.[39]

Furthermore, inventories present a problem when comparing bids across individuals. Since those individuals with higher preferences for the auction commodity are the most likely to be purchasers of the product in the outside market, they are also more likely to be holding inventories at the time of the experiment. For individuals with lower preferences, the converse is likely. Hence, there is a greater likelihood that bids by those individuals who have high preferences are pushed downwards due to them being most probable to be holding inventories. Therefore, high preference individuals may appear to the researcher as low preference individuals. This would be most problematic

[39] It could be argued that the potential impact of inventories on bids is more significant in laboratory experiments compared to field experiments given the likelihood of consumers holding smaller or no inventories when arriving to shop at the field experiment location.

for products with relatively inelastic demand curves. Again, while this may not be a problem for durable goods, when considering products such as perishable food items this could lead to bid and welfare analyses that does not appropriately characterize "next period" demand.

7.3 Summary of Auction Design

The bidding data used in this study is part of a larger project to assess consumers' willingness to pay for genetically modified (GM) and GM Free foods. Participants in the study were solicited from the general public by the Iowa State University Center for Survey Statistics and Methods. Potential participants were invited to participate in a university study for $45 in compensation, but were not told beforehand the nature of the project. Willing participants were given their choice between four different session starting times and provided with directions to the site of the experiments. The steps of each experimental session are as follows.

After participants completed a brief questionnaire and consent forms, the session leader provided instructions and examples about the random *n*th-price auction (Shogren et al., 1994) which was used in the study. Participants were further trained on the mechanism by engaging in a two-round practice auction. After the training period, participants were randomly assigned one of five different information treatments containing perspectives on genetic modification. The information treatments included combinations of pro-biotech, anti-biotech, and third-party perspectives on genetic modification. A no information treatment was also included as a control.

After participants finished reading their respective information treatments, the session monitor led the participants through a multi-round random *n*th-price auction. Bids were collected by the session monitor after each round and not posted until all bidding rounds were completed and the single binding round was announced. In each round three separate products were placed up for sale: broccoli (1 lb.), beefsteak tomatoes (1 lb.), and russet potatoes (5 lb.). For the purposes of this study, we are utilizing bidding data on GM Free labeled products and Plain labeled products ("Plain label" denotes a product that bore a label only detailing the product name and weight with no descriptor of genetic modification).

After completion of the bidding rounds participants were asked to complete an exit questionnaire. Among the included questions, three key responses are utilized in this study. For each commodity (broccoli, tomatoes, and potatoes) participants were asked if they (1) currently have any of the vegetable at home, (2) regularly purchase the vegetable, and (3) regularly eat the vegetable. After finishing the exit questionnaire, winners of the auction proceeded to a separate room to purchase their products and non-winners were free to leave.

7.4 Bid Summary

In this section, a summary of the auction participants' bids is provided. Table 7.1 shows the proportion of individuals who indicated that they (1) had the product at home at the time of the auction, (2) regularly eat the food product, and (3) regularly purchase the food product.[40] More than half of the sample regularly eats and purchases each of the three commodities. As well, slightly more than half of the sample at the time of the auction had fresh broccoli and tomatoes at home, and nearly 90% of the auction participants had fresh potatoes in inventory.

Table 7.1 Summary Statistics for Current Inventory and Habit Variables

Variable	Variable Definition	Broccoli	Tomato	Potato
Purchase	1 if regularly purchase product	0.60	0.58	0.77
Eat	1 if regularly eat product	0.61	0.65	0.81
Have	1 if currently have product at home	0.60	0.58	0.89

Table 7.2 summarizes average bids for Plain label and GM Free food products, broken-down by responses to whether bidders have the product currently at home, eat and purchase regularly. A null hypothesis of no significant difference in bid prices across responses was tested (an unpaired t-test). Individuals who currently have the commodity at home have a lower average bid price for some, but not all of the Plain label and GM Free commodities. For none of the food products is the mean difference in bids by those with and without inventory statistically different. This result, when viewed in isolation, fails to confirm the expectation that individuals with quantity owned would bid less than individuals without quantity owned.

When comparing average bids by individuals who eat or purchase the commodities with those who do not, the difference in bids is greater and statistically significant at the 10% significance level for Plain label and GM Free broccoli and

[40] As would be expected, the correlation between regularly eat and regularly purchase is nearly one.

tomatoes. This result is in line with expectations in that regularity of consumption and purchase are proxies for individual preferences for the commodities.

Table 7.2 Mean Bids for Food Products

		Have			Eat			Purchase		
Product	**Label**	**Yes**	**No**	**Diff**	**Yes**	**No**	**Diff**	**Yes**	**No**	**Diff**
Broccoli	Plain	1.21	1.28	-0.07	1.42	0.95	0.47**	1.43	0.95	0.48**
Tomato	Plain	1.42	1.12	0.30	1.67	0.59	1.08**	1.72	0.71	1.01**
Potato	Plain	2.05	1.94	0.11	2.04	1.98	0.07	2.07	1.91	0.16
Broccoli	GMF	1.41	1.49	-0.07	1.57	1.24	0.33	1.59	1.23	0.36*
Tomato	GMF	1.52	1.29	0.23	1.77	0.78	0.99**	1.82	0.88	0.93**
Potato	GMF	2.17	2.50	-0.33	2.14	2.50	-0.36	2.17	2.34	-0.17

(*), (**), and (***) denote variable significant at 10%, 5%, and 1% respectively

While the unconditional analysis of bids presented in table 7.2 does not provide substantial evidence as to whether inventories affect bid prices, this is not an unexpected result, given that other individual-specific factors affecting WTP are not controlled for. Regression analysis presented in the following section yields more conclusive evidence on the impact of inventories.

