ATTRIBUTE NON-ATTENDANCE IN FOOD CHOICE EXPERIMENTS UNDER VARYING INFORMATION LOAD

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ABSTRACT:

It is increasingly recognized that respondents use simple heuristics such as attribute non-attendance to make decisions in the discrete choice experiments. This paper use the latent class model to investigate different choice strategies and explore robust welfare estimates under varying attribute information load. We find that respondents are more likely to rely on simple heuristics to make choices when information load increases. Reinforcing previous findings, we also observe that willingness-to-pay estimates decrease, with and without accounting for attribute non-attendance.

KEYWORDS:

Discrete Choice experiments, Attribute Non-Attendance, Latent Class Model, Simple Heuristics, Willingness-to-pay

1. INTRODUCTION

Discrete Choice experiments (DCE) are widely used to elicit consumer valuation in different fields. A basic assumption of the DCE is the 'continuity axiom'. It assumes that respondents base their choice on all attributes presented in a choice set, trading off gains in one attribute for losses in another. However, recent empirical evidence on DCE has recognized that respondents use some information processing strategies to make their choice (Ryan et al., 2009; Hensher and Greene, 2010).

One of these strategies is to ignore one or more attributes which is referred to as attribute non-attendance (ANA). Many studies have found evidence of ANA in several fields including transport economics (Hensher et al., 2005, 2013; Hensher, 2006; Hess et al., 2013), environmental economics (Scarpa et al., 2009; Carlsson et al., 2010; Alemu et al., 2013) and health economics (Hole, 2011; Lagarde, 2013; Hole et al., 2013). ANA implies that respondents base their choice on a subset of attributes, violating the ‘continuity axiom'. Failure to account for ANA may lead to biased welfare estimates and poor model performance.

Overall, two approaches to detect ANA have been suggested in the literature: stated non-attendance (Stated ANA) and inferred non-attendance (Inferred ANA). The Stated ANA approach identifies ANA through supplementary questions. In contrast, the Inferred ANA approach infers ANA with the use of econometric models. Recently, several studies have found a discrepancy between Stated and Inferred ANA approaches and the Inferred ANA approach better matches the data. (Scarpa et al., 2013; Kragt, 2013). It suggests that respondents may misreport their attendance in the Stated ANA approach. The model used in the Inferred ANA has typically been a form of latent class model (LCM), where the classes represent different ANA patterns.

Although there is clear evidence of ANA, there is still limited knowledge about the underlying behavioral mechanisms. The attention allocation theory has been proposed to explain its occurrence (Cameron and DeShazo, 2010). Suppose that cognitive resources are scarce, respondents have to compare the expected marginal benefit and marginal cost of attention and optimize their allocation of attention. As a result, they may rationally attend to a subset of attributes. This theory assumes that the marginal cost of attention is increasing in the number of attributes, which implies that the larger the number of attributes, the more likely ANA occurs.

A key question about decision making is how people use a wealth of information. Recent research on decision making suggests that people make their choice based on simple heuristics, which limit search to only a few important pieces of information. (Scheibehenne et al., 2007; Gigerenzer and Gaissmaier, 2011; Schulte-Mecklenbeck et al., 2013). Considering that people make everyday food choices under conditions of limited time and cognitive resources, we thus hypothesize that:

H1: Complete Search (Full Attendance) are used less often than Limited Search (Non-attendance) to make a choice;

H2: The increasing attribute information load (Number of attributes) leads to lower likelihood of Complete Search (Full Attendance).

In term of welfare estimates, previous research used the Random Parameter Logit Model (RPL) to estimate marginal effects of additional attribute information on consumer willingness-to-pay (WTP). Results show that WTP estimates decrease when the number of attributes increases from three to four without accounting for ANA (Gao and Schroeder, 2009). In this paper, we also expect that:

H3: With accounting for ANA, the WTP estimates decrease when the number of attributes increases from three to four.

To test our hypothesis, we use the LCM model to investigate different choice strategies under varying attribute information load and explore the impact of additional attribute information on welfare estimates taking ANA into account. Our results provide support to the above hypotheses. Therefore, this paper not only contributes to enhance the understanding of simple heuristics in the context of DCE, but also help to improve the robustness of welfare estimates from DCE.

The remainder of this paper is structured as follows: Section 2 explains the latent class model; Section 3 describes the survey design and introduces the data; Section 4 presents the results; Section 5 offers concluding remarks.

