Impact of Intra-respondent Variations in Attribute Attendance on Consumer Preference in Food Choice

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Abstract: This study compares different approaches of implementing attribute non-attendance (AN-A) statements in choice experiment questions. We examine the impact of intra-respondent variations in AN-A by comparing the consumers' willingness-to-pay (WTP) between different approaches. It is shown that over attendance counts appear to be a downward trend, which indicates a learning effect. Over half of the respondents changed their AN-A patterns during the whole experiment. The marginal WTP for attribute is much higher in model without consideration of AN-A statement than that with those statements considered. The marginal WTP estimates, however, are not significantly affected by the intra-respondent variations of attribute attendance on preference estimates.

Keywords: attribute non-attendance (AN-A), intra−respondent variations, WTP, choice experiment, food decision making.

Introduction

Choice experiments (CE) are used to model consumers' choices among alternative products and services (McFadden, 2001). When the consumer is asked to make one choice among a set of alternatives, he/she usually assesses the level of utility that each alternative offers and then chooses the alternative with the highest level of utility. Typically, the utility associated with an alternative is defined as a linear combination of its attributes, implying consumer choice behavior is a compensatory process. However, due to the limitations of cognitive capabilities, consumers usually instead employ simple heuristics to make the choice (Gigerenzer & Gaissmaier, 2011). Recent innovations in choice modelling advocate models based on a two-stage, consider-then-choose decision process (Hauser, 2014; Agarwal et al., 2015). Consumers first identify a subset of attributes for consideration, and then make utility-maximizing choices based on the attribute subset (Gilbride & Allenby, 2004). Empirical evidence provides support for the use of simple heuristics to select attributes for consideration (Payne, 1976; Olshavsky, 1979; Payne et al., 1988). Many of these simplified decision rules, or "heuristics" resulted in non-attendance to certain attributes (Scarpa et al., 2013). This phenomenon is commonly referred to as attribute non-attendance (AN-A) in choice modelling literature.

AN-A has been extensively investigated in different fields including transportation economics (Hensher et al., 2005; Hensher & Greene, 2010; Hess et al., 2013), health economics (Hole, 2011; Lagarde, 2013; Hole et al., 2013), environmental economics (Scarpa et al., 2009; Campbell et al., 2011; Kragt, 2013), and agricultural economics (Scarpa et al., 2013; Balcombe et al., 2015; Bello & Abdulai, 2016). One way to elicit AN-A uses a stated approach, which asks respondents follow-up questions to state which attributes they ignored or attended to (Hensher et al., 2005; Scarpa et al., 2010; Carlsson et al., 2010; Colombo et al., 2013; Alemu et al., 2013; Ortega & Ward, 2016). The questions can either be asked after the whole choice experiment or after each individual choice task. Respondents' answers are then used to assign a weight to attribute coefficients. Past research has shown that as respondents proceed through multiple choice tasks, his/her decision strategy may change, causing a variation in attendance to attributes. A key question is whether the intra-respondent variation of attribute attendance influences consumer preference estimates. This concern is not routinely explored by researchers engaged in choice experiments as past research either use all the stated AN-A measures after each choice task or use a single AN-A measure after all choice tasks.

In our recent choice experiment study, respondents were asked to complete 12 choice tasks and to state which attributes they paid attention to after the 3rd, 7th, and 12th

choice task. Therefore, there are several approaches to employ the AN-A statements: 1) use the first AN-A statement; 2) use the middle AN-A statement; 3) use the last AN-A statement; and 4) use the all three AN-A statements. This study contributes to the literature by comparing consumers' willingness-to-pay (WTP) between different approaches to examine the impact of intra-respondent variations in AN-A. Results of this study would help researchers determine when the AN-A questions should be asked within the sequence of choice tasks and how AN-A questions should be used in choice modeling. Moreover, our study would add more insights into information processing behavior when consumers make choices.

Literature Review

In the past, food products were typically viewed as homogeneous. With the popularity of food labeling as an integral part of companies' value-added processes, food markets now include information about appealing attributes on labels to differentiate their products. Although classic economic theory suggests that the provision of more information will help consumers make better decisions, sufficient information cues may not help consumers make informed choices (Bialkova et al., 2014). In fact, consumer behavior research points out that too much information may have a negative impact on consumer decision making (Scheibehenne et al., 2010; Branco et al., 2015), because the excessive amount of available information makes the decision even harder of a choice (Kiesel et al., 2011).

