Investigating the Relationship Between Objective and Subjective Knowledge and Visual Attention to Non-GMO Labels

Alicia L. Rihn[1], Hayk Khachatryan[2], Xuan Wei[3]

[1] Assistant Professor, Department of Agricultural and Resource Economics, University of Tennessee, email: arihn@utk.edu
[2] Mid-Florida Research and Education Center & Food and Resource Economics Department, University of Florida, email: hayk@ufl.edu
[3] Postdoctoral Research Associate, Mid-Florida Research and Education Center & Food and Resource Economics Department, University of Florida, email: wei.xuan@ufl.edu

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Abstract

This research addresses the impact of consumer subjective and objective knowledge of non-GMO certification on their valuation of and visual attention to the non-GMO attribute on fruit-producing plants. Two non-GMO attribute levels are used, a logo and a text label, to determine if label format influences behavior. Online choice experiments, in-person experimental auctions, and a survey instrument were used to measure responses to live plants and computer images of the same plants. The computer image auction was included to elicit visual attention metrics. The online choice experiment participants selected their preferred options from predetermined scenario images. Similar attribute levels were presented to identify the influence of non-GMO information on choice and valuation. Random effects tobit models were used to analyze the experimental auction data, while a mixed logit model was used to analyze the choice experiment. The empirical results imply that consumers are willing to pay a premium for plants with non-GMO labels. In general, type of knowledge influenced choice experiment participants' valuation for non-GMO plants. Individuals in the high subjective knowledge groups generated higher premiums than individuals in the low subjective – low objective knowledge group. Visual attention to the non-GMO labels varied with the high subjective – low objective knowledge group fixating on the non-GMO labels more than the other knowledge groups. Results imply a disconnect between subjective and objective knowledge of non-GMO programs which ultimately impacts consumers' valuation for non-GMO labeled plants.

Keywords: Choice experiment; Experimental Auction; Fruit plants; Objective knowledge; Subjective knowledge

JEL Codes: D12, D80; M31

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Introduction

Genetic modification is defined as occurring when products are "derived from organisms whose genetic material (DNA) has been modified in a way that does not occur naturally" (World Health Organization, 2018). Genetic modification has been widely debated in agriculture, plant sciences, and the food industries as a means to improve plant genetics, cultivar development, aesthetic characteristics, disease and pest resistance, nutrient content, shelf life, and crop yields (Azadi et al., 2016; Barrows et al., 2014; De Steur et al., 2013; Goodwin et al., 2015; Perry et al., 2016; World Health Organization, 2018; Zilberman and Wesseler, 2014; Zilberman et al., 2018). Concerns related to genetic modification come from safety concerns, loss of biodiversity, resistance to chemical controls, consumption safety, marketplace acceptance, regulatory approval, and development costs (Barrows et al., 2014; Goodwin et al., 2015; Dobres, 2008; Dona and Arbanitoyannis, 2009; Henle et al., 2008; Martin et al., 2017). Together, the studies addressing benefits and concerns related to using genetic modification in cultivar development highlight the debate around genetically modified organisms (GMO) and the complexity of perceptions when approaching this research topic.

Different methods are used to address consumer valuation of value-added attributes on products. Here, we use hypothetical choice experiments and non-hypothetical experimental auctions paired with knowledge metrics to elicit consumer valuation for non-GMO fruit-producing plants. First, a choice experiment was used to collect a larger sample from a more geographically dispersed audience. However, choice experiments are susceptible to hypothetical bias and measure value indirectly (Colson and Rousu, 2013; Loomis, 2011). In contrast, experimental auctions are used to reduce hypothetical bias which may occur with hypothetical research methodologies (Lusk and Shogren, 2007). Experimental auctions are based on random utility theory where it is assumed that consumers will act rationally, take into consideration all available attributes/information, and choose the option that provides the most utility. However, research has demonstrated that consumers are selective in what they view when making decisions (Hensher and Rose, 2009). Pairing experimental auctions with eye tracking technology allows researchers to accurately record participants' visual attention and determine if visual attention to attributes impacts their behavior (Rihn and Yue, 2016). Using a mixed methodology approach (i.e., a hypothetical online choice experiment and in-person experimental auction) serves to provide more robust results to address consumer behavior toward non-GMO plants.

Consumer knowledge of non-GMO is a focal point of this research. There are several factors that make consumer knowledge metrics particularly interesting when addressing research questions on non-GMO products. First, consumer knowledge has been shown to impact their preferences and acceptance of GMO (Fernbach et al., 2019; House et al., 2004; Klerck and Sweeney, 2007; Zhu and Xie, 2015). For example, general biology knowledge increases consumer acceptance of genetically modified foods (Zammit-Mangion et al., 2012). Secondly, the debate on the benefits and concerns related to genetic modification (as previously discussed) highlights the need to better understand consumer perceptions and how those impact their behaviors (Klerck and Sweeney, 2007). Third, in 2016, the U.S. government required GMO labeling in the food industry to inform consumers if their products contained GMO ingredients; thus, allowing consumers to make their own choices (Bovay and Alston, 2018; McFadden and Lusk, 2018). However, GMO related labeling requirements have not extended into the ornamental plant industry, meaning the impact of non-GMO labeling on consumer preferences for plants themselves remains unknown. Lastly, research indicates that people with high subjective knowledge and low objective knowledge are frequently the most opposed to genetic modification and more likely to share their knowledge with others (Fernbach et al., 2019). Supporting evidence shows that consumers have a limited understanding of science but strongly emphasize topics and non-scientific information for “emotionally charged” topics (Kahan, 2017). This implies, that those who think they are more knowledgeable (i.e., high subjective knowledge) actually know less (i.e., low objective knowledge) but spread information more so than other consumers (Fernbach et al., 2019; Kahan, 2017).

