Essays on attribute inattention choice behavior

by

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B.A., Dongguk University, Republic of Korea, 2008
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

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Abstract

The main objective of this dissertation is to explore attribute non-attendance choice in food consumption research under the discrete choice framework. The standard choice analysis based on random utility maximization assumes that an agent evaluates every attribute of alternatives and selects his or her most preferred option that maximizes utility in a given choice situation. However, recent empirical evidence reveals that decision makers may ignore a certain attribute presented in a choice set. My dissertation research investigates inattention choice behaviors using stated and revealed preferences data.

The first essay, *"Out-of-sample Validity of Random Response Share Approach"*, applied the Random Response Share (RRS) approach that was proposed by Malone and Lusk (2018) for investigating inattention choice in choice experiments. The aim of the RRS approach is to identify and purge inattention observations in analysis. We applied the RRS and assessed the out-of-sample predictive performance of the RRS using 60 months of choice experiment data from 61,592 U.S households. Our results show that the RRS is not a dominant strategy to the conventional multinomial logit model in terms of out-of-sample forecasting accuracy. However, the RRS could be a way to deal with attribute nonattendance when also considering the socio-economic characteristics of respondents because it is not harmful compared to the predictive accuracy of the traditional multinomial logit model.

In the second essay, *"Incorporating Choice Heuristics in Analysis of Decision Making"*, we investigated consumers' heuristic choices when purchasing hotdog sausage products. This study applied the IRI marketing data set into the latent class structure of the discrete choice models to explore choice heuristics based on different attribute processing at the level of the household. The main contribution of this study is to incorporate attribute inattention into discrete choice model

using actual market data, instead of stated choice data. The estimation results based on multiple models reveal that marginal utilities and willingness to pay estimates for attributes of hotdog products are sensitive to model selection. Our empirical analysis suggests that accounting for heterogeneous decision rules could provide better model fit. Thus, researchers need to consider the heterogeneous decision rules as an alternative to the classic assumption that all attributes are considered in choice situations by decision makers to better understand consumers' choices and provide more accurate policy implications.

To sum up, the traditional assumption of full attribute consideration may be strong and restrictive to reflect consumer decision making rules. Recent studies are attempting to relax this assumption and reflect real choice environments. Considering ANA-based choice behaviors may help improve understanding of consumer preference through better analysis of decision making. I hope that this dissertation on attribute inattention choices will be a steppingstone to additional research in the field of discrete choice analysis.

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Dedication

To SUJUNG

Chapter 1 - Out of Sample Validity of Random Response Share Approach

1.1 Introduction

Choice experiments (CEs) have been widely used in the field of agricultural and applied economics for a variety of reasons. For example, analysts design a CE and collect stated preference data in order to improve an understanding of consumer behavior and preferences, to estimate food demand, to gain an insight of producers' decision-making process, to measure the value of non-market goods, or to evaluate welfare change by a certain policy change through marginal willingness to pay (MWTP) or marginal willingness to accept (MWTA). CEs are often based on the random utility model (RUM) framework, assuming full attribute assessment that an individual decision maker evaluates every attribute of alternatives and selects his or her most preferred option that maximizes utility in a given choice situation.

However, individual respondents in CEs may ignore a certain attribute of alternatives presented in a choice set, which could lead to an inattention bias (Hensher, Rose and Greene 2005). The problem of attribute inattention is that analysis without accounting for ANA may give rise to biased parameter and willingness to pay (WTP) estimates (Hensher et al. 2005; Scarpa et al. 2009; Hole 2011; Kragt 2013; Weller et al. 2014). Given the popularity of CE methods for policy research in the applied economics area, such as agricultural, food, environmental, transportation, and health economics, the biased choice analysis may provide misinformation to policymakers. This issue can be applied not only to public policy design but also to strategic decision makings in the industrial sectors relying on market research.

Since Hensher, Rose, and Greene (2005), there are growing methodological and empirical research interests of investigating inattention bias in CEs - attribute non-attendance (ANA) in the applied economics field. Many CE studies have attempted to investigate ANA responses based in two different ways, a stated attribute non-attendance and an inferred attribute non-attendance approaches. The former method directly asks the respondents whether they did attribute inattention choice and what attributes they did not focus on after the CE questions. In the stated ANA approach, respondents may be asked to respond to the ignored attributes whenever a CE task terminates or to answer to them after the completion of an entire CE task. Unlike the first method, the latter tries to embody respondents' ANA behaviors in analytical econometric models (Alemu et al. 2013; Hole, Kolstad and Gyrd-Hansen 2013; Scarpa et al. 2013; Kragt 2013; Van Loo et al. 2018). Studies that rely on an inferred ANA mainly use the constrained latent class specification, which was proposed by Scarpa et al. (2009). Albeit there are some reports that inferred ANA provides a little better model fits than stated ANA methods (Scarpa et al. 2013; Kragt 2013), it is not clear which method is better (Weller et al. 2014).[1] Furthermore, with technical advances, a new method is paid attention by discrete choice practitioners. That is referred to as a revealed ANA or a visual ANA, which adopts on eye-tracking measures. The revealed ANA approach utilizes an eye-tracking tool that monitors CE participants' gaze on each attribute when assessing alternatives (Van Loo et al. 2015). Across all three major methods, the standard econometric approach commonly used in ANA literature is to fix the parameters corresponding to the attributes related to ANA choice behavior to zero.

[1] Kragt (2013) pointed out the possibility that in the case of Stated ANA, CE respondents actually made an inattention choice but did not report.

The random response share (RRS) approach that is based on the constrained latent class specification as a way to identify inattention choice was proposed by Malone and Lusk (2018). The purpose of the RRS approach is to remove the observations from those who randomly select one without attention among the alternatives in a choice task. We note that the RRS approach differs in purpose not only from the standard latent class models but also from the inferred ANA methods. The standard latent class models without any constraint are for considering heterogeneity in preferences and the Inferred ANA methods attempt to reflect heterogeneity in decision makers' attribute processing protocol. The RRS has a value between 0 and 1, indicating the estimated probability that survey participant *i* is in the segment for random choice (Malone and Lusk 2018). A RRS value of 0 indicates that all participants select an option under serious consideration of every attribute. Conversely, a RRS value of 1 implies that all made a choice in random.

The aim of our study is to assess the potential validity of the RRS method in the aspect of the OOS prediction accuracy. The RRS is an alternative method to statistically detect inattention observations in stated CE data. In the RRS approach, all parameters for observations with the lack of attention are enforced to zero values within the restricted class, while only parameters for those who fully evaluate information are freely estimated within the unrestricted class and utilized for analysis. This is, parameter estimates within the unrestricted segment should be more representative of marginal utilities for each attribute for individual respondents. Malone and Lusk (2018) showed the validity of the RRS method through comparison with using a trap question to detect inattention choice. The present study employed the OOS prediction comparison as an alternative way to examine the validity of the RRS approach, following Tonsor (2018). To the best of our knowledge, there is no known literature to evaluate the RRS approach. Therefore, this is the first known empirical application of the RRS approach since it was introduced.

