ECONOMETRIC METHODS TO ANALYZE CONSUMER BEHAVIOR USING HYPOTHETICAL AND NON-HYPOTHETICAL APPROACHES

A Dissertation

by

ALBA JEANETTE COLLART DINARTE

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Chair of Committee,	Marco A. Palma
Committee Members,	David A. Bessler
	Charles R. Hall
	Gary W. Williams
Head of Department,	C. Parr Rosson III

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ABSTRACT

This dissertation examines consumer behavior using hypothetical and non-hypothetical approaches. Across the study, emphasis is made on brand awareness and Willingness-to-Pay (WTP) measures of consumer preferences and the measurement of unobserved individual heterogeneity in the econometric analysis of consumer valuations. The methodologies used to elicit valuations and gather consumer preferences are hypothetical and non-hypothetical. The statistical tools used to analyze these data include econometric models for categorical and limited dependent variables, linear and non-linear random parameters models, and Latent Class Analysis (LCA).

The first essay evaluates the effectiveness of a point-of-purchase advertising program conducted for two local horticultural brands. Results based on electronic surveys gathered before and after the program was launched suggest that the campaign size was not sufficient to significantly increase brand awareness and overall demand, yet it increased WTP by 5.5% for those consumers aware of one of the brands. A major factor found to influence preferences was purchase frequency, which suggests that other advertising methods aimed to increase buying frequency might affect demand more effectively.

The second essay involved the econometric analysis of data collected using experimental auctions, which are often multidimensional. Panel data models commonly used consider bid-censoring and random effects that capture heterogeneity in the intercepts, but overlook heterogeneity in the coefficients. This essay compares different

models, and provides evidence that a Random Parameters Tobit model extends the measurement of heterogeneity, accounts for bid-censoring, and provides the most efficient and consistent estimates. When the model is applied to data collected in a non-hypothetical Vickrey auction to elicit WTP for government (Food Safety Modernization Act, FSMA) and industry-issued (Global GAP) food safety standards in specialty melons, findings indicate that valuations are censored and heterogeneous.

Finally, heterogeneity in valuations is assumed to occur discretely. Using a LCA approach, an examination was done to segment consumers based on their unobserved motivation to participate in experimental auctions. Moreover, Random Effects Tobit models are estimated to investigate differences in WTP among latent classes. The three latent classes found were characterized as: “Fee-Chasers”, “Certification Conscious”, and “Taste Conscious”. Results reveal that the classes differed significantly in terms of their WTP estimates.

DEDICATION

This dissertation and all of the efforts put forth to obtaining my doctoral degree are dedicated to my beautiful family. My family, each in their individual way, has so selflessly provided encouragement and support during my educational accomplishments. It is through my actions rather than words that I hope to express my gratitude and appreciation to each of you.

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1. INTRODUCTION

The study of consumer behavior has always been a major research topic in economic theory that is constantly evolving. It helps marketers, producers, and policy makers understand how consumers think, feel, reason, select, and value products with different alternatives, and it forms the basis for the analysis of demand for agricultural products. Because the horticultural industry is of great importance to the U.S. agricultural economy in terms of sales or output, value added, job opportunities, labor income, and aesthetic pleasure that supports psychological well-being, several approaches have been used in previous studies of consumer tastes and preferences to identify key factors affecting consumer purchase decisions regarding horticultural demand.

This dissertation will examine, in three essays, the use of selected hypothetical and non-hypothetical preference methods in eliciting consumer valuations and obtaining preference information related to horticultural products. Emphasis is made on improving the data collection methods, the econometric analysis of consumer preferences, and the importance of fully accounting for sources of observed and unobserved consumer heterogeneity. The objectives of this work are summarized as follows:

- Evaluating the effectiveness of promotion for local horticultural brands in terms of changes in demand and consumer awareness, and identifying a consumer profile related to preferences towards branded horticultural efforts.
- Examining the use of a Random Parameters Tobit model in the analysis of experimental auction data to account for bid-censoring and unobservable factors that

may affect consumers' valuation of treatments, and providing valuation estimates of consumer preferences towards government and industry-sponsored food safety standards in specialty products.

- Identifying potential latent classes of participants in experimental auctions based on unobserved motivations for participation and observed indicators of consumers' heterogeneity, and investigating differences, if any, in consumers' valuation of specialty products, government and industry-issued food safety standards, and tasting, among members of these classes.

In Sections 2, 3, and 4 this will be done by using online surveys and non-hypothetical experimental auctions to examine consumer preferences towards selected agricultural products in a U.S. context. Section 5 concludes, outlines certain limitations of this dissertation, and provides directions for future research.

2. CONSUMER RESPONSE TO POINT OF PURCHASE ADVERTISING FOR LOCAL BRANDS*

2.1 Introduction

Agricultural brands target consumer's desire for variety and stimulate financial growth of agribusiness companies through higher margins. Even though the development of a brand name can be an expensive endeavor, it has gained increasing recognition as a marketing instrument to differentiate generic products in the horticultural industry (Nijssen and Van Trijp 1998). Moreover, given the importance of promotion in differentiating a brand from its competitors, various studies in marketing research have focused on investigating how promotion affects consumer preferences toward branding.

In the United States, state-sponsored checkoff programs for single agricultural commodities (e.g. Florida citrus, Washington apples) have been around since at least the 1930s. More recently, broad-based advertising programs that collectively promote a group of agricultural products under a state brand (e.g. Arizona grown, Jersey Fresh, Go Texan) have become widespread (Patterson 2006). It is therefore not surprising that a plethora of studies have focused on evaluating the impact of generic advertising for food commodities (Alston, Freebairn, and James 2001; Williams, Capps, and Palma 2008; Moore et al. 2009; Williams, Capps, and Trang 2010), as well as the effectiveness of

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broad-based advertising of food products marketed under state brands (Govindasamy, Italia, and Thatch 1998; Patterson et al. 1999; Carpio and Isengildina-Massa 2010).

Recent consumer interest for local products opened the door for the development of state-sponsored branding efforts for non-food products. Brands of ornamental plants that have adapted to the movement of regional branding include Florida Garden Select, Louisiana Select, Oklahoma Proven, Colorado Plant Select, Texas Superstar®, Earth-Kind®, among others. These state-wide ornamental branding efforts seek to promote plants that best adapt to local weather and soil conditions, while enhancing the profitability of green industry growers. Previous estimates suggest that the impact of these programs cannot be overlooked. Retailers of the Oklahoma Proven brand reported increases in sales of 228% as a consequence of this program (Anella et al. 2001). Mackay et al. (2001) also noticed that consumers returned to the stores based on previous purchases of Texas Superstar® and estimated that about $10 million in new plant sales were generated as a result of this program. In addition, these brands encourage a positive environmental impact from the use of suitable plants that require lower levels of water and pesticides.

Although numerous studies have been conducted to evaluate promotion effectiveness for food commodities, many questions remain regarding promotion effectiveness for brands in the ornamental sector. Given that states and industry organizations continuously invest in promotion of branded ornamentals, understanding the impact of advertising is beneficial to producers linked to the industry and to the state promoting the brand. Furthermore, firms often operate on limited marketing budgets and must choose between advertising channels to promote their brands. An examination of consumer response to Point of Purchase in-store advertising (POPA) can help brand managers adjust marketing channels and rationalize further investments.

This study considers an in-store Point of Purchase Advertising (POPA) campaign of two state-wide ornamental brands: Texas Superstar® (TS) and Earth-Kind® (EK). These brands were developed by scientists and extension specialists from the Texas A&M University System in conjunction with other state and private industry stakeholders of the Texas ornamental industry. Both brands consist of plant material that has been selected according to their adaptability to heat, drought, disease, insect tolerance, and other weather and soil local conditions. However, each brand offers different products to some extent. The TS brand includes plant material that ranges from roses to trees, whereas the EK brand includes roses and an environmental stewardship program (i.e. the EK challenge, plant selector, EK principles) that encourages the use of efficient, traditional and organic gardening techniques.

In 2010, the Texas Department of Agriculture (TDA) launched an advertising campaign, which consisted of developing on-site promotional materials to include with TS and EK products at point of purchase locations in an effort to expand consumer demand for the local brands. The promotional materials consisted of plant tags with information about the brands. The tags were distributed to growers, retailers and wholesalers in Texas that carry the brands. Since the POPA did not include other forms of mass media advertising, it is of special interest to measure the effectiveness, if any, of this type of in-store advertising on consumer demand. The objectives of this study are to evaluate the effects of POPA on consumer preferences in terms of brand awareness and willingness-to-pay (WTP), and to identify behavioral and demographic determinants of consumer preferences for branded ornamental plants. By evaluating the effects of POPA on consumer preferences for ornamental brands we contribute to the existing promotion literature in two ways. First, our focus on ornamentals helps to better understand consumer response to promotion efforts, as we may expect demand for ornamental products to behave differently than demand for agricultural food products. Moreover, the limited amount of research to date on promotion effectiveness of ornamentals has focused on aggressive media campaigns with no attention to smaller advertising programs that still require a sizable monetary investment.

2.2 Literature Review

A promotion program can shift demand, change price elasticity or both. The type of demand response to promotion depends on the components of the program including the message being spread (e.g. basic publicity versus real information), the type of products being advertised (e.g. necessities versus luxuries), the size of the campaign and choice of advertising channels, among other factors. Johnson and Myatt (2006) showed that a message that merely publicizes a product's existence, price, and other features that are clearly valued by all consumers might increase demand, whereas a message that informs consumers of their personal match with the characteristics of a product might change price elasticity of demand. Also, a message containing both basic publicity and real information may involve a shift in demand and changes in price elasticity. With regards to the type of product, Rickard et al. (2011) evaluated commodity-specific advertising, which intends to promote a category of products (i.e. all types of apples), and broad-based advertising, which refers to the promotion of a group of products that may be substitutes or complements of each other (i.e. all fruits and vegetables). By applying the theoretical framework developed by Johnson and Myatt (2006) they showed that commodity-specific advertising will lead to an upward shift and more inelastic demand, while broad-based advertising will lead to an upward shift and more elastic demand.

According to Moore et al. (2009), quantifying the magnitude of such demand responses is more complex than to measure a potential increase in sales. Because factors other than promotion affect sales of a product, statistical methods need to account for all these factors in order to isolate the effects of promotion on demand. For instance, Rickard et al. (2011) estimated constant and random parameter Tobit models to evaluate WTP increases as a result of promotion activities.

Contrary to food, ornamental plants are selected upon different quality differentiating attributes such as drought tolerance, light demand, pest vulnerability, color, etc. They are consumed because of the satisfaction consumers derive from their aesthetic characteristics and not to satisfy nutritional needs (Palma and Ward 2010). Therefore, consumer responses to ornamental promotions may differ compared to traditional food products. While many studies have analyzed the effectiveness of promotion on demand for food products, fewer studies have focused on floriculture and nursery crops. Most of the ornamental promotion literature has focused on the importance of a firm’s choice of advertising channels and campaign size. Rimal (1998) analyzed the effects of generic and brand promotions on sales of fresh cut-flowers in the U.S. and found that generic promotion efforts generated equal gains among all participating retail outlets, whereas brand promotion contributed to an increasing market share in particular outlets. Ort, Wilder, and Graham (1998) reported on the effectiveness of an extensive promotional campaign consisting of print and media advertising conducted by independent garden centers in North Carolina. They found that newspaper advertising for a specific plant produced the highest recall rates among consumers. More recently, Palma et al. (2012) quantified the effectiveness of firm promotion expenditures on sales of green industry firms accounting for firm size and types of advertising. Using cost-benefit analysis they concluded that for small and medium firms, internet-based advertising generates the highest returns of $5.90 and $7.50 in sales per $1 spent in advertising, respectively, whereas for large firms mass-media represents the most important advertising channel.

Thus far no research has examined the impact of low budget in-store advertising on consumer preferences for branded ornamentals. Understanding the reach of in-store promotions and the main behavioral and demographic factors determining consumer preferences for branded products can help ornamental firms evaluate their marketing mix, optimize their choice of advertising channels given their budget constraints, and target a more specific population of interest.

2.3 Data and Sample Weighting

Data regarding consumer perceptions of branding efforts and WTP were obtained through two electronic mail surveys administered to Texas consumers. The first survey was conducted in July of 2008, before the POPA program. From this sample of 800 individuals approximately 34% were actual consumers of ornamental products, hence the final number of usable responses was 273 observations. The second survey was conducted in August of 2010 after the program was finished and it consisted of a total of 259 observations. A random sample of 259 observations was taken from the first survey in order to balance the pre-program and post-program observations. Moreover, to ensure that the two samples were equivalent in terms of demographic characteristics, each demographic stratum in the second survey (i.e. gender, age, income, etc.) was weighted with respect to the corresponding stratum in the first survey as follows:

$$w_k = \frac{\%(Sub)Population_k}{\%Sample_k} \tag{1}$$

where the numerator indicates the percentage of stratum k in the population or sub-population of interest and the denominator indicates the percentage of stratum k in the sample. Post-stratification weighting improves comparability of the samples by ensuring that any changes measured in the statistical models are the results of the variables measured and not differences in the demographics of the two samples. The pre-POPA program sample and the weighted post-POPA program sample were pooled and used to estimate the models of brand awareness and WTP[1]. In all models, a dummy variable (POPA) is used to differentiate the pre-advertising and post-advertising data (=1 if post-advertising, 0 otherwise). This variable serves to assess the change in the population mean WTP and brand awareness as a result of the advertising campaign. Table 1 provides a comparison of the survey demographics and the general Texas population.

Table 1. Comparison of Demographic Variables from Samples Used and Texas Population

Demographic Variables		Brand Awareness *n=518* Percentage	EK Willingness-to-Pay *n=290* Percentage	TS Willingness-to-Pay *n=268* Percentage	Census[a] Percentage
Marital status	Married	62.0	62.8	61.2	51.5
	Not married	38.0	37.2	38.8	48.5
Gender	Male	48.1	45.1	46.6	49.6
	Female	51.9	54.9	53.4	50.4
Education	High School	11.7	13.2	9.8	46.0
	College	65.4	65.3	66.9	45.5
	Graduate School	23.0	21.5	23.3	8.5
Age	Less than 39	35.2	31.3	31.3	59.0
	40-55	31.6	34.0	32.8	20.4
	More than 55	33.2	34.7	35.8	20.6
Income	Under $25,000	15.8	18.6	16.4	24.8
	$25,000-$50,000	30.1	29.0	28.4	25.4
	$50,001-$75,000	20.8	14.5	17.9	18.2
	$75,001-$99,999	13.5	14.5	14.9	11.8
	$100,000-& above	19.7	20.0	22.4	19.8

[a]Source: U.S. Census Bureau 2010, American Community Survey 2006-2010.
Note: *n* indicates sample size.

[1] Similar random sampling and weighting procedures were used to obtain the samples used to estimate the models intended to explain the effect of the promotion program on WTP for TS and EK. Because the first survey contained a lower number of observations on WTP for both brands, the final samples had a total of 290 observations used to model WTP for EK and 268 observations used to model WTP for TS. Across all samples, the data were comparable to the overall Texas population. See Levy and Lemeshow (2008) and Groves et al. (2009) for a theoretical treatment of survey weights.

2.4 Methodology

The conceptual framework for this study is the Random Utility Theory (RUT). In this context, the consumer is rational and has a perfect discrimination capability. However, the analyst has incomplete information and uncertainty is taken into account. More specifically, the utility that individual *i* associates with choice *j* is described as:

(2) $$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where V_{ij} is the deterministic component of utility and ε_{ij} is an independent and identically distributed (iid) random error unobserved to the researcher that reflects characteristics of the consumer or the products. For the individual ε is known, but for the analyst ε is an unobserved random variable with some density f_{ε}, which induces a density on U (Hanemann 1984).

Using this framework, the utility obtained from consuming ornamental plants can be written as:

(3) $$U_{ik} = V_{ik}(x_k, s_i, y_i, POPA) + \varepsilon_{ik}$$

where x_k is a vector of ornamental products, s_i refers to consumer socio-demographic characteristics, y_i is income, and ε_{ik} is a random vector of consumer characteristics or ornamental plant features that are unobservable to the econometrician. Moreover, POPA is a level of advertising that is given by the firm to the consumer and affects consumer preferences (Becker and Murphy 1993).

2.4.1 Brand Awareness Models

Thilmany et al. (2011) point out that assessing the effectiveness of promotional activities should note the effects of any shift on demand, but also offer insights into the promotion methods that raise awareness and create demand. In modeling brand awareness, the individual is modeled as being aware or not of a certain brand, instead of choosing one. Specifically, we model awareness of each brand as a function of the number of monthly transactions (TRAN), purpose of the purchase (PUR), post promotion on place dummy (POPA), and several socio-demographic characteristics, including age, gender, marital status, income, educational level, and region (Table 2). Because the dependent variable is a binary variable indicating awareness of the brand, a Logit model was considered[2], and the implications for the likelihood of awareness are interpreted in terms of odds ratios. The model specification for estimating the probability of brand awareness of the *j* brand (TS or EK) is given by:

$$\begin{aligned} AWARE_j &= \alpha_j + \beta_1 AGE2 + \beta_2 AGE3 + \beta_3 FEMALE + \beta_4 MARRIED \\ &+ \beta_5 EDU2 + \beta_6 EDU3 + \beta_7 REG2 + \beta_8 REG3 + \beta_9 TRAN + \beta_{10} PUR + \delta INC2 \\ &+ \gamma_{1j} POPA_j + \varepsilon_j \end{aligned} \tag{4}$$

where ε_j is assumed to follow a standard logistic distribution. The first hypothesis investigated by the brand awareness models is whether POPA advertising will increase the likelihood of brand awareness (i.e. $\gamma_{1j} > 0$).

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[2] A two-stage model was also estimated for brand awareness and willingness-to-pay to account for the potential endogeneity of brand awareness. The results suggested that brand awareness was not an endogenous factor and hence the models were estimated independently.

2.4.2 Willingness-to-Pay Models

A rational individual is assumed to consume product *j* if the utility from this product is at least as great as the utility without the product. Following Rickard et al. (2011) the marginal value consumer *i* places on product *j*=1, denoted as c_{ij}, is defined as the amount of income that leaves the consumer's utility at least as great with or without the consumption of *j*, that is:

(5) $$V_{ij=1}(x_1, z, s_i, y_i - c_{i1}, POPA) + \varepsilon_{i1} \geq V_{ij=0}(x_0, z, s_i, y_i) + \varepsilon_{i0}$$

By the random utility assumption the consumer's WTP for *j* can be solved from the probability of individual *i* choosing *j*:

(6) $$\Pr(x_{i1}) = \Pr[V_{i1}(.) + \varepsilon_{i1} \geq V_{i0}(.) + \varepsilon_{i0}] = \Pr(WTP_{i1} \geq c_{i1})$$

which implies that the consumer WTP has to be at least as great as the marginal value for the product, otherwise the product is not consumed.

Different assumptions about the distribution of the stochastic portion of utility produce different choice models (McFadden 1974). If ε is assumed to follow a double exponential distribution ($0, \sigma = \pi^2 \mu^2 / 3$), where μ is the logit scale parameter, and utility of the nonpurchased option is normalized to 1, the probability of consuming *j* becomes:

(7) $$\Pr(WTP_{i1} \geq c_{i1}) = \Pr(x_{i1}) = \frac{\exp(V_{i1} / \mu)}{1 + \exp(V_{i1} / \mu)}$$

and after applying a logarithmic transformation on both sides of the odds ratio we obtain:

$$\ln\left(\frac{\Pr(x_{i1})}{1-\Pr(x_{i1})}\right)WTP_{i1} = V_{i1} / \mu \tag{8}$$

Finally, assuming utility is additive over its components, and normalizing $\mu = 1$ without loss of generality, the estimable equation can be written as:

$$V_{ij}\,(y_i, s_i, POPA, \varepsilon_{ij}) = \sum_l \beta_l s_{il} + \delta y_i + \gamma POPA + \varepsilon_{ij} \tag{9}$$

where β_l are the coefficients associated with l socio-demographic characteristics, δ is the coefficient associated with income, γ is the advertising coefficient and ε_{ij} is the i.i.d. error term. Based on Carpio and Isengildina-Massa (2010) if WTP elicitation is conducted before and after an advertisement campaign, the change in WTP (ΔWTP) measured by the advertising shock γ can be interpreted as the direct effect or shift in the demand curve due to the advertising campaign.

In all WTP models, the dependent variable is the average percentage price premium the consumer is willing to pay for the branded product over a regular unbranded plant and it ranges from 0 to 41 percent. Percentage premiums are used when trying to measure the premium across aggregate categories of products (Carpio and Isengildina-Massa 2010). Since the mean WTP variable theoretically has a lower threshold of zero, a Tobit specification was used in all WTP models to account for left-censoring. In the first two models, explanatory variables include the number of transactions (TRAN), the purpose of the purchase (PUR), post promotion on place dummy (POPA), awareness of the brand (TS-AWARE or EK-AWARE), and several demographic characteristics, including age, gender, marital status, income, educational level, and region (Table 2).

Table 2. Description of Variables Used in the Econometric Analyses

Variable	Description
TSAWARE	Awareness of Texas Superstar® (= 1 if true and 0 otherwise)
EKAWARE	Awareness of Earth-Kind® (= 1 if true and 0 otherwise)
TSWTP	Mean WTP for Texas Superstar®
EKWTP	Mean WTP for Earth-Kind®
Socio-demographic characteristics	
AGE2	Age between 40-55 years old (= 1 if true and 0 otherwise)
AGE3	More than 55 years old (= 1 if true and 0 otherwise)
FEMALE	Gender is female (= 1 if true and 0 otherwise)
MARRIED	Marital status is married (= 1 if true and 0 otherwise)
INC2	Income level (=1 if income equal or above $50,000 and 0 otherwise)
EDU2	Educational level (=1 if college degree, and 0 otherwise)
EDU3	Educational level (=1 if graduate school, and 0 otherwise)
Consumer habits	
TRAN	Number of monthly transactions
PUR	Purpose of the purchase (= 1 if self-consumption and 0 otherwise)
POPA	Point of Purchase Advertising (=1 if Post-advertising and 0 otherwise)
Region	
REG2	Region: Central Texas (= 1 if true and 0 otherwise)
REG3	Region: South Texas (= 1 if true and 0 otherwise)
Dummy variables base levels	
AGE1	Age group of 39 years old or less
INC1	Income group under $50,000
EDU1	Educational level is high school or less
REG1	Region is North

The mean WTP for brand *j* (TS or EK) can be written as:

$$
\begin{aligned}
(10)\quad & WTP_j^* = \alpha_j + \beta_1 AGE2 + \beta_2 AGE3 + \beta_3 FEMALE + \beta_4 MARRIED + \beta_5 EDU2 \\
& + \beta_6 EDU3 + \beta_7 REG2 + \beta_8 REG3 + \beta_9 AWARE + \beta_{10} TRAN + \beta_{11} PUR + \delta INC2 \\
& + \gamma_{2j} POPA_j + \varepsilon_j
\end{aligned}
$$

$$WTP_j = \max\{0, WTP_j^*\}$$

where $\varepsilon_j \sim N(0, \sigma^2)$ and WTP^* is a latent variable that is observed for values greater than zero and censored otherwise. The second hypothesis investigated by the willingness-to-pay models is whether POPA advertising will lead to a shift in overall demand for these products (i.e. $\gamma_{2j} > 0$).

The last two models were estimated for a subset of the sample that consisted of consumers aware of each brand. These models were estimated to isolate the effect of the POPA campaign for a specific group of consumers that has been found to be relevant in other evaluations of promotion effectiveness. For instance, Carpio and Isengildina-Massa (2010) found that only individuals previously aware of the South Carolina-grown promotion campaign expressed a change in preferences as a response to the campaign. The conditional mean WTP for brand *j* (TS or EK) can be written as:

$$
\begin{aligned}
(11)\quad & (WTP_j^* | AWARE = 1) = \alpha_j + \beta_1 AGE2 + \beta_2 AGE3 + \beta_3 FEMALE + \beta_4 MARRIED \\
& + \beta_5 EDU2 + \beta_6 EDU3 + \beta_7 REG2 + \beta_8 REG3 + \beta_9 TRAN + \beta_{10} PUR + \delta INC2 \\
& + \gamma_{3j} POPA_j + \varepsilon_j
\end{aligned}
$$

$$(WTP_j | AWARE = 1) = \max\{0, WTP_j^* | AWARE = 1\}$$

where $\varepsilon_j \sim N(0,\sigma^2)$. The third hypothesis investigated by the conditional willingness-to-pay models is whether POPA advertising will lead to a shift in demand by individuals aware of the brands (i.e. $\gamma_{3j} > 0$).

2.5 Results and Discussion

2.5.1 Texas Superstar® Brand Awareness Results

The Logit results for the TS brand awareness model are presented in Table 3. A likelihood ratio test of 32.05 (P<0.0014) is an indication of the goodness of fit of this model. Moreover, about 438 of 498 (88%) of survey participants were correctly classified as either aware or unaware of the brand. The Hosmer and Lemeshow's test of goodness of fit for logistic regression yields a very large p-value (0.87), indicating that the predicted frequency and observed frequency matched closely.

Results show no statistically significant influence of the POPA program on raising awareness of TS (i.e. $\gamma_{1,TS} = 0$), indicating that in-store POPA was not sufficient to impact consumer awareness. The results imply that consumers with high income, those with a graduate school degree, and those older than 55 years are around 1.5 times more likely to be aware of the TS brand, whereas an additional transaction makes a consumer about 1.2 times more likely to be aware of the TS brand.

These findings are consistent with the socio-demographic profile of ornamental consumers that Yue and Behe (2008) identified. They found that wealthier consumers were more likely to choose traditional freestanding floral outlets (i.e. nurseries and garden centers), where mean prices and expenditures per transaction are higher compared to other floral outlets such as box stores or general retailers. The main retail outlets for TS products are traditional freestanding floral outlets and to a lesser extent box stores or mass merchandisers (i.e. Home Depot, Lowe's). Hence, it is possible that wealthier consumers might be more likely to be aware of TS because they are more likely to visit the floral outlets where the majority of TS products are sold. Furthermore, high-income consumers may also be less sensitive to price premiums of branded ornamentals. With regards to educational level, consumers with graduate degrees might be more likely to be exposed to sources of information other than seeing the products at the marketplace. For example, agricultural extension services of universities in Texas promote both brands through marketing displays at extension offices on campus. The expected positive relationship between brand awareness and frequency of purchase indicates that as consumers increase the number of monthly transactions and physically visit the stores they are considerably more likely to become aware of the brands.

Results indicate that a female consumer is 43% less likely to be aware of the TS brand. The increasing use of landscaping contractor services by females may explain this relationship (Collart et al. 2010). Another possibility is related to the floral outlets that females prefer and the outlets where TS are offered. Yue and Behe (2008) found that females preferred to buy ornamental products at general retailers (i.e. supermarkets) followed by box stores, yet most TS products are sold through traditional freestanding outlets and have been introduced only more recently into box stores. The propensity score indicates that there is a 9.8% probability that the average consumer in Texas is aware of TS.

2.5.2 Earth-Kind® Brand Awareness Results

The Logit results for the EK brand awareness model are presented in Table 3. A likelihood ratio test of 25.92 (P<0.011) serves as an indicator of goodness of fit. This model compared with a naïve model with a 0.5 cutoff predicted 443 of 498 (89%) of the observations correctly as either aware or unaware of the brand. The Hosmer and Lemeshow's test for logistic regression yields a large p-value (0.45), indicating that the model fits the data well.

Results indicate no statistically significant influence of the POPA program on consumer awareness of the EK brand, suggesting again that in-store promotion was not enough to affect brand awareness (i.e. $\gamma_{1,EK} = 0$). Contrary to the TS case, the relationship of the variable measuring income above $50,000 (INC2) was negative. It indicated that consumers with high income are 73% less likely to be aware of EK. The negative relationship between awareness of EK and income appears consistent with consumers' choices of floral outlets. The main outlets for EK roses are box stores such as Walmart and general retailers including supermarkets such as HEB. As income level decreases consumers are more likely to choose box stores and general retailers as floral outlets because of lower prices. Thus, lower income consumers might be more likely to be aware of EK because they are more likely to use the floral outlets where EK products are available. Also, high-income level citizens are increasingly contracting professional lawn care services (Hall et al. 2006), possibly because they can afford to make more use of landscaping contractor services. In turn, these consumers may be less involved in the design of their landscape and therefore less likely to be familiar with the EK challenge, plant selector, the EK principles to design a sustainable landscape, or to actively participate in the educational component of EK.

The purpose of the purchase for self-consumption (PUR) also had a negative effect on awareness. Consumers whose purpose of purchase is self-consumption are about 39% less likely to be aware of EK products. This result suggests that ornamental consumers may be inclined to search for generic products that associate with lower prices when purchasing roses for self-consumption purposes and care more about differentiated products when purchasing roses for gifts. The number of transactions per month (TRAN) and the South Texas region (REG3) appeared to positively affect awareness of EK, implying that influencing the frequency of purchase significantly impacts brand awareness. Estimates suggest that a consumer located in South Texas is 1.7 times more likely to be aware of EK, and that an additional transaction makes the consumer about 1.2 times more likely to be aware of EK. The propensity score indicates that there is an 8.8 % probability that the average consumer in Texas is aware of the EK program, a value slightly lower than that for TS.