Based on the previous studies, the overall research goal was to investigate the relationship between consumers’ subjective and objective knowledge and valuation for fruit-producing plants using a mixed-method approach. Given consumers preferences for GM labeling on foods (McFadden and Lusk, 2018) and impact of knowledge on choice of non-GMO foods (Fernbach et al., 2019; House et al., 2004; Klerck and Sweeney, 2007; Wunderlich et al., 2018; Zammit-Mangion et al., 2012; Zhang and Liu, 2015), we test the following hypotheses:

H1. Knowledge will influence consumers’ valuation for non-GMO labeled plants.

H2. Consumers will be willing to pay premiums for non-GMO fruit-producing plants.

H3. Visual attention to the non-GMO labels will vary by label type (logo, text).

Methodology

Experimental Design – Choice Experiment

An online consumer panel completed the choice experiment using an online survey platform (Qualtrics Survey CoreXM^{TM}). Each choice scenario consisted of two products (A and B) with predetermined attribute levels and a neither option. Participants selected the product they would be willing to purchase given the provided information. Participants completed 16 choice scenarios (discussed shortly). For each scenario, the plant was pictured with the other attributes appearing below the plant image.

Experimental Design – Experimental Auction

A second price auction was used to elicit participants' bids for the plants. In a second price auction, one product is randomly drawn as "binding." To determine the winner and market price, the bids are sorted from highest to lowest and the highest bid "wins" but only pays the second highest price (the "market price"). The disconnect between participants' bids and the market price gives a weakly dominant strategy to truthfully reveal their willingness-to-pay (WTP) for the item. The experimental design included two treatments: live plants without eye tracking and images of those live plants on a computer monitor with eye tracking. Participants were randomly assigned to either treatment based on their date of participation (discussed more in the Participant Recruitment and Statistics section). In the computer simulation experiment, eye tracking cameras (Tobii x2-60) were used to record visual attention metrics. After participants completed the experiment, the winner was announced, and participants were compensated $30 except the winner who received the equivalent of $30 (i.e., plant and monetary incentive minus the market price).

Knowledge Variables

In both experiments, the same survey instrument was used to elicited subjective and objective knowledge metrics and participants' demographic information. Participants' subjective knowledge was measured using a self-revealed scale where they were asked "how knowledgeable are you about non-GMO certification?" (1=not at all knowledgeable; 7=very knowledgeable).

Objective knowledge was measured using three true or false style quiz questions. The questions were "True or false, non-GMO / GMO free certification must be traceable?" where the correct answer was "true". The second question was "true or false, non-GMO / GMO free certification includes inspection regardless of risk?" where "false" was the correct answer. The last question was "true or false, all organic products (certified and not certified) are non-GMO / GMO free?" where the correct answer is "false". The questions and answers were obtained from the Non-GMO Project Standard website (Non-GMO Project Standard, 2019).

For analysis purposes, participants' knowledge was based on their subjective rating and quiz scores. They were considered knowledgeable in both subjective and objective knowledge ($H_{sub}H_{obj}$) if they selected 5 or higher on the subjective knowledge scale and correctly answered 2 or more quiz (objective) questions. Participants were considered not knowledgeable in both subjective and objective knowledge ($L_{sub}L_{obj}$) if they rated their knowledge as 4 or below on the subjective knowledge scale and correctly answered zero or 1 quiz question. Two additional knowledge categories were defined. High subjective – low objective ($H_{sub}L_{obj}$) where participants indicated high subjective knowledge (selected 5 or above) but only correctly answered 1 or less quiz question and low subjective – high objective knowledge ($L_{sub}H_{obj}$) where participants rated their knowledge as 4 or less but correctly answered 2 or more quiz questions.

Products and Attributes

Fruit-producing plants in 1-gallon containers were selected as the product of interest due to product availability and the aesthetic and food-producing attributes of the plants. The three fruit-producing plants were blueberry, banana, and papayas (base variable).

Three value-added, credence attributes were included in the experimental design, including: A sustainability label, non-GMO label, and heirloom label. The sustainability label represented an eco-label in the ornamental plant industry that certifies the plants are produced in a sustainable way. The non-GMO label indicated the plants were not genetically modified. The heirloom label indicated the plants were heirloom varieties. Each label had three levels to capture differences in consumer WTP based on differences in format. The three levels were a logo, text label, or not present (base variable). For the non-GMO and heirloom attributes, the logo and text labels contained the same content. The sustainable attribute was different in that the text option was the logo plus informative text (ecosystem protection, fair labor practices, and product quality). Thus, the sustainable text label did not communicate the exact same information as the logo, rather it contained the logo and additional information. This was by design given that typically consumers have low awareness of ornamental plant labels. Images of the actual plants were taken and used in the computer image auction and online choice experiment.