7.5 Econometric Model and Estimates

In order to isolate whether quantity owned impacts bid-prices and to control for other potential confounding factors, a linear fixed-effects model is estimated. The dependent variable is consumers' bid-prices stacked over the three commodities (broccoli, tomato, and potato) and the two labeling treatments (Plain label and GM Free). Fixed effects are included for each of the auctioned commodities. The two key independent variables for this study are dummies for *have* and *purchase* which respectively denote if the participant responded that he/she currently have the vegetable in inventory at home and if he/she regularly purchases the vegetable.[41] Additional explanatory variables were included to control for other demographic and preference attributes that may affect bid-prices include: dummy variables for each *information treatment* (no information treatment dummy omitted), *income* (in thousands), *gender* (1 if female), *informed* (1 if participant responded as being well or extremely well informed about GM), *opinion* (1 if the participant responded as having a supportive opinion of GM), *education* (years of schooling), environmental member (1 if member of an environmental group), and *healthiness of diet* (self assessed healthiness of diet on a 10 point scale). Regression estimates are presented in table 7.3.

Table 7.3 Fixed Effects Regression Results (N=342)

Variable	Parameter Estimate	Standard Error
Have	-0.238*	0.109
Purchase	0.384**	0.115
Info Treatment 1	0.127	0.147
Info Treatment 2	-0.197	0.165
Info Treatment 3	0.456**	0.151
Info Treatment 4	-0.374*	0.176
Income	0.004**	0.001
Informed	0.285	0.223
Opinion	0.222	0.147
Gender	-0.072	0.131
Education	-0.059*	0.025
Envi Member	-0.600*	0.285
Healthiness of Diet	0.034	0.029
Constant	1.962**	0.432

(*), (**), and (***) denote variable significant at 10%, 5%, and 1% respectively

[41] Due to the high multicollinearity between responses to regularity of “purchase” and “eat”, only a dummy variable for purchase is included.

The coefficient estimate associated with *have* is negative (-0.238) and statistically significant at the five percent level (p=0.030). This result shows, controlling for other confounding factors, that participants with product inventories acquired outside of the auction do submit lower bids than those individuals who do not have outside inventories. This result supports the hypothesis that consumers in an experimental auction, even conducted in a laboratory style setting, do submit bids reflecting their global willingness to pay - conditional on both their monetary and non-monetary endowment - as standard theory suggests. In addition, this result gives further credence that despite the partially "artificial" nature of experiments, consumers evaluate their willingness to pay considering outside factors just as occurs when making decisions in a conventional market.

The coefficient for *purchase* is positive (0.384) and significant at the one percent level indicating that individuals who regularly purchase the commodity in the outside market are willing to pay more in the auction than those who do not regularly purchase the commodity. This falls in line with expectations in that we would expect individuals who are regular purchasers in the outside market (i.e. individuals with a WTP greater than the market price) to bid more than non-regular purchasers (i.e. individuals with a WTP less than the market price).

Several additional variables, which we do not focus on here, were found to be significant in explaining bid-prices including income, education, environmental member, and two of the information treatments.

7.6 Concluding Remarks

While most studies utilizing experimental auctions take care to avoid possible bid biases arising from substitution and negatively sloped demand-curve effects within an auction, this is the first study to the knowledge of the authors to consider the impact of demand-curve effects arising from inventories acquired outside the auction. The implications of this study are a bit double-edged. On the positive side, the estimates of the impact of quantity owned on bidding behavior agree with basic economic demand theory and indicate that participants in auctions do in fact consider their non-monetary endowment when placing bids on food products. If this were not the case, it would raise the question of whether experimental auctions truly capture consumers' market decisions.

Given these demand-curve effects of inventories, problems arise in interpreting bids submitted in other experimental auctions. If information about inventories is not solicited from auction participants, then it is not possible to distinguish where individuals are on their demand curve. Hence, it is not possible to distinguish whether a low bid is because an individual in fact has a low WTP for the product, or simply because they are further along their demand curve due to inventories held of similar products. Whether experimental auction bids are used for assessing market demand, policy impacts, or welfare effects, this uncertainty about what bids actually reflect presents a problem and could lead to biased or simply incorrect estimates and conclusions.

The results of this study raise a number of potential avenues for further research. A common dilemma in experimental auctions is the prevalence of bids of zero. The author is left asking whether for many experimental auctions that consider valuations for products with steep or binary demand curves if a portion of the zero bids could be explained by inventories. A second issue, not considered explicitly in this study, is what is the impact of substitute or complement goods that are already in a household's inventory? This is an interesting question not only because of the potential impact on bidding behavior, but also because it raises the possibility that researchers might need to assess a wide array of demand curve effects for each auctioned commodity. Finally, one shortcoming of this paper is that we did not ask consumers to report the exact quantity of fresh vegetables held in inventory coming into our experimental auction. While this was done by design over concerns regarding the vagaries of vegetable sizes and weights, future research might elicit this information and permit an in depth analysis of inventories on WTP curves.

CHAPTER 8: GENERAL CONCLUSION

Despite more than a decade of experience, genetic modification continues to be a highly controversial issue worldwide and a source of confusion among consumers. While, as discussed in chapter 2, many US consumers have formed strong opinions in favor or in opposition to GMOs, a significant percentage of consumers still have not been swayed and still consider themselves poorly informed about the benefits and hazards of GM. Given the immense financial stakes surrounding genetic modification and the transformative impact of domestic and global adoption of GM on agricultural production, both controversial and verifiable information has the potential to significantly affect agricultural policy and markets through shifts in consumer attitudes towards GM.

While many of the controversial issues surrounding GMOs have remained stagnant and unresolved since their emergence (e.g., labeling, traceability), GM technology itself has been evolving. Biotechnology companies have continued to develop new GM varieties with increasingly sophisticated attributes of interest to agricultural producers (e.g., insect resistance, insect protection, and herbicide tolerance), offering producers potentially greater and more stable crop yields. Continuing this trend, intragenic engineering offers the potential to dramatically alter the agricultural landscape and market for foodstuffs. Intragenics promises GM foods engineered without the use of outside genetic material or antibiotic markers, thereby shifting GMOs back towards the realm of conventional cross-bred varieties and eliminating a primary concern present in transgenic foods. As well, intragenics offer the potential for foods engineered with attributes of direct value to consumers that simply are not feasible through conventional non-GM crop development methods.