Overall results of the brand awareness models for both TS and EK show that in-store point of purchase advertising (POPA) did not have statistically significant effects on consumer awareness. Instead, the key outcomes that seem to influence awareness of local branded ornamentals are income level and frequency of buying. As the number of visits to a store increases the chances of a consumer being aware of local brands promoted through POPA also increase.

Table 3. Brand Awareness Parameter Estimates from Logit Model for the Local Brands

	Texas Superstar®		Earth-Kind®	
	Coefficient (SE)	Odds ratio	Coefficient (SE)	Odds ratio
Intercept	-1.7319*** *(0.5208)*		-1.3567*** *(0.4943)*	
AGE2 (40 to 55)	-0.3557 *(0.2216)*	0.7007	-0.1691 *(0.2189)*	0.8444
AGE3 (older than 55)	0.4385** *(0.2222)*	1.5504	0.2714 *(0.2225)*	1.3118
FEMALE	-0.8432** *(0.3618)*	0.4303	-0.5684 *(0.3618)*	0.5664
MARRIED	-0.3619 *(0.3511)*	0.6964	0.1001 *(0.3548)*	1.1052
INC2 (above $50,000)	0.3720** *(0.1667)*	1.4507	-0.3150** *(0.1581)*	0.7298
EDU2 (college degree)	-0.1767 *(0.2380)*	0.8381	-0.0808 *(0.2148)*	0.9224
EDU3 (graduate school)	0.3909* *(0.2213)*	1.4784	-0.3692 *(0.2748)*	0.6913
TRAN (number of transactions)	0.1826* *(0.0939)*	1.2003	0.1923** *(0.0926)*	1.2120
PUR (self-consumption)	-0.5232 *(0.3920)*	0.5926	-0.9426** *(0.3774)*	0.3896
POPA (point of purchase advertising)	0.4746 *(0.2931)*	1.6073	-0.3421 *(0.3070)*	0.7103
REG2 (Central Texas)	0.1072 *(0.1520)*	1.1131	-0.0280 *(0.1716)*	0.9724
REG3 (South Texas)	0.1584 *(0.3082)*	1.1716	0.5375* *(0.3072)*	1.7117
Number of usable observations	498		498	
Log-likelihood full model (L_1)	-167.18		-155.85	
Likelihood ratio	32.05		25.92	
LR *P* value	0.0014		0.011	
McFadden's R^2	0.0875		0.0768	
Hosmer and Lemeshow's *P* value	0.87		0.45	
Percentage of correct predictions	87.95		89.16	

Note: *, **, *** indicate significance at P < 0.1, 0.05, or 0.01, respectively.

2.5.3 Texas Superstar® Willingness-to-Pay Results

The parameter estimates for the WTP models for all respondents and respondents aware of each brand are presented in Table 4. The sigma parameter which refers to the estimated standard deviation of the residual shows a censoring of the data. The mean WTP is measured in percentage terms, thus a positive marginal effect denotes a price premium for the brand over a regular plant, whereas a negative marginal effect denotes a price discount.

Results of the WTP model for TS for all respondents indicate no statistically significant influence of POPA or any demographic factors on WTP, indicating that in-store promotion did not affect consumer demand for ornamentals (i.e. $\gamma_{2,TS} = 0$). The self-consumption purpose of the purchase (PUR) had a negative relationship with WTP. Its marginal effect implies a price discount of 3.7% if the purpose of the purchase is self-consumption and a price premium of 3.7% if the purpose is a gift, which suggests a predisposition of consumers to save when purchasing branded ornamentals for self-use purposes. In contrast, the number of transactions per month (TRAN) and brand awareness (TS-AWARE) had a positive relationship. Notably, the variable with the highest effects on WTP was brand awareness; consumers aware of the TS brand are willing to pay a 4.5% price premium for TS certified plants compared to regular unbranded plants. Consumers with an additional transaction per month are willing to pay a price premium for branded plants of 1% over non-branded plants. Results show that the average consumer of ornamentals in Texas is willing to pay a price premium of 10.4% for TS plants over regular plants.

Furthermore, WTP for TS was also estimated for a sub-sample of ornamental consumers aware of the TS brand (Table 4). Results show no statistically significant influence of the POPA program on WTP (i.e. $\gamma_{3,TS} = 0$). However, female consumers aware of TS have a significant price discount of about 10.3% for this brand. The previous discussion of TS awareness indicated that females may have lower probability of awareness because of their choice of retail outlets. Yet, even females aware of the brand express a price discount, which exposes the importance of gender and retail outlet selection for marketing of this brand. Regarding the frequency of monthly transactions, an additional transaction by consumers aware of TS is estimated to increase the mean WTP by 5.3%, implying that purchase frequency plays a role not only in increasing the likelihood of awareness of TS, but also in inducing price premiums.

2.5.4 Earth-Kind® Willingness-to-Pay Results

Results of the WTP model for EK for all respondents indicate there were no significant effects of in-store promotion (i.e. $\gamma_{2,EK} = 0$) or demographic factors, but once more there were strong effects from the number of monthly transactions (TRAN), the purpose of the purchase (PUR), and brand awareness (EK-AWARE). The negative sign and significance of the variable that measured purpose of the purchase imply a price discount of 3.3% if the purpose of the purchase is self-consumption, which validates the propensity of consumers to save when purchasing branded plants for self-use. The positive estimate of frequency of purchase (TRAN) indicates that an additional transaction per month carries an increase of 1.2% in mean WTP for EK. As in the TS case, the variable with the highest effect on WTP was brand awareness (EK-AWARE); consumers aware of the EK brand are willing to pay a 4.7% price premium for EK roses compared to regular roses. Based on the econometric model estimates, the average consumer of ornamentals in Texas is willing to pay a price premium of 9.8% for EK roses, a lower but close estimate to the premium that consumers are willing to pay for TS products.

Results of the model examining WTP for a sub-sample of consumers aware of the EK brand (Table 4) show that, for this segment of the buying population, the POPA program effectively shifted demand for EK products (i.e. $\gamma_{3,EK} > 0$). In spite of being a low-cost in-store promotion, the program expanded demand for consumers that have been previously exposed to EK (Table 4). For those consumers the magnitude of the increase in WTP is estimated to be about 5.5%. This model also supports a negative relationship between female consumers aware of branded ornamentals and WTP price premiums, that is, female consumers aware of EK have price discounts that reach 6.8%. Finally, frequency of purchase not only increases the likelihood of awareness of EK, but also induces price premiums in consumers aware of the brand; an additional transaction by aware consumers is estimated to increase mean WTP by 2.7%.

Table 4. Willingness-to-Pay Parameter Estimates from Tobit Model for the Local Brands

	Texas Superstar®				Earth-Kind®			
	All respondents		Aware respondents		All respondents		Aware respondents	
	Coefficient (SE)	Marginal effect	Coefficient (SE)	Marginal effect	Coefficient (SE)	Marginal effect	Coefficient (SE)	Marginal effect
Intercept	0.1044***		0.1360		0.0853***		0.1259**	
	(0.0277)		*(0.0815)*		*(0.0298)*		*(0.0510)*	
AGE2 (40 to 55)	-0.0022	-0.0019	-0.0111	-0.0101	-0.0060	-0.0048	-0.0245	-0.0235
	(0.0095)		*(0.0447)*		*(0.0097)*		*(0.0247)*	
AGE3 (older than 55)	-0.0081	-0.0068	0.0160	0.0146	-0.0123	-0.0099	-0.0701***	-0.0672
	(0.0098)		*(0.0466)*		*(0.0103)*		*(0.0238)*	
FEMALE	0.0082	0.0069	-0.1136**	-0.1033	0.0247	0.0199	-0.0711*	-0.0682
	(0.0173)		*(0.0550)*		*(0.0179)*		*(0.0388)*	
MARRIED	-0.0008	-0.0007	0.0054	0.0049	-0.0167	-0.0134	0.0120	0.0115
	(0.0167)		*(0.0538)*		*(0.0173)*		*(0.0311)*	
INC2 (above $50,000)	-0.0002	-0.0002	-0.0385	-0.0350	0.0071	0.0057	-0.0084	-0.0081
	(0.0075)		*(0.0276)*					
EDU2 (college degree)	0.0143	0.0119	-0.0207	-0.0188	0.0140	0.0113	-0.0124	-0.0119
	(0.0110)		*(0.0489)*		*(0.0107)*		*(0.0209)*	
EDU3 (graduate school)	-0.0128	-0.0107	-0.0582**	-0.0529	-0.0083	-0.0067	0.0003	0.0003
	(0.0098)		*(0.0234)*		*(0.0110)*		*(0.0239)*	
TRAN (number of transactions)	0.0105**	0.0088	0.0578***	0.0526	0.0148***	0.0120	0.0282**	0.0271
	(0.0045)		*(0.0151)*		*(0.0048)*		*(0.0108)*	
PUR (self-consumption)	-0.0427**	-0.0371	-0.0564	-0.0523	-0.0391*	-0.0327	-0.0460	-0.0446
	(0.0211)		*(0.0566)*		*(0.0220)*		*(0.0339)*	
POPA (point of purchase advertising)	0.0021	0.0018	0.0351	0.0321	0.0004	0.0003	0.0575*	0.0555
	(0.0137)		*(0.0548)*		*(0.0144)*		*(0.0328)*	
AWARE (brand awareness)	0.0520**	0.0453			0.0562***	0.0475		
	(0.0205)				*(0.0201)*			
REG2 (Central Texas)	-0.0041	-0.0034	-0.0014	-0.0013	0.0012	0.0009	0.0099	0.0095
	(0.0071)		*(0.0275)*		*(0.0076)*		*(0.0173)*	
REG3 (South Texas)	-0.0003	-0.0003	0.0006	0.0005	0.0024	0.0020	0.0164	0.0157
	(0.0141)		*(0.0421)*		*(0.0146)*		*(0.0230)*	
SIGMA	0.1062***		0.1076***		0.1145***		0.0872***	
	(0.0051)		*(0.0137)*		*(0.0055)*		*(0.0093)*	

Table 4. Continued

	Texas Superstar®		Earth-Kind®	
	All respondents	Aware respondents	All respondents	Aware respondents
Number of usable observations	259	39	278	45
Likelihood ratio	22.59	24.5	34.43	31.49
LR *P* value	0.0469	0.0174	0.001	0.0017

Note: *, **, *** indicate significance at P < 0.1, 0.05, or 0.01, respectively.

2.5.5 Industry Implications

Branding, only when combined with effective marketing, can help agribusiness firms develop awareness and increase price premiums that can lead to enhanced profitability. Results from this study suggest that in-store POPA was not sufficient to significantly increase brand awareness and total demand for local ornamental brands. However, a major factor found to increase both overall demand and likelihood of brand awareness was buying frequency, which suggests that other advertising methods aimed to increase buying intensity might affect demand more effectively.

Our findings indicated that female consumers are less likely to be aware of branding efforts such as TS, and those aware expect price discounts. Also, consumers buying for self-use are willing to pay less for branded ornamentals. Previous studies in the literature have found that buyer frequency in ornamentals increased with females, self-use purchases, and in certain months of the year (Palma and Ward 2010), which suggests that those consumers that do most floral transactions per household might be those that expect price discounts for branded ornamentals (i.e. females, self-use purchases). This implies that if marketing managers would like to increase demand for branded ornamentals among those consumers willing to pay price premiums, they could personalize their marketing strategies to increase buying frequency among male consumers and those who buy only for special occasions. An increase in buying frequency could be accomplished through specific marketing tools such as loyalty programs or online retailing. Loyalty programs differ from other strategies by their emphasis on increasing repeat-purchase loyalty rather than only on gaining market share

(Sharp and Sharp 1997). Their impact on purchase behavior has led to an increasing popularity across industries, which has also resulted in the introduction of new currencies (e.g. frequent flyer miles, rewards points) that can lower consumers' perceived cost for a product (Dreze and Nunes 2004). However, for a loyalty program to be a worthy investment that effectively increases buying intensity, it must be designed in a way that adds value to consumers. Online retailing can facilitate the purchase of products by consumers who spend large amounts of time on the internet and by time-constrained consumers (Bellman, Lohse, and Johnson 1999). In online retailing, aspects such as an easy returns process have been shown to positively influence repurchase behavior (Griffis et al. 2012).

Another factor that had a strong effect on consumer WTP was brand awareness. Marketing efforts aimed to increase buying frequency likely increase the level of consumer awareness and WTP; as consumers make more transactions and visit the stores they are more likely to be exposed to in-store promotion and to become aware of ornamental brands, which influence their WTP. However, increasing brand awareness through other types of advertising also has a direct effect on WTP. For instance, because consumers with less discretionary time are turning to the internet to search for product information and to make purchases, social media is playing an increasingly important role as a source of information, with the advantage that it can be easily tailored to the population of interest at a low cost. Our estimates suggest that once consumers are aware of a brand, in-store promotion might help boost demand.

Consumer income also had a significant effect on brand awareness. Consumers with relatively high income (above $50,000) are more likely to be aware of branded ornamentals sold at traditional freestanding floral outlets, where average prices are higher, but less likely to be aware of ornamental brands sold at general retailers that include products and educational components. This implies that marketers need to tailor their communications intended to spread brand awareness not only to the product being offered but also to consumers' demographics and their preferred floral outlets.

2.6 Summary and Conclusions

This study analyzed the effects of a low-cost Point of Purchase Advertising (POPA) program launched for the local brands Texas Superstar® (TS) and Earth-Kind® (EK) on brand awareness and willingness-to-pay (WTP). The study used two electronic surveys conducted in Texas, before and after POPA, to study the main factors affecting consumer preferences. Exposure to the POPA did not have significant effects on overall consumer demand. Instead, consumer habits of purchase including brand awareness, the purpose of the purchase and the number of transactions had the largest effects on WTP. We identified a price discount for both brands when the purpose of the purpose is self-use and price premiums when the purpose is a gift and with marginal increases in the number of transactions.

The POPA program shifted demand solely for a subpopulation of consumers that have been previously exposed to the EK brand (i.e. $\gamma_{3,EK} > 0$). Given that the consumer is already aware of EK, the presence of the POPA induces a price premium of about 5.5%.

These conditional models also evidenced a negative relationship between females and WTP. The number of transactions positively affected the likelihood of awareness of branded ornamentals, and induced price premiums in respondents aware and non-aware of TS and EK. With regards to brand awareness, consumers with relatively high income (above \$50,000) are expected to be more likely to be aware of TS, but less likely to be aware of brands with educational components such as EK. Moreover, older and more educated consumers are more likely to be aware of TS, whereas females have a lower likelihood of awareness. Self-use purchases had a significant negative effect on awareness of EK, whereas the South Texas region had a positive effect on awareness of this brand. Also, an increasing buying frequency consistently increased awareness of both brands.

These results must be interpreted with caution as other exogenous factors may have played a role in promotion effectiveness. The lack of significance of the POPA parameter suggests that in-store promotion did not have an effect on brand awareness or WTP for the overall population. However, the value of this parameter measured the difference in the population WTP between the 2008-2010 periods, hence it might also account for other exogenous factors. Particularly, the economic recession of 2009 may have had an effect in consumer spending in ornamental goods despite advertising efforts by firms and represent a limitation to our findings. In addition, because a stated preference method was used to elicit consumer valuations of branded ornamentals, our WTP measures may be an overestimate of consumers' true WTP. However, the same elicitation method was used to assess WTP before and after the advertising campaign, and we focused on the difference in WTP as a result of in-store promotion rather than the actual level of WTP. Recent literature that has also made use of stated preference methods include Tonsor and Wolf (2012), who administered an online survey to U.S. consumers in order to collect stated WTP for milk attributes, and Holmquist, McCluskey, and Ross (2012) who used hypothetical contingent valuation to elicit WTP for wine attributes. In contrast, the use of revealed preference methods may provide gains in accuracy of valuation estimates, yet even in non-hypothetical settings factors such as participatory fees, bid affiliation, and zero-bidders can potentially introduce bias into the valuations (Lusk and Hudson 2004).

The results of this study provide insights into the effectiveness of in-store advertising for local branded ornamentals in terms of brand awareness and WTP. The profile of ornamental consumers identified in this study can be helpful in the design of future marketing strategies aimed to increase buying frequency, which was found to effectively increase brand awareness and WTP for branded ornamentals.

3. MODELING UNOBSERVED CONSUMER HETEROGENEITY IN EXPERIMENTAL AUCTIONS: AN APPLICATION TO THE VALUATION OF FOOD SAFETY STANDARDS

3.1 Introduction

Non-hypothetical experimental auctions have been widely used to elicit consumers' willingness-to-pay (WTP) for a great variety of commodities and services. Because they involve a trade-off between money and goods in an active market setting, they have the advantage over stated preference methods that avoid hypothetical bias, and thus have been useful instruments to valuate novel products and quality attributes (Abidoye et al. 2011; Alfnes 2007). Because conducting experimental auctions can be a more expensive endeavor relative to other value elicitation mechanisms, data are often collected for several goods (i.e. multiple good valuation) across several bidding rounds. That is, data collected are typically multidimensional and need to be analyzed using panel data models (Lusk and Shogren 2007).

Previous experimental auction studies have used different econometric approaches to model the bid equation to take into account the panel structure of the data, including pooled linear regression (Alfnes and Rickertsen 2003), and linear and nonlinear fixed effects (Shogren, List, and Hayes 2000; List and Shogren 1999) and random effects models (Corrigan and Rousu 2006a; Corrigan and Rousu 2006b; Lusk, Feldkamp, and Schroeder 2004). However, a key limitation in these panel data models is the assumption that the regression coefficients are constant. As noted by Woolridge

(2011), it is possible that treatment effects vary widely across individuals in unobserved ways. For instance, if a coefficient is used to estimate participants' mean WTP for a given treatment, a constant coefficients model assumes that all consumers have the same valuation for that treatment; yet, it is plausible that valuations differ based on unobserved heterogeneity in consumer preferences. Random Parameters models, also referred to as Random Coefficients or Mixed models, have been used more recently in the literature to fully account for unobserved individual heterogeneity in consumers' valuations. These models allow flexible modeling of within-cluster correlation, suitable for auction sessions with multiple products and repeated rounds in which the bids submitted by the same participant tend to be strongly correlated across rounds (Lusk, Feldkamp, and Schroeder 2004). Furthermore, while many of the applications of random parameters have used a linear regression framework (McAdams et al. 2013; Yue et al. 2010), there exists a growing literature on nonlinear models with random parameters (Greene 2012; Train 2009). This article examines the usefulness of the Random Parameters Tobit model in accommodating unobserved individual heterogeneity in the coefficients and the censoring nature of the data collected in experimental auctions with multiple bids per respondent. We apply the Random Parameters Tobit, also referred to in the literature as Censored Random Parameters or Mixed Tobit model, to data collected in a non-hypothetical sealed-bid second-price Vickrey auction (Vickrey 1961) conducted to elicit consumers' valuation of specialty melons, government and industry-issued food safety standards, and tasting treatments.

The valuation of food safety as a quality attribute has been a longstanding topic in the literature (Hayes et al. 1995; van Ravenswaay 1988). After numerous food-borne illness outbreaks linked to the consumption of meat and fresh produce there have been increasing efforts to enhance the safety of the U.S. food supply. In the melon industry, outbreaks of *Salmonella* and *Listeria* in Cantaloupes and Honeydews during 2008, 2011, and 2012 resulted in consumer deaths, product recalls by the U.S. Food and Drug Administration (FDA), and disruptions of international trade and consumer confidence. Although several food safety and protection standards for fresh produce are currently being promoted by the government, private-sector retailers, producers groups, and international organizations, this article considers industry-sponsored (GlobalGAP) and government-sponsored (FSMA) programs. The recent signing into law of the Food Safety Modernization Act (FSMA) by President Obama on January 4, 2011 provides evidence of the political importance of industry regulation of food safety and preventive control in the U.S. Under the FSMA, the U.S. Food and Drug Administration (FDA) is introducing mandatory Good Agricultural Practices (GAPs) for domestic fresh produce production and harvesting. In addition, on-farm produce handling, holding, and packing operations are treated as food facilities, which are required to develop and implement a Hazard Analysis and Critical Control Points (HACCP) plan. Overall, these provisions require that produce farms establish science-based standards for safe production and harvesting of fruits and vegetables that are raw commodities to minimize the risk of illness. Similarly, GlobalGAP is a non-governmental organization that sets voluntary standards for the certification of good agricultural practices that ensure food safety in agricultural products around the world. Under this program, growers need to comply with specific practices and are audited by third-party agents trained according to International Standards Organization (ISO) 9000 quality management or ISO 14000 environmental management standards. An important motivation of this privately-sponsored food safety program, which is now established in over 80 countries around the world, is the development of uniform standards that are recognized across national boundaries to facilitate international trade (Palma et al. 2010; Paggi et al. 2013).

The objectives of this article are as follows. First, to examine the use of the Random Parameters Tobit model in the analysis of experimental auction data to account for bid-censoring and unobservable factors that may affect consumer's valuation of treatments. Second, to provide valuation estimates of consumer preferences towards selected food safety standards in specialty produce. We contribute to the literature by comparing different estimation methods including Constant Parameters Tobit, Random Effects Tobit, Random Parameters Linear, and Random Parameters Tobit, and by investigating which estimation method provides the best fit and generates the most efficient WTP estimates when data follows a panel structure (i.e. multiple bids by the same individual for multiple treatments). Because repeated rounds with multiple good valuation are becoming a standard practice in experimental auctions, the results of this article have implications for model selection in the analysis of experimental auction data. Secondly, given the plethora of food safety initiatives that producers are expected to comply with in order to avoid disruptions in revenues, remain competitive, and avoid being excluded from influential markets, the limited literature available has focused on examining the evolution of these standards and the costs that producers face as they implement the activities required for compliance (Paggi et al. 2013; Palma et al. 2010). However, less attention has been given to analyzing consumer preferences. Information on consumer valuation of selected food safety programs provides valuable input to producers, importers, marketers, and other stakeholders to more accurately weigh the costs and the benefits of complying with these standards, to help determine the welfare effects of food safety standards and food product labeling, and to gain a deeper understanding of consumer behavior.

3.2 Literature Review

Experimental economists have used different econometric models to analyze experimental auction bids. Alfnes and Rickertsen (2003) used Pooled Ordinary Least Squares regression to estimate WTP differences among different types of beef using multiple repeated trials. Yet, the use of pooled linear regression when several responses are collected from each individual may result in inefficient parameter estimates (Carlsson and Martinsson 2007). Lusk et al. (2001) used a Double Hurdle model, as an alternative to a Tobit specification, to account for the two-step process of a field study valuating steak tenderness. Their in-store experiment consisted of collecting one bid per consumer using a modified Becker-DeGroot-Marschak (BDM) mechanism. A Double Hurdle model separates the decision of whether to pay more for a tender steak (i.e. a zero bid) versus the decision of how much more (i.e. a positive bid). Various experiments in the literature that have collected multidimensional data make use of panel data models. Corrigan and Rousu (2006a) used Random Effects Linear models to study bid affiliation from posted prices across three experimental auctions. Shogren, List, and Hayes (2000) and List and Shogren (1999) found very similar results in their estimates of Fixed and Random Effects models, and report the fixed effects estimates in their studies on preference learning and price information, respectively. Lusk, Feldkamp, and Schroeder (2004) estimated a Random Effects Tobit model to evaluate the impact of experimental auction procedures on the valuation of different qualities of beef. Corrigan and Rousu (2006b) also make use of a Random Effects Tobit to test the endowment effect in the absence of loss aversion, even though they do not report whether the random effects were statistically significant in the panel data.

Importantly, unobserved individual heterogeneity may take the form of either random intercepts or random coefficients, that is, the multiple bids submitted by the same individual can be correlated through a shared random intercept or a shared random slope, or both. Despite the increasing popularity of experimental auctions with multiple goods and multiple rounds, the valuation of one good influences the valuation of subsequent goods (Lusk and Shogren 2007); hence, bids submitted by the same participant over repeated products and treatments tend to be strongly correlated (Lusk, Feldkamp, and Schroeder 2004). As a consequence, Random Parameters models have been used more recently to account for unobserved individual heterogeneity in the coefficients. In the context of experimental auctions, McAdams et al. (2013) estimated a Random Parameters Linear model to explain willingness-to-pay for novel food products and found statistically significant effects in all random parameters, suggesting heterogeneity in individual effects on WTP of the auctioned products, the product forms, and the treatments. Yue et al. (2010) estimated a Random Parameters Linear model to examine consumer WTP for biodegradable containers for flowers and compare these to their WTP estimates from conjoint analysis data. Although they found a statistically significant random intercept, indicating a correlation between the multiple bids submitted by the same participant, they do not report the random coefficients. Moreover, both studies failed to account for the censoring structure of the data. Even if experimental auctions provide continuous measures of monetary valuations, the bids are often censored at zero (Lusk and Shogren 2007). A Random Parameters Tobit model accounts for unobserved individual heterogeneity in the coefficients while modeling the censoring nature of the data. An empirical application of several econometric models using auction data collected in South Central U.S. to elicit consumers' valuations of food safety certification programs sheds light on the importance of fully considering bid-censoring and unobserved individual heterogeneity in the regression parameters in experimental auctions.

3.3 Methodology

3.3.1 Experimental Design and Data

Eight experimental sessions were conducted during three days. Each session included between 18 and 26 participants, with a total of 172 participants. The participants were representative consumers (nonstudents) recruited from central Texas through multiple newspaper and online advertisements and were matched with a study session based on their schedule availability, age, and gender to reflect the socio-demographics of U.S. grocery shoppers (Carpenter and Moore 2006). The distribution of demographic characteristics of experimental auction participants is shown in table 5.

Table 5. Demographic and Other Characteristics of Experimental Auction Participants

Variable	Category	Sample		Population [a,b,c]	
		Mean	Percent	Mean	Percent
Age	18 to 29 years of age		38.6		40.4
	30 to 49 years of age		32.2		17.8
	50 years of age or more		29.2		12.5
Education	High school degree or less		11.7		33.8
	Bachelor's degree or at least some college		60.2		45.9
	Graduate school degree or at least some graduate school		28.1		20.4
Household size (number of individuals)		2.6		2.6	
Gender	Female		58.8		49.0
	Male		41.2		51.0
Marital status	Married		54.4		33.7
	Not married		45.6		66.2
Yearly household income	Less than $50,000		60.1		62.3
	Greater or equal than $50,000 but less than $100,000		27.4		23.7
	$100,000 or more		12.5		14.0
Primary grocery shopper of the household	Yes		87.1		
	No		12.9		
Weekly household spending on fruits and vegetables ($)		26.3			
Amount of fresh fruit and vegetables on hand as percentage of full stock		66.5			

[a] Source: American Community Survey 2007-2011.
[b] Population statistics for the Bryan/College Station, TX area.
[c] The age categories available in the American Community Survey are: 20 to 34 years of age, 35 to 54 years of age, and 55 years of age or more.

To ensure that participants were regular buyers of fruits, the advertisement specified that the study would involve consumer decision-making for fruit purchases. About 87% of participants were the primary shopper of groceries in their household. After arrival to the session, participants completed a consent form and were assigned anonymous ID numbers. They were provided with written and oral explanations on the incentive-compatible sealed-bid second-price Vickrey auction (Vickrey 1961)[3] and were explained their weakly dominant strategy, that is, to bid their true WTP for a unit of each good. Because subjects were simultaneously bidding on substitute goods, which may cause demand reduction or diminishing marginal utility (Lusk and Shogren 2007), subjects were informed that while the session included several rounds of bidding and several goods per round, only one of the goods and one of the non-hypothetical bidding rounds would be randomly selected as binding at the end of the experiment. Then, subjects participated in a first practice round. To ensure that they understood the auction procedure, they took a short knowledge quiz on the auction procedures and the correct answers to the quiz were discussed by a session monitor. Next, subjects participated in a second practice round. After participating in the short quiz and practice rounds, subjects participated in non-hypothetical auctions for six fruit products that are close substitutes: Cantaloupe, Honeydew, Tuscan melon, Canary melon, Galia melon, and personal watermelon as a control product.

[3] In the Vickrey auction participants submit a sealed-bid, and the highest bidder pays a price equal to the second highest bid.