1.2 The Food Demand Survey Data

This study employed the Food Demand Survey (FooDS) data to assess the potential validity of the RRS approach.[2] The FooDS is a monthly on-line survey to track consumer preferences and behavior in food consumption. This data was introduced by Lusk (2017). The FooDS was conducted for 60 months from June 2013 to May 2018, with more than 1,000 households per month. The FooDS data collected from 61,592 survey respondents include choice experiment questions as well as socio-demographic information of respondents. The benefits of rich observations in the FooDS data allows us to evaluate the RRS approach using out-of-sample prediction comparison.

Source: Lusk (2013).

Figure 1.1 A Sample of the Choice Set

Each individual participant of the survey was requested to select the most preferred among nine alternatives in a choice set and complete nine different choice tasks (Lusk 2013). Eight of nine options are made up of the food types that refer to an alternative specific attribute, and its price. The price attribute, in 20 different levels that were between $0.00 and $8.00, is distributed

[2] Malone and Lusk (2018) also employed the FooDS data to examine their RRS concept, comparing with a trap question method. Their study used only a month of data from 1,017 U.S households. On the other hand, we carried out OOS forecasting based on a total of 60 consecutive months of CE data from 61,592 households.

across choice alternatives. The types of foods include *hamburger, steak, pork chop, deli ham, chicken breast, chicken wing, beans and rice,* and *pasta.* The other one is *something else*, meaning an option to not buying food as a status quo. In a choice set, different choice alternatives were presented with the corresponding pictures (Figure 1.1). A total of three choice experiment surveys were designed and distributed to respondents. That is, survey respondents randomly received one of three types of surveys. The difference between the types of the choice experiment is in the order of the alternative (food type) presented in the choice set and prices presented.

Table 1.1 illustrates socio-economic characteristics (SECs) of individual survey respondents for the FooDS of 60 consecutive months. In terms of age composition, the highest proportion of respondents was 21.0% for 25 to 34-year-olds, followed by 18.47% for 35 to 44-year-olds. The three age groups for over 45-year-olds (45 to 54-year-olds, 55 to 64-year-olds, and 65-year-olds or older) were similar at about 16%. The gender composition was about 52.6% for women, slightly higher than men. For the education level, 46.57% of the respondents had a bachelor's degree or higher, and 20.7% had a high school education or the lower level and 32.7% was for some college.

Table 1.1 Socio-Economic Characteristics of Individual Respondents

Socio-Economic Characteristics		Description	Frequency	Percent (%)	Cumulative Frequency
Age	1	18-24 years old	6,576	10.68	6,576
	2	25-34 years old	12,946	21.02	19,522
	3	35-44 years old	11,377	18.47	30,899
	4	45-54 years old	10,359	16.82	41,258
	5	55-64 years old	9,942	16.14	51,200
	6	65 or older	10,392	16.87	61,592
Gender	1	Male	29,210	47.42	29,210
	2	Female	32,382	52.58	61,592
Education	1	High School or Lower	12,772	20.74	12,772
	2	Some college	20,137	32.69	32,909
	3	B.S. Degree or Higher	28,683	46.57	61,592
Region	1	Northeast	13,379	21.72	13,379
	2	Midwest	12,453	20.22	25,832
	3	South	21,991	35.70	47,823
	4	West	13,769	22.36	61,592
Household	1	One person	11,408	18.52	11,408
Size	2	Two people	21,261	34.52	32,669
	3	Three people	12,169	19.76	44,838
	4	Four people	10,940	17.76	55,778
	5	Five people or More	5,814	9.44	61,592
Household	1	Less than $20,000	9,441	15.33	9,441
Income	2	$20,000 to $39,999	11,293	18.34	20,734
	3	$40,000 to $59,999	9,945	16.15	30,679
	4	$60,000 to $79,999	9,371	15.21	40,050
	5	$80,000 to $99,999	7,548	12.25	47,598
	6	$100,000 to $119,999	4,879	7.92	52,477
	7	$120,000 to $139,999	2,759	4.48	55,236
	8	$140,000 to$159,999	2,693	4.37	57,929
	9	$160,000 or Greater	3,663	5.95	61,592
Total			61,592	100.00	-

Table 1.2 describes the summary statistics of the data used for our analysis. Most of the variables are categorical variables, except survey completion time (SCTIME). The mean of survey complete time is 982.484 seconds (about 16.37 minutes). We convert SCTIME to dummy variables, 0 and 1, based on the mean value of SCTIME. 0 means respondents with SCTIME less

than the average value, while 1 indicates responders with SCTIME longer than the mean value. The conversion is carried out by month. Because in addition to the basic questions in the FooDS survey, there were some additional survey questions in a particular month, which led to a different number of questions. It is also possible that certain circumstances about the timing of the survey may have affected the response time of respondents. The SEC variables of respondents correspond to those in Table 1.1, except for household income. The data on household income was divided into nine groups in Table 1.1. For the sake of discrete choice analysis, we used high-income earners of more than $100,000 in one category. A weighting variable (wts) was derived through a SAS raking macro (Izrael, Hoaglin and Battaglia 2004) and it was used for sample balancing to the U.S. population. The raking procedure was implemented based on four demographics of household (age, education, gender, and region) and was also applied by month. The WTS variables are reflected in model estimation. The variable 'Choice' is the dependent variable in our models. If the alternative presented in the choice experiment is chosen by the respondent, the choice variable has a value of 1, otherwise, it has 0. The variable option is a variable for identifying the attributes corresponding to the food types and none (a status quo). For each choice set, respondents face nine alternatives, so that each alternative has one of the values 1 through 9. We also have the price attribute in 20 different levels that were between $0.00 and $8.00 and distributed across choice alternatives. The distribution of the price variable presented in alternatives of choice experiments across three different types was shown in appendix (Table A.2).

A total of 4,988,952 observations of long-form data were used in our discrete choice analysis, which is the product of the number of respondents multiplied by the product of the number of alternatives and the number of choice tasks that respondents faced ($61{,}592 \times 9 \times$

9, Table A.1). This rich set of the FooDS data provide enough samples for us deeply to conduct OOS forecasting.