JMP Pro software was used to generate a fractional factorial design using the Design of Experiment (DOE) routine which maximizes a D-efficiency criterion (Kuhfeld, 2010). A total of 16 choice scenarios were generated for the online choice experiment with a D-efficiency of 94.02%. For the experimental auction, a total of 14 product scenarios were generated with a D-efficiency of 83.60%.

Participant Recruitment and Statistics

Participants were recruited in Florida for the online choice experiment and central Florida for the in-person auction. To participate, participants needed to be 18 years or older and have purchased a plant within the past 12 months, given that not all consumers are able or interested in purchasing/owning a plant. For the in-person study, participants who passed the screening questions were directed to an online signup page where they selected a date/time that accommodated their schedules. Based on the date/time that the participant indicated, they were assigned to a live product auction or computer image auction. In the live product auction, they evaluated and bid on the actual plants. In the computer image-based auction, pictures of the same plants (used in the live product auction) were shown to the participants on a computer monitor, and they submitted their bids. A total of 1,680 people completed the online choice experiment while 145 people participated in the auctions with 60% bidding on the live plants and 40% participated in the computer image auction.

The sample summary demographics are presented in Table 1. Participants' mean age was 54 years old. Women were overrepresented in both samples which is consistent with the core consumer of plants (National Gardening Association, 2013). On average, participants had completed a college degree at the time of the studies. The mean household income in 2016 was nearly $60,000. The mean household size was between 2 to 3 people for both studies. Approximately 46% and 71% of the online and in-person samples indicated they were knowledgeable about non-GMO certification. For objective knowledge, participants in the online sample got 1.8 quiz questions correct (out of 3) with 54% exhibiting high objective knowledge (i.e., correctly answering 2 or 3 quiz questions), while the in-person sample got 1.9 questions correct with 76% exhibiting high objective.

Table 1. Sample Summary Statistics for an Experimental Auction Experiment

	Online Choice Experiment (n=1680)	**In-person Experimental Auction (n=145)**
Variable (definition)	***Mean***	***Mean***
Age	51.934	53.871
Gender (1=male; 0=female)	0.400	0.268
Education (1=college degree or higher; 0=otherwise)[a]	4.334	4.676

2016 household income ($1000)	62.589	59.698
Household	2.555	2.685
Live (1=live plants; 0=computer images)	---	0.32
Knowledge	***Mean***	***Mean***
Subjective knowledge (1=not at all knowledgeable; 7=very knowledgeable)	3.950	4.953
High subjective knowledge (1= 5 or greater; 0 = less than 5)	0.460	0.707
Objective knowledge (1=1 correct quiz answer; 2=2 correct answers; 3=3 correct answers)	1.867	1.947
High objective knowledge (1=2 or more correct quiz answers; 0=1 or no correct quiz answers)	0.70	0.76

[a] *Respondents indicated their level of education using predetermined categorical variables where 1=some high school, 2=high school diploma/GED, 3=some college, 4=2 year or associate's degree, 5=4 year or bachelor's degree, 6=some graduate school, and 7=a graduate or professional's degree.*

Econometric Models

A mixed logit model was used to analyze the online choice experiment data. The decision maker *i*'s utility (U_{ijt}) from choosing a product option alternative *j* in choice scenario *t*. The utility function can be written as follows:

$$U_{ijt} = V_{ijt}(\boldsymbol{x_{ijt}}, \beta_i) + \varepsilon_{ijt}. \qquad (1)$$

where utility V_{ijt} is the deterministic components and ε_{ijt} is the random component. The model follows the Random Utility Maximization (RUM) framework, according to which an individual chooses the alternative that provides the highest utility. In this study, the utility function for individual *i* can be written as:

$$U_{ijt} = \beta_{price} price_{ijt} + \boldsymbol{\beta}'_{\boldsymbol{x}} \boldsymbol{X_{ijt}} + \varepsilon_{ijt}. \qquad (2)$$

where β_{price} is the coefficient for the price of alternatives and is assumed to be a fixed parameter, and $\boldsymbol{\beta_x}$ is a vector of unknown parameters to be estimated for important plant attributes such as the presence or absence of different eco-labels. It is assumed that ε_{ijt} is independent and identically distributed with type I extreme value distribution. The choice probability that individual *i* would choose alternative *j* in choice scenario *t* can be expressed as:

$$Prob(y_i = j|\boldsymbol{X},\boldsymbol{\beta}) = \int \frac{exp\,(\beta_{price}price_{ijt} + \boldsymbol{\beta}_{ix}^{\prime}\boldsymbol{X}_{ijt})}{\sum_{j=1}^{J} exp\,(\beta_{price}price_{ijt} + \boldsymbol{\beta}_{ix}{}^{\prime}\,\boldsymbol{X}_{ijt})}\,\Phi\,(\beta_{ix}|\boldsymbol{\theta})\boldsymbol{d\beta_x},\ for\ j = 1,\ ...,J \quad (3)$$