In the non-hypothetical rounds there was one between-subjects treatment and two within-subjects treatments. The treatments were 1) Tasting: Four sessions participated in a tasting of each product prior to submitting their bids, while the other four sessions did not taste the products before bidding; 2) Industry-based Food Safety Certification Label: All participants were given information on a food safety certification label that would be issued by GlobalGAP, an industry-based effort that sets standards for the certification of agricultural products around the world; and 3) Government-based Food Safety Certification Label: All participants were given information on a food safety certification label that would be issued by the government (FSMA) through USDA. GlobalGAP is primarily based in Europe, and FSMA had not been fully implemented at the time of the auction. Therefore, participants were not familiar with either of the two food safety standards prior to the information treatments. The order of the within-subjects treatments was randomized for each session to account for ordering effects. At the time of bidding, participants were given the chance to examine the fruit products up for auction. Once all non-hypothetical rounds were finished, subjects completed a survey to gather data on purchasing habits and socio-economic characteristics while the session monitors randomly determined the binding round and product for each session. At the end of the session, the auction results were announced. Because prices were not posted between rounds, bid affiliation (Corrigan and Rousu 2006a; List and Shogren 1999) was not an issue. That is, bids were not influenced by the bids submitted previously by other participants. Finally, subjects were paid a participation fee of $30 less any fruit purchases they made during the auction. The complete written instructions given to participants are available in Appendix B.

3.3.2 Econometric Models

The experimental auction consisted of multiple goods *j=1,…,J* and multiple treatments *s=1,…S*, implying that multiple observations $(S \times J)$ were collected from each participant *i=1,…N*. Because multiple bids are collected from a given participant, the resulting pooled data set is likely to exhibit cross-sectional heterogeneity. A Random Parameters Tobit model can be specified to account for unobserved heterogeneity and the censoring of zero bids within and across individuals. We first assume that the bids are generated by an underlying latent variable and follow a Tobit specification:

$$\text{(12)} \qquad \mathrm{WTP}^{*}_{\mathrm{isj}} = f(\mathrm{x}_{\mathrm{isj}}, \eta, \beta, \theta, \mathrm{e}_{\mathrm{isj}})$$

$$\mathrm{WTP}_{\mathrm{isj}} = \max\{0, \mathrm{WTP}^{*}_{\mathrm{isj}}\}$$

where $\mathrm{WTP}^{*}_{\mathrm{isj}}$ is the latent value of individual *i*'s bid in treatment round *s* for product *j*, $\mathrm{WTP}_{\mathrm{isj}}$ is the observed value, $\mathrm{x}_{\mathrm{isj}}$ represents a set of product characteristics, treatment indicators, and socio-demographic and behavioral characteristics, η is a vector of random intercepts, β is a vector of random coefficients, θ is a vector of constant coefficients, and $\mathrm{e}_{\mathrm{isj}}$ represents a vector of random error terms. Note that the Random Effects Tobit used in panel data models results if β is zero and only η is random, whereas in a Constant Parameters Tobit specification β is zero and η is constant.

In a Random Parameters Tobit, by allowing the individual-specific parameter set β to vary randomly around a common mean-coefficient vector, it is assumed that not only the intercept, but also certain product features or treatments exhibit individual heterogeneity. The model specification for a given individual *i* is given by:

(13)
$$\mathrm{WTP}_i^* = a\eta_i + x_{1,i}\beta_i + x_{2,i}\theta + e_i$$

$$\eta_i = \bar{\eta} + u_i \text{ and } \beta_i = \bar{\beta} + \alpha_i$$

$$E(e_i) = 0, \quad E(e_i e_j') = \sigma_e^2 I_{(S\times J)} \text{ if } i = j \quad \text{or} \quad E(e_i e_j') = 0 \text{ if } i \neq j$$

$$E(\alpha_i) = 0, \quad E(\alpha_i \alpha_j') = \Delta = \begin{bmatrix} \sigma_{1,1}^2 & \cdots & \sigma_{1,k} \\ \vdots & \ddots & \vdots \\ \sigma_{k,1} & \cdots & \sigma_{k,k}^2 \end{bmatrix} \text{ if } i = j \quad \text{or} \quad E(\alpha_i \alpha_j') = 0 \text{ if } i \neq j$$

$$E(u_i) = 0, \quad E(u_i^2) = \sigma_u^2 \text{ if } i = j \quad \text{or} \quad E(u_i^2) = 0 \text{ if } i \neq j$$

where WTP_i^* is a $(S \times J) \times 1$ column vector of latent values of the dependent variable associated with each observation, a is a $(S \times J) \times 1$ column vector of 1s, η_i denotes the mean intercept for the group of observations submitted by individual *i*, $\bar{\eta}$ is a scalar that represents the grand mean or the mean of the intercepts for the observations submitted by all individuals, and u_i denotes the deviation of the mean intercept for *i* from the grand mean, that is, it captures the variation in intercepts between individuals. These random intercepts are distributed with a zero mean and variance σ_u^2, and are independent across individuals. Similarly, $x_{1,i}\beta_i$ allows for variation in the values of the specified regressors for each individual. The $K \times 1$ mean coefficients column vector β_i consists of a common-grand mean coefficient vector $\bar{\beta}$ that takes into account the observations by all individuals, plus a vector α_i that indicates unit-specific deviations of the mean coefficients vector from the set of grand mean coefficient values, and $x_{1,i}$ is a $(S \times J) \times K$ matrix of K random covariates.

For simplicity, the vector β_i does not depend on any individual invariant variables as in Lusk and Shogren (2007, p. 106) and Greene (2004). Random variation in β_i is induced by the vector of variations α_i, which captures variation in coefficients between individuals. By assumption, these unit-specific deviations are uncorrelated across individuals (i.e. $E(\alpha_i \alpha_j') = 0$ if $i \neq j$), which in turn implies that the random coefficients are uncorrelated between individuals. Within the same individual, the deviations are assumed to follow a distribution with a zero mean vector and the common variance-covariance matrix Δ, which is stable over observations. The diagonal and off-diagonal elements of this $K \times K$ matrix correspond, respectively, to the variance and covariance terms of the coefficients associated with the K random covariates, such as product features or treatment indicators. In this article, a normal distribution of the random coefficients is assumed, so that $\beta_i \sim mvn(\bar{\beta}, \Delta)$ and $\eta_i \sim N(0, \sigma_u^2)$ if $i = j$. Also, $x_{2,i}$ is a $(S \times J) \times L$ matrix of L fixed covariates, θ is a $L \times 1$ vector of coefficients that are constant for all bidders, and e_i is a conformable set of normally distributed overall error terms with mean zero and common variance matrix σ_e^2. The assumption $E(e_i e_j') = 0$ if $i \neq j$ implies that the errors are uncorrelated across individuals and there is no serial correlation, however, the variance of the *i*th individual's disturbance term is constant for any observation by *i*. This set accounts for unobserved variation within individuals by capturing the deviation of individual *i*'s unobservable WTP function value from the observed WTP by *i*.

The pooled model over all individuals *i=1,…N* takes the form:

$$\text{WTP}^* = A\eta + X_1\bar{\beta} + \widetilde{X}_1\alpha + X_2\theta + e \tag{14}$$

$$\mathrm{WTP}^* = \begin{bmatrix} \mathrm{WTP}_1^* \\ \mathrm{WTP}_2^* \\ \vdots \\ \mathrm{WTP}_N^* \end{bmatrix}, \quad \mathrm{A} = \begin{bmatrix} \mathrm{a}_{n=1} \\ \vdots \\ \mathrm{a}_N \end{bmatrix}, \quad \mathrm{a}_{n=1} = \begin{bmatrix} 1_{11,1} & \cdots & 0_{11,N} \\ \vdots & \ddots & \vdots \\ 1_{SJ,1} & \cdots & 0_{SJ,N} \end{bmatrix}, \quad \eta = \begin{bmatrix} \eta_1 \\ \vdots \\ \eta_N \end{bmatrix}, \quad \mathrm{X}_1 = \begin{bmatrix} \mathrm{x}_{1,1} \\ \vdots \\ \mathrm{x}_{1,N} \end{bmatrix}$$

$$\widetilde{\mathrm{X}}_1 = \begin{bmatrix} \mathrm{x}_{1,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mathrm{x}_{1,N} \end{bmatrix}, \quad \alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix}, \quad \mathrm{X}_2 = \begin{bmatrix} \mathrm{x}_{2,1} \\ \vdots \\ \mathrm{x}_{2,N} \end{bmatrix}, \qquad E(\alpha\alpha') = \Sigma = \begin{bmatrix} \Delta & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Delta \end{bmatrix}$$

where WTP^* is a column vector with $(S \times J \times N) \times 1$ observations, A is a $(S \times J \times N) \times N$ matrix, where each sub-matrix a_n has $(S \times J)$ rows and the nth column is composed entirely of 1s and the rest of 0s, η is an $N \times 1$ vector of random intercepts composed by the grand mean plus the deviation for each individual, X_1 is an $(S \times J \times N) \times k$ matrix of random covariates, $\bar{\beta}$ is a $k \times 1$ vector of grand means corresponding to the coefficients of the k random covariates, $\widetilde{\mathrm{X}}_1$ is a $(S \times J \times N) \times (k \times N)$ matrix of random covariates, α is a $(k \times N) \times 1$ vector of deviations, X_2 is a $(S \times J \times N) \times L$ matrix of constant covariates, θ is a $L \times 1$ vector of coefficients of the L constant covariates, and e is a conformable set of normally distributed overall error terms with mean zero and common constant variance matrix $\sigma_e^2 \mathrm{I}_{(S \times J \times N)}$. Finally, a common assumption in random coefficients models is that the random effects α, μ, e, and x are uncorrelated (Moeltner and Layton 2002; Swamy 1970).

For ease of notation hereafter let T denote the total of bids submitted by each individual (i.e. $S \times J = T$). The bids can be positive, zero, or even negative in theory[4]. If

[4] Although individuals were theoretically allowed to submit negative bids, no participants bid negative values.

there are m non-positive or censored bids out of T total bids submitted by i, the joint probability of observing this cluster of observations is:

(15) $$p(WTP_{i1} = 0, \dots, WTP_{im} = 0, WTP_{i,m+1} = WTP^*_{i,m+1}, \dots, WTP_{i,T} = WTP^*_{i,T})$$

$$= p(WTP^*_{i1} \leq 0, \dots, WTP^*_{im} \leq 0, v_{i,m+1}, \dots, v_{i,T})$$

$$= p\big(v_{i1} \leq -(a\bar{\eta} + x_{i1}\bar{\beta} + x_{i1}\theta), \dots, v_{im} \leq -(a\bar{\eta} + x_{im}\bar{\beta} + x_{im}\theta), v_{i,m+1}, \dots, v_{i,T}\big)$$

$$= \int_{-\infty}^{-(a\bar{\eta}+x_{i1}\bar{\beta}+x_{i1}\theta)} \dots \int_{-\infty}^{-(a\bar{\eta}+x_{im}\bar{\beta}+x_{im}\theta)} f(v_{i1}, \dots, v_{iT})\, dv_{im} \dots dv_{i1}$$

where $v_i = au_i + x_i\alpha_i + e_i$ is the composite error term and $f(.)$ indicates the multivariate normal distribution that has both censored and uncensored parts. If we let $v_i^c = v_{i1}, \dots, v_{im}$ and $v_i^{uc} = v_{im+1}, \dots, v_{iT}$ represent the groups of censored and uncensored components, respectively, the joint density $f(v_i^c, v_i^{uc})$ can be rewritten as:

(16) $$l_i = \int_{-\infty}^{-(a\bar{\eta}+x_i\bar{\beta}+x_i\theta)^c} f(v_i^{c*}).f(v_i^{uc})\, dv_i^{c*}$$

$$= f(v_i^{uc}). \int_{-\infty}^{-(a\bar{\eta}+x_i\bar{\beta}+x_i\theta)^c} f(v_i^{c*})\, dv_i^{c*}$$

$$= f(v_i^{uc}).F(v_i^{c*})$$

where the conditional density $f(v_i^{c*}) = f(v_i^c | v_i^{uc})$ and F(.) is the multivariate normal cumulative distribution function. The log-likelihood function for *i* is given by:

(17) $$\ln(l_i) = \ln f(v_i^{uc}) + \ln F(v_i^{c*})$$

$$= \ln(l_i^{uc}) + \ln(l_i^c)$$

The second term in this equation is a joint cdf that can include up to T integrals, i.e. if all T bids reported by *i* are censored at zero. This term does not have a closed form solution that would allow solving the log-likelihood function numerically, thus the model is estimated using Simulated Maximum Likelihood Estimation (SMLE). This procedure is similar to conventional MLE except that simulated probabilities are used instead of the exact probabilities (Train 2009). The simulated log-likelihood for all participants is then:

(18) $$\ln(\tilde{L}) = \sum_{i=1}^{N}[\ln(l_i^{uc}) + \ln(\tilde{l}_i^c)]$$

where $\tilde{l}_i^c$ is the simulated component. Once this component has been approximated, the function can be maximized using conventional MLE.

In our application, WTP bids are modeled as a function of both random and constant covariates. Random covariates include product characteristics and treatment indicators, whereas constant covariates include socio-demographic and behavioral characteristics. Product characteristics include the melon variety (Cantaloupe, Honeydew, Tuscan, Canary, or Galia), and the type of fruit (melon or watermelon), and treatment variables include dummy indicators identifying tasting and food safety standard treatments. Table 6 shows a description of the demographic and behavioral variables included in all econometric analyses. In this article we use the RPM procedure in NLOGIT5 using 500 Halton[5] draws to estimate the Random Parameters Tobit model.

Table 6. Demographic and Behavioral Variables Used in the Econometric Analyses

Variable	Definition
AGE1[a]	Value of 1 if 18 to 29 years of age, 0 otherwise
AGE2	Value of 1 if 30 to 49 years of age, 0 otherwise
AGE3	Value of 1 if 50 years of age or more, 0 otherwise
EDU1[a]	Value of 1 if high school degree or less, 0 otherwise

[5] A Halton non-random sequence has been shown to generate gains in speed and efficiency in the simulation process when compared to random sequences (Greene 2012; Moeltner and Layton 2002).

Table 6. Continued

Variable	Definition
EDU2	Value of 1 if for education x: high school degree<x<=4-year/bachelor's degree, 0 otherwise
EDU3	Value of 1 if some graduate school or more, 0 otherwise
HHSIZE	Number of individuals living in the household
FEMALE	Value of 1 if female, 0 otherwise
MARRIED	Value of 1 if married, 0 otherwise
INC1[a]	Value of 1 if household yearly income <$50,000, 0 otherwise
INC2	Value of 1 if for household yearly income x: $50,000<=x<$100,000, 0 otherwise
INC3	Value of 1 if household yearly income of $100,000 or more, 0 otherwise
ASPENDFV	Average value of household weekly expenditures on fruits and vegetables in $
FVOH	Amount of fresh fruit and vegetables on hand as percentage of full stock

[a] Used as dummy variables base levels.

3.4 Results and Discussion

3.4.1 Statistical Methods

The experimental auction bids were pooled, which resulted in 3,096 observations (6 products × 3 rounds × 172 participants). After accounting for missing data on survey questions, there were a total of 2,968 usable observations. Table 7 provides descriptive statistics for the bids by treatment rounds. Regarding the food safety treatments, consumers submitted higher mean bids for melons certified for food safety by either the government or the industry compared with non-certified products. Higher mean bids were reported for a food safety certification issued by the government compared to an industry-based certification. Equality among the two distribution functions of WTP for food safety standards was tested by means of a two-sample Kolmogorov-Smirnov test, which tests the null hypothesis that the distributions are equal. The null hypothesis could not be rejected (P = 0.624), indicating that the distributions of WTP for both food safety programs are statistically equal.

Table 7. Descriptive Statistics for the Bids

	Product	Treatment Tasting	No tasting	Industry label	Government label	All rounds
Mean	Cantaloupe	1.72	1.80	1.99	2.06	1.94
	Honeydew	1.67	1.87	1.91	1.99	1.89
	Tuscan	2.05	1.83	2.10	2.17	2.07
	Canary Yellow	1.72	1.79	1.98	2.03	1.92
	Galia	1.75	1.81	2.00	2.05	1.94
	Personal Watermelon	1.97	2.41	2.32	2.35	2.29
	All bids	1.81	1.92	2.05	2.11	2.01
Standard deviation	Cantaloupe	0.92	0.79	0.98	0.99	0.95
	Honeydew	0.97	0.98	1.08	1.13	1.07
	Tuscan	1.23	1.05	1.22	1.23	1.20
	Canary Yellow	1.17	1.16	1.20	1.23	1.20
	Galia	1.15	0.97	1.18	1.19	1.15
	Personal Watermelon	1.12	1.16	1.21	1.23	1.20
	All bids	1.10	1.04	1.15	1.17	1.14
Percentage of zero bids	Cantaloupe	1.20	0.00	0.00	0.58	0.39
	Honeydew	3.61	2.25	2.91	3.49	3.10
	Tuscan	2.41	4.49	4.09	4.07	3.88
	Canary Yellow	6.10	6.74	5.81	6.40	6.21
	Galia	4.82	4.49	5.23	5.81	5.23
	Personal Watermelon	6.02	0.00	2.33	2.91	2.71
	All bids	4.02	3.00	3.39	3.88	3.59

Note: Bids indicate the participants' reservation price, that is, their maximum willingness to pay for one unit of each good.

Table 8 shows the estimation results of the experimental auction data using Random Parameters Linear and Random Parameters Tobit models[6]. As in Rickard et al. (2011), the standard deviations of the random parameters, which capture the dispersion

[6] Constant Parameters Tobit and Random Effects Tobit models were also estimated for the bid equation. A likelihood ratio test ($Prob > \chi_1^2 = 0.00$) rejected the null hypothesis of a nested Constant Parameter Tobit regression ($H_o\colon \sigma_u^2 = \sigma_\alpha^2 = 0$) in favor of a Random Effects Tobit specification ($H_a\colon \sigma_u^2 \neq 0, \sigma_\alpha^2 = 0$), indicating that individual-specific random intercepts in the data were present. These results are available from the authors upon request.

Table 8. Random Parameters Econometric Estimates for WTP for Fruit Products

	Random Parameters Linear		Random Parameters Tobit[c]		
	Parameter	Standard Error	Parameter	Standard Error	Marginal Effect
			Means of Random Parameters		
Intercept	1.9258***	0.2088	1.3717***	0.0457	
Honeydew	-0.0526	0.0563	-0.0709**	0.0354	-0.0709
Tuscan	0.1361**	0.0674	0.0621*	0.0345	0.0621
Canary	-0.0125	0.0697	-0.0721**	0.0318	-0.0720
Galia	0.0233	0.0637	-0.0146	0.0329	-0.0146
Personal watermelon	0.3460***	0.0633	0.5345***	0.0369	0.5344
Tasting × Cantaloupe	-0.1152*	0.0635	-0.1525*	0.0895	-0.1525
Tasting × Honeydew	-0.0981	0.0668	-0.1680*	0.0970	-0.1680
Tasting × Tuscan	-0.0919	0.0652	0.0132	0.0956	0.0132
Tasting × Canary	-0.0893	0.0713	-0.1129	0.0922	-0.1129
Tasting × Galia	-0.1491**	0.0736	-0.1307	0.0922	-0.1307
Tasting × Personal watermelon	-0.0947	0.0662	-0.1489	0.0982	-0.1489
GlobalGAP food safety standards	0.1349***	0.0500	0.1251***	0.0222	0.1251
FSMA food safety standards	0.1818***	0.0419	0.1831***	0.0244	0.1831
			Demographics/Behaviors		
AGE2 (30 to 49)	-0.1720	0.1849	0.3456***	0.0324	0.3455
AGE3 (50 or more)	-0.2198	0.1878	-0.1564***	0.0324	-0.1564
EDU2 (College)	0.1393	0.1401	0.1669***	0.0229	0.1669
EDU3 (Graduate school)	0.2491	0.2259	-0.0063	0.0382	-0.0063
HHSIZE (Household size)	-0.0069	0.0587	0.1212***	0.0097	0.1212
FEMALE	-0.1703	0.1352	-0.1364***	0.0230	-0.1364
MARRIED	-0.1158	0.1876	-0.3696***	0.0322	-0.3696
INC2 ($50,000 to less than $100,000)	0.1774	0.1698	-0.0298	0.0273	-0.0298
INC3 ($100,000 or more)	-0.0712	0.2222	-0.1345***	0.0379	-0.1345
ASPENDFV (Expenditures on produce)	0.0026	0.0039	0.0090***	0.0007	0.0090
FVOH (Percentage of produce on hand)	0.0003	0.0015	0.0021***	0.0003	0.0021

Table 8. Continued

	Random Parameters Linear		Random Parameters Tobit[c]		
	Parameter	Standard Error	Parameter	Standard Error	Marginal Effect
			Standard Deviations of Random Parameters		
Intercept	0.7948***	0.0481	0.7985***	0.0096	
Honeydew	0.6631***	0.0436	0.4299***	0.0222	
Tuscan	0.8159***	0.0527	0.5496***	0.0228	
Canary	0.8471***	0.0526	0.6208***	0.0261	
Galia	0.7664***	0.0479	0.3727***	0.0225	
Personal watermelon	0.7596***	0.0466	0.8336***	0.0279	
Tasting × Cantaloupe	0.0000***	0.0000	0.1114	0.0828	
Tasting × Honeydew	0.1372**	0.1136	0.0004	0.0850	
Tasting × Tuscan	0.0002	0.0666	0.0928	0.0722	
Tasting × Canary	0.2539***	0.0761	0.1559*	0.0846	
Tasting × Galia	0.3071***	0.0698	0.1919***	0.0740	
Tasting × Personal watermelon	0.1097*	0.1377	0.1045	0.0752	
Global GAP food safety label	0.5248***	0.0326	0.3977***	0.0126	
USDA food safety label	0.3912***	0.0266	0.1592***	0.0153	
σ(e)	0.3184***	0.0065	0.5559***	0.0032	
No. of usable observations	2968		2968		
Log-Likelihood	-2701.86		-3212.84		
Likelihood ratio test	3,604.94***[a]		2,601.94***[b]		

Note: *, **, ***, indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Likelihood ratio test of Random Parameters Linear vs. Constant Parameters Linear regression.

[b] Likelihood ratio test of Random Parameters Tobit vs. Constant Parameters Tobit regression.

[c] Based on 500 Halton draws.

in intercepts and coefficients between individuals, are interpreted as unobserved individual heterogeneity. Results indicate that most of the standard deviations in both random parameters models were statistically significant, meaning that unobserved heterogeneity in the valuations is an important feature of the experimental auction data.

The random specifications of the models ($H_a: \sigma_u^2 \neq 0$ and $\sigma_\alpha^2 \neq 0$) provided better fit to the data than their constant counterparts ($H_0: \sigma_u^2 = \sigma_\alpha^2 = 0$). A likelihood ratio test ($Prob > \chi^2_{df=14} = 0.00$) rejected the null hypothesis of a nested Constant Parameters Linear regression in favor of a Random Parameters Linear specification. A likelihood ratio test ($Prob > \chi^2_{df=14} = 0.01$) rejected the null hypothesis of a nested Constant Parameters Tobit regression in favor of a Random Parameters Tobit specification. The Random Parameters Tobit specification also provided a better fit than a Random Effects Tobit ($H_0: \sigma_u^2 \neq 0, \sigma_\alpha^2 = 0$), based on a likelihood ratio test that greatly exceeded the critical value at a 99 percent confidence level ($Prob > \chi^2_{df=13} = 0.01$).

Results from both random parameters models were similar. Although the random parameters models properly account for the existing unobserved heterogeneity and within-cluster correlation of random covariates, the linear model still ignores potential bid-censoring at zero. In our pooled data, about 4% of the usable observations were left-censored at zero. Results of a Hausman specification test (Hausman 1978) of the Linear Random Parameters specification versus the Random Parameters Tobit specification indicated that the Random Parameters Tobit model was the most appropriate for the auction data. Under the null hypothesis, parameter estimates from the Random

Parameters Linear are consistent, while parameter estimates from the Random Parameters Tobit are efficient and consistent. The null hypothesis could not be rejected based on a calculated Hausman test statistic distributed $\chi^2_{df=40}$ $(P < 0.01)$. Hence, among all models considered, specifying a Random Parameters Tobit model provided the best model fit and the most efficient and consistent parameter estimates.

3.4.2 Valuation of Food Safety Standards

The marginal effects of the Random Parameters Tobit model evaluated at the mean values of the independent variables are presented in the last column of table 4. Both government-issued and industry-issued food safety certification treatments had a positive and significant effect on WTP compared with non-certified products. A government-based program (FSMA) had higher WTP compared with an industry-based (GlobalGAP) program, suggesting a greater degree of consumer trust in government food safety oversight and enforcement. Marginal effects indicate that consumers are willing to pay an average price premium of \$0.13 for a fruit product that meets industry-issued certification standards (GlobalGAP) for food safety and good agricultural practices, whereas they are willing to pay an average price premium of \$0.18 for a fruit product that meets government-issued certification standards (FSMA), compared with a non-certified product. In reference to the average WTP value, these marginal effects represent an increase in WTP of about 6.5% for an industry-based program and 8.9% for a government-based program. Although there was no statistical difference in the distributions of WTP for food safety standards as tested by a two-sample Kolmogorov-Smirnov statistic, results of the Random Parameters Tobit indicate that the mean parameter estimate of WTP for government-sponsored food safety standards (FSMA) is statistically higher than the mean parameter estimate of WTP for industry-sponsored standards (GlobalGAP). Using the estimated variance/covariance matrix to calculate a right-tailed z-test, the null hypothesis of equality ($H_0: \hat{\beta}_{FSMA} = \hat{\beta}_{GLOBAL}$) was rejected in favor of the alternative hypothesis ($H_a: \hat{\beta}_{FSMA} > \hat{\beta}_{GLOBAL}$) at a 1 percent significance level. The significance of the food safety parameter estimates was robust across all econometric models considered. Furthermore, results from both random parameter models indicate that the coefficients associated with the food safety treatments are heterogeneous as indicated by the strong significance of their standard deviations, implying that the valuation of a food safety certification label varies significantly across participants. That is, consumers may value the presence of food safety standards, however, their valuations do not depend only on observed variables, but also on unobservable differences that give rise to heterogeneous preferences across participants (e.g. previous experiences related to food-borne diseases).

Differences in product varieties and a tasting treatment were also investigated. Estimates show that consumers expressed price discounts of \$0.07 for Honeydew and Canary varieties, and price premiums of \$0.06 for Tuscan and \$0.53 for a personal watermelon, compared with the benchmark Cantaloupe melon variety. The Tuscan melon seems to be a promising specialty variety in terms of willingness-to-pay and consumer preferences. It was the only specialty melon that had a statistically significant price premium compared with Cantaloupe, and it was the only variety for which mean bids increased after tasting the product, though the latter effect was not statistically significant. All the coefficients associated with the product varieties were significantly random, indicating that preference valuations for these fruit products vary by individual. In contrast, tasting had a significant negative effect on WTP for Cantaloupe and Honeydew melons, and this effect was homogeneous across participants. After tasting the melons, all consumers expressed a homogeneous price discount of $0.15 for Cantaloupe and $0.17 for Honeydew.

The constant covariates of the model included socio-demographic and behavioral characteristics of participants. Regarding the socio-demographic profile, results show that consumers aged 30 to 49 years old, and those with at least a college education, are willing to pay price premiums for these fruit products. Consumers with 50 years of age or older, females, married, and with relatively high yearly household income (greater than $100,000), expressed price discounts. Related to the effect of gender, Corrigan and Rousu (2006a) found that in some treatments male participants' bids for candy bars and mugs increased at a higher rate than those of female participants, suggesting that men may submit higher bids as they may be more driven to be declared the winner of an auction. Regarding behavioral characteristics, a higher WTP is linked to consumers that are consistent purchasers of fruits, specifically, those with higher average expenditures on fruits and vegetables, those with a higher amount of fresh fruits and vegetables on hand as a percentage of their full stock, and larger households.

Results from this article show that a Random Parameters Tobit model provided the best model fit and the most efficient and consistent parameter estimates. We use this model to provide estimates of consumer valuation of selected food safety programs, which can aid producers, importers, marketers, and other stakeholders carry out analysis of the costs and benefits of compliance, and further understand consumer preferences.

3.5 Summary and Conclusions

Econometric models for panel data currently used in the analysis of experimental auction data have used different approaches to regression analysis of the bid equation to take into account the panel structure of the data. Some of the models used include pooled linear regression, and linear and nonlinear fixed effects and random effects models. Panel data model structures typically build unobserved individual heterogeneity into the intercept term. However, an important limitation in these models is the assumption that the regression coefficients are constant, since the valuation of a certain treatment may differ by individual due to unobserved factors. In this article, we used a Random Parameters Tobit model, also referred to as Censored Random Parameters or Mixed Tobit model, in the analysis of experimental auction data to extend the measurement of heterogeneity to other parameters, such as the treatment indicators. This model provides the flexibility of fitting models with constant and random coefficients with the possible assumption of correlation among the random components. An important implication for experimental economists is that they could employ a within-subjects design in experimental auctions, which results in a larger number of observations under treatment and control, while accounting for the correlation among bids submitted by the same individual for multiple products and treatments. We apply this model to data collected in a non-hypothetical sealed-bid second-price Vickrey auction conducted in central Texas.

Among all estimation methods considered the Random Parameters Tobit model provided the best model fit and most efficient estimates, while accounting for bid-censoring and effectively capturing heterogeneity in preferences.