Table 1.2 Descriptive Statistics of the FooDS Data Used for Discrete Choice Models

Variable		Description	Number of Samples	Mean	Std. Dev.	Minimum	Maximum
Year		Year	4,988,952	2015.420	1.495	2013.000	2018.000
Month		Month	4,988,952	6.514	3.457	1.000	12.000
SCTIME		Survey Completion Time (seconds)	4,988,952	982.484	2442.010	0.000	126476.000
Household Size	1 2 3 4 5	One person Two people Three people Four people Five people or More	4,988,952	2.651	1.233	1.000	5.000
Household Income	1 2 3 4 5 6	Less than $20,000 $20,000 to $39,999 $40,000 to $59,999 $60,000 to $79,999 $80,000 to $99,999 $100,000 or Greater	4,988,952	3.589	1.771	1.000	6.000
Age	1 2 3 4 5 6	18-24 years old 25-34 years old 35-44 years old 45-54 years old 55-64 years old 65 or older	4,988,952	3.573	1.625	1.000	6.000
Education	1 2 3	High School or Lower Some college B.S. Degree or Higher	4,988,952	2.258	0.779	1.000	3.000
Gender	1 2	Male Female	4,988,952	1.526	0.499	1.000	2.000
Region	1 2 3 4	Northeast Midwest South West	4,988,952	2.587	1.060	1.000	4.000
wts		Weighting variables	4,988,952	1.000	0.680	0.160	12.090
Choice	0 1	Not chosen alternative Chosen alternative	4,988,952	0.111	0.314	0.000	1.000
Option		Identifier to alternative	4,988,952	5.000	2.582	1.000	9.000
Burger	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Steak	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Pork chop	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Ham	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Chicken breast	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Chicken wing	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Bean and Rice	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
Pasta	0 1	Otherwise If attribute corresponds to alternative	4,988,952	0.111	0.314	0.000	1.000
None	0 1	Otherwise If alternative is for something else	4,988,952	0.111	0.314	0.000	1.000
Price		Price presented for each alternative	4,988,952	3.063	2.026	0.000	8.000

1.3 Conceptual Framework

1.3.1 Multinomial Logit Model (MNL)

This study used the traditional Multinomial Logit model (MNL) and the Latent Class Logit model (LCM) with RRS constraint based on the Random Utility Model (RUM) Framework. Let U_{itj} be utility when decision maker *i* selects alternative *j* in choice situation *t*. It consists of two separate components, a systematical component, V_{itj}, and an unobservable component, ε_{itj}.

$$U_{itj} = V_{itj} + \varepsilon_{itj} \tag{1}$$

The observed part of the utility involved with alternative *j*, V_{itj}, is specified as:

$$V_{itj} = \beta' X_{itj} \tag{2}$$

Where X_{itj} is a vector of the *C* attributes of alternative *j* in choice tasks *t* when agent *i* faced. And a parameter vector, β, indicate the marginal utility of attribute *c* of alternative *j*.

A necessary and sufficient condition for the RUM with independent errors to satisfy the independence of irrelevant alternatives (IIA) is that the unobservable error part, ε_{itj}, be identically and independently distributed (IID) with a type I extreme value distribution. Under these assumptions, the choice probability that decision maker *i* chooses alternative *j* in choice situation *t* usually takes the following multinomial logit expression (McFadden 1974; Train 2009; Hensher, Rose and Greene 2015).

$$P_{itj} = P_{(y_{itj}=j)} = \frac{\exp(V_{itj})}{\sum_{k \in J} \exp(V_{itj})} \tag{3}$$

With the above specification for the observed component in the equation (2), the logit probability becomes

$$P_{itj} = P_{(y_{itj}=j)} = \frac{\exp\,(\beta\prime X_{itj})}{\sum_{k\in J}\exp\,(\beta\prime X_{itj})} \tag{4}$$

1.3.2 Latent Class Structure

The underlying theory of the Latent Class Model (LCM) postulates that individual behavior depends not only on observable attributes but also on latent heterogeneity that varies with factors that are unobserved by analysts. That is, the LCM assumes that preferences of decision makers are heterogeneous across classes, but they are homogeneous within each class as in the conventional MNL (McKendree, Tonsor and Wolf 2018). The LCM of discrete choice is more flexible than the MNL but somewhat less flexible than the Random Parameter Logit model (RPL), in which the LCM of discrete choice accounts for latent heterogeneity through a model with discrete parameter variation while the MNL assumes homogeneous perspectives of the interest parameters across individuals and the RPL considers heterogeneity using continuous distributions of parameters across individuals (Greene and Hensher, 2003).

The Latent Class Discrete Choice Model (LC-DCM) assumes that individuals are implicitly sorted into a set of Q classes, but which class contains any particular individual, whether known or not to that individual, is unknown to the researcher (Greene and Hensher, 2003). The LC-DCM consists of two MNL formation components. The first part is for the probability of individual choice and the second part is for the prior probability of the class assignment.

The choice behavior within the class of q is estimated by a logit model for discrete choice of alternative j among J alternatives, by individual i, observed in choice situation t, (Hensher and Greene 2010).

$$P_{it|q(j)} = Prob(y_{it} = j \mid class = q) = \frac{\exp(\beta'_q X_{itj})}{\sum_{k\in J} \exp(\beta'_q X_{itk})} \tag{5}$$

For the given class assignment *(class=q)*, the contribution of individual *i* to the likelihood is the joint probability of the sequence (Hensher and Greene 2010), given in equation (6)

$$P_{i|q(j)} = \prod_{t=1}^{T} P_{it|q(j)} \tag{6}$$

The prior probability for class q for household *i* also has the MNL form as equation (7).

$$P_{(class=q)} = H_{iq} = \frac{\exp(\theta'_q Z_i)}{\sum_{q=1}^{Q} \exp(\theta'_q Z_i)}, \quad q = 1, 2, \ldots, Q \text{ and } \theta_Q = 0, \tag{7}$$

Where Z_i denotes a set of observable characteristics of individuals that enter the model for class membership. Note that the Q^{th} parameter vector, θ_Q, is normalized to zero to secure identification of the model (Hensher and Greene 2010).

Finally, the likelihood for respondent *i* is the expectation (over classes) of the class-specific contributions and is expressed by equation (8) (Hensher and Greene 2010).

$$P_{ij} = \sum_{q=1}^{Q} H_{iq}\, P_{i|q(j)} \tag{8}$$

1.3.3 The RRS approach

The random response share approach uses the LC-DCM framework with a constraint to force all attribute coefficients for inattention observations to zero within the restricted segment and to estimate only parameters within the unrestricted segment for those who fully evaluate respective attributes. After that, the RRS method utilizes only parameter estimates within the unconstrained segment for analysis. The RRS approach is a way to capture ignoring attributes, assuming only two different classes, the first class for decision makers who fully account for attribute information and the second class for those who select in a random way. We note that this is not for reflecting heterogeneous preferences in the model. The aim of the RRS model is to reduce hypothetical bias by removing the observations from those who did purely random selection in a choice task. On the other hand, the unconstrained LC-DCMs that are generally applied to account for preference heterogeneity. For example, the LC-DCMs may reveal that some consumers prefer ham to chicken wing but others don’t. In addition, the constrained LC-DCMs try to improve choice analysis by accounting for heterogeneity in attribute processing. For instance, researchers can distinguish between those who evaluate all information about alternatives and those who only consider price by using the restricted LC-DCMs.