2. MODLE

We assume that individual i makes the choice among J alternatives at choice occasion t. Each choice can be viewed as a two-stage process. In the first stage, the individual decides which attributes to take into consideration. To be more specific, the individual is assumed to choose a subset from K attributes. So the total number of subsets, or classes, is given by 2^K. The classes represent different ANA patterns, which are not revealed to the analyst. In the second stage, the individual make the choice to maximize his/her utility conditional on the choice of attribute subset in the first stage.

Following the Random Utility Model (RUM), the utility of individual i for alternative j at choice occasion t given that individual i is in class c can be written as:

$$U_{jit|c} = \beta_c' X_{jit} + \varepsilon_{jit}$$

Where β_c is a vector of class specific parameters and X_{jit} is a union of all attributes. If some attributes are ignored, then the corresponding coefficients are set to zero.

Within the class, the choice probability is assumed to be generated by the Multinomial Logit Model (MNL):

$$P_{it|c}(j) = Prob[y_{it} = j | class = c] = \frac{exp(\beta_c' X_{jit})}{\sum_j exp(\beta_c' X_{jit})}$$

So the conditional joint probability of the sequence of choices is:

$$P_{i|c} = \prod_t P_{it|c}$$

Since the classes are not observed, then the prior class probabilities can be assumed to take the MNL form:

$$\pi_{ic} = Prob[\text{class} = \text{c}] = \frac{exp(\theta_c' Z_i)}{\sum_c \exp(\theta_c' Z_i)}, \theta_C = 0$$

Where Z_i is an optional set of invariant individual-specific characteristics. In our case, the prior class are a set of fixed constants since such individual-specific characteristics are not specified.

For a given individual, the unconditional joint probability of the sequence of choices is:

$$P_i = Prob[y_{it} = \text{j}] = \sum\nolimits_c \pi_{ic} P_{i|c}$$

The model is estimated by maximizing the log-likelihood function:

$$lnL = \sum\nolimits_i ln\, P_i$$

Using Bayes theorem, we can obtain an individual specific posterior estimate of class probabilities:

$$\hat{\pi}_{c|i} = Prob(class = c|choice) = \frac{\hat{P}_{i|c}\hat{\pi}_{ic}}{\sum_c \hat{P}_{i|c}\hat{\pi}_{ic}}$$

We can also obtain an individual specific posterior estimate of the parameter vectors;

$$\hat{\beta}_i = \sum\nolimits_c \hat{\pi}_{c|i}\hat{\beta}_c$$

3. DATA

The data are drawn from online DCE surveys to elicit consumer preferences for beef steak characteristics. All attributes and levels, presented in Table 1, were identified from literature reviews and pilot surveys. Two sets of attributes were used compose alternatives in choice sets. The first set of attributes (Set C) included *Price*, *COOL*, *Tender*, and *Lean*. The second set of attributes (Set W) included *Price*, *Tender*, *Lean*, and *Freshness.* To test the effect of additional attribute information on ANA, two types of DCE with three and four attributes were constructed.

Table 1. Attributes and Levels in the DCE

Attributes	Levels
Price per 12-ounce steak (Price)	4.64, 6.93, 9.22, 11.50 $/lb.
Certified U.S. Product (COOL)	Yes, No
Guaranteed Tender (Tender)	Yes, No
Guaranteed Lean (Lean)	Yes, No
Days before Sell-by Date (Freshness)	8, 2 days

We took two steps to design each DCE. In the first step, we used D-optimal design to generate eight original profiles (with D-efficiency of 100%) and denoted these profiles as Option A. In the second step, the originally generated profiles were randomly ordered to generate Option B. A ‘None’ option was also added in each choice set in case that respondents were not satisfied with either Option A or B. So each DCE consisted of eight choice sets and each choice set had three alternatives: Option A, Option B, or Neither A nor B. This design was applied to both sets of attributes. Thus, we constructed a total of four DCE. For convenience, we denotes them DCE C3, C4, W3 and W4. Finally, a group of respondents was randomly selected to take the survey including C3 and C4 (Survey C34). Another group of respondents took the survey including W3 and W4 (Survey W34). Questions regarding respondent demographic characteristics were placed between the two DCE in each survey to reduce order effect. The outline of surveys are presented in Table 2 and more details of the survey design are in Gao and Schroeder (2009).