Results of our empirical application show that participants are willing to pay a price premium of \$0.13 for a product that meets industry-issued (GlobalGAP) certification standards for food safety and good agricultural practices, and a price premium of \$0.18 for a fruit product that meets government-issued certification standards (FSMA), compared with a non-certified product. Perhaps the most notable result is the statistical significance of the standard deviations of the random parameters associated with both food safety standards, meaning that the valuations are heterogeneous across individuals. With regard to product varieties, estimates show price premiums for Tuscan melon and personal watermelon, and price discounts for Honeydew and Canary, compared with Cantaloupe. These price premiums and discounts were significantly heterogeneous. Conversely, the tasting sessions had homogeneous and significant negative effects on WTP for Cantaloupe and Honeydew, indicating that tasting these products significantly reduced all consumers' WTP homogeneously. Constant covariates related to socio-demographic and behavioral characteristics such as age, gender, income, consumer expenditures, household size, and produce on hand, also had a statistically significant effect on WTP. Overall, the results indicate that unobserved heterogeneity is an important feature of experimental auction data that needs to be accounted for in the econometric analysis.

Additional research could test the applicability of the Random Parameters Tobit model to the analysis of experimental auction data under different procedures (i.e. product, auction mechanism), and whether this model is appropriate for other value elicitation methods that result in a censored panel structure for the dependent variable. Moreover, other econometric specifications can be investigated. As explained by Greene (2012), simulation-based random parameters estimators are flexible, allowing these models to be extended beyond the assumption of a normal distribution for the random parameters. Also, the random parameters corresponding to the treatments could be constrained to be positive to be consistent a priori with theoretical restrictions, or could be extended to depend on other individual invariant variables that affect the mean of the random parameters.

4. WHO PARTICIPATES IN EXPERIMENTAL AUCTIONS? A LATENT CLASS ANALYSIS WITH INDIVIDUAL HETEROGENEITY

4.1 Introduction

Experimental auctions have become an increasingly common method of value elicitation that provides direct estimates of consumers' valuations. A well-known advantage of non-hypothetical experimental auctions over hypothetical stated preference methods is that individuals are put in a simulated market environment where there are real monetary consequences to stating a valuation different than their true valuation (Lusk and Shogren 2007). In order to resemble real traders, individuals are usually provided with a participation fee that serves as an initial endowment to bid and compensates individuals for their participation time. The magnitude of this endowment has been shown to influence willingness-to-pay estimates (Loureiro, Umberger, and Hine 2003).

Although the provision of cash compensation enhances participation rates, it is also likely that other driving forces might serve as motivators to participate in an experimental auction and play a role in influencing bidding behavior. For instance, individuals might have a personal preference for the category of products being investigated, desire to support the entity conducting the research, availability of time and willingness to help, among other potential motivations that may be interrelated. All of these factors could result in unobserved individual heterogeneity that has not yet been accounted for in experimental auction design.

Previous studies have investigated bidding behavior from a behavioral and psychological stand-point (Adam et al. 2011; Ding et al. 2005). However, no information is available concerning the underlying motivation for individuals to participate in experimental auctions and its influence on actual willingness-to-pay (WTP). This article extends the knowledge and understanding of experimental auctions by analyzing unobserved and observed heterogeneity among experimental auction participants and its effect on willingness-to-pay estimates. The objectives are as follows: First, identifying potential latent classes of participants in experimental auctions based on unobserved motivations and observed indicators of participants' heterogeneity. Second, investigating differences, if any, in consumers' valuation of specialty melons, government and industry-issued food safety standards, and tasting, amongst members of these classes. Using a non-hypothetical second-price Vickrey auction (Vickrey 1961) conducted to elicit willingness-to-pay for government and industry-issued food safety standards, we segment participants into latent classes based on observed indicators of motivations to participate. We contribute to the experimental auction literature by identifying and characterizing three distinct classes of experimental auction participants based on motivation, a latent construct that has been of little attention in the literature, and by quantifying the ways in which this latent construct influences bidding behavior. Understanding the motivational, behavioral and demographic composition of different unobserved latent classes of participants may help experimenters to understand discrepancies in their WTP estimates.

4.2 Literature Review

Consumer preferences for commodities, rights, and services are characterized by observed and unobserved heterogeneity. The increasing use in the literature of Random Parameters models to analyze experimental auction data (Yue et al. 2010, McAdams et al. 2013) suggests that individual unobserved heterogeneity is a significant feature of data collected in experimental auctions that deserves attention prior to making inferences about consumers' valuations of products. Yet, while procedures that allow the parameters to vary randomly over individuals effectively account for unobserved heterogeneity, they are not well-suited to explaining the sources of heterogeneity. Alternatively, heterogeneity in preferences can be assumed to occur discretely using a latent class approach, which consists of sorting individuals into a number of latent classes, each composed of homogeneous individuals (Boxall and Adamowicz 2002).

Latent Class Analysis (LCA), also known as finite mixture modeling, serves to identify a set of mutually exclusive and exhaustive classes or subgroups that are unobserved. LCA assumes that there is an unobserved categorical variable, such as the number of distinct subgroups, types, or categories of individuals, which are measured by observed categorical indicators that are interrelated. This statistical tool has been used in the social (Coffman et al. 2007), psychological (Lubke and Muthen 2005), political (Breen 2000; Feick 1989; McCutcheon 1985), and health sciences (Laumann, Paik, and Rosen 1999) to investigate theoretical concepts that cannot be directly observed, such as ability, racial prejudice, religious commitment, or motivation. For instance, Coffman et al. (2007) made use of observed indicators of drinking motivations among high school seniors to identify four latent classes of drinking behavior and to suggest prevention programs targeted to each class. LCA has also been used in choice-based conjoint analysis to cluster respondents into distinct classes based on observable attributes of choice (Ortega et al. 2011; Boxall and Adamowicz 2002; Ouma, Abdulai, and Drucker 2007; Swait 1994). Boxall and Adamowicz (2002) used a branded choice experiment to identify four classes of recreationists based on attitudinal measures of motivation for taking a trip to a wilderness park, and to examine welfare measures.

The use of LCA in the context of auctions has not been widespread, but previous studies have looked into participants' behavior and motivations to win the auction. Adam et al. (2011) suggest that past auction outcomes which trigger emotions such as the joy of winning or loser regret, and the economic environment of perceived competition, may impact future bidding behavior. Ding et al. (2005) studied a formal representation of the impact of emotional bidders on bids across consumers and the way in which past bidding behavior influenced future bids. They found that there is a strong motivation effect associated with bidding, and such emotions change dynamically based on the outcome of the previous bids. They present a detailed theoretical framework of emotional bidding behavior and refer to auction fever as the interplay of past auction outcomes, the economic competition environment, and auction events. However, even if LCA has been applied to a wide range of issues in various fields, it has not yet been used to identify classes of participants in experimental auctions based on their motivation to attend the auction in the first place. This distinction allows the estimation of more accurate cost-benefit analyses and provides insights into the differential welfare impacts of a policy change, such as policies related to the implementation of industry and government-based food safety standards.

4.3 Methodology

4.3.1 Experimental Design and Data

Eight experimental auction sessions were conducted during three days. Each session included between 18 and 26 participants, with a total of 172 participants. The participants were representative consumers (nonstudents) recruited from central Texas through multiple newspaper and online advertisements and were matched with a study session based on their schedule availability, age, and gender to reflect the socio-demographics of U.S. grocery shoppers (Carpenter and Moore 2006). To ensure that participants were regular buyers of fruits, the advertisement specified that the study would involve consumer decision-making for fruit purchases. About 87% of participants were the primary shopper of groceries in their household.

After arrival to the session, participants completed a consent form and were assigned anonymous ID numbers. They were provided with written and oral explanations on the incentive-compatible sealed-bid second-price Vickrey auction (Vickrey, 1961)[7] and were explained their weakly dominant strategy, that is, to bid their true WTP for a unit of each good. Because subjects were simultaneously bidding on substitute goods, which may cause demand reduction or diminishing marginal utility

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[7] In the Vickrey auction participants submit a sealed-bid, and the highest bidder pays a price equal to the second highest bid.

(Lusk and Shogren 2007), subjects were informed that while the session included several rounds of bidding and several goods per round, only one of the goods and one of the non-hypothetical bidding rounds would be randomly selected as binding at the end of the experiment. Then, subjects participated in a first practice round. To ensure that they understood the auction procedure, they took a short knowledge quiz on the auction procedures and the correct answers to the quiz were discussed by a session monitor. Next, subjects participated in a second practice round. After participating in the short quiz and practice rounds, subjects participated in non-hypothetical auctions for six fruit products that are close substitutes: Cantaloupe, Honeydew, Tuscan melon, Canary melon, Galia melon, and personal watermelon as a control product.

In the non-hypothetical rounds there was one between-subjects treatment and two within-subjects treatments. The treatments were 1) Tasting: Four sessions participated in a tasting of each product prior to submitting their bids, while the other four sessions did not taste the products before bidding; 2) Industry-based Food Safety Certification Label: All participants were given information on a food safety certification label that would be issued by GlobalGAP, an industry-based effort that sets standards for the certification of agricultural products around the world; and 3) Government-based Food Safety Certification Label: All participants were given information on a food safety certification label that would be issued by the government (FSMA) through USDA. GlobalGAP is primarily based in Europe, and FSMA had not been fully implemented at the time of the auction. Therefore, participants were not familiar with any of the two food safety standards prior to the information treatments. The order of the within-subjects treatments was randomized for each session to account for ordering effects. At the time of bidding, participants were given the chance to examine the fruit products up for auction. Once all non-hypothetical rounds were finished, subjects completed a survey to gather data on purchasing habits, socio-economic characteristics, and binary indicators ("Yes" or "No") of unobserved motivation to participate, while the session monitors randomly determined the binding round and product for each session. At the end of the session, the auction results were announced. Because prices were not posted between rounds, bid affiliation (Corrigan and Rousu 2006a; List and Shogren 1999) was not an issue. That is, bids were not influenced by the bids submitted previously by other participants. Finally, subjects were paid a participation fee of $30 less any fruit purchases they made during the auction. The complete written instructions given to participants are available from the authors upon request.

4.3.2 Statistical Models

4.3.2.1 Latent Class Analysis

Heterogeneity in preferences is assumed to occur discretely using a latent class approach where the n consumers are sorted into a number of S latent classes. Suppose we estimate a latent class model with $s=1,\ldots,k,\ldots,S$ classes from a set of J observed categorical indicators, each of which contains M_j possible outcomes, for individuals $i = 1, \ldots, n$. Let the vector $Y_i = (Y_{i1}, \ldots, Y_{iJ})$ represent individual i's observed responses to the $j=1,\ldots J$ indicators, where the m possible outcomes of Y_{ij} are $m = 1, \ldots, M_j$. Let the indicator function $I(y_{ij} = m)$ equal 1 if individual i gives the m^{th} response to the j^{th} variable, and 0 otherwise. Dependence between indicators in the overall sample is expected, but within a class the indicators are assumed to be independent (Linzer and Lewis 2011; Lanza et al. 2007). Therefore, the unconditional probability density function of the vector of responses Y_i across all classes is approximated by a mixture of S component distributions, as in:

(19) $$Y_i \sim f_i(y_i; \varphi) = \sum_{s=1}^{S} \pi_s \, f_{i|s}(y_i; \theta_s)$$

$$= \sum_{s=1}^{S} \pi_s \prod_{j=1}^{J} \prod_{m=1}^{M_j} (\theta_{jm|s})^{I(y_{ij}=m)}$$

where the class membership probabilities $\pi = (\pi_1, \ldots, \pi_S)$ are the mixture weights or prior probabilities and the conditional probability density functions $f_{i|s}(.)$ are the mixture components. By local or conditional independence, the component distributions are assumed to be multi-way cross-classification tables with all categorical indicators mutually independent. The parameters of the component densities, $\theta = (\theta_1, \ldots, \theta_S)$, correspond to vectors of indicator-response probabilities for each class. The purpose of LCA is to estimate the parameters $\varphi = (\pi, \theta)$ given realized values of Y and a value of S provided by the analyst. The likelihood function for φ is given by:

(20) $$\mathcal{L}(\varphi|Y) = \prod_{i=1}^{n} f_i(y_i; \varphi)$$

Maximizing the corresponding log-likelihood function with respect to each of the parameters is equivalent to doing a weighted likelihood maximization, in which the weights are given by the posterior probabilities of observing y_i into each of the latent classes. For instance, the posterior probability that each individual belongs to each class, conditional on the observed indicators, can be calculated using Bayes' Theorem:

(21) $$P(s = k|Y_i = y_i) = \alpha_{ik} = \frac{\pi_k \prod_{j=1}^{J} f_{ij|k}(y_{ij}; \theta_k)}{\sum_{s=1}^{S} \pi_s \prod_{j=1}^{J} f_{ij|s}(y_{ij}; \theta_s)}$$

However, these weights depend on the parameters φ being estimated. This is solved by using the iterative Expectation-Maximization (EM) algorithm (Dempster, Laird, and Rubin, 1977). The EM algorithm is applicable because each individual's class membership is unknown and may be treated as missing data (Linzer and Lewis 2011; McLachlan and Peel 2000; McLachlan and Krishnan 1997). The log-likelihood is given by:

(22) $$ln\mathcal{L}(\varphi) = \sum_{i=1}^{n} \ln\left[\sum_{s=1}^{S} \pi_s f_{i|s}(y_i; \theta_s)\right]$$

In the E-Step, the expectation of $ln\mathcal{L}(\varphi)$ is obtained by using random initial estimates of the mixture components and mixture weights to calculate the missing class membership probabilities using equation 21, as in:

(23) $$P\left(s = k | Y = y_{i,} \varphi^{(0)}\right) = \hat{\alpha}_{ik}^{(0)}$$

Once the non-observed class membership probabilities are replaced by their initial random estimates, the M-Step consists of maximizing the $E[ln\mathcal{L}(\varphi^{(0)})]$ with respect to φ subject to:

(24) $$\sum_{s=1}^{S} \pi_s = 1, \qquad \pi_s > 0,\ s = 1, \ldots, S$$

which yields maximum likelihood estimates of π_s and θ_s for s=1,…,S. These estimates are used to recalculate the posterior probabilities and return to the E-step. The iterative EM algorithm repeats the Expectation-Maximization process until a certain convergence criteria is met (Wedel and DeSarbo 1994).

Since the actual number of classes is unknown, information criteria are used as a guide to assist in determining S. Atkinson (1980) generalized the information criterion as:

(25) $$IC = -2lnL + Ap$$

where p indicates the number of parameters to be estimated. Akaike's information Criterion (AIC; Akaike 1973) sets $A = 2$ and tends to favor larger models. The Bayesian Information Criterion (BIC; Schwartz 1978) sets $A = \ln(n)$, where n denotes sample size; it imposes an additional sample size penalty on the log-likelihood, tending to favor more parsimonious models. The Adjusted BIC (Sclove 1987) imposes a lighter penalty than that of BIC by setting $A = ln\left(\frac{n+2}{24}\right)$. All of these criteria are compared for different specified values of S, and the model with the minimum values is chosen. Because the different criteria often do not result in the same model being selected, theory, judgment, and interpretability also play a role in model selection (Dziak et al. 2012). Once an optimal model has been identified and the corresponding φ parameters that maximize the expected log-likelihood function have been estimated, the final posterior probabilities $\hat{\alpha}_{is}$ provide a mean to classify the n individuals into the S classes by assigning each individual to the class with the highest posterior probability. That is, individual i belongs to class k if $\hat{\alpha}_{ik} > \hat{\alpha}_{is}$ for all $s \neq k$.

4.3.2.2 Willingness-to-Pay

To investigate differences in willingness-to-pay among latent classes, a Random Effects Tobit model is estimated for each class. The experimental auction consisted of multiple goods g=*1,…,*G and multiple treatments t=*1,…*T, implying that multiple observations ($G \times T$) were collected from each participant i=*1,…n*. Because multiple bids are collected from a given participant, the resulting pooled data set is likely to exhibit cross-sectional heterogeneity. The Random Effects Tobit is commonly used in auction data to account for bid-censoring and the panel structure of data typically collected in experimental auctions. We first assume that the bids are generated by an underlying latent variable and follow a Tobit specification:

(26) $$WTP_{itg}^{s*} = f(x_{itg}, \beta, u_i, \mathrm{e_{itg}})$$

$$WTP_{itg}^{s} = \max\{0, WTP_{itg}^{s*}\} \quad \text{for } s = 1, \ldots S$$

where WTP_{itg}^{*} is the latent value of individual i's bid in treatment round t for product g, WTP_{itg} is the observed value, x_{itg} represent a set of product characteristics, treatment indicators, and socio-demographic and behavioral characteristics, β is a vector of coefficients, u_i is a vector of random effects, and $\mathrm{e_{itg}}$ represents a vector of random error terms. The random effects u_i are i.i.d. N(0, σ_u^2), and $\mathrm{e_{itg}}$ are i.i.d. N(0, σ_e^2) independently of u_i. The Random Effects Tobit model specification for a given individual i is given by:

(27) $$WTP_i^{*} = x_{itg}\beta + u_i + \mathrm{e_{itg}}$$

where WTP_i^{*} is a $(T \times G) \times 1$ column vector of latent values of the dependent variable associated with each individual. Table 9 shows a description of the demographic and behavioral variables included in all econometric analyses. In this article, the Latent Class Model and Random Effects Tobit parameters were estimated using Stata 12 (StataCorp 2011).

Table 9. Demographic and Behavioral Variables Used in the Econometric Analyses

Variable	Definition
AGE1[a]	Value of 1 if 18 to 29 years of age, 0 otherwise
AGE2	Value of 1 if 30 to 49 years of age, 0 otherwise
AGE3	Value of 1 if 50 years of age or more, 0 otherwise
HHSIZE	Number of individuals living in the household
FEMALE	Value of 1 if female, 0 otherwise
MARRIED	Value of 1 if married, 0 otherwise
AVINCOME	Average household yearly income in thousand dollars
ASPENDFV	Average value of household weekly expenditures on fruits and vegetables in US$
FVOH	Amount of fresh fruit and vegetables on hand as percentage of full stock

[a] Used as dummy variables base levels.

4.4 Results and Discussion

4.4.1 Latent Class Analysis

4.4.1.1 Choosing the Number of Latent Classes

When applying LCA the actual number of classes is unknown. Thus, a sequence of latent class models with 2 to 9 classes were estimated. The log-likelihood values, AIC, BIC and adjusted BIC for each model are summarized in table 10. Because the assumption of a χ^2 distribution in a likelihood ratio G^2 or deviance test is not met in LCA (Lanza et al. 2007; Lin and Dayton 1997; Wedel and Desarbo 1994), this statistic is used only in a rough way to compare models. The minimum AIC and adjusted BIC statistics favored a three-class model, whereas the minimum BIC statistic favored a two-class model[8]. When the criteria differ, AIC often tends to choose a large model (i.e. overfitting), while BIC often tends to choose a small model (i.e. underfitting). However,

[8] In practice, $-2lnL$ in the generalized information criterion is often replaced by the practically equivalent likelihood ratio G^2 (i.e. the deviance statistic) following the procedure in Dziak et al. (2012). Although the two definitions return different numerical values, they lead to equal model selection decisions.

Dziak et al. (2012) note that when the sample size n is small, the most likely error is underfitting, so the criterion with lower underfitting rates, such as AIC is preferred. Moreover, the estimated class-membership probabilities for the two-class model[9] were 6.19% and 93.81% for each class, whereas the estimated probabilities for the three-class model were 6.06%, 38.64%, and 55.30%. As discussed by Lanza et al. (2007) the size of each class should be nontrivial, meaning that each class should be distinguishable from the others on the basis of its probabilities. Therefore, given the estimated values of the information criteria and the sample size relative to the population complemented with judgment and interpretability, a three-class model was chosen. In terms of model performance, this is equivalent to balancing sensitivity, which refers to having enough parameters to adequately model the relationships among variables in the population, with specificity, which refers to not overfitting the model or suggesting nonexistent relationships (Dziak et al. 2012).

4.4.1.2 Characterizing the Latent Classes

Table 11 shows the estimated class membership probabilities and indicator-response probabilities. The class membership probabilities determined that 6.06% of individuals were members of Class 1, 38.64% were members of Class 2, and the remaining 55.30% were assigned to Class 3. The indicator-response probabilities represent the probability of endorsing the observed indicator for each latent class. That is, there is a 99% probability that consumers in Class 1 were participating for the first time in an experimental auction. Individuals in this class were also very likely to consider that all

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[9] Estimates of φ for the two-class model are provided in Appendix C.

studies must include a compensation fee, and were not likely to participate with the intention of helping advance research efforts, supporting the educational institution, or due to interest in the auctioned products. Moreover, only 22% of individuals in this class would have participated if there was no payment.

Table 10. Comparison of Latent Class Models

Number of latent classes (S)	Number of parameters (p)	Log likelihood at convergence	Likelihood ratio G^2	AIC[a]	BIC[b]	Adjusted BIC
2	23	-1053.1	482.4	528.4	600.6	527.8
3	35	-1036.6	449.3	519.3	629.2	518.4
4	47	-1025.6	427.3	521.3	669.0	520.2
5	59	-1016.9	410.1	528.1	713.4	526.6
6	71	-1011.6	399.3	541.3	764.4	539.6
7	83	-1002.8	381.8	547.8	808.6	545.8
8	95	-996.8	369.8	559.8	858.2	557.4
9	107	-985.0	346.1	560.1	896.2	557.4

Note: Boldface type indicates the selected model.
[a] AIC (Akaike Information Criterion).
[b] BIC (Bayesian Information Criterion) uses n=171.

Individuals in Class 1 and Class 2 were very likely to participate with the intention of supporting the educational institution and expressed more interest in the auctioned products. They had a 58% probability of attending the experiment even if there was no payment, and were not so concerned about the requisite of a participation fee in experimental studies. All consumers in both classes were motivated by their desire to help advance research efforts. However, individuals in Class 2 were very likely to be participating for the first time in an experimental auction, were not necessarily residents of the area where the study was conducted, and did not have any affiliation to the educational institution conducting the research. Individuals in Class 3 were more experienced in experimental auctions relative to the rest of the participants, had a 90% probability of being permanent residents of the area where the study was conducted, and certain individuals were associated with the educational institution conducting the research.

Table 11. Latent Class Parameter Estimates for Three-Class Model

		Class 1	Class 2	Class 3
		Latent class membership probabilities (π)		
		6.06%	38.64%	55.30%
Variable	Definition	Indicator-response probabilities (θ)		
FIRST	Participating for the first time in an experimental auction	0.99	0.88	0.56
RELATIVES	Relatives work at the university	0.29	0.01	0.45
HELPU	Signed up to support the educational institution	0.13	0.93	0.85
PAYMENT	Would have participated even without payment	0.22	0.58	0.58
FRUITS	Signed up because of interest in the auctioned products	0.22	0.58	0.52
RESIDENT	Permanent resident in the area	0.40	0.40	0.90
HELPRES	Signed up to help advance research efforts	0.06	1.00	1.00
FEE	Considers that all studies must include a participation fee	0.88	0.32	0.40
FULLTIME	Employed full time	0.11	0.16	0.38
POSTPONED	Postponed other activities to be able to participate	0.41	0.61	0.47
DEGREE	Earned a degree at the educational institution	0.21	0.17	0.37

Table 12 shows a description of demographic and behavioral characteristics of experimental auction participants by latent class, for the entire sample, and for the Bryan/College Station, TX population. Class 1 was composed of young individuals (60% aged 18 to 29 years old) and certain individuals aged 50 years old or more (30%).

Class 2 was composed mainly of young individuals (about 85% between 18 to 49 years old), while about 80% of individuals in Class 3 were older than 30 years old. Regarding gender and marital status, Class 1 had mostly males that were not married; Class 2 had both males and females that were not married, while Class 3 included mostly married females.

Household size and income were two variables that followed a trend from one class to the other, that is, households in Class 3 were larger in average than those in Class 2, and households in Class 2 were larger than those in Class 1. Average yearly household income for Class 1, Class 2, and Class 3 was \$25,000, \$34,485, and \$68,279, respectively. Although 60% of all participants had on average a bachelor's degree or at least some college, and this percentage held across classes, participants in Class 3 were the most educated as this class included the highest percentage of participants with graduate education and the lowest percentage of high school education only. Class 2 was also more educated relative to Class 1. Perhaps related to household size, those participants in Class 3 expressed the highest weekly household spending on fruits and vegetables, and the highest amount of fresh produce on hand as a percentage of their full stock.

Table 12. Demographic and Other Characteristics of Experimental Auction Participants by Latent Class

Variable	Category	All Participants		Class 1		Class 2		Class 3		Population[a]	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Age	18 to 29 years of age		38.6		60.0		60.3		20.4		40.4
	30 to 49 years of age		32.2		10.0		25.0		39.8		17.8
	50 or more years of age		29.2		30.0		14.7		39.8		12.5
Education	High school degree or less		11.7		20.0		14.7		8.6		33.7
	Bachelor's degree or at least some college		60.2		60.0		58.8		61.3		45.9
	Graduate school degree or at least some graduate school		28.1		20.0		26.5		30.1		20.4
Household size (number of individuals)		2.6		2.0		2.4		2.8		2.6	
Gender	Female		58.8		40.0		47.8		68.8		49.0
	Male		41.2		60.0		52.2		31.2		51.0
Marital status	Married		54.4		20.0		38.2		70.3		33.8
	Not married		45.6		80.0		61.8		29.7		66.2

Table 12. Continued

Variable	Category	All Participants		Class 1		Class 2		Class 3		Population[a]	
		Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent	Mean	Percent
Yearly household income ($)		52,309		25,000		34,485		68,279			
Primary grocery shopper	Yes		87.1		80.0		89.7		86.0		
Weekly household spending on fruits and vegetables ($)		26.3		22.0		21.9		30.0			
Amount of fresh produce on hand as percentage of full stock		66.5		67.1		55.9		74.3			

[a] Source: U.S. Census Bureau, 2007-2011 American Community Survey (ACS). Statistics correspond to the Bryan/College Station, TX population.

Table 13. Random Effects Estimates for WTP for Fruit Products by Latent Classes

	Class 1			Class 2			Class 3			All Participants		
	Fee Chasers			*Certification Conscious*			*Taste Conscious*					
E[y]	1.52			2.05			2.03			2.01		
	Parameter	S.E.	∂E[y]/∂x	Parameter	S.E.	∂E[y]/∂x	Parameter	S.E.	∂E[y]/∂x	Parameter	S.E.	∂E[y]/∂x
Intercept	-2.0332	1.2898		2.1277***	0.3081		2.4403***	0.2861		2.1024***	0.1881	
Honeydew	0.0605	0.1666	0.0600	-0.0037	0.0825	-0.0036	-0.0994	0.0646	-0.0965	-0.0557	0.0494	-0.0534
Tuscan	0.1425	0.1664	0.1415	0.1046	0.0826	0.1007	0.0635	0.0647	0.0618	0.0819*	0.0495	0.0789
Canary	-0.4382***	0.1679	-0.4304	0.0654	0.0825	0.0629	-0.0615	0.0648	-0.0597	-0.0339	0.0495	-0.0325
Galia	-0.1068	0.1671	-0.1056	0.0514	0.0825	0.0494	-0.0425	0.0648	-0.0413	-0.0113	0.0495	-0.0108
Watermelon	-0.1160	0.1671	-0.1147	0.3329***	0.0825	0.3220	0.4374***	0.0645	0.4285	0.3676***	0.0493	0.3561
Tasting × Cantaloupe	0.0379	0.2991	0.0376	-0.0520	0.1501	-0.0498	-0.1341	0.1384	-0.1299	-0.1191	0.0963	-0.1139
Tasting × Honeydew	-0.0382	0.3003	-0.0378	0.0097	0.1512	0.0093	-0.2776**	0.1385	-0.2674	-0.1407	0.0968	-0.1345
Tasting × Tuscan	-0.0190	0.2995	-0.0189	0.2506*	0.1509	0.2426	0.0584	0.1385	0.0569	0.1165	0.0966	0.1124
Tasting × Canary	-0.0820	0.3043	-0.0812	-0.0259	0.1526	-0.0248	-0.1230	0.1391	-0.1192	-0.1053	0.0974	-0.1008
Tasting × Galia	0.2302	0.2999	0.2289	0.0125	0.1512	0.0120	-0.2217	0.1391	-0.2141	-0.0994	0.0969	-0.0952
Tasting × Watermelon	-0.0983	0.3021	-0.0973	-0.2018	0.1510	-0.1922	-0.2492*	0.1386	-0.2403	-0.2763***	0.0967	-0.2624
Global GAP	0.0225	0.1691	0.0223	0.2668***	0.0754	0.2570	0.0819	0.0517	0.0798	0.1355***	0.0417	0.1304
FSMA	0.1130	0.1691	0.1120	0.2875***	0.0754	0.2769	0.1369***	0.0517	0.1333	0.1787***	0.0417	0.1721
AGE2	-1.7101	1.1110	-1.4457	0.0381	0.3230	0.0366	-0.3570	0.2703	-0.3463	-0.1419	0.1949	-0.1361
AGE3	1.7968**	0.8118	1.7791	-0.2863	0.3877	-0.2724	-0.6118**	0.2754	-0.5916	-0.4177**	0.2044	-0.3980
HHSIZE	0.5443*	0.3150	0.5394	0.0658	0.1094	0.0632	-0.0653	0.0716	-0.0636	-0.0283	0.0620	-0.0272

Table 13. Continued

	Class 1			Class 2			Class 3			All Participants		
	Fee Chasers			*Certification Conscious*			*Taste Conscious*					
E[y]	1.52			2.05			2.03			2.01		
	Parameter	S.E.	∂E[y]⁄∂x	Parameter	S.E.	∂E[y]⁄∂x	Parameter	S.E.	∂E[y]⁄∂x	Parameter	S.E.	∂E[y]⁄∂x
FEMALE	-4.1989***	1.0403	-3.1845	-0.3745	0.2388	-0.3591	-0.2597	0.1897	-0.2533	-0.2973**	0.1459	-0.2861
MARRIED	-0.3567	0.6420	-0.3514	-0.0825	0.3525	-0.0791	-0.0929	0.2473	-0.0905	0.0503	0.1998	0.0483
AVINCOME (Average yearly income)	0.1111***	0.0275	0.1101	-0.0084*	0.0043	-0.0081	0.0021	0.0022	0.0020	0.0001	0.0019	0.0001
ASPENDFV (Expenditures on produce)	-0.0370***	0.0127	-0.0366	0.0051	0.0091	0.0049	0.0051	0.0045	0.0050	0.0056	0.0042	0.0054
FVOH (Produce on hand)	0.0286***	0.0065	0.0283	-0.0021	0.0027	-0.0021	-0.0001	0.0020	-0.0001	-0.0004	0.0016	-0.0003
σ(u) [a]	0.3208***	0.0885		0.8889***	0.0800		0.7784***	0.0604		0.8756***	0.0498	
σ(e) [b]	0.5570***	0.0314		0.7387***	0.0158		0.7034***	0.0130		0.7155***	0.0097	
ρ [c]	0.2491	0.1048		0.5915	0.0447		0.5505	0.0395		0.5996	0.0280	
Log-Likelihood			-151.41		-1448.39			-1891.46			-3537.99	
Likelihood ratio test [d]			26.87***		844.47***			1012.17***			2167.53***	
Number of usable observations			180		1204			1638			3022	

Note: Single (*), double (**), and triple (***) asterisks are used to denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

[a] Standard deviation of individual-specific error.