Yet, when attempting to evaluate the potential for intragenic foods with enhanced consumer attributes, two key questions loom. First, do consumers sufficiently value attributes such as enhanced levels of antioxidants and vitamin C if it is derived through genetic modification (intragenic and transgenic) and is this value sufficiently great to overcome the discount that consumers place on GM foods? Second, as consumers gain more experience with intragenic foods and are exposed to information on the benefits and risks of GM, how will information affect consumers' valuations and the market potential for intragenic foods? Both of these questions are at the heart of this dissertation and are critical for policymakers and the various actors with a stake in GM and conventional food markets.

Our results provide evidence for the first time that consumers are willing to pay a premium for a GM food relative to a conventional product (chapter 3). Specifically, bid price data for three types of fresh vegetables collected through an experimental auction indicate that the additional benefit of enhanced vitamin and antioxidant outweighs the negative attribute of intragenic production methods, thus resulting in a premium over conventional vegetables. This result indicates that, for the first time, the food industry may have an incentive to voluntarily label GM food products as GM (or with a trademark). Chapter 6 provides estimates of the welfare gain from labeling policies that permit differentiation of intragenic foods from transgenic foods.

Yet, while the bid price data provides evidence in support for the potential of intragenic foods with enhanced attributes, the results presented in chapters 3 and 4 clearly indicate that information (controversial and verifiable) has a significant impact on valuations and has the potential to open or close the market on these new foods. Given the novelty of intragenic foods and the still prevalent uncertainty in general over GM among consumers, verifiable information by independent organizations can serve a valuable role in enabling consumers to make informed product purchase decisions (chapter 5).

In addition to the new policy issues addressed in this dissertation, the methods and models employed for analysis offer several advancements for the economics literature. The experimental procedure utilized for soliciting consumers' WTP extends recent procedural advances to control for additional factors including potential group treatment effects within the experiment. Furthermore, the consideration of the impact of outside product inventories on bidding behavior is a previously overlooked issue. The Bayesian SUR Tobit model used to assess the impact of information on WTP is new to auction bid-price analysis. The econometric model, with minimal researcher imposed structure, simultaneously addresses censoring and correlation issues. Both issues have been highlighted in the literature and addressed previously through more restrictive modeling approaches. The model developed to assess the impact of different labeling policies on consumer welfare is uniquely general. As well, using experimental auction data to calibrate a vertically differentiated market model is new to the literature and is shown to yield richer results. It is hoped that the methodological advancements of this dissertation will aid researchers in better addressing the many issues surrounding food and other agricultural products that are critical to consumers, producers, and policymakers.

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APPENDIX

I.D.#__________

Welcome! Thank you for choosing to participate in an experiment about decision making. The information you provide today is a very important contribution to ongoing research by Iowa State University and Pennsylvania State University.

In this folder is a packet of information that you will need during the session. Once you have looked at a form during the session, feel free to go back and reexamine that form again if needed, but please do not look ahead until we reach the right point in the session.

Please follow instructions carefully. To ensure accuracy, please do not talk to any other participants during the session.

We would like to emphasize that all information obtained today will be used only for group comparisons. No personal or individual information will be divulged for any reason.

Please turn to the next page, and fill out the questionnaire.

Ref: EIV

Please answer the following questions by circling the appropriate choice or filling in the appropriate line. Please try to answer all questions.

1. Regarding genetically modified foods, how informed do you consider yourself?
   1 = Extremely well informed
   2 = Well informed
   3 = Somewhat informed
   4 = Not very informed
   5 = Not informed at all

2. How many people (out of about 300 million) do you think get sick from genetically modified food each year in the United States? ____________________

3. What percentage of corn grown in the United States do you think is genetically modified?
   ______%

4. What percentage of potatoes grown in the United States do you think are genetically modified?
   ______%

5. What percentage of broccoli grown in the United States do you think is genetically modified?
   ______%

6. Does the government require a label on foods indicating that they contain genetically modified content?
   1 = Yes
   2 = No

7. Which statement best describes your opinion towards genetically modified food?
   1 = Strongly support
   2 = Support
   3 = Neutral
   4 = Oppose
   5 = Strongly oppose

8. Please rank the following three organizations in order of who you trust most to provide information regarding food safety (1 = Most trusted, 3 = Least trusted). **Please use each number (1, 2, and 3) only once.**
   ____ Leading Environmental groups (ex. Greenpeace and Friends of the Earth)
   ____ Leading Biotechnology Companies (ex. Monsanto and Syngenta)
   ____ Government organizations (ex. USDA and FDA)

9. Please rank the following three organizations in order of who you trust most to provide information regarding the healthiness of food (1 = Most trusted, 3 = Least trusted). **Please use each number (1, 2, and 3) only once.**

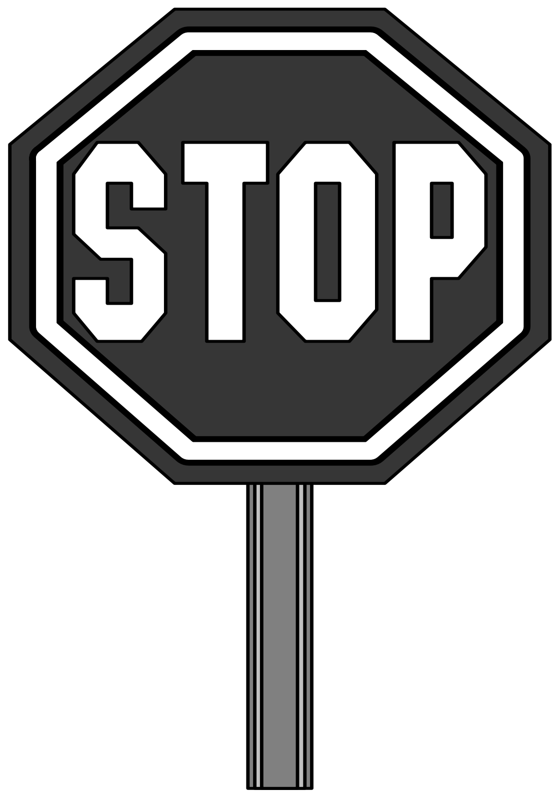
____ Leading Environmental groups (ex. Greenpeace and Friends of the Earth)
____ Leading Biotechnology Companies (ex. Monsanto and Syngenta)
____ Government organizations (ex. USDA and FDA)