where $\Phi\,(\beta_{ix}|\boldsymbol{\theta})$ is specified as normal distribution. The estimation of the mixed logit (ML) model uses a maximizing simulated likelihood $LL(\theta) = \sum_{i=1}^{N} lnProb_i\,(\theta)$. Since this expression cannot be solved analytically, it is approximated using simulation methods, and the ML model produces a set of means and standard deviations (SD) of the parameters (Train, 2003). The coefficient β_{price} is a fixed parameter, and WTP estimates can be generated using the coefficients from the mixed logit model, specifically:

$$WTP = -1\left(\frac{\beta_{attribute}}{\beta_{price}}\right). \quad (4)$$

Since participants' bids were left censored at 0 in the experimental auction, a tobit regression based model can be utilized (Tobin, 1958; Yue et al., 2016). Given the panel nature of the data, where each participant *i* submitted multiple bids for products *j*, a random effects tobit model was used to estimate the relationship between the product attributes, participants' knowledge, and their WTP bids for the fruit-producing plants. The random effects tobit model can be expressed as:

$$bid_{ij} = max\left[bid_{ij}^{*}, 0\right], \quad (5)$$

$$bid_{ij}^{*} = \boldsymbol{x_{ij}\beta} + c_i + u_{ij} > 0, \quad (6)$$

$$u{\sim}N(0, \sigma_u^2), \quad (7)$$

where bid_{ij} is the bid of participant i for product j. The bid_{ij}^{*} variable captures the participant's WTP for product j which is assumed to align with the linear unobserved effects model (eq. 6) (Wooldridge, 2002). The attributes of product j and the participants' demographics are captured with $\boldsymbol{x}_{ij}$. The c_i is the unobserved individual heterogeneity that varies across individuals (i) but not by product (j). The u_{ij} is the random error term with normal distribution and zero mean and variance σ_u^2. Stata software was used to analyze the results using mixlogit Stata command for the choice experiment and the xttobit command for the experimental auction.

Online Choice Experiment Results

The mixed logit estimates are presented for important attributes in Model 1 and with interaction terms between the non-GMO attributes and individual knowledge variables in Model 2 (Table 2). Price negatively impacted probability of choice which aligns with economic theory. The opt_out option was negative and statistically significant, indicating participants received greater utility from choosing at least one of the plants rather than neither option. Blueberry and banana plants improved probability of choice when compared to papaya plants (base level). The sustainable text label was the most preferred followed by the sustainable logo when compared to plants without the sustainable attribute. Both the non-GMO logo and text labels were preferred to plants without a non-GMO attribute. Similarly, participants preferred plants with the heirloom logo or label when compared to plants without the attribute. The standard deviation estimates were also statistically significant for the sustainable text label, non-GMO logo, and heirloom logo, indicating that parameters vary among the participants. In contrast, the standard deviations for the sustainable logo, non-GMO text label, and heirloom text label were statistically insignificant, indicating homogenous preferences among participants.

Table 2. Mixed Logit Estimates from an Online Choice Experiment (n=1680)

Attributes	Model 1			Model 2		
	Coefficients		*Std. Err.*	*Coefficients*		*Std. Err.*
Mean Estimates						
Price	-0.172	***	0.013	-0.172	***	0.013
Opt_out	-3.032	***	0.192	-2.985	***	0.193
Blueberry	1.090	***	0.069	1.063	***	0.069
Banana	0.373	***	0.066	0.383	***	0.068
Papaya	*Base*			*Base*		
Sustainable logo	1.035	***	0.053	1.054	***	0.054
Sustainable text	1.602	***	0.061	1.625	***	0.062
Sustainable (none)	*Base*			*Base*		
Non-GMO logo	0.852	***	0.062	0.617	***	0.137
Non-GMO text	0.364	***	0.050	0.236	**	0.113
Non-GMO (none)	*Base*			*Base*		
Heirloom logo	0.730	***	0.054	0.733		0.054
Heirloom text	0.500	***	0.045	0.502		0.046
Heirloom (none)	*Base*			*Base*		
Non-GMO Attributes Interacted with Knowledge Groups[a]						
Non-GMO logo × $\boldsymbol{H_{sub}H_{obj}}$	—			0.518	***	0.171
Non-GMO text × $\boldsymbol{H_{sub}H_{obj}}$	—			0.277	**	0.137
Non-GMO logo × $\boldsymbol{H_{sub}L_{obj}}$	—			0.635	***	0.210
Non-GMO text × $\boldsymbol{H_{sub}L_{obj}}$	—			0.451	***	0.172
Non-GMO logo × $\boldsymbol{L_{sub}H_{obj}}$	—			-0.073		0.162
Non-GMO text × $\boldsymbol{L_{sub}H_{obj}}$	—			-0.090		0.134
S.D. of Mean Estimates						