[b] Standard deviation of overall error.

[c] Percent contribution of the panel-level variance to the total variance.

[d] Likelihood ratio test that σ(u) = 0.

4.4.2 Willingness-to-Pay

Differences in willingness-to-pay estimates were estimated to complement the characterization of the latent classes. Table 13 contains parameter estimates from the Random Effects Tobit (RET) models per class and for all participants. A likelihood ratio test ($P = 0.000$) rejected the null of a nested Constant Parameter Tobit regression ($H_o\colon \sigma_u^2 = 0$) in favor of a Random Effects Tobit specification ($H_a\colon \sigma_u^2 \neq 0$), indicating that individual-specific random intercepts in the data were present. These random effects capture the combined effect of all other individual-specific variables besides motivation that are constant over bidding rounds and are omitted because they are unobserved. The significance of σ_u^2 is interpreted as the presence of correlation between the multiple bids (i.e. G goods $\times$ T treatments) submitted by the same participant.

Coefficients from the RET for all participants indicate that all consumers place value on food safety standards. The magnitude of the marginal effects indicate that consumers are willing to pay price premiums of \$0.17 and \$0.13 for food safety standards issued by the government (Food Safety Modernization Act, FSMA) and the industry (Global GAP), respectively, for a certified fruit product compared with a non-certified product. Coefficients also indicate that all consumers are willing to pay a price premium for a Tuscan melon compared with the baseline Cantaloupe, and that although they are willing to pay about \$0.36 for a watermelon compared with a Cantaloupe, their WTP for a watermelon actually decreases by \$0.26 after tasting it.

Estimating WTP equations separately for each cluster provides more detailed information than a model which pools the clusters. Consumers in Class 1 (6.1% of participants) had no statistically significant price premiums for food safety standards, and except for a significant price discount for Canary melons compared to Cantaloupes, nothing can be said about their preferences for the rest of the fruit products or the tasting treatment. The average consumer in Class 1 is willing to pay $1.52 per fruit. Recall Class 1 is composed of individuals who were very likely to consider that all studies must include a compensation fee, and most likely would have not participated if there was no payment. Moreover, most of them were not interested in helping advance research efforts, supporting the educational institution, or in the auctioned products. This leads us to refer to the first latent class of consumers as "Fee Chasers". As discussed previously, this class was composed mainly of young males that were not married and were aged 18 to 29 years old (60%) or older than 50 years old (30%), were not married, had a relatively lower average yearly household income, smaller household size, and comparatively the lowest educational level.

In contrast, consumers in Class 2 (38.6% of participants) significantly care about the certification of credence attributes, such as food safety and good agricultural practices. They had price premiums of about $0.28 for fruit products certified for food safety and good agricultural practices by the government and $0.26 for fruit products certified by the government, compared with non-certified products. These participants are not willing to pay a price premium for a Tuscan melon compared with Cantaloupe, however, their average bids increased significantly after tasting the Tuscan melon. They also had a price premium of about $0.32 for a watermelon compared with a Cantaloupe. Since these consumers value food safety certification standards the most out of all classes, we refer to them as "Certification Conscious". Perhaps derived from their food safety concerns, the average consumer in Class 2 is willing to pay $2.05 per fruit, which represents an increase of $0.53 from that of Class 1. Consumers in this class were supportive of the research and fruit products, but did not have previous experience in experimental auctions, were not residents of the area where the study was conducted, and did not have any affiliation to the institution conducting the experiment. They were characterized by being relatively young males and females that were not married and had an average household size, yearly income, and educational level greater than those in Class 1.

Consumers in Class 3 (55.3% of participants) expressed a partial interest in food safety certification standards. They are willing to pay a price premium of about $0.13 for a fruit product certified for food safety by the government; a lower estimate than that of Class 2. Moreover, they are not willing to pay any premium for industry-issued standards, suggesting that these consumers may have the perception that firms are more driven by profits than by concerns of food safety compliance. Yet, they expressed greater concern about the taste of the products. Coefficients indicate that consumers in Class 3 are willing to pay a price premium of $0.43 for a personal watermelon, and that their WTP for watermelon and Honeydew significantly decreases after the tasting treatment by $0.24 and $0.27, respectively. Since this class of consumers does not gain as much value from food safety certification standards, but place more emphasis on tasting attributes, we refer to them as "Taste Conscious". The average consumer in Class 3 is willing to pay $2.03 per fruit, a close but lower estimate than that of Class 2. "Taste

Conscious" consumers were supportive of the research and the fruit products, most likely residents of the area where the study was conducted, partially affiliated to the institution conducting the experiment, and had more experience in experimental auctions than consumers in Class 2. This class of consumers is characterized by older and married females, with the largest average household size, yearly income, and educational level.

4.5 Summary and Conclusion

Experimental auctions are now widely used as a method of value elicitation that provides direct estimates of consumers' valuations of goods, right, and services. Although the usual provision of cash compensation to participants enhances participation rates, and gives them an initial endowment to bid, there may be other reasons that motivate people to participate in consumer experiments. In this article, a latent class approach was used to study the underlying motivations of individuals to participate in experimental auctions, and to investigate significant differences, if any, in willingness-to-pay (WTP) values among latent classes.

Using data collected in a non-hypothetical second-price Vickrey auction conducted to elicit willingness-to-pay for government and industry-issued food safety standards in specialty melons, three latent classes of participants were identified. Based on observed indicators of motivations to participate, demographic and behavioral characteristics, and WTP estimates, three latent classes were found and characterized as: "Fee Chasers" (6.06% of participants), "Certification Conscious" (38.64% of participants), and "Taste Conscious" (55.3% of participants). Results from the Random

Effects Tobit models reveal that estimating WTP equations separately for each cluster provides more detailed information than a model which pools the clusters. The classes differed significantly in terms of their unobserved motivation to participate in the experimental study, socio-demographic profile, willingness-to-pay, and preferences towards the products. Not accounting for these differences might lead researchers to make erroneous inferences regarding product valuation that could be used subsequently in cost-benefit analyses and the calculation of welfare impacts of policy changes. Our results shed light on the importance of modeling important sources of unobserved individual heterogeneity in order to obtain more precise estimates of consumer's valuation of treatments and make more accurate inferences from data collected in experimental auction studies.

5. CONCLUSIONS, LIMITATIONS, AND FURTHER RESEARCH NEEDS

5.1 Conclusions

This dissertation examined consumer behavior and willingness-to-pay using hypothetical and non-hypothetical preference methods to elicit consumer valuations. Several econometric models of panel data, and Latent Class Analysis (LCA), were used to examine:

- The effectiveness of in-store promotion expenditures for local horticultural brands in terms of consumer demand and brand awareness.
- The use of a Random Parameters Tobit model in the analysis of experimental auction data to account for bid-censoring and unobserved consumer heterogeneity in the valuation of products and treatments.
- The segmentation of experimental auction participants based on their unobserved motivation to participate, and differences in the valuation of products and treatments among latent classes.

Specifically, Section 2 evaluated the effectiveness of a Point of Purchase Advertising (POPA) program conducted by the Texas Department of Agriculture (TDA) in support of the Texas Superstar® (TS) and Earth-Kind® (EK) local horticultural brands. Using data from two electronic surveys completed before and after the POPA took place, it was found that exposure to the POPA did not have significant effects on overall consumer demand. A shift in demand occurred solely for a subpopulation of consumers that have been previously exposed to the EK brand: given that the consumer is already aware of

EK, the presence of the POPA induces a price premium of about 5.5%. Instead, consumer habits of purchase including brand awareness, the purpose of the purchase and the number of transactions had the largest statistically significant effects on WTP, suggesting that other advertising methods might affect demand more effectively.

Section 3 reported the results of several panel data econometric models applied to data collected in a non-hypothetical sealed-bid second-price Vickrey auction conducted in central Texas. Among all estimation methods considered, the Random Parameters Tobit model provided the best model fit and most efficient estimates while accounting for bid-censoring and effectively capturing unobserved individual heterogeneity in preferences. Results showed that participants are willing to pay a price premium of $0.13 for a product that meets industry-issued (GlobalGAP) certification standards for food safety and good agricultural practices, and a price premium of $0.18 for a fruit product that meets government-issued certification standards (FSMA), compared with a non-certified product. Importantly, these valuations were heterogeneous across individuals.

Finally, Section 4 identified three latent classes of participants in experimental auctions. Based on observed indicators of motivations to participate, demographic and behavioral characteristics, and WTP estimates, three latent classes were found and characterized as: "Fee Chasers" (6.06% of participants), "Certification Conscious" (38.64% of participants), and "Taste Conscious" (55.3% of participants). Results from the Random Effects Tobit models reveal that estimating WTP equations separately for each cluster provides more detailed information than a model that pools the clusters.

Overall, results of Section 3 and 4 suggest that incorporating and understanding unobserved heterogeneity provides information that can be used to make more reliable inferences about policy impacts and subsequent decision-making.

5.2 Limitations

This dissertation contains a number of limitations, which include:

- The lack of significance of the POPA parameter in Section 2 suggests that in-store promotion did not have an effect on brand awareness or WTP for the overall population. However, other exogenous factors may have played a role in promotion effectiveness. Particularly, the economic recession of 2009 may have had an effect in consumer spending in ornamental goods despite advertising efforts by firms and represent a limitation to our findings.
- In Section 2, the use of stated preference methods, in which consumers are asked to state their hypothetical willingness-to-pay for branded ornamentals, may result in an overestimation of consumers' true WTP. This limitation was alleviated by the fact that we focused on the difference in WTP estimates between the 2008-2010 periods and not in the total WTP estimate. However, the use of a hypothetical preference method must be recognized as a potential source of bias in valuations.
- Models in Section 3 and 4 used data collected using a non-hypothetical experimental auction. Compared to stated preference methods, this method does not suffer from hypothetical bias, and compared to revealed preference methods,

valuations are directly inferred. Yet, in non-hypothetical experimental auctions factors such as participatory fees, bid affiliation, and zero-bidders can still potentially introduce bias into the valuations.

5.3 Suggestions for Further Research

Several opportunities to develop further research can be derived from this study. In particular, an extension to Section 2 would be the use of non-hypothetical preference methods to evaluate the effectiveness of promotion. Although this might be a more expensive endeavor to pursue, this could account for hypothetical bias and, given any budget constraints, the sample size could be maximized following the econometric approach provided in Section 3.

Concerning Section 3, additional research could test the applicability of the Random Parameters Tobit model to the analysis of experimental auction data under different procedures (i.e. product, auction mechanism), and whether this model is appropriate for other value elicitation methods that result in a censored panel structure for the dependent variable. Moreover, other econometric specifications can be investigated by allowing these models to be extended beyond the assumption of a normal distribution for the random parameters or by constraining the random parameters corresponding to the treatments to be positive, consistent a priori with theoretical restrictions, or could be extended to depend on other individual invariant variables that affect the mean of the random parameters.

Finally, the Latent Class Analysis (LCA) could be extended in several ways. In Section 4 all indicators were categorical. However, the basic idea of LCA, that parameters of a statistical model differ across unobserved subgroups, can also be applied with variables of other scales types. For instance, clustering with continuous observed indicators and a categorical latent variable, also known as Latent Profile Analysis, replaces the probabilities by densities. Moreover, LCA can be extended by relating covariates to the class membership probabilities and by examining the latent classes by grouping variables. In general, all models could be refined with the availability of more observations, which may result in more accurate state-of-the-art panel data econometric models.

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APPENDIX A

A.1 Web Survey

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

1 During the past year, have you bought any type of ornamental plants?

YES NO

SUBMIT

Survey Page 1

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

CONSUMER HABITS

2 Normally, how often do you purchase ornamental plants?

- Weekly
- Monthly
- Yearly
- Special occasions only

3 Approximately, how many transactions have you done during the past month?

4 How would you better describe the main purpose of these purchases?

- Self consumption
- Gifts

5 Where do you usually buy omamental plants? Check all that apply

- [ ] Garden centers
- [ ] Supermarkets
- [ ] Chain stores
- [ ] Nurseries
- [ ] OTHER, PLEASE SPECIFY

6 Please, rate from 1-5 where 5 is the highest score and 1 the lowest, all the following significant aspects in your purchase decision when buying ornamental plants:

	1	2	3	4	5
Price	1	2	3	4	5
Low-care demanding	1	2	3	4	5
Organically growth	1	2	3	4	5
Light demand	1	2	3	4	5
Guaranteed growth	1	2	3	4	5
Drought tolerant	1	2	3	4	5
Vibrant colors	1	2	3	4	5
Season	1	2	3	4	5

20% of survey completed

SUBMIT

Awareness & Usage of Texas Superstar ^{TM} and Earthkind ^{TM} Programs

TEXAS SUPERSTAR ^{TM} PROGRAM

7 Are you aware of the Texas Superstar ^{TM} certified plants?

- Yes
- No

23% of survey completed

SUBMIT

Survey Page 3

Awareness & Usage of Texas Superstar ^{TM} and Earthkind ^{TM} Programs

8 Please, rate from 1-5 where 5 is the highest score and 1 the lowest, all the following Texas Superstar ^{TM} features:

	1	2	3	4	5
Minimal water usage	1	2	3	4	5
No pesticides usage	1	2	3	4	5
Minimal soil preparation	1	2	3	4	5
High temperatures resistance	1	2	3	4	5
Guaranteed growth	1	2	3	4	5

9 How satisfied are you with Texas Superstar TM plants?

- Very dissatisfied
- Dissatisfied
- Neutral
- Satisfied
- Very satisfied

10 How did you first learn about Texas Superstar TM certified plants?

- In-store display
- Ads/promotion
- Friend/relative
- Salesperson
- Via the Internet/website
- OTHER, PLEASE SPECIFY

11 How likely are you to use/purchase Texas Superstar TM certified plants again?

- Definitely not
- Probably not
- Not sure
- Probably
- Definitely

37% of survey completed

SUBMIT

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

Please, review the following information of the Texas Superstar ™ Program before answering the following question:

Texas Superstar ™ is a program developed by the Texas A&M Coordinated and Educational Marketing Assistance Program (CEMAP) that is constantly searching for outstanding plants specifically adapted to Texas.

Researchers identify promising plants and do multiyear testing at many locations throughout the state at sites that represent all the diverse climatic areas, rainfall, evaporation rates, temperatures and soils in Texas. Plants with superior performance in a majority of test locations are designated "Texas Superstars ™" and display a tag at the point of sale.

The goal is to ensure that highlighted plants will perform well for Texas consumers increasing chances for gardening success and helping protect the environment. A few cents for the sale of each label is returned to Texas A&M University to fund additional research.

SUBMIT

Awareness & Usage of Texas Superstar ^{TM} and Earthkind ^{TM} Programs

12 How much more if any, would you be willing to pay for a Texas Superstar ^{TM} certified plant compared to a regular plant?

- 0%
- 1-10%
- 11-20%
- 21-30%
- 31-40%
- 41% or more

40% of survey completed

SUBMIT

Survey Page 6

Awareness & Usage of Texas Superstar ^{TM} and Earthkind ^{TM} Programs

EARTHKIND ^{TM} PROGRAM

13 Are you aware of the Earthkind ^{TM} program?

- Yes
- No

43% of survey completed

SUBMIT

Awareness & Usage of Texas Superstar TM and Earthkind TM Programs

14 Please, rate from 1-5 where 5 is the highest score and 1 the lowest, all the following Earthkind TM plants features:

	1	2	3	4	5
Minimal water usage	1	2	3	4	5
Minimal fertilizers usage	1	2	3	4	5
Adapted to local conditions	1	2	3	4	5
Minimal pesticides usage	1	2	3	4	5
Minimal yard wastes	1	2	3	4	5

15 How satisfied are you with the Earthkind TM program?

- Very dissatisfied
- Dissatisfied
- Neutral
- Satisfied
- Very satisfied

16 How likely are you to use/purchase Earthkind TM plants again?

- Definitely not
- Probably not
- Not sure
- Probably
- Definitely

17 Is it important that the plants identified as Earthkind ™ are certified with a tag at the point of sale?

YES NO

57% of survey completed

SUBMIT

Survey Page 8

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

18 Have you ever used any of the Earthkind ™ landscaping advised techniques?

YES NO

60% of survey completed

SUBMIT

Survey Page 9

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

19 Please, mark which of the following Earthkind ™ landscaping advised techniques have you ever used? Check all that apply

- [ ] Pre planning and design of the landscape
- [ ] Use of professional help for the planning stage
- [ ] Use of organic matter when preparing the soil
- [ ] More square and less narrow turf areas
- [ ] Selection of locally adapted plants
- [ ] Efficient irrigation: watering only when needed

- Use of mulches wherever possible
- Fertilize once in the spring
- Fertilize once in the fall
- Elimination of water demanding weeds
- OTHER, PLEASE SPECIFY

63% of survey completed

SUBMIT

Survey Page 10

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

20 How did you first learn about the Earthkind ™ program?

- Friend/relative
- Ads/promotion
- In-store display
- Salesperson
- Via the Internet/website
- OTHER, PLEASE SPECIFY

21 Would you recommend Earthkind ™ identified plants or Earthkind landscaping techniques to others?

- Definitely not
- Probably not
- Not sure
- Probably
- Definitely

70% of survey completed

SUBMIT

Survey Page 11

Awareness & Usage of Texas Superstar TM and Earthkind TM Programs

Please, review the following information of the Earthkind TM program before answering the following question:

Earth Kind TM uses research-proven techniques to provide maximum gardening and landscape enjoyment while protecting the environment. The objective is to combine the best of organic and traditional gardening and landscaping principles to create a horticultural system based on real world effectiveness and environmental responsibility.

Extension professionals conduct educational programs through out Texas promoting environmental friendly landscaping techniques and encouraging the selection of plants that are better adapted to every particular region. The plants database can be found in the Earthkind TM program website as well as other advised landscaping tools.

Earthkind TM goals include:

-Landscaping for water and energy conservation
-Safe use and handling of fertilizers & pesticides in the landscape
-Reduction of yard wastes entering landfills

SUBMIT

Survey Page 12

Awareness & Usage of Texas Superstar TM and Earthkind TM Programs

22 How much more if any, are you willing to pay for an Earthkind TM plant compared to a regular plant?

- 0%
- 1-10%
- 11-20%
- 21-30%
- 31-40%
- 41% or more

73% of survey completed

SUBMIT

Survey Page 13

Awareness & Usage of Texas Superstar TM and Earthkind TM Programs

23 Are you familiar with any of the following programs? Check all that apply

- Wave TM (Petunias)
- Proven Winners TM
- Plants that work TM
- None
- OTHER, PLEASE SPECIFY

77% of survey completed

SUBMIT

Survey Page 14

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

DEMOGRAPHIC DATA

THE FOLLOWING INFORMATION WILL BE KEPT CONFIDENTIAL AND IT IS ONLY FOR PURPOSE OF SURVEY INTERPRETATION

SUBMIT

Survey Page 15

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

24 Please indicate your marital status

- Married
- Single

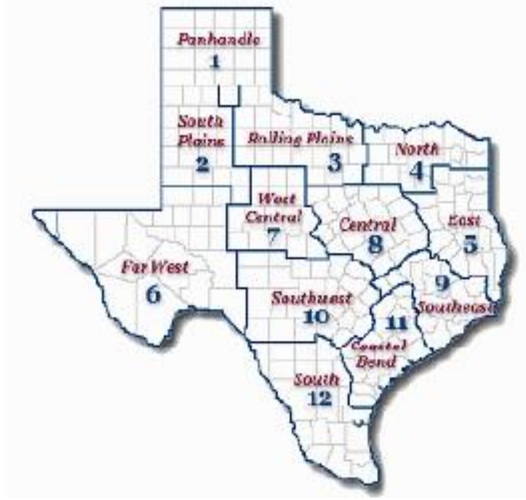
25 Please indicate your gender

- Male
- Female

26 Please select your education level

- Some high school
- Completed high school
- Some college
- Completed College
- Graduate School
- None

27



According to the Texas map above, in which district do you live right now? Please select the number.

(For a detailed list of counties in each district click here)

- 1 (Panhandle)
- 2 (South Plains)
- 3 (Rolling Plains)
- 4 (North)
- 5 (East)
- 6 (Far West)
- 7 (West Central)
- 8 (Central)
- 9 (Southeast)
- 10 (Southwest)
- 11 (Coastal Bend)
- 12 (South)

90% of survey completed

SUBMIT

Survey Page 16

Awareness & Usage of Texas Superstar ™ and Earthkind ™ Programs

28 Please select your ethnicity

- African American
- Caucasian
- American Indian
- Hispanic
- Asian/Pacific Islander
- Middle Eastern
- OTHER, PLEASE SPECIFY

29 Please indicate your range of age

- Less than 25
- 25-39
- 40-55
- 55 or more

30 Which group describes better your annual family income?

- Under $25,000
- $25,000-$50,000
- $50,001-$75,000
- $75,001-$99,999
- $100,000-& above