On this regard, previous decision-making studies have concluded that, if consumers are provided with too much information, their processing ability will become cognitively overloaded (Jacoby et al., 1974; Malhotra, 1982; Keller and Staelin, 1987). To avoid information overload, consumers usually resort to simple heuristics and selective use of information (Payne, 1976; Olshavsky, 1979; Payne et al., 1988), of which many simplified decision rules result in AN-A to certain attributes (Scarpa et al., 2013).

To address the issue of AN-A in the choice experiments, some studies employ self-reported statements on AN-A (Hensher 2006; Islam et al. 2007; Carlsson, Kataria, and Lampi 2010; Hensher and Rose 2009) which ask respondents follow-up questions to state the attributes they ignore; while others try to infer AN-A behavior from suitable statistical models based on panel data (Rigby and Burton, 2006; Scarpa et al. 2009; Balcombe, Burton and Rigby 2011; Scarpa et al., 2013). Previous studies, thus have compared and addressed the concordance between stated and inferred AN-A. Some studies (Scarpa et al., 2013) prefer inferential approaches mostly because of the lower cost and simplicity to employ. However, compared to the stated approach, the inferred approach, where the most common model used is the equality constrained latent class model (Hensher and Greene, 2010), has some limitations. First, it is difficult to capture all attribute processing strategies. In this model, different latent classes represent different attendance patterns. The number of classes grows exponentially with the number of attributes. Due to limited sample size, most studies need to pre-define some focus classes (Campbell et al., 2011; Lagarde, 2013; Kragt, 2013). Second, it does not account for preference heterogeneity. This model assumes homogeneity within a class but can vary between classes. Therefore, the inferred AN-A may be confounded with preference heterogeneity. Recent studies suggest that the equality constrained latent class model would overestimate AN-A (Hess et al., 2013; Hensher et al., 2013).

That being said though, stated attendance used in the present study is not perfect. Even though costs and the survey length are not major concerns as in this study, previous studied (Scarpa et al., 2013) point out that it suffers from being prone to procedural invariance (How is the question asked? How is it interpreted? How well can it represent the respondent?). Nevertheless, this study tries to investigate the intra-respondent variations in AN-A, the weakness of stated attendance on the contrary justify the approach we use and provide the variations needed. By using different approaches of employing AN-A measurements, the self-reported attendance along with the variations convey useful information about respondents' attribute processing strategies along the survey process (Hole et al., 2013).

Previously, information on AN-A is commonly collected by asking each respondent at the end of the sequence of choice tasks (Scarpa et al., 2010). Participants are asked to indicate the attributes which they have ignored in the whole sequence of choice tasks in their panel. This approach is usually named "serial AN-A" since it extends to all the choice tasks performed by the same individual. This approach has been questioned by numerous researchers such as Puckett and Hensher (2009) who point out that AN-A may vary from choice to choice as the participants progress in the panel. They have argued to allocate the AN-A question after each of the choice tasks, and this approach is termed "choice task AN-A". However, considering the huge additional cost and time investment on AN-A questions which are allocated after every single choice task, the worthy of such approach is reevaluated and cast doubt upon (Scarpa et al., 2010).

In this study, we combine two approaches and put forward an intermediate approach with several AN-A methods allocated in different places along the choice tasks. We hope to contribute the literature by providing insights on how the intra-respondent variations from different AN-A approach affect consumer preference, which has seldom studied in previous research.

Data

The data were collected from online survey panels that elicit consumer preferences for a 16 oz. box of fresh strawberries. The final questionnaire consisted of four sections: screening section, warm-up section, choice experiment section, and demographic section. The screening section identified primary grocery shoppers who were over 18 and had purchased fresh strawberries within the last month. Before the choice tasks, the warm-up section described the type of product, their major attributes, and the structure of the choice experiments. In the CE section, respondents were asked to complete 12 choice tasks. In each choice task, respondents were presented with labels on two boxes of strawberries and asked to select which box of strawberries they liked the most. If they were not satisfied with either, they could select the no-purchase option. Respondents were informed that all other aspects of the strawberries were assumed to be exactly the same except for the labels on the box.

The labels on the box described a combination of attributes and levels: retail price ($1.99/box, $2.99/box, $3.99/box, and $4.99/box), place of origin (California or Florida), USDA organic (Yes or No), and pesticide-residue-free (Yes or No). Except for the price attribute that was specified four levels, the other three attributes had only two levels. All attributes and levels, presented in Table 1, were identified from literature reviews and pilot surveys.