Despite these characteristics, the inferred ANA methods based on the constrained LC-DCMs are not capable to distinguish whether the coefficient estimate for a certain attribute has a value of zero actually or if the coefficient estimate is zero because of the restriction that the attribute is ignored (reflection preference indifference). In other words, the inferred ANA approaches are not able to separate the case that the actual coefficient estimate for a certain attribute is a value of 0 from the case that the estimate is 0 because the attribute was ignored within the constrained segment. Note that for the RRS model, the second class is likely to cover both cases. The second class of the RRS method includes a purely random selection that ignores all attributes and a case where all attributes evaluate to zero.

1.3.4 Willingness to pay estimates

We estimated consumer willingness to pay (WTP) for food types in each model. The WTP estimates are based on the estimation group that is 2/3 portion of the total observations. The WTP for a food type is the ratio of the coefficient of the food type to the coefficient of price, which allows us to interpret the estimation results using the economic concept of the marginal rate of substitution. For the base models (the MNL 1 and the RRS 1) and the RRS 2, WTP for an alternative j is calibrated as:

$$WTP_j = -\frac{\beta_j}{\alpha} \tag{19}$$

Because of the heterogeneous preferences in the utility function, in the case of the MNL 2 and the RRS 3, WTP for an alternative j consider additional shift terms as

$$WTP_j = -\frac{\beta_j + \mu_j \times H}{\alpha + \gamma \times H} \tag{20}$$

1.3.5 Out-of-Sample Assessment

The out-of-sample (OOS) prediction comparisons were conducted to evaluate the forecasting performance of the RRS approach. Under both the MNL and the RRS, we used a delete-a-group process to compare the accuracy of forecasting individual decision makers' choice, following Tonsor (2018).

For OOS, we first randomly divided observations into two groups, an estimation group (66.7% of a given month's data) and a holdout group (33.3% of a month's data), and then estimated the MNL and the RRS models using the estimation group. Next, parameter estimates were used to predict respondents' indirect utilities for each alternative in the holdout group in both the MNL and the RRS models. For the conventional MNL, predicted utilities were calculated based on all parameter estimates. For the RRS approach, on the other hand, they were derived only using the parameter estimates within the first segment.

Third, we use estimated utility functions to derive individuals' choices within each choice situation that maximize the indirect utility for both the MNL and the RRS and then compared the predicted choices with the actual choice. OOS prediction accuracy, A_{it}, represents the correct prediction of a choice model for individual *i* in choice situation *t* which is generated by comparing the predicted choice with the actual choice.

$$A_{it} = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{if } j \neq k \end{cases} \tag{21}$$

Where *j* is the actual alternatives chosen by the agent and *k* is the choice alternative predicted by the model.

Lastly, we computed the prediction accuracy ratio of OOS, which is calculated as the ratio of the number of cases where the predicted choice is matched with the actual choice matched ($A_{it} = 1$) to the number of total choice tasks, *T*.

1.4 Empirical Application

This study used Out-of-sample (OOS) forecasting comparison to evaluate the RRS approach compared to the conventional MNL. We estimated the MNL and LCM with RRS based on FooDS CE data, conducted the OOS forecasting from both models, and made a comparison of predictive accuracy of the respective models. This study also analyzed WTPs derived from each model to see how they differ depending on the approaches. We note that all model estimations and WTPs calculations were based on each month's data. We did not use 60 months of data at once. Because we want to compare our estimation results with the monthly reports of the Oklahoma State University. Also, we thought that certain situations such as food safety or seasonality may affect respondents' choices in CEs. If the paper analyzes the entire 60 months of data at once, the estimates could potentially be affected by those factors.

Our base models are the simplest MNL (called as MNL 1) and LCM with RRS restriction (called as RRS 1), assuming homogeneous preferences. This study estimated both the MNL 1 and the RRS 1, and compared WTP estimates for each food type. We also compared the OOS forecasting accuracy of each model. Next, this study considers heterogeneous preferences in order to examine how the OOS forecasting accuracy, the probability of random response, and WTP estimates for each food type change when accounting for heterogeneity in preferences. First, one of the socio-economic characteristics (SECs) was added to the RRS 1 as a membership variable that enters into the segment probability (called RRS 2) and examined how WTP estimates and OOS forecasting accuracy change as a membership variable enters into each model. Second, we put an interaction term of the price and SEC and an interaction term of the food type and the SEC into the indirect utility function of both base models, the MNL 1 and the RRS 1 (called as MNL 2 and RRS 3).

1.4.1 Model Specifications

1.4.1.1 MNL 1 (Homogeneous preference)

We begin with the simplest MNL with alternative-specific food type and price effects. We assume the unobservable stochastic part of the RUM framework, ε_{itj}, is identically and independently distributed (IID) with the type I extreme value (Lusk 2013). For the base model, the indirect utility function (the systematical part) can be specified as (9).[3]

$$V_{itj} = P'_{tj}\alpha + X'_{itj}\beta_j \tag{9}$$

Where α is the marginal (dis)utility of the price, P_{tj}, faced by individual *i* for option *j* in choice situation *t*, and β_j is the marginal utility of food product type, *j = 1 (hamburger), 2 (steak), 3 (pork chop), 4 (deli ham), 5 (chicken breast), 6 (chicken wing), 7 (beans and rice), 8 (pasta), 9 (something else)*. X_{itj} is an indicator for food product type *j* and it has a value of 1 or 0.

Given equation (9) and 9 choice tasks for each respondent, the MNL estimates the probability of individual decision makers choosing food product *j* in as below:

$$P_{ij} = \prod_{t=1}^{9} \frac{\exp\,(P'_{tj}\alpha + X'_{itj}\beta_j)}{\sum_{j=1}^{J} \exp\,(P'_{tj}\alpha + X'_{itj}\beta_j)} \tag{10}$$

1.4.1.2 RRS 1 (Homogeneous preference within a class)

Within the class, the probability of decision maker *i* selecting food product *j* among 9 alternatives is conditional on the latent class *q* and the behavioral model can be expressed as

[3] Our base models used the same specification for indirect utility function as that in Malone and Lusk (2018). This allows us to compare directly with Malone and Lusk (2018).

$$P_{i|q(j)} = Prob\big(y_{ij} = j \,\big|class = q) = \prod_{t=1}^{9} \frac{\exp\,(P'_{tj}\alpha_q + X'_{itj}\beta_{jq})}{\sum_{j=1}^{9} \exp\,(P'_{tj}\alpha_q + X'_{itj}\beta_{jq})} \tag{11}$$