99% of survey completed

SUBMIT

Survey Page 17

A.2 Stata Code 1st Essay

```
*-------------------------------------------------------------------------
*DO FILE TO ANALYZE ONLINE SURVEYS
*TOBIT, PROBIT, LOGIT
*ALBA J. COLLART
*-------------------------------------------------------------------------

*START DO FILE
log using output, text replace
set more off, permanently
clear

***	Import data from Purchasers.txt
insheet using Purchasers.txt, clear

***	Start
drop if id == .

***	Generate income dummies for >50K and <50K
generate inc1 = 1 if (ic1+ic2)==1
replace inc1=0 if inc1==.
replace inc1 =. if id==214

generate inc2 = 1 if (ic3+ic4+ic5)==1
replace inc2=0 if inc2==.
replace inc2 =. if id==214

***	Aggregate age and calculate means
gen age12= age1 + age2

sort pop, stable
by pop: count

***		Generate variables for categorical product attributes
tab lcd, gen(demand)
tab og, gen(organic)
tab ld, gen(light)
tab gg, gen(growth)
tab dt, gen(drought)
tab vc, gen(color)
tab s, gen(season)
tab p, gen(price)

***	Summary statistics of the original sample (273/259)
* Survey of 2008, n=273
* Survey of 2010, n=259

by pop: sum ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3

***	Take random sample from Survey of 2008 to downsize to n=259
```

```
preserve

set seed 123456789
sort age1, stable
by age1: count
sample 60 if pop==0 & age1==1
sort age1, stable
by age1: count

sort pop, stable
by pop: count

keep if pop==0
save zero.dta, replace

restore

* Now we have a new data file for Survey of 2008 with n=259
* Next, lets create a data file with only observations from Survey of 2010
preserve

keep if pop==1
count
save one.dta, replace

restore

clear

*Put both together and start using that data file
use zero.dta
append using one.dta
save pooled.dta, replace

sort pop, stable
by pop: count

clear
use pooled.dta

***	Summary statistics of the sample (259/259)
sort pop, stable
by pop: summarize ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 ic1 ic2 ic3
ic4 ic5 reg1 reg2 reg3

***	Generate weighted variables
*Note: Logit - It doesn't make a difference to weight awareness variable (0/1)
gen mweight= 0.620155 /0.7258687
gen wmar = mar*mweight if pop==1

gen gweight= 0.5193798/0.7075099
gen wgen = gen*gweight if pop==1
```

```
gen ed1weight = 0.1167315/0.1312741
gen wedu1 = edu1*ed1weight if pop==1

gen ed2weight = 0.6536965/0.7142857
gen wedu2 = edu2*ed2weight if pop==1

gen ed3weight = 0.229572/0.1544402
gen wedu3 = edu3*ed3weight if pop==1

gen a12weight = 0.3515625/0.0894942
gen wage12 = age12*a12weight if pop==1

gen a3weight = 0.3164063/0.2996109
gen wage3 = age3*a3weight if pop==1

gen a4weight = 0.3320313/0.6108949
gen wage4 = age4*a4weight if pop==1

gen inc1weight = 0.4594595/0.3449612
gen winc1 = inc1*inc1weight if pop ==1

gen inc2weight = 0.5405405/0.6550388
gen winc2 = inc2*inc2weight if pop ==1

gen reg1weight = 0.1891892/0.2046332
gen wreg1 = reg1*reg1weight if pop ==1

gen reg2weight = 0.6640927/0.3243243
gen wreg2 = reg2*reg2weight if pop ==1

gen reg3weight = 0.1467181/0.4710425
gen wreg3 = reg3*reg3weight if pop ==1

*Verify that the means for demographics are equal
sum ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3 if
(pop==0)
sum ekaw tsaw ekwtp tswtp wmar wgen wedu1 wedu2 wedu3 wage12 wage3 wage4 winc1 winc2 wreg1
wreg2 wreg3 if (pop==1)

*Replace variables with new weighted variables in Survey of 2010
replace mar=wmar if pop==1
replace gen=wgen if pop==1
replace edu1=wedu1 if pop==1
replace edu2=wedu2 if pop==1
replace edu3=wedu3 if pop==1
replace age12=wage12 if pop==1
replace age3=wage3 if pop==1
replace age4=wage4 if pop==1
replace inc1=winc1 if pop==1
replace inc2=winc2 if pop==1
replace reg1=wreg1 if pop==1
replace reg2=wreg2 if pop==1
replace reg3=wreg3 if pop==1
```

```
*** Generating dummies
gen dedu2 = edu2 - edu1
gen dedu3 = edu3 - edu1
gen dage3 = age3 - age12
gen dage4 = age4 - age12
gen dinc2 = inc2 - inc1
gen dreg2 = reg2 - reg1
gen dreg3 = reg3 - reg1

gen ddemand2 = demand2 - demand1
gen ddemand3 = demand3 - demand1
gen ddemand4 = demand4 - demand1
gen ddemand5 = demand5 - demand1
gen dorganic2 = organic2 - organic1
gen dorganic3 = organic3 - organic1
gen dorganic4 = organic4 - organic1
gen dorganic5 = organic5 - organic1
gen dlight2 = light2 - light1
gen dlight3 = light3 - light1
gen dlight4 = light4 - light1
gen dlight5 = light5 - light1
gen dgrowth2 = growth2 - growth1
gen dgrowth3 = growth3 - growth1
gen dgrowth4 = growth4 - growth1
gen dgrowth5 = growth5 - growth1
gen ddrought2 = drought2 - drought1
gen ddrought3 = drought3 - drought1
gen ddrought4 = drought4 - drought1
gen ddrought5 = drought5 - drought1
gen dcolor2 = color2 - color1
gen dcolor3 = color3 - color1
gen dcolor4 = color4 - color1
gen dcolor5 = color5 - color1
gen dseason2 = season2 - season1
gen dseason3 = season3 - season1
gen dseason4 = season4 - season1
gen dseason5 = season5 - season1
gen dprice2 = price2 - price1
gen dprice3 = price3 - price1
gen dprice4 = price4 - price1
gen dprice5 = price5 - price1


***	After replacing, obtain statistics for all variables and corresponding dummies
summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur pop

sort pop, stable
by pop: summarize mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3
by pop: summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur
pop
```

```
*******************************************************************************
***	Estimate Logit for EKAW using logit command, use mfx for marginal effects,
*** fitstat for goodness of fit and lstat for fraction of correct predictions

logit ekaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
estimates store Model1
mfx
fitstat
lstat
lfit, group(10) table

***	Estimate odds ratio using logistic command
logistic ekaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3

*******************************************************************************

***	Estimate Logit for TSAW using logit command, use mfx for marginal effects,
*** fitstat for goodness of fit and lstat for fraction of correct predictions

logit tsaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
estimates store Model2
mfx
fitstat
lstat
lfit, group(10) table

***	Estimate odds ratio using logistic command
logistic tsaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3

*******************************************************************************

* Test for endogeneity EK
preserve

***	Heckman correction: 1st stage probit
probit  ekaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
estimates store Model3
mfx
fitstat
lstat

*** Compare Model1 is ekaw logit, Model3 is ekaw probit
estimates stats Model1 Model3

***	Calculate probability of awareness
predict EVENTPROB
predict PROBITXB, xb

***	Calculate pdf, cdf and mills ratio
gen PDFPROBIT = normalden(PROBITXB)
gen CDFPROBIT = normprob(PROBITXB)
gen IMR = PDFPROBIT/CDFPROBIT
```

```
***      Heckman correction: 2nd stage tobit
version 8.2: tobit ekwtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop ekaw dreg2 dreg3 IMR,
ll(0)
test _b[_se]=0
dtobit, brief

restore


* Test for endogeneity TS
preserve

***      Heckman correction: 1st stage probit
probit  tsaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
estimates store Model4
mfx
fitstat
lstat

*** Compare Model2 is tsaw logit, Model4 is tsaw probit
estimates stats Model2 Model4

***      Calculate probability of awareness
predict EVENTPROB
predict PROBITXB, xb

***      Calculate pdf, cdf and mills ratio
gen PDFPROBIT = normalden(PROBITXB)
gen CDFPROBIT = normprob(PROBITXB)
gen IMR = PDFPROBIT/CDFPROBIT

***      Heckman correction: 2nd stage tobit
version 8.2: tobit tswtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop tsaw dreg2 dreg3 IMR, ll(0)
test _b[_se]=0
dtobit, brief

restore



*********************************************************************************
* Clear to start with the WTP models. We start by using the (259/259) sample

clear
use pooled.dta

*** To estimate EKWTP, notice that the Survey of 2010 has 259 observations on WTP,
*** but the Survey of 2008 has only 145. Thus, take a random sample from Survey
*** of 2010 when ekwtp is not a missing value to have n=145.

preserve

set seed 123456789
```

```
sort pop, stable
by pop: count if ekwtp!=.
sample 56 if ekwtp!=. & pop==1
sort pop, stable
by pop: count if ekwtp!=.

drop if ekwtp==.
by pop: count

* Now both surveys have the same number of non-missing observations on EKWTP

***	Summary statistics of the sample (145/145)
sort pop, stable
by pop: summarize ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 ic1 ic2 ic3
ic4 ic5 reg1 reg2 reg3

***	Generate weighted variables (Tobit-Weight ekwtp variable)
gen ekwtpweight =  0.1093103/0.0713793
gen wekwtp = ekwtp*ekwtpweight if pop==1

gen mweight= 0.6275862 /0.7310345
gen wmar = mar*mweight if pop==1

gen gweight= 0.5486111 /0.7357143
gen wgen = gen*gweight if pop==1

gen ed1weight = 0.1319444/0.1655172
gen wedu1 = edu1*ed1weight if pop==1

gen ed2weight = 0.6527778/0.7517241
gen wedu2 = edu2*ed2weight if pop==1

gen ed3weight = 0.2152778/0.0827586
gen wedu3 = edu3*ed3weight if pop==1

gen a12weight = 0.3125/0.1041667
gen wage12 = age12*a12weight if pop==1

gen a3weight =  0.3402778/0.3125
gen wage3 = age3*a3weight if pop==1

gen a4weight =  0.3472222/0.5833333
gen wage4 = age4*a4weight if pop==1

gen inc1weight = 0.4758621/0.3680556
gen winc1 = inc1*inc1weight if pop ==1

gen inc2weight = 0.5241379/0.6319444
gen winc2 = inc2*inc2weight if pop ==1

gen reg1weight = 0.1862069/0.2206897
gen wreg1 = reg1*reg1weight if pop ==1
```

```
gen reg2weight = 0.6482759/0.2896552
gen wreg2 = reg2*reg2weight if pop ==1

gen reg3weight = 0.1655172/0.4896552
gen wreg3 = reg3*reg3weight if pop ==1

*Verify that the means for demographics and ekwtp are equal
sum ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3 if
(pop==0)
sum ekaw tsaw wekwtp tswtp wmar wgen wedu1 wedu2 wedu3 wage12 wage3 wage4 winc1 winc2
wreg1 wreg2 wreg3 if (pop==1)


*Replace variables with new weighted variables in Survey of 2010
replace ekwtp=wekwtp if pop==1
replace mar=wmar if pop==1
replace gen=wgen if pop==1
replace edu1=wedu1 if pop==1
replace edu2=wedu2 if pop==1
replace edu3=wedu3 if pop==1
replace age12=wage12 if pop==1
replace age3=wage3 if pop==1
replace age4=wage4 if pop==1
replace inc1=winc1 if pop==1
replace inc2=winc2 if pop==1
replace reg1=wreg1 if pop==1
replace reg2=wreg2 if pop==1
replace reg3=wreg3 if pop==1

*** Generating dummies
gen dedu2 = edu2 - edu1
gen dedu3 = edu3 - edu1
gen dage3 = age3 - age12
gen dage4 = age4 - age12
gen dinc2 = inc2 - inc1
gen dreg2 = reg2 - reg1
gen dreg3 = reg3 - reg1

***     After replacing, obtain statistics for all variables and corresponding dummies
summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur pop

sort pop, stable
by pop: summarize mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3
by pop: summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur
pop

***     Estimate Tobit for EKWTP for all respondents
version 8.2: tobit ekwtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop ekaw dreg2 dreg3, ll(0)
test _b[_se]=0

***     Estimate the four types of Marginal effects for Tobit
dtobit, brief
```

```
********************************************************************************

* Test for endogeneity EK

***     Heckman correction: 1st stage probit
*probit  ekaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
*mfx

***     Calculate probability of awareness
*predict EVENTPROB
*predict PROBITXB, xb

***     Calculate pdf, cdf and mills ratio
*gen PDFPROBIT = normalden(PROBITXB)
*gen CDFPROBIT = normprob(PROBITXB)
*gen IMR = PDFPROBIT/CDFPROBIT

***     Heckman correction: 2nd stage tobit
*version 8.2: tobit ekwtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop ekaw dreg2 dreg3 IMR,
ll(0)
*test _b[_se]=0
*dtobit, brief

********************************************************************************

***     Estimate Tobit for EKWTP for aware respondents
keep if ekaw==1
*histogram ekwtp, normal discrete freq
version 8.2: tobit ekwtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3, ll(0)
test _b[_se]=0

***     Estimate the four types of Marginal effects for Tobit
dtobit, brief

********************************************************************************
*** Restore to pooled.dta (259/259) sample
restore

********************************************************************************

*** To estimate TSWTP, notice that the Survey of 2010 has 259 observations on
*** TSWTP, but the Survey of 2008 has only 134. Thus, take a random sample from
*** Survey of 2010 when TSWTP is not a missing value to have n=134.

preserve

set seed 123456789
sort pop, stable
by pop: count if tswtp!=.
sample 52 if tswtp!=. & pop==1
sort pop, stable
by pop: count if tswtp!=.
```

```
drop if tswtp==.
by pop: count

* Now both surveys have the same number of non-missing observations on TSWTP

***	Summary statistics of the sample (134/134)
sort pop, stable
by pop: summarize ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 ic1 ic2 ic3
ic4 ic5 reg1 reg2 reg3

***	Generate weighted variables (Tobit-Weight tswtp variable)
gen tswtpweight =  0.1085075/0.0839552
gen wtswtp = tswtp*tswtpweight if pop==1

gen mweight=  0.6119403/0.7313433
gen wmar = mar*mweight if pop==1

gen gweight=   0.5338346/0.7461538
gen wgen = gen*gweight if pop==1

gen ed1weight = 0.0977444/0.1641791
gen wedu1 = edu1*ed1weight if pop==1

gen ed2weight =  0.6691729/0.761194
gen wedu2 = edu2*ed2weight if pop==1

gen ed3weight = 0.2330827/0.0746269
gen wedu3 = edu3*ed3weight if pop==1

gen a12weight =  0.3134328/0.1052632
gen wage12 = age12*a12weight if pop==1

gen a3weight =   0.3283582/0.3157895
gen wage3 = age3*a3weight if pop==1

gen a4weight = 0.358209/0.5789474
gen wage4 = age4*a4weight if pop==1

gen inc1weight = 0.4477612/0.3834586
gen winc1 = inc1*inc1weight if pop ==1

gen inc2weight = 0.5522388/0.6165414
gen winc2 = inc2*inc2weight if pop ==1

gen reg1weight = 0.1940299/0.2164179
gen wreg1 = reg1*reg1weight if pop ==1

gen reg2weight = 0.6567164/0.2835821
gen wreg2 = reg2*reg2weight if pop ==1

gen reg3weight = 0.1492537/0.5
gen wreg3 = reg3*reg3weight if pop ==1
```

```
*Verify that the means for demographics and tswtp are equal
sum ekaw tsaw ekwtp tswtp mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3 if
(pop==0)
sum ekaw tsaw ekwtp wtswtp wmar wgen wedu1 wedu2 wedu3 wage12 wage3 wage4 winc1 winc2
wreg1 wreg2 wreg3 if (pop==1)


*Replace variables with new weighted variables in Survey of 2010
replace tswtp=wtswtp if pop==1
replace mar=wmar if pop==1
replace gen=wgen if pop==1
replace edu1=wedu1 if pop==1
replace edu2=wedu2 if pop==1
replace edu3=wedu3 if pop==1
replace age12=wage12 if pop==1
replace age3=wage3 if pop==1
replace age4=wage4 if pop==1
replace inc1=winc1 if pop==1
replace inc2=winc2 if pop==1
replace reg1=wreg1 if pop==1
replace reg2=wreg2 if pop==1
replace reg3=wreg3 if pop==1

*** Generating dummies
gen dedu2 = edu2 - edu1
gen dedu3 = edu3 - edu1
gen dage3 = age3 - age12
gen dage4 = age4 - age12
gen dinc2 = inc2 - inc1
gen dreg2 = reg2 - reg1
gen dreg3 = reg3 - reg1

***     After replacing, obtain statistics for all variables and corresponding dummies
summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur pop

sort pop, stable
by pop: summarize mar gen edu1 edu2 edu3 age12 age3 age4 inc1 inc2 reg1 reg2 reg3
by pop: summarize ekaw tsaw ekwtp tswtp mar gen dedu2 dedu3 dage3 dage4 dinc2 dreg2 dreg3 tran pur
pop

********************************************************************************

***     Estimate Tobit for TSWTP for all respondents
version 8.2: tobit tswtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop tsaw dreg2 dreg3, ll(0)
test _b[_se]=0

***     Estimate the four types of Marginal effects for Tobit
dtobit, brief


********************************************************************************

* Test for endogeneity TS
```

```
***	Heckman correction: 1st stage probit
*probit  tsaw dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3
*mfx

***	Calculate probability of awareness
*predict EVENTPROB
*predict PROBITXB, xb

***	Calculate pdf, cdf and mills ratio
*gen PDFPROBIT = normalden(PROBITXB)
*gen CDFPROBIT = normprob(PROBITXB)
*gen IMR = PDFPROBIT/CDFPROBIT

***	Heckman correction: 2nd stage tobit
*version 8.2: tobit tswtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop tsaw dreg2 dreg3 IMR,
ll(0)
*test _b[_se]=0
*dtobit, brief


*********************************************************************************

***	Estimate Tobit for TSWTP for aware respondents
keep if tsaw==1
version 8.2: tobit tswtp dage3 dage4 gen mar dinc2 dedu2 dedu3 tran pur pop dreg2 dreg3, ll(0)
test _b[_se]=0

***	Estimate the four types of Marginal effects for Tobit
dtobit, brief

************************************************************************************

restore

************************************************************************************

*END DO FILE
log close
```

APPENDIX B

B.1 Experiment Advertisement in The Eagle Newspaper

CANCER (June 21-July 22) ★★★★ Your creativity allows more spontaneity than is the norm. Don't allow yourself to be cornered into a situation or obligation. Play plans by ear, as you could be far more tired than you are aware. Make it OK not to always be in top form. Tonight: Know when enough is enough.

LEO (July 23-Aug. 22) ★★★★ You might be slow to get going, but once you do, you could be quite a force to deal with. The unexpected occurs out of the blue. Many different options mark your decisions. Tonight: Go with the flow.

VIRGO (Aug. 23-Sept. 22) ★★★ Squeeze in an important get-together for brunch or early on. You will feel more upbeat as a result. A misunderstanding could become a problem if you do not remain easygoing. Give up being so picky. That behavior is only creating more distance between you and the other party. Tonight: Entertain from home.

LIBRA (Sept. 23-Oct. 22) ★★★★ A purchase does not need to break the bank. Do some shopping around and a bit of research. Though you might be confused at first, a resolution will appear soon enough. Screen your calls if you feel overwhelmed. Tonight: Lots of people, lots of chatter, lots of fun.

SCORPIO (Oct. 23-Nov. 21) ★★★★ Use the daylight hours to the max, as a misunderstanding could mar your evening. Do not allow it to become a big deal, or you could be sorry. What happens was not intended to be a slight. Tonight: Relish every moment.

SAGITTARIUS (Nov. 22-Dec. 21) ★★★★ Get your key errands done early on. You could be overtired and dragging. A nap also might not hurt. When you perk up, you engage others — especially your immediate circle — in a dynamic manner. You might be taken aback by someone's offer. Tonight: Let your hair down.

CAPRICORN (Dec. 22-Jan. 19) ★★★★ You waver between establishing your presence and becoming more detached. Others might not properly interpret these changes. Verbalize your thoughts and be as clear as possible. Step back and center yourself. Tonight: A force to be dealt with.

AQUARIUS (Jan. 20-Feb. 18) ★★★★ Interactions with friends and loved ones are best had before else. Detach and understand where this person is coming from. Tonight: Follow the music.

PISCES (Feb. 19-March 20) ★★★★★ Others seek you out. Be flattered by all the attention rather than feel overwhelmed. You may have to sort through your priorities and make choices accordingly. Finally, a treasured loved one opens up. Tonight: Add more spice to your life.

ARIES (March 21-April 19) ★★★★ Allow others to dominate a conversation. You are looking for some answers, and you will get them if you listen. Note what is not being said. Detach and give someone the benefit of the doubt. Tonight: Use your dreams as a source of ideas.

TAURUS (April 20-May 20) ★★★★★ Others command the ship today, no matter what. You might as well go along with the present trend; you cannot fight it. Someone close to you will want some personal time. You might misunderstand this person's message at first, but it will come through loud and clear if you listen carefully. Tonight: Sprinkle in some romance.

GEMINI (May 21-June 20) ★★★★ Complete a project or venture early on. You'll want to accept a suggestion or invitation that forces you out and about. Your immediate reaction might be to say no. Don't. It will be worth every single minute. Tonight: Go with a friend's suggestion.

— **Jacqueline Bigar**

Unscramble these four Jumbles, one letter to each square, to form four ordinary words.

GITTH

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SLSIB

KANBIG

MRUEES

Now arrange the circled letters to form the surprise answer, as suggested by the above cartoon.

A:

(Answers Monday)

Yesterday's | Jumbles: NOVEL OCTET LESSON PARADE
Answer: As the owner of the most successful sandwich shop in town, he was this — ON A ROLL

Please note our holiday early deadlines.

RETAIL

Publish Date	Space Deadlines
Thursday, July 5	Monday, July 2, 5pm
Friday, July 6	Tuesday, July 3, 5pm

SUNDAY/WRAPPER

Publish Date	Space Deadlines
Sunday, July 8	Monday, July 2, 5pm

BRAZOS LIFE

Publish Date	Space Deadlines
Sunday, July 8	Tuesday, July 3, NOON

CLASSIFIED DISPLAY/LEGALS:

Publish Date	Space Deadlines
Tuesday, July 3	Friday, June 20 @ 5 pm
Wednesday, July 4	Monday, July 2 @ NOON
Thursday, July 5	Monday, July 2@ 5 pm
Friday, July 6	Tuesday, July 3 @ 5 pm
Saturday, July 7	Tuesday, July 3 @ 5 pm
Sunday, July 8	Thursday, July 5@ NOON

CLASSIFIED LINE AD DEADLINES:

Publish Date	Space Deadlines
Tuesday, July 3	Monday, July 2 @ 5 pm
Wednesday, July 4	Tuesday, July 3@ NOON
Thursday, July 5	Tuesday, July 3@ 3 pm
Friday, July 6	Thursday, July 5 @ 4 pm
Saturday, July 7	Friday, July 6 @ 1 pm

The Eagle

Classified (979) 731-4737 Retail (979) 731-4738

SUDOKU

					3			6
		4	6			8	7	
			4	2	5			
								5
6	7						4	8
1						9		
			5	8	6			
	6	1			7	5		
4			2		1			

Level: MODERATE

Complete the grid so each row, column and 3-by-3 box (in bold borders) contains every digit 1 to 9 without repeating a digit. For strategies on how to solve Sudoku, visit www. sudoku.org.uk.

The solution for today's puzzle will appear in tomorrow's Classified section.

Solution for Friday's Sudoku

7	5	8	4	9	3	1	6	2
2	4	1	7	6	8	9	3	5
6	9	3	5	2	1	8	7	4
4	6	9	1	7	2	5	8	3
5	3	7	9	8	4	2	1	6
8	1	2	3	5	6	7	4	9
3	2	4	8	1	5	6	9	7
9	8	5	6	3	7	4	2	1
1	7	6	2	4	9	3	5	8

Tribune Media Services

ATTENTION SHOPPERS OF FRUITS!

The Dept. of Agricultural Economics at Texas A&M University is looking for individuals to participate in a study on **fruit purchasing decisions**. Participants are needed for either **July 5, 6 or 7, 2012**. The study will take place on the campus of Texas A&M University.

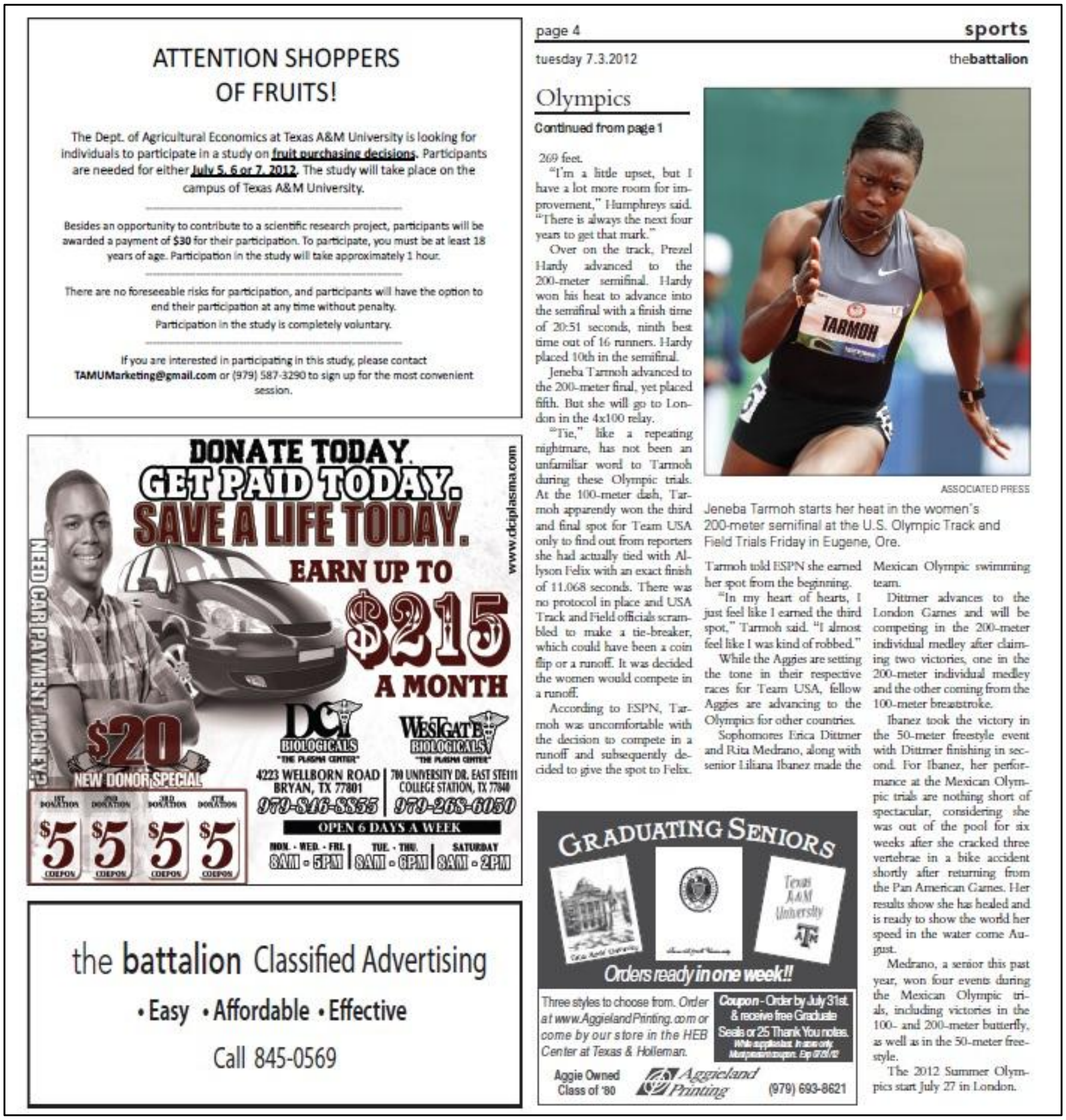
Besides an opportunity to contribute to a scientific research project, participants will be awarded a payment of **$30** for their participation. To participate, you must be at least 18 years of age. Participation in the study will take approximately 1 hour.

There are no foreseeable risks for participation, and participants will have the option to end their participation at any time without penalty.

Participation in the study is completely voluntary.

If you are interested in participating in this study, please contact **TAMUMarketing@gmail.com** or (979) 587-3290 to sign up for the most convenient session.

B.2 Experiment Advertisement in The Battalion Newspaper



ATTENTION SHOPPERS OF FRUITS!

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Olympics

Continued from page 1

269 feet.

"I'm a little upset, but I have a lot more room for improvement," Humphreys said. "There is always the next four years to get that mark."

Over on the track, Prezel Hardy advanced to the 200-meter semifinal. Hardy won his heat to advance into the semifinal with a finish time of 20:51 seconds, ninth best time out of 16 runners. Hardy placed 10th in the semifinal.

Jeneba Tarmoh advanced to the 200-meter final, yet placed fifth. But she will go to London in the 4x100 relay.

"Tie," like a repeating nightmare, has not been an unfamiliar word to Tarmoh during these Olympic trials. At the 100-meter dash, Tarmoh apparently won the third and final spot for Team USA only to find out from reporters she had actually tied with Allyson Felix with an exact finish of 11.068 seconds. There was no protocol in place and USA Track and Field officials scrambled to make a tie-breaker, which could have been a coin flip or a runoff. It was decided the women would compete in a runoff.

According to ESPN, Tarmoh was uncomfortable with the decision to compete in a runoff and subsequently decided to give the spot to Felix.

ASSOCIATED PRESS

Jeneba Tarmoh starts her heat in the women's 200-meter semifinal at the U.S. Olympic Track and Field Trials Friday in Eugene, Ore.

Tarmoh told ESPN she earned her spot from the beginning.

"In my heart of hearts, I just feel like I earned the third spot," Tarmoh said. "I almost feel like I was kind of robbed."

While the Aggies are setting the tone in their respective races for Team USA, fellow Aggies are advancing to the Olympics for other countries.

Sophomores Erica Dittmer and Rita Medrano, along with senior Liliana Ibanez made the Mexican Olympic swimming team.

Dittmer advances to the London Games and will be competing in the 200-meter individual medley after claiming two victories, one in the 200-meter individual medley and the other coming from the 100-meter breaststroke.

Ibanez took the victory in the 50-meter freestyle event with Dittmer finishing in second. For Ibanez, her performance at the Mexican Olympic trials are nothing short of spectacular, considering she was out of the pool for six weeks after she cracked three vertebrae in a bike accident shortly after returning from the Pan American Games. Her results show she has healed and is ready to show the world her speed in the water come August.

Medrano, a senior this past year, won four events during the Mexican Olympic trials, including victories in the 100- and 200-meter butterfly, as well as in the 50-meter freestyle.

The 2012 Summer Olympics start July 27 in London.

B.3 Institutional Review Board-Approved Consent Form

Version 6/14/2012

CONSENT FORM
Fruit Purchasing Decisions Study

Introduction
The purpose of this form is to provide you information that may affect your decision as to whether or not to participate in this research study. If you decide to participate in this study, this form will also be used to record your consent.

You have been asked to participate in a research project studying purchase decision-making. The purpose of this study is to look at how decisions to purchase fruit and fruit products are made. You were selected to be a possible participant because you responded to an advertisement for this study.

What will I be asked to do?
If you agree to participate in this study, you will be asked to complete a survey, complete a short knowledge quiz, participate in two practice auctions and several auction rounds on fruit purchasing. During the rounds on fruit purchasing, you will be asked to examine several fruit products and indicate your preferences and the amount that you are willing to pay for several fruit products. This study will take less than 2 hours to complete.

What are the risks involved in this study?
The risks associated in this study are minimal, and are not greater than risks ordinarily encountered in daily life.

What are the possible benefits of this study?
You will receive no direct benefit from participating in this study; however, society will potentially benefit from a better understanding of what fruit products are most desirable to consumers.

Do I have to participate?
No. Your participation is voluntary. You may decide not to participate or to withdraw at any time without your current or future relations with Texas A&M University being affected.

Will I be compensated?
You will receive a payment of $30 for your participation today. Disbursement of payments will occur at the conclusion of today's session. If you purchase an item during today's session, the purchase price will be deducted from the original compensation amount. If you choose not to continue to participate, the compensation you receive will be pro-rated relative to the amount of time that you participated. If you fail to follow the written instructions and/or the instructions of a session monitor, you will be asked to leave and will not receive payment.

Who will know about my participation in this research study?
This study is confidential, and the records of this study will be kept private. No identifiers linking you to this study will be included in any sort of report that might be published. Research records will be stored securely and only Alba J. Collart (Graduate Research Assistant, TAMU Dept. of Agricultural Economics) and Dr. Marco Palma (Assistant Professor, TAMU Dept. of Agricultural Economics) will have access to the records.

Texas A&M University IRB Approval	From: 06/15/12	To: 06/14/13
IRB Protocol # 2012-0324		Authorized by: KM

Version 6/14/2012

Whom do I contact with questions about the research?
If you have questions regarding this study, you may contact Alba Collart, acollart@tamu.edu or Dr. Marco Palma, (979)845-5284, mapalma@ag.tamu.edu.

Whom do I contact about my rights as a research participant?
This research study has been reviewed by the Human Subjects' Protection Program and/or the Institutional Review Board at Texas A&M University. For research-related problems or questions regarding your rights as a research participant, you can contact these offices at (979)458-4067 or irb@tamu.edu.

Signature
Please be sure you have read the above information, asked questions and received answers to your satisfaction. You will be given a copy of the consent form for your records. By signing this document, you consent to participate in this study.

Signature of Participant: ____ **Date:** _____________

Printed Name: ____

Signature of Person Obtaining Consent: ___________________________ **Date:** _____________

Printed Name: ____

Texas A&M University IRB Approval From: 06/15/12 To: 06/14/13
IRB Protocol # 2012-0324 Authorized by: KM

B.4 Experimental Auction Questionnaire

Introductory Instructions

Welcome! Thank you for agreeing to participate in today's session.

When you entered the room you received this **packet of information**. You should have also been assigned a participant **ID number**, located on the front page of this packet of information. You should use this ID number to identify yourself throughout the session today. The use of identification numbers ensures individual confidentiality.

As a reminder before we start today's session, your participation is **completely voluntary**. At any time you may elect to end your participation in the session. However, in order to receive the participation fee you must complete the session. All information collected today will be kept confidential and will not be used for any purpose other than this research.