10. Given a choice, would you prefer to receive information regarding (circle only one)

1 = The positive attributes of genetically modified food
2 = The negative attributes of genetically modified food

11. Below is the title of five different newspaper articles. Given a choice which article would you prefer to read (circle only one)

1 = "The GM threat to health, wildlife and biodiversity"
2 = "International scientists raise concerns over genetically modified food"
3 = "Debate rages over genetically modified crops"
4 = "GM crops lead to savings, less use of pesticides for farmers"
5 = "GM food is answer to poverty and hunger"



Please do not turn the page until instructed by your monitor.

Once again, we would like to thank you for participating in this study today.

Today we will be holding auctions of some common products. Details for how the auction works will be provided shortly.

Because we are trying to determine values for different products, we ask that you please refrain from communicating with the other participants. If you have any questions, the monitors can assist you.

How the Auction Works

We are going to hold today what is called an **n^{th} price auction**. For those of you who have participated in auctions before, please note that the n^{th} price auction is slightly different than what you may have encountered. The auction works as follows:

1. Examine the products to be auctioned

   Before we ask you to bid on a product, we will let you come up to the front of the room and examine the products that you will be bidding on.

2. Write down your bid for the products

   After examining the products, write down what you would like to bid for each of the products being auctioned on a provided "bid sheet".

3. Choosing of the n^{th} price

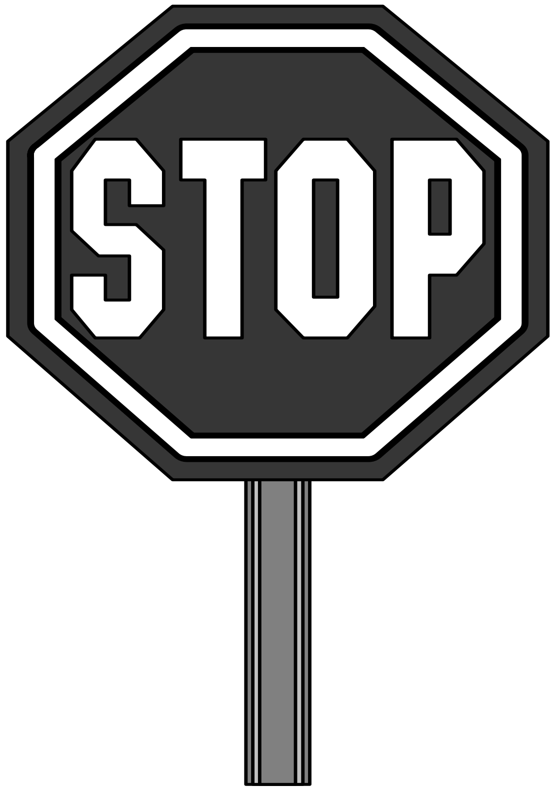
   Once everyone has bid, we will determine what will be called the "n^{th} price". Everyone who bids **higher** than this price will win the product, and pay the n^{th} price.

   (Your monitor will go through an example of this)

4. Determining who wins the auction

   (Your monitor will go through an example of this)

Please note that in this auction it is **always in your best interest to bid your true value for a product**. Unlike many auctions in which you might bid less than your true value to try to get a deal, this auction **does not reward that**. This is because you do not necessarily pay your bid price, but you pay the n^{th} price that is randomly chosen. Likewise, it is not in your interest to bid more than you are truly willing to pay because you may have to pay more than you wanted to for the product.



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Short Quiz on the n^{th} Price Auction Format

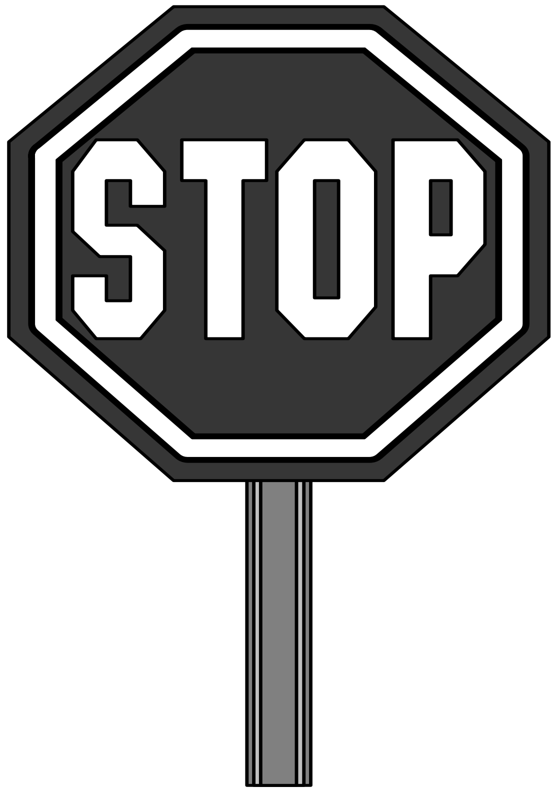
Please note, this sheet will not be collected

1. The people who win will always pay the amount they bid for a product.
   1 = True
   2 = False

2. If you have the 4^{th} highest bid and the randomly drawn n^{th} price is the 2^{nd}, you will win the auction.
   1 = True
   2 = False

3. I might get to pay less than my bid for a product, but I will never have to pay more than my bid for a product.
   1 = True
   2 = False

4. If the binding price that is randomly drawn is the 7^{th} price, how many people win the good?
   4
   5
   6
   7
   8



Please do not turn the page until instructed by your monitor.