Opt_out	3.308	***	0.143	3.278	***	0.138
Blueberry	2.373	***	0.080	2.377	***	0.081
Banana	1.941	***	0.090	1.969	***	0.092
Papaya		*Base*			*Base*	
Sustainable logo	-0.032		0.064	-0.056		0.065
Sustainable text	0.774	***	0.056	0.772	***	0.057
Sustainable (none)		*Base*			*Base*	
Non-GMO logo	0.744	***	0.081	0.592	***	0.118
Non-GMO text	0.100		0.117	0.118		0.101
Non-GMO (none)		*Base*			*Base*	
Heirloom logo	-0.663	***	0.071	-0.668	***	0.071
Heirloom text	-0.032		0.087	-0.044		0.087
Heirloom (none)		*Base*			*Base*	
Non-GMO logo $\times \boldsymbol{H_{sub}H_{obj}}$		—		0.836	***	0.223
Non-GMO text $\times \boldsymbol{H_{sub}H_{obj}}$		—		-0.051		0.138
Non-GMO logo $\times \boldsymbol{H_{sub}L_{obj}}$		—		-0.560	**	0.274
Non-GMO text $\times \boldsymbol{H_{sub}L_{obj}}$		—		-0.434	***	0.169
Non-GMO logo $\times \boldsymbol{L_{sub}H_{obj}}$		—		0.072		0.166
Non-GMO text $\times \boldsymbol{L_{sub}H_{obj}}$		—		-0.317	**	0.161
Observations		40,320			40,320	
Log-likelihood (LL)		-9,518.05			-9,587.26	

****, **, and * indicate significance at ≤0.010, ≤0.050, and ≤0.100 when compared to the base variables.*

Note: [a] Participants with low subjective and low objective knowledge are used as the base group.

The estimates generated from the mixed logit models were used to estimate participants' WTP for plants with the different attributes (Table 3). The low subjective – low objective knowledge group was used as a base for comparison purposes. Depending upon the model specifications, participants were willing to pay the highest premium for a plant with the sustainable text label at $9.31 - $9.33 relative to a plant without that label. They were also willing to pay a $6.02 or $6.06 premium for plants with the sustainable logo compared to unlabeled plants. The non-GMO attribute also generated a premium at $4.95 - $3.65 and $2.12 - $1.27 for plants with the non-GMO logo and text labels compared to unlabeled plants. Participants were willing to pay $4.24-$4.45 for plants with the heirloom logo and $2.91-$2.99 for plants with the heirloom text label compared to plants that were not labeled as heirloom. In Model 2, the knowledge groups were interacted with the non-GMO attribute levels to estimate premiums. The high subjective – low objective knowledge group was willing to pay the highest premium at $7.89 for plants with non-GMO logos and $4.38 for plants with non-GMO text labels relative to the low subjective – low objective knowledge group. The high subjective – high objective knowledge group had the next highest premiums at $7.03 for non-GMO logoed plants and $3.17 for non-GMO text labeled plants. The low subjective – high objective knowledge group had the lowest premiums relative to the low subjective – low objective knowledge group at $3.23 for a non-GMO logo and $0.86 for the non-GMO text label.

Table 3. Willingness-to-Pay Estimates from an Online Choice Experiment (n=1,680)

Attributes	**Model 1**			**Model 2**		
	WTP		***(Std. Err.)***	***WTP***		***(Std. Err.)***
Blueberry	$6.33	***	(0.587)	$6.19	***	(0.569)
Banana	$2.17	***	(0.414)	$1.64	***	(0.393)
Papaya	*Base*			*Base*		
Sustainable logo	$6.02	***	(0.515)	$6.06	***	(0.523)

Sustainable text	\$9.31	***	(0.699)	\$9.33	***	(0.697)
Sustainable (none)		*Base*			*Base*	
Non-GMO logo	\$4.95	***	(0.481)	\$3.65	***	(0.820)
Non-GMO text	\$2.12	***	(0.314)	\$1.27	*	(0.668)
Non-GMO (none)		*Base*			*Base*	
Heirloom logo	\$4.24	***	(0.414)	\$4.45	***	(0.428)
Heirloom text	\$2.91	***	(0.331)	\$2.99	***	(0.343)
Heirloom (none)		*Base*			*Base*	
Non-GMO Attributes Interacted with the Knowledge Groups[a]						
Non-GMO logo × $\boldsymbol{H_{sub}H_{obj}}$		—		\$7.03	***	(0.788)
Non-GMO text × $\boldsymbol{H_{sub}H_{obj}}$		—		\$3.17	***	(0.534)
Non-GMO logo × $\boldsymbol{H_{sub}L_{obj}}$		—		\$7.89	***	(1.032)
Non-GMO text × $\boldsymbol{H_{sub}L_{obj}}$		—		\$4.38	***	(0.794)
Non-GMO logo × $\boldsymbol{L_{sub}H_{obj}}$		—		\$3.23	***	(0.601)
Non-GMO text × $\boldsymbol{L_{sub}H_{obj}}$		—		\$0.86	*	(0.470)

****, **, and * indicate within model significance at ≤0.001, ≤0.050, and ≤0.100 when compared to the base variables.*

Note: [a] Participants with low subjective and low objective knowledge are used as the base group.