The purpose of today's session is to gather some general information on the decision making process for purchasing fruit. We will now go through a series of instructions. These instructions will be read from a script to make sure the procedures are accurately described. There will be an opportunity for questions once we go through the instructions**.**

For the rest of today's session, it is very important that there be no further talking or other communication between participants. If you have questions or comments, please inform a session monitor. If you are not able to comply with these requests you may be disqualified from the experiment.

If you have any questions, please direct them to a session monitor who will gladly answer them.

Overview

***Please follow all instructions presented in this booklet carefully. If you have any questions, please ask a session monitor.

The purpose of today's experiment is to help us understand purchasing decisions for fruit and fruit products. To accomplish this purpose, you will be asked to submit bids for several items in an auction setting and complete a survey. If you are one of the buyers of the auctions, you will pay the auction price and in exchange you will receive the item. You will be given more information on the auction procedures shortly.

The experiment will proceed in several stages as described below.

STAGE 1: Learn How Bids Are Submitted
STAGE 2: Learn How Prices and Buyers of the Auction Are Determined
STAGE 3: First Practice Round
STAGE 4: Complete Short Knowledge Quiz
STAGE 5: Second Practice Round
STAGE 6: Submit Bids for Fruit Products
STAGE 7: Complete Survey
STAGE 8: Determine Auction Buyers
STAGE 9: Receive Payment

However, first please review the Consent Form if you have not already done so. Once you have read the form, you should print your name and sign and date on the second page. You can be provided with a copy of this form if you desire.

STAGE 1: Learn How Bids Are Submitted

The Auction: The auction that you will participate in today is called a "sealed bid 2nd-price auction".

1. You will examine the products that will be auctioned.
   You will be given the opportunity to re-evaluate each item if you would like to do so.

2. **Write down** your bid.
   After you examine the items, please write down the maximum amount that you would be willing to pay for each item on the corresponding "Bid Sheet."

3. Return to your seat and wait for the Bid Sheet to be collected.

STAGE 2: Learn How the Auction Price and Buyers Are Determined

<u>How The Auction Price is Determined</u>: Today you will be participating in a sealed bid 2nd-price auction. Choosing the market price:

> After all the bids for the items have been collected from all participants, we will sort the bids from highest to lowest. The 2nd highest bid will be the market price. The highest bidder will pay the market price for the product.

<u>How Buyers are Determined</u>:

1. Auction Buyers:
   You will participate in more than one round of auctions today. However, only one round will be binding, we will select at random which one of these rounds will be binding. All rounds have an equal chance of being drawn. Once the binding round is drawn, a single product from that round will be selected. **Therefore, you will only have a chance to purchase one fruit item from today's session**.

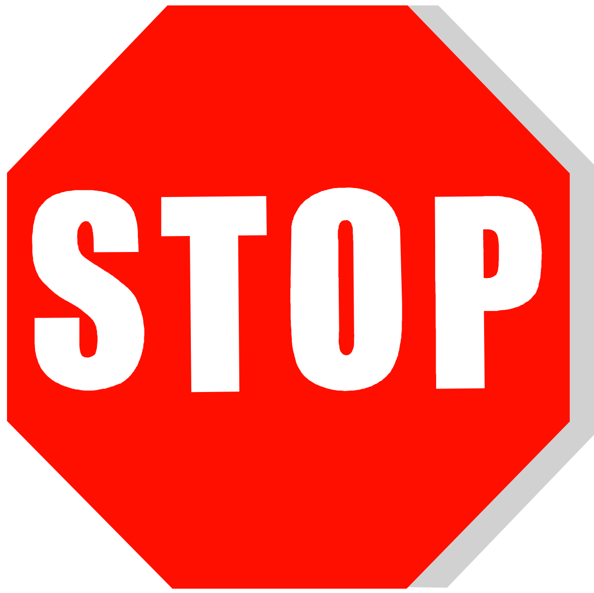
   For the round that is binding, the person who bid the highest price will purchase the item at the market price. This buyer will pay the market price for that round, which will be deducted from the participation fee, and will take home the product.

IMPORTANT REMINDERS: For the auction it is in your best interest to truthful bid your value.
****Remember, in the auction it is in your best interest to submit a bid of EXACTLY your true value for the good***. If you submit a bid for less than your value, then other bidders may win the item at a price equal to your value and you may miss out on having the item at a price you would be actually willing to pay. If you submit a bid for more than you value the item, then you may win the auction for that price and pay more than you wanted to pay for the item.

* ***The practice rounds are hypothetical, but the auction rounds for fruit products are not***. The buyer of the auction will actually pay money to obtain the fruit item.
* ***When deciding on your bid, consider the alternatives for what you could spend that much money on.*** For example, if you did not buy the product up for auction, how many gallons of gas could you purchase with the amount you bid? Consider other options when deciding what your true value is for that good.

******You will not buy more than one fruit item from this market***. We will randomly select one product to be binding.

****At least one session participant will take home ONE fruit product today***. There will be a session participant who will buy a product based on the auction bids. Therefore, you should think carefully about your valuations.



Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 3: First Practice Round of Auction

INSTRUCTIONS:
In this stage you will participate in the first hypothetical practice round. First you will be asked to bid on four types of snack products. The stage will proceed as follows:

1. When instructed by a session monitor, you may go to the tables to examine each product. Please do not talk with each other during bidding. We will be happy to answer any of your questions.
2. On the practice-bidding sheet, you will write down your bid for each item. Then, return to your seat.
3. Wait until a session monitor collects the practice-bidding sheets.

While you wait for the price and buyers of this practice round to be determined, you will complete a short knowledge quiz on your understanding of the auction procedures. The knowledge quiz starts on the next page (8).

STAGE 4: Short Knowledge Quiz

INSTRUCTIONS:
This is a brief quiz designed for you to check your understanding of how the auctions you will participate in today will operate. Please choose the answer you feel is correct. Once all participants have completed the quiz, we will go over the answers together.

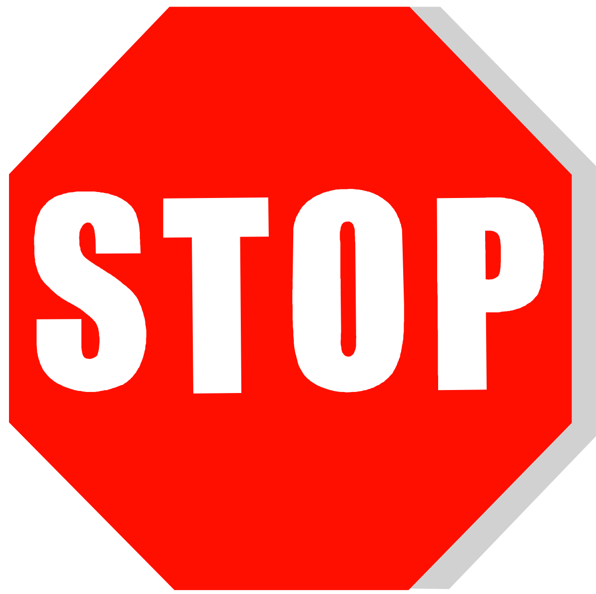
About the Auction:

1. In a sealed bid 2nd-price auction, the highest bidder wins the auctioned item.
   - **a.** True
   - **b.** False

2. The person who wins the auction for the binding round and product will pay the amount he/she bid for the item.
   - **a.** True
   - **b.** False

3. More than one round of bidding on several products will be done today, but only one round and one product will be randomly selected to be binding.
   - **a.** True
   - **b.** False

4. There will be the opportunity to actually purchase and take home more than one fruit product today.
   - **a.** True
   - **b.** False

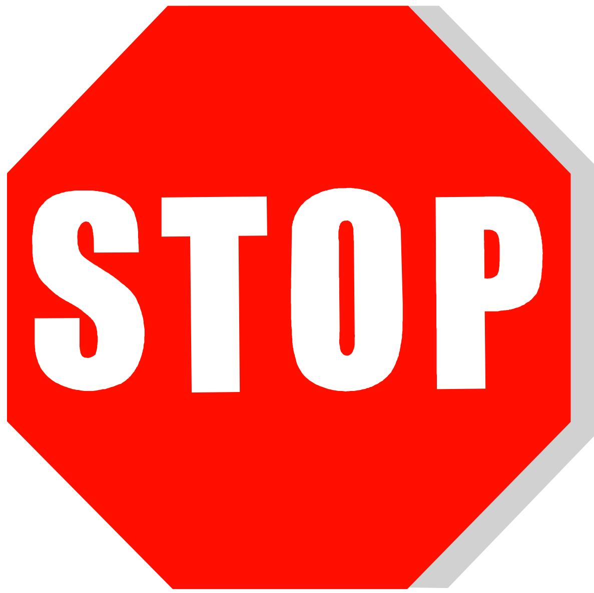


Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 5: Second Practice Round of Auction

INSTRUCTIONS:
You have completed half of the practice. Now you will be asked to bid on three types of coffee mugs. The practice round will proceed as follows:

1. When instructed by a session monitor, you may go to the tables to examine each product. Please do not talk with each other during bidding. We will be happy to answer any of your questions.
2. On the practice-bidding sheet, you will write down your bid for each item. Then, return to your seat.
3. Wait until a session monitor collects the practice-bidding sheets.



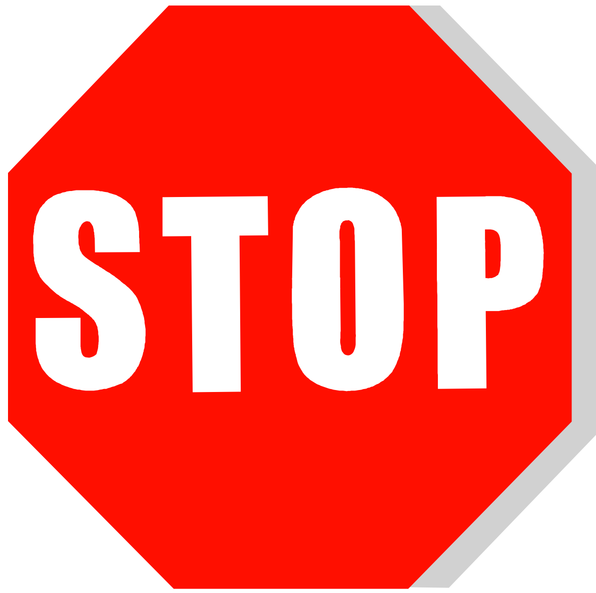
Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

TASTING REPORT

As you enjoy the fruit products, please rate from 0 (worst) to 10 (best) *each* of the following characteristics for *each* product:

	Color	**Smell**	**Taste**	**Freshness**	**Sweetness**	**Overall Appearance**
Cantaloupe						
Honeydew						
Tuscan Melon						
Canary Melon						
Galia Melon						

If you have any questions, please direct them to a session monitor who will gladly answer them.



Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 6: FRUIT AUCTIONS

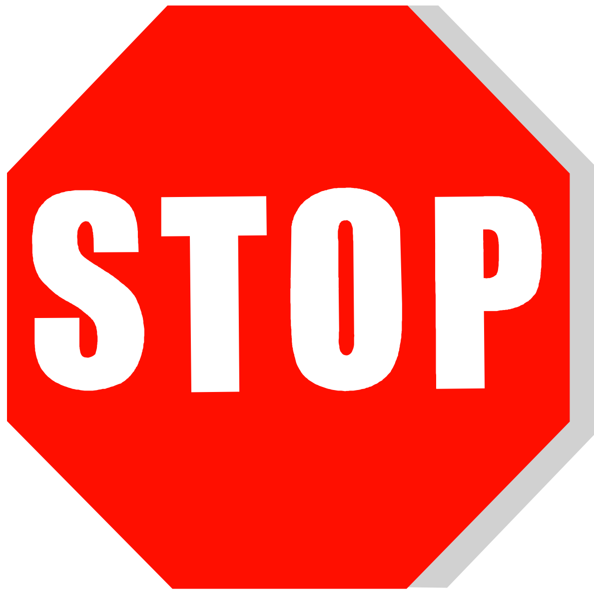
Thank you for participation so far. The next auction rounds will be for several fruit products, but only one of the rounds will be binding. The binding round will be selected at random after all rounds have been completed.

INSTRUCTIONS: The stage will proceed as follows:

1. When instructed to do so, you may go to the tables to examine each product. Please do not talk with each other during bidding. The monitor will be happy to answer any of your questions.
2. On the bidding sheet, write down your bid for each item. Then, return to your seat.
3. Wait until a session monitor collects your sheets.

Please do not turn the page until directed to do so. We will repeat the auction procedure whenever indicated.

The market price for the binding fruit auction will not be posted until the end of today's session.



Please do not read any further until instructed to do so by the session monitor. Your cooperation is greatly appreciated!

STAGE 7: SURVEY

INSTRUCTIONS: Please select only one answer by marking an "X" in the blank unless otherwise indicated. There is no right or wrong answer. Your survey responses are very important to the results of today's sessions. **Please remember that all responses will be kept confidential**.

1. **PRIMARY SHOPPER: Are you the PRIMARY grocery shopper for your household?**
   a. ___ Yes   **b.** ___ No

2. **WEEKLY FOOD EXPENDITURES: How much, on average, does your household spend on food PER WEEK?** (Include grocery, snacks, restaurants, and any other food purchases).
   a. ___ $0-$49   **f.** ___ $250 - $299
   b. ___ $50 - $99   **g.** ___ $300 - $399
   c. ___ $100 - $149   **h.** ___ $400 - $499
   d. ___ $150 - $199   **i.** ___ $500 - $749
   e. ___ $200 - $249   **j.** ___ $750 or more

3. **WEEKLY FRUIT AND VEGETABLE EXPENDITURES: How much, on average, does your household spend on fruits and vegetables PER WEEK?**
   a. ___ $0-$24   **d.** ___ $75 - $99
   b. ___ $25 - $49   **e.** ___ $100 or more
   c. ___ $50 - $74

4. **FRESH FRUIT AND VEGETABLE EXPENDITURES: Approximately what portion of your fruit and vegetable purchases are for <u>FRESH</u> fruits and vegetables (Please exclude any canned, frozen, and/or processed fruits and vegetables).**
   - **a.** ___ None of the fruits and vegetables purchased are fresh.
   - **b.** ___ 1-24% of the fruits and vegetables purchased are fresh.
   - **c.** ___ 25-49% of the fruits and vegetables purchased are fresh.
   - **d.** ___ 50-75% of the fruits and vegetables purchased are fresh.
   - **e.** ___ 76-100% of the fruits and vegetables purchased are fresh.

5. **LOCATION OF FRUIT AND VEGETABLE PURCHASES: Of the following options, where does your household make the LARGEST PORTION of its fruit and vegetable purchases?**
   - **a.** ___ Mass-merchandiser (e.g., Walmart, Target)
   - **b.** ___ Supermarket/ Grocery Store (e.g. HEB, Kroger, Albertsons)
   - **c.** ___ Roadside Fruit and Vegetable Stand
   - **d.** ___ Farmers' Market
   - **e.** ___ Other (Please

   Indicate:____)

6. **LAST PURCHASE OF FRUIT AND VEGETABLES: When was the last time someone in your household purchased fruits and vegetables?**
   - **a.** ___ Less than 2 days ago
   - **b.** ___ 2-4 days ago
   - **c.** ___ 5-7 days ago
   - **d.** ___ 8- 10 days ago
   - **e.** ___ 11-14 days ago
   - **f.** ___ More than 2 weeks ago

7. **FREQUENCY OF FRUIT AND VEGETABLE PURCHASES: How often do your household purchase fresh fruits and vegetables?**
   - **a.** ___ Less than once a month
   - **b.** ___ Once a month
   - **c.** ___ Two to three times / month
   - **d.** ___ Once a week
   - **e.** ___ More than once a week

8. **FRESH FRUIT ON HAND: Please estimate the amount of FRESH FRUIT that you currently have on hand in your home as a percentage of your full stock.**
   - **a.** ___ 0%
   - **b.** ___ 1-24%
   - **c.** ___ 25-49%
   - **e.** ___ 50-74%
   - **f.** ___ 75-100%

9. **FRESH VEGETABLES ON HAND: Please estimate the amount of FRESH VEGETABLES that you currently have on hand in your home as a percentage of your full stock.**
   - **a.** ___ 0%
   - **b.** ___ 1-24%
   - **c.** ___ 25-49%
   - **e.** ___ 50-74%
   - **f.** ___ 75-100%

How important are the following factors to you when making melon purchasing decision? (Please select only one level of importance per row).				
	Not Important At All	**Not Very Important**	**Somewhat Important**	**Very Important**
10. PRICE				
11. TASTE				
12. NUTRITION				
13. CONVENIENCE				
14. VISUAL APPEARANCE				
15. SIZE				
16. FRESHNESS				
17. GROWING LOCATION				
18. CERTIFIED PRODUCTION PRACTICES				

19. Prior to today's session, had you heard the term "food safety" before?

a. ___ Yes **c.** ___ Don't Know/ Don't Remember

b. ___ No

20. Do you look for certification labels (e.g. origin certified, organic certified, etc.) on fruit products before you purchase them?

a. ___ Never

b. ___ Rarely

c. ___ Sometimes

d. ___ Most of the time

e. ___ Always

21. **Do you think <u>most persons</u> look for certification labels on food products before they purchase them?**
    - **a.** ___ Never
    - **b.** ___ Rarely
    - **c.** ___ Sometimes
    - **d.** ___ Most of the time
    - **e.** ___ Always

22. **Have you ever experienced food poisoning from consuming fruits and vegetables?**
    - **a.** ___ Yes
    - **b.** ___ No
    - **c.** ___ Don't Know/ Don't Remember

23. **Do you believe there to be benefits of consuming fruits and vegetables that have been certified for appropriate food safety?**
    - **a.** ___ Yes
    - **b.** ___ No
    - **c.** ___ Don't Know/ Not Sure

24. PARTICIPANT: Please mark an "X" below the corresponding column for each row

	Yes	No
I am participating for the 1st time in a study like this		
I have relatives that currently work at Texas A&M		
I am curious and want to learn about studies like this		
I signed up because I wanted to help Texas A&M		
Even if there was no payment, I would have signed up to participate in this study		
I signed up because the study involved fruits		
I postponed other activity(ies) to be here today		
I am a Bryan/College Station permanent resident		
I have a degree from Texas A&M University		
I signed up because I wanted to help research efforts		
All studies must include a participation fee		

25. AGE: Please indicate your age in years:

a. ___ 18- 19

b. ___ 20-29

c. ___ 30-39

d. ___ 40-49

e. ___ 50-59

f. ___ 60-69

g. ___ 70 or over

26. EDUCATION: Please indicate the <u>highest</u> level of education you have completed:

a. ___ Some High School or less **e.** ___ 4 year/ Bachelor's

Degree

b. ___ High School Diploma **f.** ___ Some Graduate School

c. ___ Some College **g.** ___ Graduate Degree

d. ___ 2 year/ Associates Degree

27. HOUSEHOLD SIZE: Including yourself, <u>how many</u> people live in your household? Include yourself, your spouse, and any dependents. Please do NOT include your roommates if you share an apartment/house.

a. ___ People

28. CHILDREN: <u>How many</u> children live in your household, if any?

a. ___ Children

29. GENDER: Please indicate your gender:

a. ___ Female **b.** ___ Male

30. RACE: Please indicate your race:

a. ___ Asian/Pacific Islander

b. ___ African American

c. ___ Caucasian/White

d. ___ Native American/ Indigenous

e. ___ Hispanic

f. ___ Other (Please List: ____)

31. MARITAL STATUS: What is your current marital status?

a. ___ Single **b.** ___ Married

32. INCOME: Please indicate your household yearly income for 2011 for all the people in your household. (Include all forms of income, including salary, interest and dividend payments, tips, scholarship support, student loans, parental support, social security, child support, and allowance).

a. ___ Less than $30,000 **f.** ___ $70,000-$79,999

b. ___ $30,000-$39,999 **g.** ___ $80,000-$89,999

c. ___ $40,000-$49,999 **h.** ___ $90,000-$99,999

d. ___ $50,000-$59,999 **i.** ___ $100,000-$149,999

e. ___ $60,000-$69,999 **j.** ___ More than $150,000

33. EMPLOYMENT: Which of these best describes your employment status?

a. ___ Unemployed **e.** ___ Retired

b. ___ Stay-at-Home Parent **f.** ___ Disabled

c. ___ Part-time Employed **g.** ___ Student

d. ___ Full-time Employed

34. Please, provide any additional comments about today's experience:

Thank you for your participation! *Your responses are very important for us. A session monitor will collect your questionnaire.*

Please do not discuss the procedures of today's study with anyone who will be participating in later rounds of the study until after they have completed their session. This will help ensure the validity of our results.

Shortly, you will receive your participation fee minus any purchases. Please wait for further instructions.

B.5 Bidding Sheets

STAGE 3: PRACTICE ROUND 1: Snack Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. CHIPS	B. CHEESE PUFFS	C. COOKIE	D. CRACKERS
BID:$_______	BID:$_______	BID:$_______	BID:$_______

STAGE 5: PRACTICE ROUND 2: Coffee Mug Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below.

A. TEXAS A&M LOGO MUG	B. WHITE CERAMIC MUG	C. THERMAL MUG
BID:$_______	BID:$_______	BID:$_______

STAGE 6: ROUND 3-A Fruit Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. Cantaloupe	**B.** Honeydew	**C.** Tuscan Melon	**D.** Canary Melon	**E.** Galia Melon	**F.** Personal Watermelon
BID:$_____	**BID:$_____**	**BID:$____**	**BID:$_____**	**BID:$_____**	**BID:$_____**

STAGE 6: ROUND 3-B Fruit Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. Industry Certified Cantaloupe	**B.** Industry Certified Honeydew	**C.** Industry Certified Tuscan Melon	**D.** Industry Certified Canary Melon	**E.** Industry Certified Galia Melon	**F.** Personal Watermelon
BID:$____	**BID:$___**	**BID:$___**	**BID:$____**	**BID:$____**	**BID:$_____**

STAGE 6: ROUND 3-C Fruit Product Bidding

INSTRUCTIONS: Please indicate the maximum amount that you would be willing to pay for each of these items. Write the amount of your bid (in dollars and cents) in the "Bid" column in the chart below. **Please be sure to write a bid for ALL products listed.**

A. USDA Certified Cantaloupe	**B.** USDA Certified Honeydew	**C.** USDA Certified Tuscan Melon	**D.** USDA Certified Canary Melon	**E.** USDA Certified Galia Melon	**F.** Personal Watermelon
BID:$______	**BID:$___**	**BID:$____**	**BID:$____**	**BID:$_____**	**BID:$_____**

B.6 NLOGIT 5 Code 2nd Essay

```
IMPORT;
FILE="C:\Users\acollart\Desktop\DISSERTATION\AUCTION\MIXED\NLOGIT\RPM\nlogit.csv"$
NAMELIST; ALLX = ONE, HONEY, TUS, CANA, GAL, WAT, TCANTA, THONEY, TTUS, TCANA,
TGAL, TWAT, INDUSTRY, GOVERN, DAGE2, DAGE3, DEDU2, DEDU3, HHSIZE, FEMALE,
MARRIED, DINC2, DINC3, ASPENDFV, FVOH $
NAMELIST; RPX = ONE, HONEY, TUS, CANA, GAL, WAT, TCANTA, THONEY, TTUS, TCANA,
TGAL, TWAT, INDUSTRY, GOVERN $
SETPANEL; Group = id ; Pds = groupti $


? Random Parameters Linear
REGRESS; Lhs = wtp
; Rhs = ALLX
; RPM
; Fcn = ONE(n), HONEY(n), TUS(n), CANA(n), GAL(n), WAT(n), TCANTA(n), THONEY(n),
TTUS(n), TCANA(n), TGAL(n), TWAT(n), INDUSTRY(n), GOVERN(n)
; Panel
; Pts = 500
; Halton
; Covariance Matrix $

MATRIX; b0 = b
; v0 = varb $


? Random Parameters Tobit
TOBIT; Lhs = wtp
; Rhs = ALLX
; RPM
; Fcn = ONE(n), HONEY(n), TUS(n), CANA(n), GAL(n), WAT(n), TCANTA(n), THONEY(n),
TTUS(n), TCANA(n), TGAL(n), TWAT(n), INDUSTRY(n), GOVERN(n)
; Panel
; Pts = 500
; Halton
; Partial Effects
; Covariance Matrix $

MATRIX; b1 = b
; v1 = varb $


?Hausman Test
MATRIX; d=b1-b0
; List
; V = Nvsm(v1,-v0)
; H = d'*V*d
; c = Rank(V) $
```