Practice Auction

To make sure everyone is comfortable with how the n^{th} price auction works we will have two rounds of practice bidding.

Since some of the products in the two rounds are similar, only one of the two practice rounds will be "binding". By "binding" we mean that only one of the two practice rounds will be selected as the round where people will win goods and pay money for them (i.e. only one round "counts"). The round that is binding will be randomly selected by a computer and will be revealed after the second practice round. Since you do not know which round will be chosen, it is in your best interest to **bid your true value for the products in both practice rounds**.

These two rounds are **practice** so no goods will actually be purchased and no money will be exchanged.

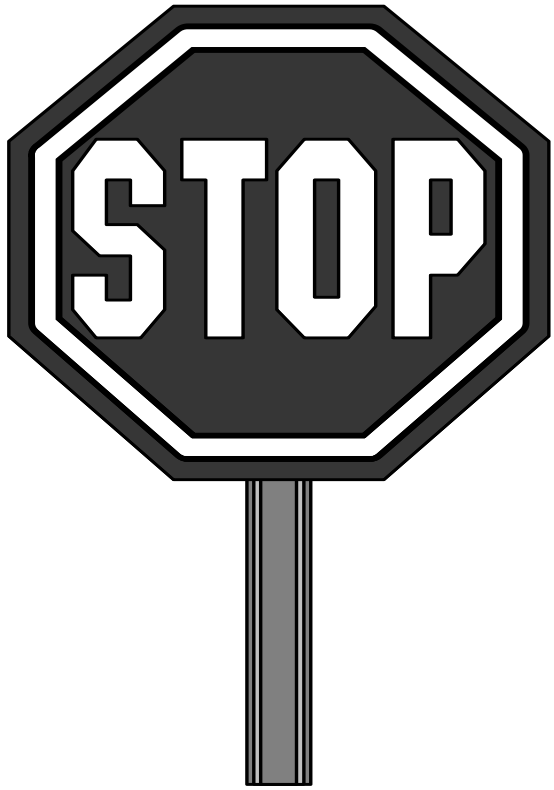
Practice Bidding Round 1 of 2

Step 1 - Examine the 3 products

Examine the products in practice round 1

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products



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Practice Bidding Round 2 of 2

Step 1 - Examine the 3 products

Examine the products in practice round 2

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products

Step 3 – Determine the binding round (computer generated)

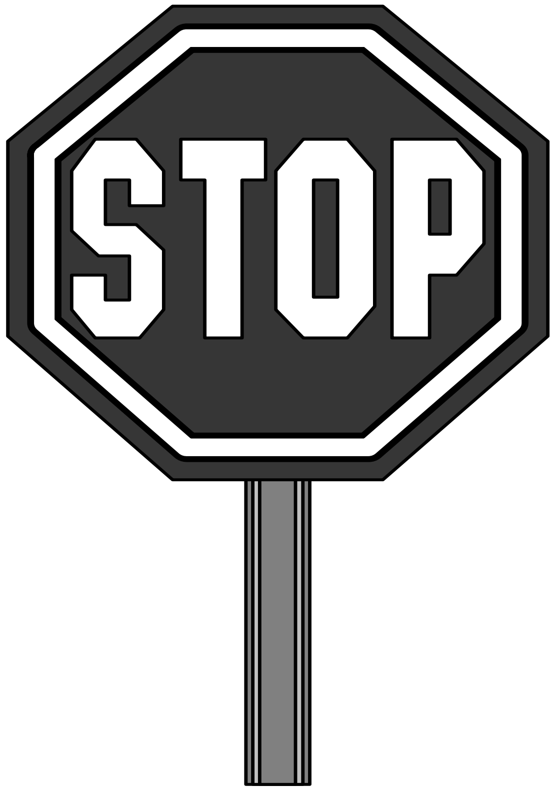
A computer randomly determines which of the two rounds of bidding will be binding.

Step 4 – Determine the n^{th} price for each product (computer generated)

A computer randomly determines the n^{th} price for each of the three products in the binding round.

Step 5 – Announcement of the auction winners for each product

If this auction was real, the winners in the binding round would exchange money for the goods in the room next door.



Please do not turn the page until instructed by your monitor.

Auction

We are about to begin the real auction. In this auction there will be 4 rounds of bidding. Only 1 round of the 4 will be binding. In each round there will be 3 products. The products may or may not be the same in each round. Remember, please bid on each product in each round with your true value.

Please take a few minutes and read the information on the following 3 pages.

The following is a collection of statements and information on genetic modification from Greenpeace, a leading environmental group.

General Information

Genetic modification (GM) takes genes from one organism and places then into another. The process lets scientists manipulate genes in an unnatural way. Inadequate safety testing of GM plants and food products has occurred. Humans and the Earth are being used as guinea pigs for testing whether “Frankenfoods” are safe. GM foods should be banned because their effect on consumers and the environment is unknown and potentially catastrophic! Genetic modification is one of the most risky things being done to your food sources today and should be stopped before more damage is done.

Scientific Impact

All genetic modifications of plants are risky. All GM techniques are relatively new and no one can guarantee that consumers or the environment will not be harmed. The biggest potential hazard of GM foods is the unknown.

Human Impact

Genetically modified foods could pose serious risks to human health. Some foods contain allergens, and the potential exists for allergens to be transferred into a GM food product that no one would suspect. For example, if the genes from a peanut were transferred into a tomato, and someone who is allergic to peanuts eats this GM tomato, he could display a peanut allergy.

Another problem with transgenic foods is a moral issue. Many GM techniques transfer genes across species. We believe it is morally wrong to alter life forms on such a fundamental level.

Financial Impact

GM foods are being pushed onto consumer by big businesses which only care about their own profits and ignore possible negative side effects. These groups are actually patenting new life forms they create with plans to sell for profits. Studies have shown that GM crops may even get lower yields than conventional crops.