Table 2. Outline of Surveys

	Survey C34		Survey W34	
DCE	C3	C4	W3	W4
Price	√	√	√	√
COOL	√	√		
Tender	√	√	√	√
Lean		√	√	√
Freshness				√

The surveys were distributed to faculty members, staff, and graduate students at Kansas State University through surveymonkey.com. We collected 211 completions of Survey C34 and 198 completions of Survey W34. With each respondent answering eight choice tasks, Survey C34 resulted in 1688 observations and Survey W34 resulted in 1584 observations for model estimation. Table 3 reports summary statistics of demographics for the two surveys.

Table 3. Summary Statistics of Respondent Demographics by Survey

	Survey C34	Survey W34
Age	41.30	40.28
	(13.62)	(13.06)
Income	5.20	5.25
	(2.50)	(2.48)
No. of adults	1.91	1.88
	(0.78)	(0.76)
No. of children	0.52	0.59
	(0.91)	(0.96)
Gender		
Male	63%	58%
Female	37%	42%
Education		
1st through 8th grade	0%	0%
Some high school graduate	6%	8%
Some college/two year associate's degree	0%	0%
Four-year college degree	14%	15%
Master's or PhD degree	80%	77%
Marriage		
Single	28%	28%
Married	67%	70%
Other	5%	2%
Employment		
Full time	67%	72%
Part time	8%	5%
Unemployed	0%	0%
Student	22%	23%
Retired	3%	0%
No. of respondents	211	198

Note: Income: 1=under $10,000; 2=$10,000 to $24,999…13=$300,000 to $399,999; 14=$400,000 and more. Reported statistics of age, income, no. of adults, and no. of children are mean values. Numbers in parentheses are standard deviations.

Reported statistics of gender, education, marriage, and employment are frequency of the variable levels among respondents.

4. RESULT

For the DCE in Survey C34 and C45, four MNL and LCM were respectively estimated using NLOGIT 5 (Econometric Software, 2012), resulting in a total of eight models. Table 4 reports the coefficient estimates and model fit statistics. The LCM model, with a lower log-likelihood, AIC and higher prediction rate, is significantly better than the corresponding MNL model. With respect to coefficient estimates, both the LCM and MNL models give similar results in terms of the sign and significance. The negative price coefficients indicated downward sloping price-demand relationships. All other beef attributes were positive, indicating an increasing likelihood of respondents choosing alternatives processing those attributes. It is worth noting that the coefficients from LCM and MNL differ since each model is subject to a different scaling (Campbell et al., 2011).

Table 4. Coefficient Estimates and Model Fit Statistics for Surveys

	Survey C34				Survey W34			
	C3		C4		W3		W4	
Coefficient	MNL	LCM	MNL	LCM	MNL	LCM	MNL	LCM
Price	-0.17 (0.00)	-0.53 (0.00)	-0.20 (0.00)	-0.53 (0.00)	-0.20 (0.00)	-0.52 (0.00)	-0.27 (0.00)	-0.50 (0.00)
COOL	1.37 (0.00)	4.48 (0.00)	1.15 (0.00)	3.76 (0.00)				
Tender	0.88 (0.00)	3.05 (0.00)	1.02 (0.00)	3.67 (0.00)	1.30 (0.00)	4.00 (0.00)	1.28 (0.00)	2.53 (0.00)
Lean			0.65 (0.00)	3.45 (0.00)	0.77 (0.00)	3.07 (0.00)	0.95 (0.00)	1.54 (0.00)
Freshness							0.08 (0.00)	0.33 (0.00)
Log likelihood	-1853	-1345	-1572	-1324	-1501	-1294	-1394	-1245
AIC	3247	2711	3153	2686	3008	2609	2795	2529
Correctly predicted	55%	92%	60%	92%	50 %	92%	62%	84%

Note: Numbers in parentheses are p-values.

Appendix describes the various ANA patterns and estimated class probabilities. According to the literature on decision making (Payne et al., 1993), different ANA patterns can be classified into four types of information processing strategies, as are presented in Table 5.

Weighted Additive (attending to all attributes): Within each alternative, multiply each attribute with its subjective weight. Add up these weighted attribute values. Choose the alternative with the highest sum.

Frugal Weighted (attending to some attributes): Within each alternative, focus on the set of important attributes, multiply each attribute with its subjective weight. Add up these weighted attribute values. Choose the alternative with the highest sum.

Lexicographic Choice (attending to one attribute): Choose the alternative with the most preferable value on the most important attribute.

Random Choice (not attending to any attribute): Do not look up any attribute, but choose randomly.