B.7 Stata Code 2nd Essay

```
*--------------------------------------------------------------------------
*DO FILE TO ANALYZE EXPERIMENTAL AUCTION DATA
*TOBIT, RANDOM EFFECTS TOBIT, RANDOM EFFECTS LINEAR, RANDOM PARAMETERS
LINEAR
*ALBA J. COLLART
*--------------------------------------------------------------------------

*START DO FILE
log using output, text replace
set more off, permanently
clear

cd "C:\Users\acollart\Desktop\DISSERTATION\AUCTION\MIXED\STATA\Reshape"


*LEGEND
* rp=round.product

*round:         =1 tasting (between)
*                       =2 industry (within)
*                       =3 government (within)

*product:       =1 cantaloupe
*                       =2 honeydew
*                       =3 tuscan
*                       =4 canary
*                       =5 galia
*                       =6 watermelon

***     Import data
insheet using Reshape.txt, clear

reshape long wtp, i(id) j(rp)

*-----------------------------------
*Variable manipulation
*-----------------------------------

*Generate indicators for product varieties

gen canta:1= rp==11|rp==21|rp==31
gen honey:1= rp==12|rp==22|rp==32
gen tus:1= rp==13|rp==23|rp==33
gen cana:1= rp==14|rp==24|rp==34
gen gal:1= rp==15|rp==25|rp==35
gen wat:1= rp==16|rp==26|rp==36


*Generate indicator for treatments, and interactions of tasting*product
```

```
gen tasting:1= (id<419)
gen industry:1= (20<rp) & (rp<27)
gen government:1= (30<rp) & (rp<37)

gen tcanta:1= (tasting==1) & (rp==11)
gen thoney:1= (tasting==1) & (rp==12)
gen ttus:1 = (tasting==1) & (rp==13)
gen tcana:1= (tasting==1) & (rp==14)
gen tgal:1= (tasting==1) & (rp==15)
gen twat:1 = (tasting==1) & (rp==16)


*Generate age: AGE1 is 18-29, AGE2 is 30-49, AGE3 is 50 or over

gen dage1=(age==1 | age==2) if!missing(age)
gen dage2=(age==3|age==4) if!missing(age)
gen dage3=(age==5|age==6|age==7) if!missing(age)


*Generate edu: EDU1 is high school diploma or less, EDU2 is some college-bachelor's degree, EDU3 is some grad school or more

gen dedu1=(edu==1 | edu==2) if!missing(edu)
gen dedu2=(edu==3|edu==4|edu==5) if!missing(edu)
gen dedu3=(edu==6|edu==7) if!missing(edu)


*Generate income: INC1 is <50k, INC2 is 50K to <100K, INC3 is 100K or more

gen dinc1=(income==1 | income==2|income==3) if!missing(income)
gen dinc2=(income==4|income==5|income==6|income==7|income==8) if!missing(income)
gen dinc3=(income==9|income==10) if!missing(income)


*Generate average value of weekly expenditures on fruits and vegetables: ASPENDFV

recode wfv (1=12) (2=37) (3=62) (4=87) (5=100), generate (aspendfv)


*Generate average percentage of fresh fruit on hand: APFOH

recode freshf (1=0) (2=12.5) (3=37) (4=62) (5=87.5), generate (apfoh)


*Generate average percentage of fresh vegetables on hand: APVOH

recode freshv (1=0) (2=12.5) (3=37) (4=62) (5=87.5), generate (apvoh)


*Generate paired sum of pounds of fresh fruit and vegetables on hand: FVPOH

gen fvoh=apfoh+apvoh
```

```
*-----------------------------------
*SUMMARIZE
*-----------------------------------
sum hhsize aspendfv fvoh

*-----------------------------------
*DISTRIBUTION TESTS
*-----------------------------------
*Separate wtp by treatement rounds
gen wtpb=wtp if (10<rp) & (rp<17)
gen wtpbt=wtp if (10<rp) & (rp<17) & tasting==1
gen wtpbnt=wtp if (10<rp) & (rp<17) & tasting==0
gen wtpind=wtp if(20<rp) & (rp<27)
gen wtpgvt=wtp if(30<rp) & (rp<37)

*To graph CDFs
*cumul wtpb, gen(Baseline)
*cumul wtpind, gen(Ind)
*cumul wtpgvt, gen(Gvt)
*stack Baseline wtpb Ind wtpind Gvt wtpgvt, into(c wtp) wide clear
*line Baseline Ind Gvt wtp, sort

gen issuer:1= (industry==1)
replace issuer=. if industry==0 & government==0

gen indbas:1= (industry==1)
replace indbas=. if rp>30 & rp<37

gen gvtbas:1= (government==1)
replace gvtbas=. if rp<20 & rp<27

ksmirnov wtp, by(tasting)
ksmirnov wtp, by(issuer)
ksmirnov wtp, by(indbas)
ksmirnov wtp, by(gvtbas)

*tasting
sum wtp if tasting==1 & rp==11
sum wtp if tasting==1 & rp==11 & wtp==0
sum wtp if tasting==1 & rp==12
sum wtp if tasting==1 & rp==12 & wtp==0
sum wtp if tasting==1 & rp==13
sum wtp if tasting==1 & rp==13 & wtp==0
sum wtp if tasting==1 & rp==14
sum wtp if tasting==1 & rp==14 & wtp==0
sum wtp if tasting==1 & rp==15
sum wtp if tasting==1 & rp==15 & wtp==0
sum wtp if tasting==1 & rp==16
sum wtp if tasting==1 & rp==16 & wtp==0

*no tasting
sum wtp if tasting==0 & rp==11
```

```
sum wtp if tasting==0 & rp==11 & wtp==0
sum wtp if tasting==0 & rp==12
sum wtp if tasting==0 & rp==12 & wtp==0
sum wtp if tasting==0 & rp==13
sum wtp if tasting==0 & rp==13 & wtp==0
sum wtp if tasting==0 & rp==14
sum wtp if tasting==0 & rp==14 & wtp==0
sum wtp if tasting==0 & rp==15
sum wtp if tasting==0 & rp==15 & wtp==0
sum wtp if tasting==0 & rp==16
sum wtp if tasting==0 & rp==16 & wtp==0

*industry
sum wtp if rp==21
sum wtp if rp==21 & wtp==0
sum wtp if rp==22
sum wtp if rp==22 & wtp==0
sum wtp if rp==23
sum wtp if rp==23 & wtp==0
sum wtp if rp==24
sum wtp if rp==24 & wtp==0
sum wtp if rp==25
sum wtp if rp==25 & wtp==0
sum wtp if rp==26
sum wtp if rp==26 & wtp==0

*government
sum wtp if rp==31
sum wtp if rp==31 & wtp==0
sum wtp if rp==32
sum wtp if rp==32 & wtp==0
sum wtp if rp==33
sum wtp if rp==33 & wtp==0
sum wtp if rp==34
sum wtp if rp==34 & wtp==0
sum wtp if rp==35
sum wtp if rp==35 & wtp==0
sum wtp if rp==36
sum wtp if rp==36 & wtp==0

*all
sum wtp if canta==1
sum wtp if canta==1 & wtp==0
sum wtp if honey==1
sum wtp if honey==1 & wtp==0
sum wtp if tus==1
sum wtp if tus==1 & wtp==0
sum wtp if cana==1
sum wtp if cana==1 & wtp==0
sum wtp if gal==1
sum wtp if gal==1 & wtp==0
sum wtp if wat==1
sum wtp if wat==1 & wtp==0
```

```
*AVERAGE BIDS EQUAL OR ABOVE LOCAL PRICES
*tasting
sum wtp if tasting==1 & rp==11
sum wtp if tasting==1 & rp==11 & wtp>2.48
sum wtp if tasting==1 & rp==11 & wtp<2.48
sum wtp if tasting==1 & rp==12
sum wtp if tasting==1 & rp==12 & wtp>3.98
sum wtp if tasting==1 & rp==12 & wtp<3.98
sum wtp if tasting==1 & rp==13
sum wtp if tasting==1 & rp==13 & wtp>2.99
sum wtp if tasting==1 & rp==13 & wtp<2.99
sum wtp if tasting==1 & rp==14
sum wtp if tasting==1 & rp==14 & wtp>2.99
sum wtp if tasting==1 & rp==14 & wtp<2.99
sum wtp if tasting==1 & rp==15
sum wtp if tasting==1 & rp==15 & wtp>2.99
sum wtp if tasting==1 & rp==15 & wtp<2.99
sum wtp if tasting==1 & rp==16
sum wtp if tasting==1 & rp==16 & wtp>2.50
sum wtp if tasting==1 & rp==16 & wtp==2.50
sum wtp if tasting==1 & rp==16 & wtp<2.50

*no tasting
sum wtp if tasting==0 & rp==11
sum wtp if tasting==0 & rp==11 & wtp>2.48
sum wtp if tasting==0 & rp==11 & wtp<2.48
sum wtp if tasting==0 & rp==12
sum wtp if tasting==0 & rp==12 & wtp>3.98
sum wtp if tasting==0 & rp==12 & wtp<3.98
sum wtp if tasting==0 & rp==13
sum wtp if tasting==0 & rp==13 & wtp>2.99
sum wtp if tasting==0 & rp==13 & wtp<2.99
sum wtp if tasting==0 & rp==14
sum wtp if tasting==0 & rp==14 & wtp>2.99
sum wtp if tasting==0 & rp==14 & wtp<2.99
sum wtp if tasting==0 & rp==15
sum wtp if tasting==0 & rp==15 & wtp>2.99
sum wtp if tasting==0 & rp==15 & wtp<2.99
sum wtp if tasting==0 & rp==16
sum wtp if tasting==0 & rp==16 & wtp>2.50
sum wtp if tasting==0 & rp==16 & wtp==2.50
sum wtp if tasting==0 & rp==16 & wtp<2.50

*Industry
sum wtp if rp==21
sum wtp if rp==21 & wtp>2.48
sum wtp if rp==21 & wtp<2.48
sum wtp if rp==22
sum wtp if rp==22 & wtp>3.98
sum wtp if rp==22 & wtp<3.98
sum wtp if rp==23
sum wtp if rp==23 & wtp>2.99
```

```
sum wtp if rp==23 & wtp<2.99
sum wtp if rp==24
sum wtp if rp==24 & wtp>2.99
sum wtp if rp==24 & wtp<2.99
sum wtp if rp==25
sum wtp if rp==25 & wtp>2.99
sum wtp if rp==25 & wtp<2.99
sum wtp if rp==26
sum wtp if rp==26 & wtp>2.50
sum wtp if rp==26 & wtp==2.50
sum wtp if rp==26 & wtp<2.50

*Government
sum wtp if rp==31
sum wtp if rp==31 & wtp>2.48
sum wtp if rp==31 & wtp<2.48
sum wtp if rp==32
sum wtp if rp==32 & wtp>3.98
sum wtp if rp==32 & wtp<3.98
sum wtp if rp==33
sum wtp if rp==33 & wtp>2.99
sum wtp if rp==33 & wtp<2.99
sum wtp if rp==34
sum wtp if rp==34 & wtp>2.99
sum wtp if rp==34 & wtp<2.99
sum wtp if rp==35
sum wtp if rp==35 & wtp>2.99
sum wtp if rp==35 & wtp<2.99
sum wtp if rp==36
sum wtp if rp==36 & wtp>2.50
sum wtp if rp==36 & wtp==2.50
sum wtp if rp==36 & wtp<2.50

*all
sum wtp if canta==1 & wtp>2.48
sum wtp if canta==1 & wtp<2.48
sum wtp if honey==1 & wtp>3.98
sum wtp if honey==1 & wtp<3.98
sum wtp if tus==1 & wtp>3.99
sum wtp if tus==1 & wtp<3.99
sum wtp if cana==1 & wtp>3.99
sum wtp if cana==1 & wtp<3.99
sum wtp if gal==1 & wtp>3.99
sum wtp if gal==1 & wtp<3.99
sum wtp if wat==1 & wtp>3.99
sum wtp if wat==1 & wtp==3.99
sum wtp if wat==1 & wtp<3.99

*----------------------------------
*FULL BIDS
*----------------------------------

        *----------------------------------
```

```
*Constant Parameters Tobit Model
*-----------------------------------

tobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 dedu2 dedu3 hhsize female married dinc2 dinc3 aspendfv fvoh, ll(0)
estimates store ctobit

*-----------------------------------
*Random Effects Tobit
*-----------------------------------

xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 dedu2 dedu3 hhsize female married dinc2 dinc3 aspendfv fvoh, ll(0) tobit
estimates store retobit
xtset, clear

*-----------------------------------
*Random Effects Linear
*-----------------------------------

xtset id
xtreg wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 dedu2 dedu3 hhsize female married dinc2 dinc3 aspendfv fvoh, mle
estimates store relinear
xtset, clear

*or

*xtmixed wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 dedu2 dedu3 hhsize female married dinc2 dinc3 aspendfv fvoh || id:
*estimates store relinear

*-----------------------------------
*Random Parameters Linear/Mixed Linear
*-----------------------------------

xtmixed wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 dedu2 dedu3 hhsize female married dinc2 dinc3 aspendfv fvoh || id: honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government, mle covariance(independent)
estimates store lmixed


*Note: An independent covariance structure allows for a distinct variance for each random effect within a random-effects equation, and assumes that all covariances are zero (and thus correlations=0)


*Calculate correlation matrix to see whether random effects are actually correlated
estat vce, correlation

*This matrix displays the coefficient estimates and the naturallog(standard deviations) of the random effects, where s1_1_1 is Honey.
matrix list e(b)
```

```
*Test the standard deviations (i.e. random effects) for significance
test  _b[/lns1_1_1]=0
test  _b[/lns1_1_2]=0
test  _b[/lns1_1_3]=0
test  _b[/lns1_1_4]=0
test  _b[/lns1_1_5]=0
test  _b[/lns1_1_6]=0
test  _b[/lns1_1_7]=0
test  _b[/lns1_1_8]=0
test  _b[/lns1_1_9]=0
test  _b[/lns1_1_10]=0
test  _b[/lns1_1_11]=0
test  _b[/lns1_1_12]=0
test  _b[/lns1_1_13]=0
test  _b[/lns1_1_14]=0
test  _b[/lnsig_e]=0

*Calculate 95% intervals for the random parameters using the estimated standard deviations
*HONEY
gen ihoneyu=_b[honey]+1.96*(exp((_b[/lns1_1_1])))
gen ihoneyl=_b[honey]-1.96*(exp((_b[/lns1_1_1])))

*TUSCAN
gen itusu=_b[tus]+1.96*(exp((_b[/lns1_1_2])))
gen itusl=_b[tus]-1.96*(exp((_b[/lns1_1_2])))

*CANARY
gen icanau=_b[cana]+1.96*(exp((_b[/lns1_1_3])))
gen icanal=_b[cana]-1.96*(exp((_b[/lns1_1_3])))

*GALIA
gen igalu=_b[gal]+1.96*(exp((_b[/lns1_1_4])))
gen igall=_b[gal]-1.96*(exp((_b[/lns1_1_4])))

*WATERMELON
gen iwatu=_b[wat]+1.96*(exp((_b[/lns1_1_5])))
gen iwatl=_b[wat]-1.96*(exp((_b[/lns1_1_5])))

*TASTINGxCANTALOUPE
gen itcantau=_b[tcanta]+1.96*(exp((_b[/lns1_1_6])))
gen itcantal=_b[tcanta]-1.96*(exp((_b[/lns1_1_6])))

*TASTINGxHONEY
gen ithoneyu=_b[thoney]+1.96*(exp((_b[/lns1_1_7])))
gen ithoneyl=_b[thoney]-1.96*(exp((_b[/lns1_1_7])))

*TASTINGxTUSCAN
gen ittusu=_b[ttus]+1.96*(exp((_b[/lns1_1_8])))
gen ittusl=_b[ttus]-1.96*(exp((_b[/lns1_1_8])))

*TASTINGxCANARY
gen itcanau=_b[tcana]+1.96*(exp((_b[/lns1_1_9])))
```

```
gen itcanal=_b[tcana]-1.96*(exp((_b[/lns1_1_9])))

*TASTINGxGALIA
gen itgalu=_b[tgal]+1.96*(exp((_b[/lns1_1_10])))
gen itgall=_b[tgal]-1.96*(exp((_b[/lns1_1_10])))

*TASTINGxWATERMELON
gen itwatu=_b[twat]+1.96*(exp((_b[/lns1_1_11])))
gen itwatl=_b[twat]-1.96*(exp((_b[/lns1_1_11])))

*INDUSTRY
gen iindustryu=_b[industry]+1.96*(exp((_b[/lns1_1_12])))
gen iindustryl=_b[industry]-1.96*(exp((_b[/lns1_1_12])))

*GOVERNMENT
gen igovernmentu=_b[government]+1.96*(exp((_b[/lns1_1_13])))
gen igovernmentl=_b[government]-1.96*(exp((_b[/lns1_1_13])))

*INTERCEPT
gen iinteru=_b[_cons]+1.96*(exp((_b[/lns1_1_14])))
gen iinterl=_b[_cons]-1.96*(exp((_b[/lns1_1_14])))

*That is, 95% of the individual's random parameters are expected to lie in these intervals
sum ihoneyu ihoneyl itusu itusl icanau icanal igalu igall iwatu iwatl itcantau itcantal ithoneyu ithoneyl ittusu ittusl itcanau itcanal itgalu itgall itwatu itwatl iindustryu iindustryl igovernmentu igovernmentl iinteru iinterl


*END DO FILE
log close
```

APPENDIX C

C.1 Estimated Parameters for the Two-class Model

Table C-1. Latent Class Parameter Estimates for Two-Class Model

		Class 1	**Class 2**
		Fee Chasers	*Good Folks*
		Latent class membership probabilities (π)	
		6.19%	93.81%
Variable	Definition	Indicator-Response Probabilities (θ)	
FIRST	Participating for the first time in an experimental auction	0.98	0.69
RELATIVES	Relatives work at the university	0.29	0.27
HELPU	Signed up to support the educational institution	0.14	0.88
PAYMENT	Would have participated even without payment	0.22	0.58
FRUITS	Signed up because of interest in the auctioned products	0.23	0.54
RESIDENT	Permanent resident in the area	0.40	0.70
HELPRES	Signed up to help advance research efforts	0.09	1.00
FEE	Considers that all studies must include a participation fee	0.87	0.36
FULLTIME	Employed full time	0.11	0.29
POSTPONED	Postponed other activities to be able to participate	0.42	0.53
DEGREE	Earned a degree at the educational institution	0.20	0.29

C.2 Stata Code 3rd Essay

```
*--------------------------------------------
*DO FILE ANALYZE EXPERIMENTAL AUCTION DATA
*LCA / RANDOM EFFECTS TOBIT PER LATENT CLASS
*ALBA J. COLLART
*--------------------------------------------

*START DO FILE
log using output, text replace
set more off, permanently
clear

discard
//set trace on
drop _all

cd "C:\Users\acollart\Desktop\DISSERTATION\AUCTION\LCA\STATA\Results" /*CHANGE THIS
PATH TO MATCH THE FILE LOCATION ON YOUR MACHINE*/

use "C:\Users\acollart\Desktop\DISSERTATION\AUCTION\LCA\STATA\Results\LCA.dta"
/*CHANGE THIS PATH TO MATCH THE FILE LOCATION ON YOUR MACHINE*/

*------------------------
* Latent Class Analyses
*------------------------
*2 Classes
doLCA first relatives helpam payment fruits resident helpresearch fee fulltime postponed degree, ///
    nclass(2) ///
                        seed(861551) ///
                        categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        criterion(0.000001)  ///
                        rhoprior(1.0)

                        return list
* Class membership probabilities
matrix list r(gamma)
matrix list r(gammaSTD)
* Item-response probabilities
matrix list r(rho)
matrix list r(rhoSTD)
* Posterior probabilities
*matrix list r(post_prob)

*3 Classes
doLCA first relatives helpam payment fruits resident helpresearch fee fulltime postponed degree, ///
    nclass(3) ///
                        seed(861551) ///
                        categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        criterion(0.000001)  ///
```

```
                        rhoprior(1.0)

return list
* Class membership probabilities
matrix list r(gamma)
matrix list r(gammaSTD)
* Item-response probabilities
matrix list r(rho)
matrix list r(rhoSTD)
* Posterior probabilities
*matrix list r(post_prob)


*4 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree,
///
    *nclass(4) ///
                        *seed(861551) ///
                        *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        *criterion(0.000001)  ///
                        *rhoprior(1.0)


*5 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree,
///
    *nclass(5) ///
                        *seed(861551) ///
                        *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        *criterion(0.000001)  ///
                        *rhoprior(1.0)


*6 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree,
///
    *nclass(6) ///
                        *seed(861551) ///
                        *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        *criterion(0.000001)  ///
                        *rhoprior(1.0)


*7 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree,
///
    *nclass(7) ///
                        *seed(861551) ///
                        *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                        *criterion(0.000001)  ///
                        *rhoprior(1.0)
```

```
*8 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree, ///
    *nclass(8) ///
                *seed(861551) ///
                *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                *criterion(0.000001)  ///
                *rhoprior(1.0)


*9 Classes
*doLCA experience relatives helpam payment fruits resident helpresearch fee fulltime postponed degree, ///
    *nclass(9) ///
                *seed(861551) ///
                *categories(2 2 2 2 2 2 2 2 2 2 2)  ///
                *criterion(0.000001)  ///
                *rhoprior(1.0)

*Note: The posterior probabilities has been already pasted in the LCA.dta file.
*For the ecmtr models Class 1 in LCA results is Class 3 in the regressions. Class 2 is Class 1 and Class 3 is Class 2.
*-----------------
*Econometric models
*-----------------

*LEGEND
* rp=round.product

*round:              =1 tasting (between)
*                          =2 industry (within)
*                          =3 government (within)

*product:         =1 cantaloupe
*                          =2 honeydew
*                          =3 tuscan
*                          =4 canary
*                          =5 galia
*                          =6 watermelon

reshape long wtp, i(id) j(rp)

*-----------------------------------
*Variables manipulation
*-----------------------------------

*Generate indicators for product varieties

gen canta:1= rp==11|rp==21|rp==31
gen honey:1= rp==12|rp==22|rp==32
gen tus:1= rp==13|rp==23|rp==33
gen cana:1= rp==14|rp==24|rp==34
gen gal:1= rp==15|rp==25|rp==35
```

```
gen wat:1= rp==16|rp==26|rp==36

*Generate indicator for treatments, and interactions of tasting*product

gen tasting:1= (id<419)
gen industry:1= (20<rp) & (rp<27)
gen government:1= (30<rp) & (rp<37)

gen tcanta:1= (tasting==1) & (rp==11)
gen thoney:1= (tasting==1) & (rp==12)
gen ttus:1 = (tasting==1) & (rp==13)
gen tcana:1= (tasting==1) & (rp==14)
gen tgal:1= (tasting==1) & (rp==15)
gen twat:1 = (tasting==1) & (rp==16)


*Generate age: AGE1 is 18-29, AGE2 is 30-49, AGE3 is 50 or over

gen dage1=(age==1 | age==2) if!missing(age)
gen dage2=(age==3|age==4) if!missing(age)
gen dage3=(age==5|age==6|age==7) if!missing(age)


*Generate edu: EDU1 is high school diploma or less, EDU2 is some college-bachelor's degree, EDU3 is
some grad school or more

gen dedu1=(edu==1 | edu==2) if!missing(edu)
gen dedu2=(edu==3|edu==4|edu==5) if!missing(edu)
gen dedu3=(edu==6|edu==7) if!missing(edu)


*Generate income: INC0 is <30k, INC1 is 30K to <50k, INC2 is 50K to <100K, INC3 is 100K or more
gen dincd0=(income==1) if!missing(income)
gen dincd1=(income==2|income==3) if!missing(income)
gen dincd2=(income==4|income==5|income==6|income==7|income==8) if!missing(income)
gen dincd3=(income==9|income==10) if!missing(income)

**Generate income: INC1 is <30k, INC2 is 30K or more
gen dinc1=(income==1) if!missing(income)
gen
dinc2=(income==2|income==3|income==4|income==5|income==6|income==7|income==8|income==9|inc
ome==10) if!missing(income)

*Generate average income
gen avincome=0
replace avincome=14999.5 if income==1
replace avincome=34999.5 if income==2
replace avincome=44999.5 if income==3
replace avincome=54999.5 if income==4
replace avincome=64999.5 if income==5
replace avincome=74999.5 if income==6
replace avincome=84999.5 if income==7
replace avincome=94999.5 if income==8
```

```
replace avincome=124999.5 if income==9
replace avincome=150000 if income==10

gen navincome=avincome/1000

*Generate average value of weekly expenditures on fruits and vegetables: ASPENDFV

recode wfv (1=12) (2=37) (3=62) (4=87) (5=100), generate (aspendfv)


*Generate average percentage of fresh fruit on hand: APFOH

recode freshf (1=0) (2=12.5) (3=37) (4=62) (5=87.5), generate (apfoh)


*Generate average percentage of fresh vegetables on hand: APVOH

recode freshv (1=0) (2=12.5) (3=37) (4=62) (5=87.5), generate (apvoh)


*Generate paired sum of pounds of fresh fruit and vegetables on hand: FVPOH

gen fvoh=apfoh+apvoh

*-----------------------------------
*Summary statistics
*-----------------------------------
*Indicators, 1=yes 2=no
preserve

replace first=0 if first==2
replace relatives=0 if relatives==2
replace helpam=0 if helpam==2
replace payment=0 if payment==2
replace fruits=0 if fruits==2
replace resident=0 if resident==2
replace helpresearch=0 if helpresearch==2
replace fee=0 if fee==2
replace fulltime=0 if fulltime==2
replace curious=0 if curious==2
replace postponed=0 if postponed==2
replace degree=0 if degree==2

sum first relatives helpam payment fruits resident helpresearch fee fulltime
sum curious postponed degree

restore

*All Participants
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary

*For 2 classes
```

```
preserve
keep if c2s1==1
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary
restore

preserve
keep if c2s2==1
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary
restore


*For 3 classes
preserve
keep if c3s1==1
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary
restore

preserve
keep if c3s2==1
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary
restore

preserve
keep if c3s3==1
sum wtp dage1 dage2 dage3 dedu1 dedu2 dedu3 hhsize female married avincome dincd0 dincd1 dincd2
dincd3 highlast aspendfv fvoh primary
restore

*For highlast sessions
sum wtp if id<125 | 300<id & id<324 | 500<id & id<521 | 700<id & id<726
*For lowlast sessions
sum wtp if 200<id & id<219 | 400<id & id<419 | 600<id & id<619 | 800<id & id<827

*-----------------------------------
*Random Effects Tobit for All
*-----------------------------------
*Educational level removed in all models with demographics because of perfect collinearity with age in
class 3

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3
hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitdemo

*Marginal effects
*For the latent dependent variable
*mfx compute
*For the probability of being uncensored
```

```
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh,
ll(0) tobit
estimates store retobit

lrtest retobit retobitdemo, force stats
xtset, clear

*Mkt Penetration (on sale prices)
sum wtp if wtp>2.99
sum wtp if wtp==2.99
sum wtp if wtp<2.99
sum wtp if canta==1 & wtp>2.48
sum wtp if canta==1 & wtp==2.48
sum wtp if canta==1 & wtp<2.48
sum wtp if honey==1 & wtp>3.98
sum wtp if honey==1 & wtp==3.98
sum wtp if honey==1 & wtp<3.98
sum wtp if tus==1 & wtp>2.99
sum wtp if tus==1 & wtp==2.99
sum wtp if tus==1 & wtp<2.99
sum wtp if cana==1 & wtp>2.99
sum wtp if cana==1 & wtp==2.99
sum wtp if cana==1 & wtp<2.99
sum wtp if gal==1 & wtp>2.99
sum wtp if gal==1 & wtp==2.99
sum wtp if gal==1 & wtp<2.99
sum wtp if wat==1 & wtp>2.50
sum wtp if wat==1 & wtp==2.50
sum wtp if wat==1 & wtp<2.50

*-----------------------------------
*Random Effects Tobit for 2 classes
*-----------------------------------
*Class 1
preserve
keep if c2s1==1

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3
hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitc2s1demo

*Marginal effects
*For the latent dependent variable
*mfx compute
```

```
*For the probability of being uncensored
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
*mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh,
ll(0) tobit
estimates store retobitc2s1

lrtest retobitc2s1 retobitc2s1demo, force stats
xtset, clear

restore

*Class 2
preserve
keep if c2s2==1

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3
hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitc2s2demo

*Marginal effects
*For the latent dependent variable
*mfx compute
*For the probability of being uncensored
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
*mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh,
ll(0) tobit
estimates store retobitc2s2

lrtest retobitc2s2 retobitc2s2demo, force stats
xtset, clear

restore
```

```
*----------------------------------
*Random Effects Tobit for 3 classes
*----------------------------------
*Educational level removed in all models with demographics because of perfect collinearity with age in class 3

*Class 1
preserve
keep if c3s1==1

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3 hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitc3s1demo

*Marginal effects
*For the latent dependent variable
*mfx compute
*For the probability of being uncensored
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh, ll(0) tobit
estimates store retobitc3s1

lrtest retobitc3s1 retobitc3s1demo, force stats
xtset, clear

*Mkt Penetration (on sale prices)
sum wtp if wtp>2.99
sum wtp if wtp==2.99
sum wtp if wtp<2.99
sum wtp if canta==1 & wtp>2.48
sum wtp if canta==1 & wtp==2.48
sum wtp if canta==1 & wtp<2.48
sum wtp if honey==1 & wtp>3.98
sum wtp if honey==1 & wtp==3.98
sum wtp if honey==1 & wtp<3.98
sum wtp if tus==1 & wtp>2.99
sum wtp if tus==1 & wtp==2.99
sum wtp if tus==1 & wtp<2.99
sum wtp if cana==1 & wtp>2.99
sum wtp if cana==1 & wtp==2.99
sum wtp if cana==1 & wtp<2.99
sum wtp if gal==1 & wtp>2.99
sum wtp if gal==1 & wtp==2.99
sum wtp if gal==1 & wtp<2.99
```

```
sum wtp if wat==1 & wtp>2.50
sum wtp if wat==1 & wtp==2.50
sum wtp if wat==1 & wtp<2.50

restore

*Class 2
preserve
keep if c3s2==1

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3
hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitc3s2demo

*Marginal effects
*For the latent dependent variable
*mfx compute
*For the probability of being uncensored
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh,
ll(0) tobit
estimates store retobitc3s2

lrtest retobitc3s2 retobitc3s2demo, force stats
xtset, clear

*Mkt Penetration (on sale prices)
sum wtp if wtp>2.99
sum wtp if wtp==2.99
sum wtp if wtp<2.99
sum wtp if canta==1 & wtp>2.48
sum wtp if canta==1 & wtp==2.48
sum wtp if canta==1 & wtp<2.48
sum wtp if honey==1 & wtp>3.98
sum wtp if honey==1 & wtp==3.98
sum wtp if honey==1 & wtp<3.98
sum wtp if tus==1 & wtp>2.99
sum wtp if tus==1 & wtp==2.99
sum wtp if tus==1 & wtp<2.99
sum wtp if cana==1 & wtp>2.99
sum wtp if cana==1 & wtp==2.99
sum wtp if cana==1 & wtp<2.99
sum wtp if gal==1 & wtp>2.99
sum wtp if gal==1 & wtp==2.99
sum wtp if gal==1 & wtp<2.99
```

```
sum wtp if wat==1 & wtp>2.50
sum wtp if wat==1 & wtp==2.50
sum wtp if wat==1 & wtp<2.50

restore

*Class 3
preserve
keep if c3s3==1

*Demographics
xtset id
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government dage2 dage3
hhsize female married navincome aspendfv fvoh, ll(0) tobit
estimates store retobitc3s3demo

*Marginal effects
*For the latent dependent variable
*mfx compute
*For the probability of being uncensored
*mfx compute, predict (p(0,.))
*For the expected value of y conditional on being uncensored
*mfx compute, predict (e(0,.))
*For the unconditional expected value of y
mfx compute, predict (ys(0,.))

*No Demographics
xttobit wtp honey tus cana gal wat tcanta thoney ttus tcana tgal twat industry government aspendfv fvoh,
ll(0) tobit
estimates store retobitc3s3

lrtest retobitc3s3 retobitc3s3demo, force stats
xtset, clear

*Mkt Penetration (on sale prices)
sum wtp if wtp>2.99
sum wtp if wtp==2.99
sum wtp if wtp<2.99
sum wtp if canta==1 & wtp>2.48
sum wtp if canta==1 & wtp==2.48
sum wtp if canta==1 & wtp<2.48
sum wtp if honey==1 & wtp>3.98
sum wtp if honey==1 & wtp==3.98
sum wtp if honey==1 & wtp<3.98
sum wtp if tus==1 & wtp>2.99
sum wtp if tus==1 & wtp==2.99
sum wtp if tus==1 & wtp<2.99
sum wtp if cana==1 & wtp>2.99
sum wtp if cana==1 & wtp==2.99
sum wtp if cana==1 & wtp<2.99
sum wtp if gal==1 & wtp>2.99
sum wtp if gal==1 & wtp==2.99
sum wtp if gal==1 & wtp<2.99
```

```
sum wtp if wat==1 & wtp>2.50
sum wtp if wat==1 & wtp==2.50
sum wtp if wat==1 & wtp<2.50

restore

log close
```