Table 1. Attributes and Levels in the Choice Experiment.

Attributes	Levels
Retail Price	1.99, 2.99, 3.99, 4.99 $/16 oz. box.
Place of Origin	California, Florida
USDA Organic	Yes, No
Pesticide Residue Free	Yes, No

The retail price used in our case was the amount of money that consumers paid for the 16 oz. box of strawberries in grocery stores. The four levels of pricing ($1.99/box, $2.99/box, $3.99/box, and $4.99/box) were specified based on prices prevailing at the major local grocery stores. The price range reflected both the low-end price that could be found in wholesale stores and the high-end price found in specialty food stores.

Place of origin (California or Florida) labeling informs consumers where food products are produced. Place of origin has been recognized as an important cue that may influence consumers' preferences (Umberger, 2010; USDA, 2015). Most of the strawberries in the United States are grown in either California or Florida. Although strawberry imports from Mexico have increased dramatically, previous studies suggest that American consumers prefer U.S.-grown produce to imported produce (Lim et al., 2013; Xie et al., 2016). Thus, we chose California and Florida to further investigate whether American consumers' preference for domestically produced fruits differ by state.

Organic produce (Yes or No) is grown using methods that preserve the environment and avoid most synthetic materials. In the United States, organic standards have been set forth by the National Organic Program since 2002 and only qualifying products can use the USDA organic claim. The organic claim was included in the design because such claims have been widespread on food packages and have been found to influence consumers purchasing decisions significantly (Hughner et al., 2007; Rödiger & Hamm, 2015). According to the Organic Trade Association, organic fruit and vegetable sales have risen by 10.5% to $14.4 billion in 2015, with nearly 13% of produce sold in the United States now organic. This attribute was represented by the presence or absence of the USDA organic claims.

Pesticide-residue-free (Yes or No) means that there are no detected pesticide residues above the limits of widely used testing methods. The pesticide-residue-free claim certified by some third-party institutions like SCS Global Services has begun to appear on produce sold in some grocery stores. In fact, organic produce is not always pesticide-residue-free because non-synthetic pesticides are allowed in organic farming. Although several studies have used experimental auctions to investigate the relationship between pesticide-free and organic claims (Bernard & Bernard, 2010; Bazoche et al., 2014), we included the pesticide-residue-free claim into our CE design to further compare consumers' valuation of organic and pesticide-residue-free claims. This attribute was represented by the presence or absence of the pesticide-residue-free claims.

Based on the selected attributes and levels, an 'optimal orthogonal in the differences' (OOD) design was adopted to generate 12 pairs of choice profiles. A no-purchase option was added in each choice set in case respondents were not satisfied with either profile. In each choice task, respondents were asked to select the box of strawberries they liked the most. If they were not satisfied with either, they could select the no-purchase option to opt out. After the 3rd, 7th, and 12th choice task, respondents were asked about attributes they paid attention to. They can select all the attributes which seemed important to them when making the choice. When respondents were answering choice questions, the online survey tool recorded the amount of time that respondents spent on each choice task[1]. At the end of the CE section, respondents rated the importance of various strawberry attributes using a 5-point Likert scale. At the end of the questionnaire, we collected information on socio-demographic characteristics.

In line with previous research (Vista et al., 2009; Bonsall & Lythgoe, 2009; Borger, 2015), response time per choice task is recorded by the online survey tool to ensure data quality and capture choice processes. Survey Sampling International, an online survey company, has delivered surveys to its representative consumer panels in June 2015. Following Gao et al. (2015) and John et al. (2015), this survey used a validation instrument to screen out mindless respondents who did not read the question carefully and randomly selected an answer. Following Bonsall and Lythgoe (2009), the top and bottom 5% of respondents were filtered out based on their average response time. Our final sample consists of 389 valid responses.

Table 2 reports the number of valid responses and socio-demographic characteristics for all four CE designs. Compared to the 2010-2014 American Community Survey, the age and the percentage of female respondents in our sample are modestly higher than those of the U.S. population respectively due to the restriction of recruiting

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[1] In line with previous research (Vista et al., 2009; Bonsall & Lythgoe, 2009; Borger, 2015), response time is recorded in this study to ensure data quality and capture choice processes.

primary grocery shoppers only. Similar to previous studies using online survey (Olsen, 2009; Lindhjem & Navrud, 2011; Gao et al., 2015), our sample has higher education and income levels than the national average.