In-Person Experimental Auction Results

Regarding visual attention to the different attributes, the sustainable label with text captured the highest number of fixations, followed by the non-GMO logo, non-GMO text, and sustainable logo (Table 4). The heirloom logo and text labels were viewed least frequently. Interestingly, for the non-GMO and heirloom labels, the logos captured significantly more fixations than the text versions. The opposite was true with the sustainable logo which likely occurred due to the text being added to the logo rather than replacing the logo resulting in the sustainable text label being substantially larger and containing more content. A similar pattern was observed across the knowledge groups. When considering the knowledge groups' visual attention to the non-GMO labels, the high subjective – low objective knowledge group ($\mathrm{H_{sub}L_{obj}}$) fixated more on the non-GMO logo than any of the other knowledge groups. For the non-GMO text label, the high subjective – low objective knowledge group ($\mathrm{H_{sub}L_{obj}}$) and low subjective – low objective knowledge group ($\mathrm{L_{sub}L_{obj}}$) fixated similar amounts which was greater than the other knowledge groups. Interestingly, the knowledge groups with high objective knowledge fixated the least on the non-GMO attributes.

Table 4. Fixation Count Data from An Experimental Auction

	Total Sample		$\mathbf{H_{sub}H_{obj}}$		$\mathbf{H_{sub}L_{obj}}$		$\mathbf{L_{sub}H_{obj}}$		$\mathbf{L_{sub}L_{obj}}$		
Attribute	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Sign.*** ^{z}
FC_Sustainable Logo	1.724*	1.937	1.810	2.093	2.25	1.958	0.900	0.774	1.833	1.631	abdf
FC_Sustainable Text	4.906*	5.272	5.421	5.323	5.292	5.112	2.200	2.710	5.500	7.515	bdf
FC_Non-GMO Logo	2.023*	2.278	1.889	1.909	3.208	3.685	1.483	1.860	2.417	2.335	abdef
FC_Non-GMO Text	1.891*	1.811	1.863	1.726	2.313	1.823	1.325	1.122	2.750	3.125	abcdf
FC_Heirloom Logo	1.509*	1.311	1.457	1.206	1.625	1.508	1.260	1.008	2.450	2.045	cdef
FC_Heirloom Text	1.039*	1.440	0.964	1.247	1.688	1.235	0.500	0.594	1.875	1.649	abcdf

* *indicates significance between logo and text attribute levels at the 5% level. Significance was tested using pairwise t-tests.*

^{z} *The Sign. column indicates significance between the number of fixations on each attribute for the knowledge groups. Significance was tested using ANOVA and Tukey's honest significance test. The following letters indicate significance at the 5% level, where: a indicates significance between* $H_{sub}H_{obj}$ *and* $H_{sub}L_{obj}$*; b indicates significance between* $H_{sub}H_{obj}$ *and* $H_{sub}L_{obj}$*; c* *indicates significance between $H_{sub}H_{obj}$ and $L_{sub}L_{obj}$; d indicates significance between $H_{sub}L_{obj}$ and $L_{sub}H_{obj}$; e indicates significance between $H_{sub}L_{obj}$ and $L_{sub}L_{obj}$; f indicates significance between $L_{sub}H_{obj}$ and $L_{sub}L_{obj}$.*

The random effects tobit model estimates is presented in Table 5. Model 1 shows the results without the knowledge variables while Model 2 presents the knowledge variables. Given that the dependent variable is participants' bids on the items, the coefficients can be interpreted as the amount participants are willing to pay relative to the base variable. Overall, participants indicated they are willing to pay \$0.87 and \$0.51 more for blueberry and banana plants relative to papaya plants. They were willing to pay \$0.77 and \$1.25 more for plants with the sustainable logo and text labels compared to plants without a sustainable label. They were also willing to pay premiums of \$1.31 and \$1.00 for plants with the non-GMO logo and text label, respectively. The heirloom logo generated a premium of \$0.40 relative to an unlabeled product. Participants with high subjective – low objective knowledge were willing to pay \$4.23 more for the plants, but only statistically significant at 10% significance level. Education negatively impacted participants' bids. Model 2 incorporated interaction effects between the knowledge variables and non-GMO attributes, however, no significant effect was observed.

Table 5. Random Effects Tobit Model Estimates from an Experimental Auction (n=145)

Attributes	**Model 1**			**Model 2**		
	Coefficients		***Std. Err.***	***Coefficients***		***Std. Err.***
Blueberry	0.873	***	0.209	0.873	***	0.208
Banana	0.509	**	0.208	0.509	**	0.208
Papaya	*Base*			*Base*		
Sustainable logo	0.770	***	0.200	0.770	***	0.200
Sustainable text	1.249	***	0.241	1.249	***	0.241
Sustainable (none)	*Base*			*Base*		
Non-GMO logo	1.313	***	0.198	0.895		0.562
Non-GMO text	0.996	***	0.219	0.576		0.614