This study goes with a latent class specification of two classes based on the RUM framework. However, we differently specified the systematical component of the utility, V_{itj}, across classes. For the first class (q = 1), we used the non-restricted model that is exactly the same as the MNL in equation (10), as that $U_{itj} = P'_{tj}\alpha_1 + X'_{itj}\beta_{j1} + \varepsilon_{itj}$. The first class indicates that individual respondents evaluate every attribute and choose product *j* in choice situation *t*. For the second class (q = 2), the restricted model is specified as that $U_{itj} = \varepsilon_{itj}$ by enforcing all parameters to zero values (i.e., $\alpha_2 = \beta_{j2} = 0$), meaning that $V_{itj} = 0$ and that individual *i* randomly selects product *j* in choice situation *t*. So, the probability of household *i* selecting food product *j* among 9 different alternatives can be rewritten as

$$P_{i|q(j)} = \begin{cases} \prod_{t=1}^{9} \frac{\exp\,(P'_{tj}\alpha_1 + X'_{itj}\beta_{j1})}{\sum_{j=1}^{9} \exp\,(P'_{tj}\alpha_1 + X'_{itj}\beta_{j1})} & \text{if } q = 1 \\ \prod_{t=1}^{9} \frac{\exp\,(0)}{\sum_{j=1}^{9} \exp(0)} = \prod_{t=1}^{9} \frac{1}{9} & \text{if } q = 2 \end{cases} \tag{12}$$

The prior probability that household *i* belongs to the class *q* has the MNL form as below.

$$P_{(class=q)} = H_{iq} = \frac{\exp(Z'_i\theta_q)}{\sum_{q=1}^{2} \exp(Z'_i\theta_q)}, \quad q = 1, 2 \text{ and } \theta_2 = 0, \tag{13}$$

Where Z_i denotes a set of observable characteristics of individuals that enter the model for class allocation. Note that in the RRS 1 and the RRS 2, we didn't set a membership variable for the prior probability. The second parameter vector, θ_2, is normalized to zero to secure identification of the model (Hensher and Green. 2010).

Given the equation (8) and the fact that each respondent was required to answer to 9 choice tasks, the probability for decision maker *i* is the expectation of the class-specific contributions as:

$$P_{i|q(j)} = \begin{Bmatrix} \frac{\exp(Z'_i\theta_1)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)}\prod_{t=1}^{9}\left\{\frac{\exp\,(P'_{tj}\alpha_1+X'_{itj}\beta_{j1})}{\sum_{j=1}^{9}\exp\,(P'_{tj}\alpha_1+X'_{itj}\beta_{j1})}\right\} & \text{if } q=1 \\ \frac{\exp(Z'_i\theta_2)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)}\prod_{t=1}^{9}\left\{\frac{1}{9}\right\} & \text{if } q=2 \end{Bmatrix} \tag{14}$$

Now, we move to accounting for heterogeneous preferences in two different ways. The first way is to put SECs for interaction terms into both base models. Second, we add SECs as a membership variable to the base model for the RRS.

1.4.1.3 RRS 2 (adding membership variables)

Firstly, we consider latent heterogeneity in preferences through membership variables. The RRS 2 adds a SEC as a membership variable to the RRS 1, which provides the probability of choosing alternative j across the class as below:

$$P_{i|q(j)} = \begin{Bmatrix} \frac{\exp(Z'_i\theta_1)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)}\prod_{t=1}^{9}\left\{\frac{\exp\,(P'_{tj}\alpha_1+X'_{itj}\beta_{j1})}{\sum_{j=1}^{9}\exp\,(P'_{tj}\alpha_1+X'_{itj}\beta_{j1})}\right\} & \text{if } q=1 \\ \frac{\exp(Z'_i\theta_2)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)}\prod_{t=1}^{9}\left\{\frac{1}{9}\right\} & \text{if } q=2 \end{Bmatrix} \tag{15}$$

Where Z_i includes age, education, gender, household size, household income, and survey completion time.

The RRS 1 and the RRS 2 seem to have the identical choice probability formula within the class. Unlike in RRS 1, however, the RRS 2 reflects heterogeneity in a way that allows SECs (Z_i) to affect the prior segment probability. In the RRS 1, we do not set Z_i variable but the segment is divided by a latent variable.

1.4.1.4 MNL 2 and RRS 3 (adding interaction terms with SECs)

Second, we relax the homogeneous preferences assumption of the base models, adding interaction terms with socio-economic characteristics into the indirect utility to account for heterogeneity in preferences as below:

$$V_{itj} = P'_{tj}\alpha + X'_{itj}\beta_j + PH'_{jt}\gamma + XH'_{itj}\mu_j \tag{16}$$

Where *H* indicates respondent's socio-economic characteristics (SECs), including age, education, gender, household size, and household income. *PH* notes interactions term of price and household socio-economic characteristics and *XH* indicates interaction terms of food types and household socio-economic characteristics. In this specification, γ and μ_j allow us to consider heterogeneity for price and product preferences. In this case, SECs of individuals affect the likelihood of choosing alternative *j* within the class, not the prior probability.

We use the MNL 2 to compare how the WTP estimates driven from the MNL 1 and the RRS 2 and also to compare the OOS prediction of the RRS differ from the OOS predictions of the MNL given the household characteristics. In the MNL 2, the probability of respondent *i* selecting food product *j* among 9 different alternatives can be rewritten as:

$$P_{ij} = \prod_{t=1}^{9} \frac{\exp\left(P'_{tj}\alpha + X'_{itj}\beta_j + PH'_{jt}\gamma + XH'_{itj}\mu_j\right)}{\sum_{j=1}^{9} \exp\left(P'_{tj}\alpha + X'_{itj}\beta_j + PH'_{jt}\gamma + XH'_{itj}\mu_j\right)} \tag{17}$$

For the RRS 3, the likelihoods for respondent i is the expectation of the class-specific contributions as below.

$$P_{i|q(j)} = \begin{Bmatrix} \frac{\exp(Z'_i\theta_1)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)} \prod_{t=1}^{9} \left\{ \frac{\exp\,(P'_{tj}\alpha_1 + X'_{itj}\beta_{j1} + PH'_{jt}\gamma_1 + XH'_{itj}\mu_{j1})}{\sum_{j=1}^{9}\exp\,(P'_{tj}\alpha_1 + X'_{itj}\beta_{j1} + PH'_{jt}\gamma_1 + XH'_{itj}\mu_{j1})} \right\} & \text{if } q = 1 \\ \frac{\exp(Z'_i\theta_2)}{\sum_{q=1}^{2}\exp(Z'_i\theta_q)} \prod_{t=1}^{9} \left\{ \frac{1}{9} \right\} & \text{if } q = 2 \end{Bmatrix}$$

(18)

The RRS 1 and the RRS 3 have the identical prior probability formula due to the absence of setting for a membership variable in both models. The different thing is in the specification of utility function.