Table 5. Categorization Results for the Use of Choice Strategies in Percent

	Survey C34			Survey W34		
Strategy	C3	C4	Difference	W3	W4	Difference
Weighted Additive	19%	0%	-19%	18%	16%	-3%
Frugal Additive	36%	61%	25%	42%	54%	12%
Lexicographic Choice	24%	25%	1%	15%	23%	8%
Random Choice	21%	14%	-7%	25%	7%	-17%

The LCM models show that just less than 20% of respondents used the Weighted Additive strategy while more than 55% of them instead adopted the Frugal Weighted or Lexicographic Choice strategy, which is in support of H1. When the number of attributes rose from three to four, the proportion of respondents who used the Weighted Additive strategy decreased while the percentage of them who adopted the Frugal Weighted or Lexicographic Choice strategy increased. In a comparison of DCE C3 and C4, the proportion of respondents who looked at all attributes dropped from 18% under low information load to 0% under high information load. However, the percentage of them who attended to one or a few attributes increased by 26%. The comparison of DCE W3 and W4 demonstrates similar pattern regarding information processing strategies in that when the number of attributes increased, less people used the Weighted Additive strategy while more people used the Frugal Additive or Lexicographic strategy. Therefore, people are more likely to rely on simple heuristics to make choices when information load increases, which provides support to H2. It should be noted that the proportion of respondents who chose randomly declined which implies that they noticed the additional attribute.

To measure the impact of additional attribute information on respondents' valuation of attributes, we take simple heuristics into account to estimate their WTP. The WTP estimate for a non-price attribute can be calculated:

$$WTP = -\beta_{np}/\beta_p$$

Where β_{np} and β_p are respectively coefficient of the non-price and price attribute.

To account for ANA, we need to pay attention to two issues: First, if $\beta_{np} = 0$ which means the non-price attribute is ignored, then we set WTP $= 0$ since this attribute seems to play no role in respondents' utilities. Second, if $\beta_p = 0$ which means the price attribute is ignored, then we have to exclude these respondents since WTP will go to infinity. Results in Table 6 show that comparing to the WTP estimates obtained from MNL, the WTP estimates from LCM were smaller when ANA was accounted for. It is more striking to notice that WTP estimates indeed decreased when the number of attributes increased from three to four, which is consistent with previous findings without accounting for ANA.

Table 6. WTP Estimates for Surveys

	Survey C34				Survey W34			
	C3		C4		W3		W4	
WTP	MNL	LCM	MNL	LCM	MNL	LCM	MNL	LCM
COOL	7.81	6.09	5.62	4.58				
Tender	5.03	2.56	4.99	2.40	6.40	5.47	4.66	4.58
Lean			3.20	1.30	3.79	2.44	3.48	2.37
Freshness							0.31	0.19

Note: WTP values are dollars for a 12-ounce beef steak ($/lb).

5. CONCLUSION

A growing DCE literature have highlighted the phenomenon of respondents using different information processing strategies including ANA. In this paper, we use the LCM model to investigate different choice strategies under varying attribute information load and explore the impact of additional attribute information on welfare estimates taking ANA into account.

First, it is be shown that the LCM model outperforms the MNL model in term of model fit and produce smaller WTP estimates. This verifies that failure to account for ANA may lead to higher welfare estimates and poor model performance.

Second, we find that less than 20% of respondents use the Weighted Additive strategy and this percentage will further decrease if additional attribute information is given. It implies that respondents are more likely to rely on simple heuristics to make choices, especially when information load increases.

Third, our results suggests that WTP estimates from LCM decrease when the number of attributes increases from three to four, which is consistent with previous findings without accounting for ANA.

There are some limitations that are left for future research. One of the limitations of using the LCM model to infer ANA is, the number of classes grows exponentially with the number of attributes. Indeed, it is always difficult to estimate all ANA combination due to the sample size. Another limitation is the ability to provide detailed insight into how respondents process attribute information when making choices. In fact, the process between stimulus presentation and final decision is still a kind of 'black box' in DCE research. In the decision making field, processing tracing techniques are widely used to capture information processing behavior. Those techniques includes thinking-aloud protocols, information boards and eye tracking. A combination of discrete choice experiments and processing tracing techniques will help us answer the question of how respondents process information and make decisions in choice tasks (Meissner and Decker, 2010; Balcombe et al., 2014).