Non-GMO (none)	*Base*		*Base*	
Heirloom logo	0.403 **	0.191	0.403 **	0.190
Heirloom text	0.309	0.259	0.309	0.259
Heirloom (none)	*Base*		*Base*	
$H_{sub}H_{obj}$	1.470	2.028	1.059	2.067
$H_{sub}L_{obj}$	4.225 *	2.423	3.632	2.471
$L_{sub}H_{obj}$	1.914	2.242	1.973	2.287
$L_{sub}L_{obj}$	*Base*		*Base*	
Non-GMO logo × $H_{sub}H_{obj}$	—		0.584	0.603
Non-GMO text × $H_{sub}H_{obj}$	—		0.916	0.738
Non-GMO logo × $H_{sub}L_{obj}$	—		-0.191	0.686
Non-GMO text × $H_{sub}L_{obj}$	—		0.552	0.659
Non-GMO logo × $L_{sub}H_{obj}$	—		0.692	0.808
Non-GMO text × $L_{sub}H_{obj}$	—		0.071	0.749
Age	0.010	0.043	0.010	0.043
Gender	-1.223	1.290	-1.224	1.290
Education	-0.638 *	0.369	-0.639 *	0.369
Income	0.003	0.019	0.003	0.019
Household	0.152	0.390	0.152	0.390
Live plant	1.285	1.179	1.285	1.179
constant	5.543	3.757	5.846	3.773
σ_u	6.567 ***	0.395	6.567 ***	0.395
σ_c	3.286 ***	0.055	3.282 ***	0.055
ρ	0.800	0.020	0.800	0.020
Observations	2,029		2,029	
Log-likelihood (LL)	-5,412.49		-5,410.22	

***, **, and * indicate within model significance at ≤0.001, ≤0.050, and ≤0.100 when compared to the base variables.

Discussion

In general, the inclusion of value-added attributes improved consumers' bids for fruit producing plants. The sustainable logo and label generated value which was amplified for the informative text label. This may indicate low consumer awareness and the inclusion of different information increased value due to a better understanding of the benefits of the product. The non-GMO label improved participants' valuation for fruit producing plants indicating they obtained greater utility from plants with those attributes. This finding supports hypothesis 2 (that consumers are willing to pay premiums for non-GMO fruit plants) and aligns with previous research addressing non-GMO labeling on food products (De Steur et al., 2013).

Interestingly, the model estimates indicate that knowledge appears to impact consumers' valuation of the plants displaying different attributes. In general, high subjective knowledgeable groups exhibited the highest premiums for plants with non-GMO information with the logo generating the highest premiums. Participants exhibiting high subjective – low objective knowledge had the highest premiums relative to the low subjective – low objective knowledge group (supporting hypothesis 1 that knowledge will influence consumers' valuation for non-GMO plants). This knowledge-based WTP differentiation is clearly observed in the online choice experiment sample but less evident with the experimental auction sample.

Lastly, participants fixated more on the non-GMO logo than the non-GMO text label, supporting hypothesis 3 (visual attention to non-GMO labels will vary by label type). Similar results were observed for the heirloom attribute. This observation may be attributed to several factors, including: the logos may be more visually appealing than the text versions, the logo may have provided more visual information (e.g., color, pictures, etc.) requiring additional attention, or that the logos were less straightforward to understand which required additional attention whereas the text was easier to interpret. Future studies could incorporate metrics to gain a deeper understanding on why visual attention varies by format. Overall, the high subjective – low objective knowledge group fixated on the non-GMO attributes more than other knowledge groups. This may reflect greater interest in the information since, as discussed by Fernbach et al. (2019), people with high subjective knowledge often overemphasize their knowledge, especially for controversial topics (Kahan, 2017). These results provide guidance to green industry firms interested in promoting non-GMO attributes of their plants. Specifically, the use of a non-GMO logo generates more value and attention than a non-GMO text label.

Literature Cited

Azadi, P., Bagheri, H., Nalousi, A.M., Nazari, F., & Chandler, S.F. (2016). Current status and biotechnological advances in genetic engineering of ornamental plants. *Biotechnol Adv.* 34, 1073-1090.

Barrows, G., Sexton, S., & Zilberman, D. (2014). Agricultural biotechnology: The promise and prospects of genetically modified crops. *J. Econ Perspect.* 28(1), 99-120. doi: 10.1257/jep.28.1.99

Bovay, J., & Alston, J.M. (2018). GMO food labels in the United States: Economic implications of the new law. *Food Policy*, 78, 14-25. doi: 10.1016/j.foodpol.2018.02.013

Colson, G., & Rousu, M.C. (2013). What do consumer surveys and experiments reveal and conceal about consumer preferences for genetically modified foods? *GM Crops & Food*, 4(3), 158-165. doi: 10.4161/gmcr.26322.

De Steur, H., Buysse, J., Feng, S., & Gellynck, X. (2013). Role of information on consumers' willingness-to-pay for genetically-modified rice with health benefits: An application to China. *Asian Econ J.* 27(4), 391-408.

Dobres, M.S. (2008). Barriers to genetically engineered ornamentals: An industry perspective. In: Teixeria da Silva JA, editor. *Floriculture, Ornamental and Plant Biotechnology*, Volume 5. Kagawa ken: Global Science Books. pp. 1-14.

Dona, A., Arvanitoyannis, I.S. (2009). Health risks of genetically modified foods. *J of Crit Rev in Food Sci and Nutr*, 49(2), 164-175. doi: 10.1080/10408390701855993

Fernbach, P.M., Light, N., Scott, S.E., Inbar, Y., Rozin, P. (2019). Extreme opponents of genetically modified foods know the least but think they know the most. *Nat Hum Behav.* doi: 10.1038/s41562_018_0520_3

Goodwin, B.K., Marra, M.C., Piggott, N.E. (2015). The cost of a GMO-free market basket of food in the United States. *AgBioForum* 18(3), 25-33.