1.5 Results

Table 1.3 summarizes the in-sample willingness-to-pay estimates (WTP), random response share estimates (RRS) and the out-of-sample predictive accuracy rates (OOS Pred. Accuracy) that were derived by averaging the estimated values for each month in different models. Those are average prediction accuracy rates over 60 different estimations.

1.5.1 WTP estimates and Random Response Shares

The WTP estimates for 8 different food types are shown in Table 1.3. The ranking of preferences for food types based on the WTP estimates was the same for all models except ham and chicken wing, although the WTP values slightly differed by models. Steak has the highest premium value, followed by chicken breast, burger, pork chop, and pasta. The preference for beans and rice was the lowest in all models. The ranking of preferences for ham and chicken wing differed depending on the models. In the MNL 1, the MNL 2 with age, and the RRS3 with age, chicken wing was preferred to ham, but other models showed the opposite preference.

First, we compare the WTPs in the base models (the RRS 1 and the MNL 1). Steak had the highest WTP value, followed by chicken breast, burger, pork chop, and pasta, while beans and rice had the lowest WTPs in both the MNL 1 and the RRS 1 models. The WTP estimates for steak in the MNL 1 is $6.68, which is greater than that of $6.14 in the RRS 1. The WTPs for chicken breast are $5.42 in the MNL 1 and $5.18 in RRS 1. The WTPs for burger are $4.65 and $4.55, respectively. The WTPs for steak, chicken breast, burger, and beans and rice in the MNL 1 were higher than in the RRS 1, respectively. On the other hand, the WTPs for pork chop, ham, and chicken wing in the RRS 1 were higher average values than in the MNL 1, and Pasta's WTP estimates were similar at the level of $3.19 in both models.

Second, this study also considers the WTP estimates for food types based on the RRS 2, which were comparable to those of the RRS1. There are some differences depending on whether membership variables that enter into the prior segment probability is applied. For example, in the RRS 2, the WTP estimates for steak ranged from $6.11 to $6.14. The WTPs for chicken breast and burger were calculated to be from $5.14 to $5.17 and from $4.51 to $4.55, respectively. Despite the addition of SECs or survey completion time (SCTIME) as a membership variable in the RRS 2 model, the WTP estimates for each food type were not considerably different compared to the RRS 1 model. Thus, the preference ranking and WTP comparisons for food type were similar as when comparing the MNL1 with the RRS1.

Next, this study moves to the results of the RRS 3 and the MNL 2 models that reflect the SECs in the models by using interaction terms.[4] Similarly, in both the MNL 2 and the RRS 3, steak had the highest WTP values, followed by chicken breast, burger, pork chop, pasta, ham, and beans and rice, excepting some cases where the MNL 2 and the RRS 3 with age, the MNL 2 with household size, and the MNL 2 with survey completion time as a membership variable.[5] The WTP estimates for steak in the RRS 3 are formed in a range between $6.02 and $ 6.67, while those are between $6.50 and $7.07 in the MNL 2. The WTPs for chicken breast had a range from $5.24 to $5.85 and between $5.00 and $5.74, respectively, in the MNL 2 and the RRS 3. Those values for burger are between $4.52 and $5.03 in the MNL 2 and between $4.42 and $5.09 in the RRS 3.

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[4] This study considered the SECs of survey respondents with the interaction terms of the food types and the SECs. However, the impacts of the SECs were not reported here because the purpose of this essay is to assess the OOS validity of the RRS method, and the SECs impact based on estimation results by monthly data may be too broad to obscure the objective of this study.

[5] In these models, chicken wing was preferred to ham, the ranking of WTP values for the other food types are the same.

These results indicate that the WTP values for steak, chicken breast, pasta, and beans and rice in MNL 2 are higher than those in RRS 3. But WTPs for pork chop, ham, and chicken wing are larger in the RRS 3 than those in MNL 2.[6]

Overall, WTPs are the lowest when adding survey completion time (SCTIME) into the prior likelihood, while WTPs are the highest when considering age or household size (HINC) as a membership variable.

In addition to WTP estimates, the probability of random response of the different constrained LC DCMs was shown in the second last column of Table 1.3. The RRS ranged from 35.5% to 38.0% depending on the RRS model. In the base model (RRS 1), the RRS was estimated to be 36.7%, which is lower than that in RRS 2, excepting the RRS 2 with the membership variable of age, but higher than that in RRS 3. The RRS 2 models putting SECs and SCTIME into the prior class probability result in higher RRS than that in the RRS 3 models that reflect heterogeneous preferences in the indirect utility function.

[6] The WTP estimates for burger in the MNL 2 were lower than those in the RRS 3 when accounting for age and education as a membership variable. However, in other cases, the MNL 2 results in a larger WTPs than the RRS 3.

Table 1.3 WTP Estimates, RRS, and OOS Prediction Accuracy Rates by models

Model	Heterogeneity	WTP ($)								RRS (%)	OOS Pred. Accuracy (%)
		Steak	Chicken Breast	Burger	Pork Chop	Ham	Chicken Wing	Bean and Rice	Pasta		
MNL1	Base Model	6.68	5.42	4.65	3.77	2.33	2.33	1.98	3.19	-	32.59
		(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)		(1.68)
RRS1	Base Model	6.14	5.18	4.55	3.94	2.49	2.41	1.77	3.19	36.7	31.64
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(2.13)
RRS2	Gender	6.13	5.17	4.54	3.93	2.49	2.41	1.76	3.19	36.7	32.69
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
	AGE	6.11	5.14	4.51	3.92	2.47	2.38	1.74	3.16	36.6	32.69
		(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
	EDU	6.14	5.17	4.55	3.94	2.49	2.41	1.76	3.19	38.0	32.69
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
	HSIZE	6.14	5.17	4.54	3.94	2.49	2.41	1.76	3.19	36.8	32.69
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
	HINC	6.13	5.16	4.54	3.93	2.49	2.40	1.76	3.18	37.2	32.69
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
	SCTIME	6.14	5.17	4.54	3.94	2.49	2.41	1.76	3.19	36.8	32.69
		(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
MNL2	Gender	6.76	5.50	4.74	3.86	2.41	2.41	2.03	3.20	-	32.62
		(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.17)	(0.18)	(0.20)		(1.73)
RRS3		6.29	5.29	4.68	4.06	2.60	2.52	1.85	3.21	35.8	32.78
		(0.23)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.22)	(0.03)	(1.75)
MNL2	AGE	7.07	5.85	5.03	3.97	2.64	2.73	2.32	3.51	-	32.76
		(0.21)	(0.23)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)		(1.75)
RRS3		6.67	5.74	5.09	4.27	2.94	2.98	2.23	3.63	34.8	32.86
		(0.28)	(0.26)	(0.26)	(0.25)	(0.25)	(0.25)	(0.25)	(0.26)	(0.04)	(1.78)
MNL2	EDU	6.85	5.60	4.72	3.89	2.40	2.40	2.12	3.30	-	32.49
		(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.18)	(0.20)		(1.61)
RRS3		6.30	5.33	4.62	4.05	2.56	2.48	1.86	3.28	36.2	32.82
		(0.22)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.03)	(1.70)
MNL2	HSIZE	7.06	5.81	5.01	4.08	2.64	2.71	2.26	3.50	-	32.56
		(0.21)	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)		(1.66)
RRS3		6.41	5.44	4.81	4.16	2.72	2.70	1.96	3.42	36.0	32.64
		(0.25)	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)	(0.25)	(0.04)	(1.73)
MNL2	HINC	6.97	5.72	4.85	4.02	2.48	2.47	2.16	3.40	-	32.84
		(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.18)	(0.19)	(0.20)		(1.58)
RRS3		6.42	5.41	4.71	4.15	2.59	2.50	1.84	3.32	35.5	33.06
		(0.22)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.20)	(0.21)	(0.03)	(1.71)
MNL2	SCTIME	6.50	5.24	4.52	3.71	2.27	2.29	1.92	3.13	-	32.64
		(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.18)	(0.20)		(1.69)
RRS3		6.02	5.00	4.42	3.85	2.41	2.35	1.73	3.10	36.5	32.76
		(0.22)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.22)	(0.04)	(1.79)