Table 2. Summary Statistics for Survey Respondents.

	Sample	U.S. Census[a]
Age (Median)	45.0	37.4
Gender (%)		
Male	44.2	48.6
Female	55.8	51.4
Education (%)		
Less than high school	0.8	13.6
High school	17.7	28.0
Some college	29.3	21.2
Associate's degree	10.3	7.9
Bachelor's degree	26.5	18.3
Graduate or professional degree	15.4	11.0
Annual Household Income (%)		
Less than $14,999	6.9	12.5
$15,000~$24,999	9.6	10.7
$25,000~$34,999	13.4	10.2
$35,000~$49,999	14.0	13.5
$50,000~$74,999	21.9	17.8
$75,000~$99,999	14.3	12.2
$100,000~$149,999	13.2	13.0
$150,000~$199,999	4.9	5.0
$200,000 or more	1.9	5.0
No. of respondents	389	

Note: [a] Source: 2010-2014 American Community Survey, United States Census Bureau.

Method

Respondents were asked to select attributes they paid attention to after the 3rd, 7th, and 12th choice tasks during the CE section. Therefore, we are not only able to count how many attributes have been paying attention, but also able to observe which attributes have been taken into the consideration during the process. Because the attendance measurement was taken on the same respondent three times, there might be some difference among the three measurements due to learning and fatigue effects.

Let I_{iks} denote a binary response indicating whether a given attribute has been attended to ($I_{iks} = 1$) or not ($I_{iks} = 0$) for each respondent i, attribute k, and stage s where $s = 1, 2, 3$ represents the three measurements.

First, we can obtain the overall attendance counts ($CT_i = \sum_{k=1}^{K} I_{ik}$) and three-stage attendance counts ($CT_{is} = \sum_{k=1}^{K} I_{iks}$). We can use the three-stage attendance counts ($CT_{is}, s = 1, 2, 3$) to perform ANOVA tests to detect differences across stages.

Next, based on the stage attribute attendance measurement $I_{i1s}, I_{i2s}, \dots, I_{iKs}$, we can use Chi-square tests to examine variations of attendance patterns. Using the overall attribute attendance $I_{i1}, I_{i2}, \dots, I_{iK}$, overall attendance patterns can be categorized into three types: "complete search" in which a respondent pays attention to all attributes ($A_{is} = 2\ if\ \sum_{k=1}^{K} I_{iks} = K, \mathrm{s} = 1, 2, 3$ or $A_i = 2\ if\ \sum_{k=1}^{K} I_{ik} = K$), "selective search" in which a respondent pays attention to some attributes ($A_{is} = 1\ if\ 0 < \sum_{k=1}^{K} I_{iks} < K, s = 1, 2, 3$ or $A_i = 1\ if\ 0 < \sum_{k=1}^{K} I_{ik} < K$), and "no search" in which a respondent does not pay attention to any attribute ($A_{is} = 0\ if\ \sum_{k=1}^{K} I_{iks} = 0, \mathrm{s} = 1, 2, 3$ or $A_i = 0\ if\ \sum_{k=1}^{K} I_{ik} = 0$).

Discrete choice models are used in marketing research to model decision makers' choices among alternative products and services. When the choices being made are of an economic nature, discrete choice models are derived under the assumption of utility-maximizing behavior by decision makers. When decision makers are asked to make one choice among a set of alternatives, they usually assess the level of utility that each alternative offers and then choose the alternative with the highest level of utility. Within the random utility theory framework proposed by Nobel laureate Daniel McFadden (McFadden 2001), a consumer i is assumed to choose among J alternative products, with a number of attributes of differing levels, in choice scenario t to maximize his/her utility. The utility of consumer i from choosing alternative j in choice scenario t can be represented as:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, i = 1, \ldots, N, j = 1, \ldots, J, t = 1, \ldots, T$$

V_{ijt} is the systematic component of utility which relates observed factors to the utility, and ε_{ijt} is the stochastic component of utility which captures the unobserved factors that determine the utility. The stochastic component ε_{ijt} is often assumed to be independently identically distributed with the Gumbel distribution. Following Lancaster's (1966) approach that consumer utility associated with a product can be derived from the bundle of attributes, we model the systematic component V_{ijt} as a linear function of product attributes:

$$V_{ijt} = \beta_i' x_{ijt} = \beta_{iPRICE} PRICE_{ijt} + \sum_{k=1}^{K-1} \beta_{iNONPRICE}\, NONPRICE_{ijt}$$