Environmental Impact

GM foods could pose major environmental hazards. Little testing of GM plants for environmental impacts has occurred. One potential risk of GM crops is their impact on wildlife, including wild species of plants and insects. A study showed that one type of GM plant killed Monarch butterflies.

Another potential environmental hazard could come from pests that become resistant to new naturally occurring toxic substances engineered into plants to kill pests—insects and worms—or to make a plant resistant to a particular herbicide application. The target pests that get exposed to these new GM crops could quickly develop tolerances and wipe out many of the potential advantages of GM pest resistance.

The following is a collection of statements and information on genetic modification provided by a group of leading biotechnology companies, including Monsanto, Pioneer and Syngenta.

General Information

Genetically modified (GM) plants have the potential to be one of the greatest discoveries in the history of farming. GM crops have lowered food production costs by improving insect and disease resistance and weed control in plants. New genetic engineering techniques could dramatically enhance consumer benefiting attributes of food such as vitamins, antioxidants, flavor, and shelf life. These improvements to plant quality can only be attained through GM, not conventional breeding.

The process of genetic modification takes genes from one organism and places them into another. There are two distinct types of GM used by biotechnology companies. *Transgenic* GM transfers genes between two *unrelated* organisms, for example from soil bacteria to corn. *Intragenic* GM involves transferring genes between two breeds of the *same* organism, for example, from wild species of corn to a commercial variety of corn.

Scientific Impact

Both *transgenic* and *intragenic* techniques are used to produce food products that are approved by the Food and Drug Administration (FDA). *Intragenic* modification is a genetic technique for significantly speeding up the conventional process of plant cross-breeding, which has been undertaken by farmers and plant breeders for thousands of years. Many industry groups believe *intragenics* should require minimal FDA testing because no foreign genes or proteins are added to the GM plant. We have only seen the tip of the iceberg of the future potential of GM for improving worldwide health and nutrition through enhanced plants.

Human Impact

The potential exists for GM to dramatically enhance traits that have direct value to consumers, such as increased vitamins and antioxidants, more flavor, longer shelf life, lower pesticide use, and reduced cost of production. Superior GM plants will help reduce worldwide malnutrition and improve the healthiness of foods. The FDA has approved GM food for human consumption, and Americans have been consuming GM foods for a decade. While every food (modified or not) poses some risks, there has never been a documented case of a person getting sick from GM food.

Financial Impact

With the introduction of enhanced nutrition, antioxidants, shelf life, flavors and other consumer-desired attributes using GM technology, consumers will for the first time enjoy the direct benefits of genetic engineering. GM plants have reduced farmers' costs, which mean lower food prices. Worldwide the number of hungry people is declining. GM technology is helping to feed the world and improve worldwide nutrition.

Environmental Impact

Genetic modification of plants has the potential to be one of the most environmentally helpful discoveries ever. GM technology has produced new methods of insect control that reduce chemical insecticide application by 50% or more. GM weed control is providing new methods to control weeds, which are a problem in no-till farming. This means greater crop yields and less environmental damage.

The following is a statement on genetic modification approved by a third-party group consisting of a variety of individuals knowledgeable about genetically modified foods including: scientists, professionals, religious leaders, and academics. These parties have no financial stake in GM foods.

General Information

The process of genetic modification (GM) takes genes from one organism and places them into another. There are two distinct types of GM used by biotechnology companies. *Transgenic* GM transfers genes between two *unrelated* organisms, for example from soil bacteria to corn. *Intragenic* GM involves transferring genes between two breeds of the *same* organism, for example from wild species of corn to a commercial variety of the crop. Hence, *intragenic* modification has much in common with conventional plant breeding.

Scientific Impact

The Food and Drug Administration (FDA) standard for GM food products is based on the principle that they have essentially the same ingredients, although modified from the original plant. Almost all GM crops meet the FDA's substantive equivalent requirement. Hence, they do not require special testing before commercial marketing can occur.

Human Impact

Many scientists see *intragenics* as having real potential for enhancing consumer attributes of plants such as dramatically increasing vitamin and antioxidant levels, extending shelf life, and reduced chemical pesticide application without concerns about gene transfer across species. These improvements to plants are only possible using genetic modification and not conventional breeding.

All foods present a risk of an allergic reaction to a small fraction of the population. No FDA approved GM food poses any known unique human health risks, but when genes are transferred across species, a new allergen is possible. This is more likely with *transgenics* than *intragenics*. While GM crops can result in higher yields and enhanced nutrition, there is no consensus whether GM foods have or will reduce worldwide hunger.

Many people have moral or religious objections to GM. Some groups see *intragenic*s as being more acceptable because genes are transferred between two breeds of the same species.

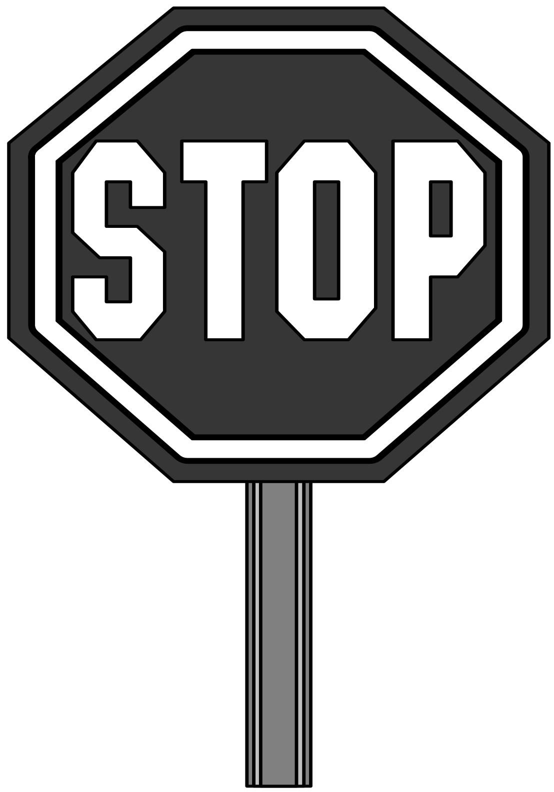
Financial Impact

GM seeds and other organisms are produced by businesses that seek profits. For farmers to switch to GM crops, they must see benefits from making a change. Consumers must also see benefits from consuming GM foods—lower price or enhanced consumer attributes. However GM technology may lead to changes in the organization of the agri-business industry and farming.