Note: RRS, In-sample (IS) willingness-to-pay (WTP) for each food type, Out-of-sample (OOS) prediction accuracy are the averages of values from 60 individual model estimations. Numbers described in parentheses for IS WTP are also the mean values of 60 individual standard errors for willingness to pay for each food type. We use the delta method to get the standard errors in NLOGIT 7.0. Numbers presented in parentheses for RRS and OOS Predictive Accuracy are the standard deviations.

1.5.2 OOS Forecasting Accuracy

This paper then moves to the analysis of OOS prediction accuracy. In the case of the base models (MNL 1 and RRS 1), the OOS predictive accuracy rate of the MNL 1 is 32.59% which is slightly larger than that of the RRS1, 31.64%, indicating that the MNL 1 is likely to perform somewhat better than the RRS 1 in the light of model predictability. The monthly OOS forecasts of the MNL 1 and the RRS 1 reveals that the MNL 1 was superior to the RRS 1 in 43 cases while the RRS 1 was better than the MNL 1 in 14 cases among a total of 60 monthly analyzes. In three cases, the same degree of the correct prediction was shown. This result implies that the RRS is not likely to be a dominant strategy to the standard MNL in terms of the OOS forecasting accuracy, when not accounting for SECs of individual decision makers.

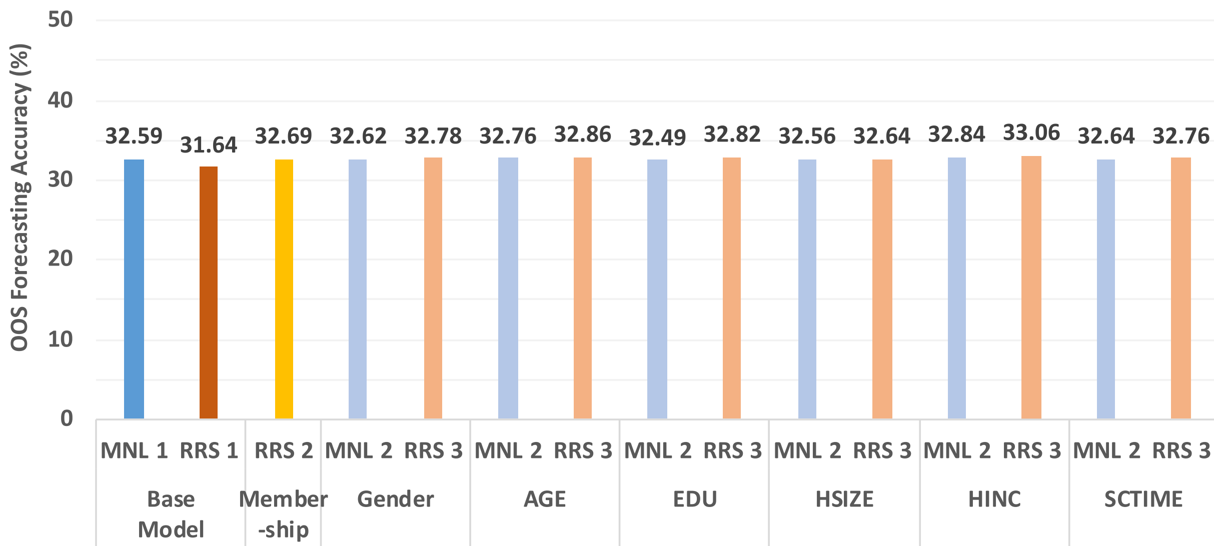
On the other hand, the consideration of the SECs for decision makers may advance the forecasting performance of the RRS approach. We applied two different ways to reflect the SECs of respondents in each model in order to account for the heterogeneity of preferences.

First, we see the RRS 2 which used a membership variable with the MNL 1. In the case of the RRS 2, the accurate prediction rate of 32.69% is a little better than 32.59% of the MNL 1, which was improved by 1.05% from that of the RRS1. This means that using the RRS approach with SECs for a membership variable may have the potential to yield better OOS predictions that using the MNL 1. For the RRS 2, we have the same OOS prediction results across different SECs as a membership variable. We note that no matter what membership variable we used in the RRS 2, the OOS prediction accuracy was invariant. That is, whether we used gender, age, education level, household size, or household income as a membership variable, the correct prediction percent results did not change. [7] This no change in the OOS correct forecasting is due to the fact that a membership variable does directly affect the probability of class allocation but indirectly influences food attribute specific parameters that are evaluated by the systematic part of the random utility.

Second, we compare the RRS 3 with the MNL 2 model reflecting SECs in the models by using interaction terms. Unlike the RRS 2 model, the inclusion of interaction terms in the utility function directly affects the estimation of food-specific parameters, so the food-specific parameter estimates vary greatly depending on which interaction terms enter the model. We can see the difference in the OOS prediction accuracy by SEC in the last column of Table 1.3. The correct predicted rates of the RRS 3 are at least 32.64%, which better performed than 31.64% of the RRS 1, across SECs for heterogeneity of preferences. According to the OOS prediction of the RRS 3 by the membership variable, the correct prediction rates were from 32.64% to 33.07%, specifically, 32.76% for gender, 32.86% for age, 32.82% for education, 32.64% for household size, and 33.07% for household income. Those accuracy rates are marginally greater than the case of the MNL 2. In the MNL 2, the predictive accuracy rates were 32.62% for gender, 32.76% for age, 32.49% for education, 32.56% for household size, and 32.87% for household income. The introduction of the interaction term in both the MNL and the RRS slightly increased the OOS predictive accuracy rates, but that's a small amount. In particular, the increase in predictive power in the RRS was greater than in the MNL. The predictive accuracy improvements in the RRS were from 1.00% to 2.42%, while those of MNL ranged from 0.00% to 0.28%. The monthly OOS forecasts of the MNL

[7] SECs used for a membership variable does affect the WTP estimates for each food product because they bring about a change in marginal utility of food products and marginal (dis) utility of price, although did not lead to a change in the OOS prediction accuracy.