β_i is a vector of unknown individual-specific coefficients and x_{ijt} is a vector of observed attributes of alternative j which include the price attribute and other non-price attributes. For the four CE, the systematic components V_{ijt} are specified as follows:

$$V_{ijt} = \beta_{iPRI} \times PRI_{ijt} + \beta_{iORI} \times ORI_{ijt} + \beta_{iORG} \times ORG_{ijt} + \beta_{iPES} \times PES_{ijt}$$

PRI represents the price of strawberries, ORI represents the dummy variable of the origin claim, ORG represents the dummy variable of the organic claim, PES represents the dummy variable of the pesticide-residue-free claim.

In most cases, not every individual has the same preference for each attribute. The heterogeneity in consumer preference can be accounted for by allowing certain coefficients to vary from one individual to another, which leads to the mixed logit model. In the mixed logit model (MXL), β_i is specified as a random vector following density function $f(\beta|\theta)$, where θ are the parameters of the distribution. We used repeated choice data, under the assumption of intra-respondent homogeneity, so that the probability of the observed sequence of choices for respondent is written as:

$$Prob_i = \int \prod_{t=1}^{T} \frac{e^{\beta' x_{ijt}}}{\sum_{j=1}^{J} e^{\beta' x_{ijt}}} f(\beta|\theta)\, d\beta$$

This choice probability is thus a weighted average of a product of logit formulas evaluated at different values of β, with the weights given by the density $f(\beta|\theta)$. Since this expression cannot be solved analytically, then it is approximated using simulation (Train, 2009). Therefore, the mixed logit model is estimated by maximizing the simulated log-likelihood function:

$$lnL = \sum_{i=1}^{N} ln\left\{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\frac{e^{\beta_{ir}' x_{ijt}}}{\sum_{j=1}^{J} e^{\beta_{ir}' x_{ijt}}}\right\}$$

R is the number of replications and β_{ir} is the r-th draw from $f(\beta|\theta)$. The individual-level coefficients can be obtained as follows using Bayes' rule:

$$\widehat{\beta_\imath} = \frac{\frac{1}{R}\sum_{r=1}^{R}\hat{\beta}_{ir}\prod_{t=1}^{T}\frac{e^{\widehat{\beta}_{ir}' x_{ijt}}}{\sum_{j=1}^{J} e^{\widehat{\beta}_{ir}' x_{ijt}}}}{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\frac{e^{\widehat{\beta}_{ir}' x_{ijt}}}{\sum_{j=1}^{J} e^{\widehat{\beta}_{ir}' x_{ijt}}}}$$

Based on the individual-level estimates of β_i, each consumer's willingness-to-pay (WTP) for a non-price attribute can be calculated as the negative ratio of the attribute coefficient to the price coefficient (Hensher et al., 2006):

$$WTP_{iNONPRICE} = -\frac{\hat{\beta}_{iNONPRICE}}{\hat{\beta}_{iPRICE}}$$

The information obtained from attendance questions can be used to condition the coefficient estimates in order to account for attribute non-attendance (AN-A).

It has been conventional to set the coefficients of ignored attributes to zero (Hensher et al., 2005; Scarpa et al., 2010; Colombo et al., 2013; Alemu et al., 2013; Ortega and Ward, 2016). Some studies have suggested that stated AN-A may indicate lower sensitivity and the corresponding attribute coefficients should be reduced by means of either covariates or scaling factors (Hess & Hensher, 2010; Kehlbacher et al., 2013; Chalak et al., 2016). However, it remains an open question as to how stated AN-A should be incorporated in discrete choice models. We follow the standard approach by restricting the corresponding attribute coefficients to zero in the linear utility function. Since we already know the overall attribute attendance $I_{i1}, I_{i2}, \dots, I_{iK}$, then the systematic component V_{ijt} is modeled as:

$$V_{ijt} = (\beta_{iPRICE} I_{iPRICE}) PRICE_{ijt} + \sum_{k=1}^{K-1} (\beta_{iNONPRICE} I_{iNONPRICE})\, NONPRICE_{ijt}$$

This approach to model attribute attendance allows for the possibility of a different utility function for every respondent. It can readily be implemented in the NLOGIT software by coding the ignored attributes to -888 for each respondent. With this data convention, the program will restrict the corresponding attribute coefficients to zero automatically.