Environmental Impact

The long-term effects of GM on the environment are largely unknown. Bioengineered insect resistance has reduced farmers' applications of environmentally hazardous insecticides, but resistance to this bio-control system will increase over time. More studies are occurring to help assess the impact of bioengineered plants on the environment. Some studies reported harm to Monarch butterflies from GM crops, but other scientists were not able to recreate the results.

Enhanced consumer attributes, such as vitamins, antioxidants, and longer shelf life due to *intragenics* pose no known environmental hazards.



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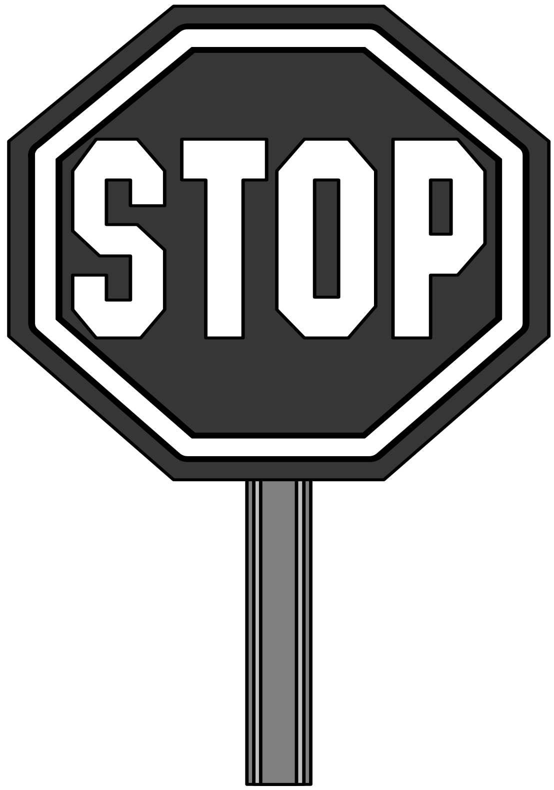
Bidding Round 1 of 4

Step 1 - Examine the 3 products

Examine the products in round 1

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products



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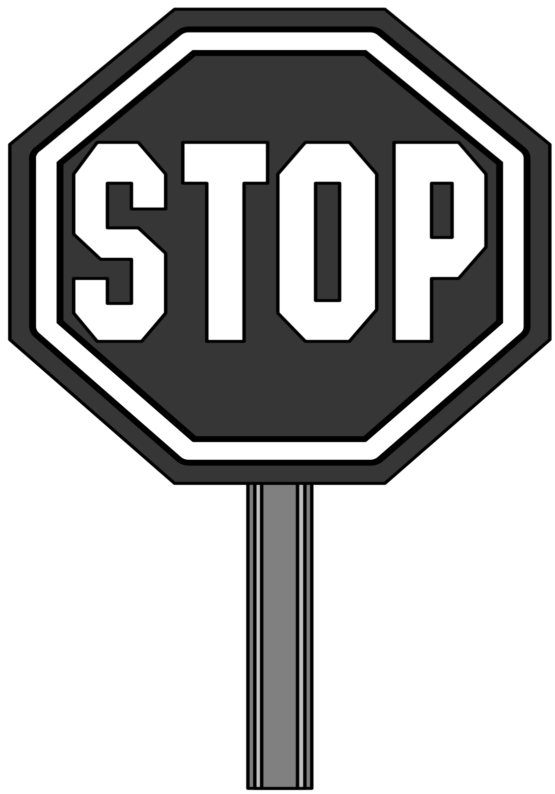
Bidding Round 2 of 4

Step 1 - Examine the 3 products

Examine the products in round 2

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products



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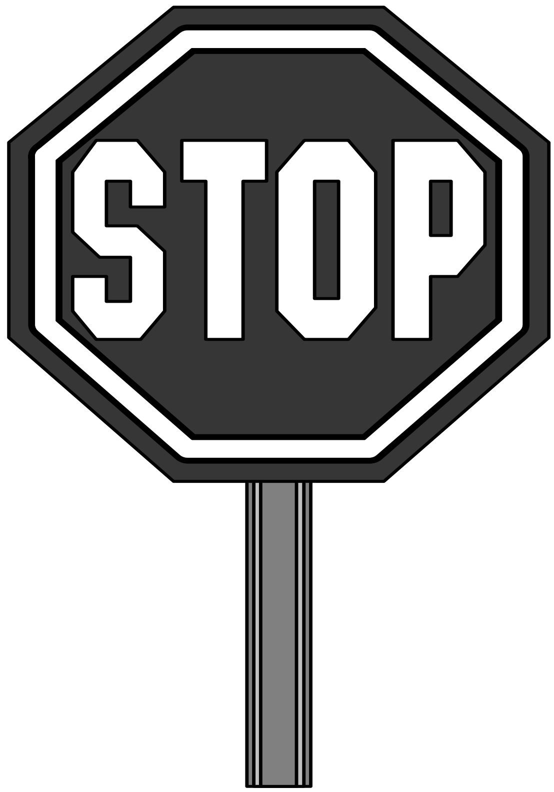
Bidding Round 3 of 4