Henle, K., Alard, D., Clitherow, J., Cobb, P., Firbank, L., Kull, T., et al. (2008). Identifying and managing the conflicts between agriculture and biodiversity conservation in Europe – A review. *Agri, Ecosys & Enviro,* 124(1-2), 60-71. doi: 10.1016/j.agee.2007.09.005

Hensher, D.A., & Rose, J. M. (2009). Simplifying choice through attribute preservation or non-attendance: Implications for willingness to pay. *Transportation Res Part E: Logistics and Transportation Rev.* 45(4), 583–590.

House, L., Lusk, J., Jaeger, S., Traill, W.B., Moore, M., Valli, C., et al. (2004). Objective and subjective knowledge: Impacts on consumer demand for genetically modified foods in the United States and the European Union. *AgBioForum,* 7(3), 113-123.

Kahan, D. (2017). On the sources of ordinary science knowledge and extraordinary science ignorance. In: Jamieson, K.H., Kahan, D., Scheufele, D.A., editors. *The Oxford Handbook of The Science of Science Communication*. New York: Oxford University Press. pp. 35-49.

Klerck, D., & Sweeney, J.C. (2007). The effect of knowledge types on consumer-perceived risk and adoption of genetically modified foods. *Psych & Mark*, 24(2), 171-193. doi: 10.1002/mar.20157

Kuhfeld, W.F. (2010). *Marketing Research Methods In SAS*. Cary: SAS Institute Inc.

Loomis, J. (2011). What's to know about hypothetical bias in stated preference valuation studies? *J of Econ Surveys*, 25(2), 363-370. doi: 10.1111/j.1467-6419.2010.00675.x

Lusk, J., & Shogren, J.F. (2007). *Experimental Auctions Methods and Applications in Economic and Marketing Research*. Cambridge: University Press.

Martin, H.M., Durr, D., Smith, L.M., Finke, R., & Cherry, A. (2017). Analysis of GMO food products companies: Financial risks and opportunities in the global agriculture industry. *Afr J of Econ and Sust Devel*, 6(1), 1-17.

McFadden, B.R., & Lusk, J.L. (2018). Effects of the national bioengineered food disclosure standard: Willingness to pay for labels that communicate the presence or absence of genetic modification. *Appl Econ Persp and Pol*. 40(2), 259-275.

National Gardening Association. (2013). The National Gardening Association's comprehensive study of consumer gardening practices, trends and product sales. National Gardening Association Inc., Williston, VT.

Non-GMO Project Standard. (2019). Non-GMO Project Standard. Available from: https://www.nongmoproject.org/wp-content/uploads/Non-GMO-Project-Standard-Version-15.pdf.

Perry, E.D., Moschini, G., & Hennessy, D.A. (2016). Testing for complementarity: Glyphosate tolerant soybeans and conservation tillage. *Am J Agric Econ* 98(3), 765-784. doi: http://dx.doi.org/10.1093/ajae/aaw001

Rihn, A.L., & Yue, C. (2016). Visual attention's influence on consumers' willingness-to-pay for processed food products. *Agribusi,* 32(3), 314-328.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Economet,* 26(1), 24-36. doi: 10.2307/1907382

Train, K. (2003). *Discrete Choice Methods with Simulation.* 1st ed. Cambridge: University Press.

Wooldridge, J.M. (2002). *Econometric Analysis of Cross Section and Panel Data.* Boston: The MIT Press.

World Health Organization. (2018). Food, genetically modified. Available from: http://www.who.int/topics/food_genetically_modified/en/.

Wunderlich, S., Gatto, K., & Smoller, M. (2018). Consumer knowledge about food production systems and their purchasing behavior. *Enviro Devel Sust,* 20, 2871-2881. doi: 10.1007/s10668-017-0021-y

Yue, C., Campbell, B., Hall, C., Behe, B., Dennis, J., & Khachatryan, H. (2016). Consumer preference for sustainable attributes in plants: evidence from experimental auctions. *Agribusi,* 32(2), 222-235. doi: 10.1002/agr.21435

Zammit-Mangion, M., Al-Qallaf, A., & Vella, J. (2012). Acceptance of genetically modified foods among Maltese youths: Can exposure to formal knowledge make a difference? *AgBioForum,* 15(1), 106-113.

Zhang, M., & Liu, G.L. (2015). The effects of consumer's subjective and objective knowledge on perceptions and attitude towards genetically modified foods: Objective knowledge as a determinant. *Int J of Food Sci and Tech* 60, 1198-1205. doi: 10.1111/ijfs.12753

Zhu, X., Xie, X. (2015). Effects of knowledge on attitude formation and change toward genetically modified foods. *Risk Anal* 35(5), 790-810. doi: 10.1111/risa.12319

Zilberman, D., Holland, T.G., & Trilnick, I. (2018). Agricultural GMOs – What we know and where scientists disagree. *Sustainability* 10(5), 1514. doi: 10.3390/su10051514.

Zilberman, D., and Wesseler, J. (2014). The impacts and acceptance of agricultural biotechnology: an introduction to the special issue. *Environ Dev Econ,* 669-675. doi: https://doi.org/10.1017/S1355770X1400062X