Finally, the mixed logit model is estimated using Halton draws with 500 simulations. The coefficients of non-price attributes are assumed to be normally distributed. Economic theory suggests that the price coefficient should be strictly negative. Therefore, we specified the price coefficient to be log-normally distributed which implies it is positive. The negative price coefficient can be accommodated by entering the price variable multiplied by -1 in the estimation. Note that the estimated price parameters are the mean (m) and standard deviation (s) of the natural logarithm of the coefficient of the negative price variable ($ln\, \beta_{-PRICE}$). The corresponding mean and standard deviation of the price coefficient is given by $exp(m + s^2/2)$ and $\sqrt{(exp(s^2) - 1) exp(2m + s^2)}$ (Hole, 2007). Because respondents ignore certain attributes, we should be cautious about two exceptions when calculating the WTP:

First, if $\hat{\beta}_{iNONPRICE} = 0$ implying that the non-price attribute is ignored, then we set $WTP_{iNONPRICE} = 0$ because this attribute plays no role in a respondent's utility;

Second, if $\hat{\beta}_{iPRICE} = 0$ implying that the price attribute is ignored, then we set $WTP_{iNONPRICE} = null$ due to lack of trade-offs between price and other attributes.

The information obtained from attendance questions can be used to condition the coefficient estimates in order to account for AN-A in choice modeling. It has been conventional to set the coefficients of ignored attributes to zero (Hensher et al., 2005; Scarpa et al., 2010; Colombo et al., 2013; Alemu et al., 2013; Ortega and Ward, 2016). This approach to model attribute attendance allows for the possibility of a different utility function for every respondent. Due to the three-stage attribute attendance measurements, we can fit a series of mixed logit models to account for AN-A: 1) MXL1 using the first AN-A statement; 2) MXL2 using the middle AN-A statement; 3) MXL3 using the last AN-A statement; 4) MXLALL using the all three AN-A statements. Finally, we can compare WTP derived from the above models to evaluate the influence of intra-respondent variations of attribute attendance.

Results

Attendance Count

For the attendance counts, Table 3 summarizes the descriptive statistics of attendance counts. Generally, the total attendance counts appear a downward trend, which is indicative of a learning effect. The original response time for each choice task is demonstrated in Table in the Appendix.

Table 3. Descriptive Statistics of Attendance Counts.

N	Variable	Mean	Ratio[a]	Median	SD	Min	Max
389	Attendance1	2.43	0.61	2.00	1.10	0.00	4.00
	Attendance2	2.31	0.58	2.00	1.13	0.00	4.00
	Attendance3	2.32	0.58	2.00	1.14	1.00	4.00
	Attendancet	2.37	0.59	2.00	1.15	0.00	4.00

Note: [a] denotes the ratio to the number of attended attributes to the number of available attributes in CEs. The ratios shown in the table are average of individual ratios.

Attendance Pattern

For the attendance patterns across the survey, Table 4 demonstrates overall attribute attendance and overall attendance pattern. Previous literature (Payne et al., 1993) has further classify the attendance patterns into three types: “complete search” (attending to all attributes), “selective search” (attending to some attributes), and “no search” (not attending to any attributes). As it is shown in Table 4, only a very small amount of respondents (1.03%) claimed did not focus on any attributes. Over one-fifth (23.14%) of respondents claimed that they paid attention to all the four attributes. To rank the frequency of attendance of each attribute in a descending order, price attracted most attendance (287), followed by pesticide-free (254), organic (199), and origin (183).

Table 4. Overall Attribute Attendance and Overall Attendance Pattern

AN-A Pattern	Price	Origin	Organic	Pesticide-free	Row Freq.	Row Pct. (%)
0000	0	0	0	0	4	1.03
0001	0	0	0	1	37	9.51
0010	0	0	1	0	8	2.06
0011	0	0	1	1	22	5.66
0100	0	1	0	0	6	1.54
0101	0	1	0	1	4	1.03
0110	0	1	1	0	1	0.26
0111	0	1	1	1	20	5.14
1000	1	0	0	0	58	14.91
1001	1	0	0	1	31	7.97

1010	1	0	1	0	11	2.83
1011	1	0	1	1	35	9.00
1100	1	1	0	0	35	9.00
1101	1	1	0	1	15	3.86
1110	1	1	1	0	12	3.08
1111	1	1	1	1	90	23.14
Col Freq.	287	183	199	254	N=389	
Col Pct. (%)	73.78	47.04	51.16	65.30		

Note: "1" means that such an attribute is taken into account and "0" means that it is not taken into account. "Row Freq (or Pct)" refers to the number (or the percentage) of respondents representing certain specific attendance pattern. "Col Freq (or Pct)" refers to the total number (or the percentage) of respondents who pay attention to certain attribute.