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APPENDIX

Table Ⅰ. Details of the LCM model specifications and estimated class probabilities for DCE C3

Class No.	Category	Parameters estimated in the class			Class Prob.
1	Weighted Additive	β_{price}	β_{COOL}	β_{tender}	18.68%
2	Frugal Weighted	β_{price}	β_{COOL}	0	22.77%
3	Frugal Weighted	β_{price}	0	β_{tender}	12.86%
4	Frugal Weighted	0	β_{COOL}	β_{tender}	0.43%
5	Lexicographic Choice	β_{price}	0	0	2.84%
6	Lexicographic Choice	0	β_{COOL}	0	7.46%
7	Lexicographic Choice	0	0	β_{tender}	13.84%
8	Random Choice	0	0	0	21.12%

Table Ⅱ. Details of the LCM model specifications and estimated class probabilities for DCE C4

Class No.	Category	Parameters estimated in the class				Class Prob.
1	Weighted Additive	β_{price}	β_{COOL}	β_{tender}	β_{lean}	0.00%
2	Frugal Weighted	β_{price}	β_{COOL}	β_{tender}	0	13.56%
3	Frugal Weighted	β_{price}	β_{COOL}	0	β_{lean}	8.44%
4	Frugal Weighted	β_{price}	0	β_{tender}	β_{lean}	1.91%
5	Frugal Weighted	0	β_{COOL}	β_{tender}	β_{lean}	0.83%
6	Frugal Weighted	β_{price}	β_{COOL}	0	0	17.28%
7	Frugal Weighted	β_{price}	0	β_{tender}	0	11.27%
8	Frugal Weighted	0	β_{COOL}	β_{tender}	0	2.38%
9	Frugal Weighted	β_{price}	0	0	β_{lean}	3.37%
10	Frugal Weighted	0	β_{COOL}	0	β_{lean}	1.53%
11	Frugal Weighted	0	0	β_{tender}	β_{lean}	0.28%
12	Lexicographic Choice	β_{price}	0	0	0	3.34%
13	Lexicographic Choice	0	β_{COOL}	0	0	7.48%
14	Lexicographic Choice	0	0	β_{tender}	0	7.55%
15	Lexicographic Choice	0	0	0	β_{lean}	6.72%
16	Random Choice	0	0	0	0	14.07%

Table Ⅲ. Details of the LCM model specifications and estimated class probabilities for DCE W3

Class No.	Category	Parameters estimated in the class			Class Prob.
1	Weighted Additive	β_{price}	β_{tender}	β_{lean}	18.30%
2	Frugal Weighted	β_{price}	β_{tender}	0	27.74%
3	Frugal Weighted	β_{price}	0	β_{lean}	13.69%
4	Frugal Weighted	0	β_{tender}	β_{lean}	0.83%
5	Lexicographic Choice	β_{price}	0	0	2.99%
6	Lexicographic Choice	0	β_{tender}	0	4.74%
7	Lexicographic Choice	0	0	β_{lean}	7.19%
8	Random Choice	0	0	0	24.54%

Table Ⅳ. Details of the LCM model specifications and estimated class probabilities for DCE W4

Class No.	Category	Parameters estimated in the class				Class Prob.
1	Weighted Additive	β_{price}	β_{tender}	β_{lean}	β_{sellby}	15.70%
2	Frugal Weighted	β_{price}	β_{tender}	β_{lean}	0	41.15%
3	Frugal Weighted	β_{price}	β_{tender}	0	β_{sellby}	8.72%
4	Frugal Weighted	β_{price}	0	β_{lean}	β_{sellby}	0.00%
5	Frugal Weighted	0	β_{tender}	β_{lean}	β_{sellby}	0.00%
6	Frugal Weighted	β_{price}	β_{tender}	0	0	0.00%
7	Frugal Weighted	β_{price}	0	β_{lean}	0	0.00%
8	Frugal Weighted	0	β_{tender}	β_{lean}	0	0.00%
9	Frugal Weighted	β_{price}	0	0	β_{sellby}	4.41%
10	Frugal Weighted	0	β_{tender}	0	β_{sellby}	0.00%
11	Frugal Weighted	0	0	β_{lean}	β_{sellby}	0.00%
12	Lexicographic Choice	β_{price}	0	0	0	2.44%
13	Lexicographic Choice	0	β_{tender}	0	0	4.39%
14	Lexicographic Choice	0	0	β_{lean}	0	15.84%
15	Lexicographic Choice	0	0	0	β_{sellby}	0.00%
16	Random Choice	0	0	0	0	7.37%