Step 1 - Examine the 3 products

Examine the products in round 3

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products



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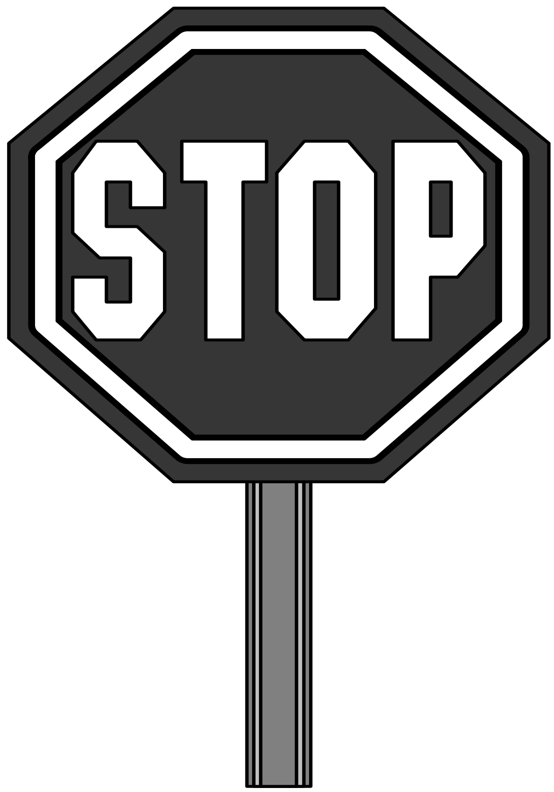
Bidding Round 4 of 4

Step 1 - Examine the 3 products

Examine the products in round 4

Step 2 - Write down your bid for the 3 products

Please fill out your bid sheet for all 3 products



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Step 3 – Determine the binding round (computer generated)

A computer randomly determines which of the four rounds of bidding will be binding.

Step 4 – Determine the nth price for each product (computer generated)

A computer randomly determines the nth price for each of the three products in the binding round.

Step 5 – Announcement of the auction winners for each product

Step 6 – Post auction questionnaire

Please fill out the questionnaire on the following page. Once you have completed the questionnaire, please return your information packet to the session monitor.

Step 7 – Auction winners exchange money for goods

Please answer the following questions by circling the appropriate choice or filling in the appropriate line.

1. What is your gender?
   1 = Male
   2 = Female

2. What is your age? ______

3. What best describes your marital status?
   1 = Married
   2 = Single with live-in partner
   3 = Single
   0 = Other

4. How many people live in your household? ______

5. How many children in each age group are living in your household? (if you have no children, enter zero for all age groups)
   0-3 years old ______
   4-6 years old ______
   8-12 years old ______
   13-18 years old ______
   Older than 18 ______

6. What city and state do you live in?
   City ____________________
   State ____________________

7. What is the highest level of schooling that you have completed?
   1 = Some high school
   2 = Graduated from high school
   3 = Some college
   4 = 2 year college degree
   5 = 4 year college degree
   6 = Beyond 4 year college degree

8. What is your racial-ethnic background?
   1 = Hispanic
   2 = White (non-Hispanic)
   3 = African-American
   4 = Asian-American
   5 = Native American
   0 = Other (please fill in) ____________________

9. What was your total household income (before taxes) in 2006?
   1 = Under $10,000
   2 = $10,000-$14,999
   3 = $15,000-$19,999
   4 = $20,000-$24,999
   5 = $25,000-$29,999
   6 = $30,000-$34,999
   7 = $35,000-$39,999
   8 = $40,000-$49,999
   9 = $50,000-$59,999
   10 = $60,000-$74,999
   11 = $75,000-$99,999
   12 = $100,000-$124,999
   13 = $125,000-$149,999
   14 = Over $150,000

10. What was your religious affiliation when you were young, say age 12?
   1 = Baptist
   2 = Catholic
   3 = Jewish
   4 = Lutheran
   5 = Methodist
   6 = Muslim
   7 = Other
   8 = No religion when young

11. Are you actively engaged in farming?
   1 = Yes
   2 = No

12. Have you ever been actively engaged in farming?
   1 = Yes
   2 = No

13. What best describes your current work industry?
   1 = Professional (such as a physician, dentist, attorney, or teacher)
   2 = Management, business, and finance
   3 = Construction and extraction/mining
   4 = Installation, maintenance, and repair
   5 = Transportation and material moving
   6 = Sales and related
   7 = Farming, fishing, and forestry
   8 = Production/manufacturing
   9 = Service (such as motel or restaurant work)

10 = Housework or Retired
11 = Unemployed

14. Are you a member of an environmental group?
    1 = Yes
    2 = No

15. When purchasing new food items, how often do you read labels?
    1 = Always
    2 = Often
    3 = Sometimes
    4 = Rarely
    5 = Never

16. Are you a vegetarian or vegan?
    1 = Yes
    2 = No

17. Do you smoke?
    1 = Yes
    2 = No

18. Do you exercise regularly, i.e., 3 or more times per week of moderate or vigorous activity for 30 minutes or more per each episode?
    1 = Yes
    2 = No

19. On a scale of 1 to 10, with 1 being unhealthy and 10 being very healthy, how healthy is your diet? ______

20. On a scale of 1 to 10, with 1 being unhealthy and 10 being very healthy, how do you consider your physical health? ______

21. Whom do you most trust to provide you with information on food safety? (fill in blank)

    ____

22. Whom do you least trust to provide you with information on food safety? (fill in blank)

    ____

23. How safe do you think Intragenic GM is compared to Transgenic GM?
    1 = Much Less safe
    2 = Less safe
    3 = About as safe
    4 = More safe
    5 = Much more safe
    9 – I don't know

24. How safe do you think Intragenic GM food is compared to GM Free food?
    1 = Much Less safe
    2 = Less safe
    3 = About as safe
    4 = More safe
    5 = Much more safe
    9 – I don't know

25. Please circle the products that you purchase regularly. (circle all that apply)
    1 = Broccoli
    2 = Tomatoes
    3 = Potatoes

26. Please circle the products that you eat regularly. (circle all that apply)
    1 = Broccoli
    2 = Tomatoes
    3 = Potatoes

27. Please circle the products that you currently have in your home. (circle all that apply)
    1 = Broccoli
    2 = Tomatoes
    3 = Potatoes