Willingness-to-Pay

Estimation results of the conditional logit model and mixed logit model (MXL) with and without accounting for attribute attendance are reported in Table 5. The MXL1 model stands for using the first AN-A statement (after 3rd); MXL2 using the second AN-A statement (after 7th); MXL3 using the third AN-A statement (after 12th); MXLALL using all the three AN-A statements. Note that the standard deviation estimates of all variables are highly significant, implying that there is considerable preference heterogeneity across respondents. We observe no statistical significant changes when moving from a MXL1 through a MXL2, MXL3, MXLALL model. Generally, the coefficients of origin claims are negatively significant across the four approaches, implying that consumers had preference for California-grown strawberries to Florida-grown ones. In terms of signs, the coefficients of organic claims and pesticide-residue-free claim are positive. This suggests that consumers preferred strawberries with an organic claim and a pesticide-residue-free claim. It is worth noting that the coefficient of the 'None' variable is negative and significant, which implies that respondents tended to choose any strawberry as opposed to the no-purchase option.

Table 5. Utility Function Parameter Estimates.

	CL		MXL1				MXL2			
Varibale			Mean		St. Dev		Mean		St. Dev	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Price	-0.743***	0.027	-1.267 [a]		0.957 [a]		-1.436 [a]		1.316 [a]	
ln(-Price)			0.011	0.054	0.671***	0.043	0.057	0.058	0.781***	0.049
Origin	-0.139***	0.038	-0.290***	0.106	1.037***	0.091	-0.438***	0.130	1.177***	0.116
Organic	0.625***	0.044	0.699***	0.137	1.466***	0.117	0.809***	0.155	1.834***	0.085
Pesticide-Free	1.258***	0.046	2.307***	0.147	1.908***	0.178	2.312***	0.162	2.157***	0.148
None	-1.027***	0.109	-3.817***	0.061			-3.920***	0.063		
Log-likelihood	-3879.97		-3088.67				-3071.84			
No. of Obs	4668		4668				4668			
No. of Res	389		389				389			
			MXL3				MXLALL			
Varibale			Mean		St. Dev		Mean		St. Dev	
			Coef	SE	Coef	SE	Coef	SE	Coef	SE
Price			-1.289 [a]		1.057 [a]		-1.229 [a]		0.980 [a]	
ln(-Price)			-0.003	0.054	0.717***	0.041	-0.040		0.702***	0.042
Origin			-0.276***	0.125	1.266***	0.077	-0.269**		1.325***	0.097
Organic			1.032***	0.147	1.533***	0.138	0.869***		1.641***	0.105
Pesticide-Free			2.210***	0.156	2.256***	0.210	2.005***		2.112***	0.148
None			-3.769***				-3.966***			

Log-likelihood			-3089.70				-3110.09			
No. of Obs			4668				4668			
No. of Res			389				389			

Note: "CL" refers to the conditional logit models, "MXL1" refers to the mixed logit models using the first attribute attendance (after 3rd), "MXL2" refers to the mixed logit models using the second attribute attendance (after 7th), "MXL3" refers to the mixed logit models using the third attribute attendance (after 12th),and "MXLALL" refers to the mixed logit models using all the three attribute attendances; Asterisks *, **, and *** denote variables significant at the 10%, 5%, and 1% levels, respectively; [a] indicates the values are derived from the mean (m) and standard deviation (s) of $ln\,\beta_{-price}$.

Willingness-to-pay (WTP) provides a more convenient consumer preference measurement for various attributes. Based on the individual-level parameter estimates in the mixed logit model, the calculated marginal WTP is presented in Table 6. We find that almost all WTP estimates are attenuated when accounting for attribute attendance. The marginal WTPs show the same trend in both conditional logit and mixed logit models, although the magnitude varies. In general, when no attendance attribute counts are taken into the model, the CL model would provide with larger marginal WTP estimates for all the attributes. Among the three, pesticide-free has the highest marginal WTP, meaning that the surveyed consumers were willing to pay more premium for pesticide-residue-free claims than organic claims or origin claims. Notice that both origin has a decreasing magnitude when using the AN-A measurements in the later part of the process, meaning that respondents graduately become less sensitive to the origin between California and Florida when near the end of the choice tasks. Organic and pesticide-free do not follow such trend and the employment of AN-A measurements decrease the respondents marginal WTP for each attribute significantly.

Table 6. Willingness-to-pay Estimates.

WTP for	CL	MXL1	MXL2
Origin	-0.37*	-0.12*	-0.12*
	[-0.44, -0.30]	[-0.20, -0.04]	[-0.22, -0.02]
Organic	0.87**	0.66*	0.60*
	[0.77, 0.97]	[0.50, 0.83]	[0.43, 0.76]
Pesticide-free	2.00*	1.20*	1.23*
	[1.80, 2.20]	[1.00, 1.41]	[1.00, 1.45]
		MXL3	MXLALL
Origin		-0.07	-0.10*
		[-0.16, 0.02]	[-0.20, -0.00]

Organic	0.63*	0.58*
	[0.47, 0.79]	[0.42, 0.74]
Pesticide-free	1.19*	1.16*
	[1.00, 1.39]	[0.96, 1.35]

Note: "CL" denotes the WTP estimates from the conditional logit models using Delta methods, "MXL1" refers to the mixed logit models using the first attribute attendance (after 3rd), "MXL2" refers to the mixed logit models using the second attribute attendance (after 7th), "MXL3" refers to the mixed logit models using the third attribute attendance (after 12th),and "MXLALL" refers to the mixed logit models using all the three attribute attendances. Numbers in the square brackets are 95% confidence interval of the WTP estimates; Asterisks * indicates the mean WTP estimate is significantly different from zero.

Conclusions

This study compares different approaches of implementing attribute non-attendance (AN-A) statements in the context of choice experiment. The overall attendance counts response time both indicate a learning effect along the choice tasks. Among the attributes, price and pesticide-free are the two attributes receive most attendance. When AN-A statements are not taken into the regression of conditional logit model, we find the marginal WTP is about 3.7 times, 1.5 times, 1.7 times that in the mixed logit model with AN-A statement, for origin, organic, and pesticide-free respectively. Among the four cases in the study when we take AN-A allocated in different positions of the survey, there seems not a significant effect on the marginal WTP for each attribute as well as the utility function parameters. Future research would try to improve by putting more attention in the middle statement as we postulate the learning effect is the main role in the first part, while the heuristic generally become more significant as people wish to finish the survey at a quicker pace.

In terms of implications for welfare estimates from the structural models of choice, we note that estimates from constrained latent classes addressing non-attendance provide lower marginal WTP values than multinomial logit models. The difference is found to be stronger in data without incentives for truthful revelation, as one would expect because of the lower motivation that respondents have to attend to price in these choice contexts. We conclude that marginal WTP estimation robust to and accounting for attribute non-attendance is likely to produce lower marginal WTP estimates for product attributes. Ignoring this form of choice heuristic would therefore appear to lead to over-estimates of welfare changes. This result not only makes intuitive sense, but also echoes previous results based on similar approaches published in the literature of non-market valuation of public goods.

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Appendix

Table. Descriptive Statistics of Original Response Time.

N	Variable	Mean	Median	SD	Min	Max
	Time1	10.00	8.17	6.96	2.14	70.22
	Time2	7.99	6.45	6.58	2.01	87.51
	Time3	9.35	7.77	8.07	1.66	94.40
	Time4	7.93	6.78	5.16	2.03	52.32
	Time5	7.73	6.30	5.15	2.14	39.37
	Time6	7.23	6.30	4.71	1.83	49.29
389	Time7	6.55	5.53	4.51	2.04	40.78
	Time8	7.84	6.77	6.33	1.96	101.72
	Time9	5.93	4.82	4.66	1.82	49.49
	Time10	5.62	4.56	4.29	1.59	54.25
	Time11	6.45	5.11	5.15	1.72	63.90
	Time12	6.03	4.87	4.69	1.50	49.45
	Mean Time	7.39	6.94	2.92	3.21	16.29

Response time for each CE appears to be a downward trend, which is indicative of a learning effect: as respondents progress through choice tasks, they may discover their preference, evaluate the importance of attributes, and invoke heuristics to complete the survey as quickly as possible (Czajkowski et al., 2014).