2 and the RRS 3 reveals that the RRS 3 was better than the MNL 2 in over 34 cases among 60 monthly analyzes, which depends on interaction terms for SECs of individuals. Whereas the MNL 2 was better than the RRS 3 in a maximum of 24 cases. This result implies that the RRS approach may perform better than the standard MNL in sense of the OOS forecasting when accounting for SECs of individual respondents, but there is no significant difference.



Note: For the RRS 2, we have the same OOS prediction results across the SECs as a membership variable.

Figure 1.2 OOS Forecasting Accuracy Comparisons by Models

1.6 Conclusions

This study applied the random response share (RRS) approach for reducing hypothetical bias due to inattention decisions and assessed the validity of the RRS based on OOS forecasting performance. The aim of the RRS model is to purge the observations from those who did a totally random choice in a choice task. Given that the RRS approach focuses on parameter estimates within the unrestricted segment, examining their representativeness is crucial in evaluation of the validity of the RRS. Our study employed the FooDS data. The FooDS data was collected from 61,592 survey respondents and includes choice experiment questions and socio-demographic information of individual respondents. We took advantage of rich observations of the FooDS to assess Malone and Lusk (2018)'s the RRS model by the out-of-sample prediction comparisons.

Our results revealed that the RRS is not likely to be a dominant strategy to the conventional MNL in terms of OOS forecasting accuracy. This is because the OOS predictive power of the base model (the RRS 1), which does not reflect SECs, remained at 31.64%, lower than 32.59% for the MNL 1. In addition, adding SECs to the model increased the predictability of the RRS models, despite not much higher than that of the MNL models. The RRS 2 showed the OOS correct forecasting rate of 32.69%. The predictive accuracies for the MNL 2 and the RRS 3 were between 32.56% and 32.84% and between 32.64% and 33.06%, depending on socio-economic characteristics (SECs), respectively.

The RRS model may be improved by also considering the SECs of respondents in the sense of its predictive performance but it is hard to say that a big improvement was found. This study attempted to increase the predictive performance of discrete choice analysis by incorporating the SEC variables into the model in two ways. The first way is to add the SECs to the RRS base model as a membership variable. Another way is to put an interaction term of the attribute and the SECs into the indirect utility function of the base MNL and RRS models. In particular, the results reported that there is little difference between adding SECs as a membership variable into the segment probability and putting them into the indirect utility function in terms of the OOS prediction accuracy ratio. Practically, the approach to include SECs as a membership variable into the class probability is simpler than the other way to account for heterogeneous preferences. This implies that we could improve the forecasting power of the RRS through a relatively convenient method. Nevertheless, we could not find a significant improvement in terms of the predictive performance. At the same time our results show that RRS is not harmful compared to the conventional MNL. Therefore, it is recommended for analysts to apply the RRS with a setting for appropriate membership variables that enter the prior likelihood in order to address inattention choice, instead of adding interaction terms with SECs to the systematical part of the utility function in the RRS model. Also, analysts also should recognize that willingness-to-pay estimates for each product and the probability of random response vary depending on the model.

The present study considered heterogeneous preferences by putting one of the various SECs, and examined how WTP estimates, RRS, and OOS prediction accuracy changed. Given the various combinations of SECs, the predictive power of the RRS model is expected to be higher. We leave this work for future research. In addition, in spite of the use of more plentiful observations in this study than the validation based on a trap question in Malone and Lusk (2018), the analysis results were basically derived from the same CE data. Therefore, we expect that additional research continues to apply the RRS model to other CE data for further validation.

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Chapter 2 - Incorporating Choice Heuristics in Analysis of Decision Making

2.1 Introduction

Given the cognitive burden and the information process cost, it is not easy for an agent to choose his or her best option among several alternatives available, taking into account every attribute of the alternatives and trade-offs across the options. Rather, agents' decision-making often relies on some heuristic process of attribute substitution (Tversky and Kahneman 1974; Kahneman 2003a). To simplify the choice tasks, agents may ignore some attributes of the alternatives and focus on only a subset of them (Tversky 1972; Weller et al. 2014).

Discrete choice literature has attempted to incorporate the decision heuristics in analytical models. Many choice analysis studies have taken the form of considering the heterogeneity of attribute processing in discrete choice models (DCMs), which has been in full swing since Hensher, Rose, and Greene (2005). Hensher, Rose, and Greene (2005) argued that respondents in stated choice experiments may ignore attributes of alternatives presented in a choice task and may choose one. It questioned the traditional assumption of the discrete choice modeling that all attributes are considered and evaluated by agents when they make a choice. [8] Hensher, Rose, and Greene (2005) stated three potential reasons for attribute inattention: (1) attribute non-attendance (ANA) is to address complex tasks respondents are asked; (2) the benefit of the full attribute assessment (FAA) is lower than the cost of evaluating attribute; (3) an attribute does not affect

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[8] The standard discrete choice model assume that rational agents select their most preferred option that maximizes their utility based on evaluating all attributes when making choices. Considering every characteristics in choice tasks is called , classic decision rules, full attribute assessment or full attribute preservation.

choices respondents make. It had raised a question about the fundamental assumption of classical economics that rational agents make a choice that maximizes their utility.

Recent choice analysis reported better model fit in the case of accommodating ANA decision strategies than in accounting for only the FAA, supporting the position that agents may choose an alternative without full attribute preservation (Campbell, Hutchinson and Scarpa 2008; Hensher and Rose 2009; Scarpa et al. 2009; Hess and Hensher 2010; Scarpa, Thiene and Hensher 2010; Balcombe, Burton and Rigby 2011; Scarpa et al. 2013; Heidenreich et al. 2018; Malone and Lusk 2018; Thiene, Franceschinis and Scarpa 2018; Collins, Rose and Hensher 2013; Hensher, Collins and Greene 2013; Hess et al. 2013; Hole, Kolstad and Gyrd-Hansen 2013; Lagarde 2013). In particular, with the advance of online survey tools and the popularity of choice experiments (CEs), many empirical studies based on stated preference data have investigated heuristic processes through econometric models. DCM is a key econometric framework for a stated choice method that is of analysis on agents' decision-making processes or preferences in the applied economics field. Remarkably, there are a number of works using the stated choice data in the area of agricultural, environmental, food, and health economics. Given the popularity of stated choice analysis for policy evaluation and market research, more refined approaches in CEs are required to avoid misguide policy recommendations and strategical decision makings.

Heuristics are known as a simple and intuitive decision-making strategy. A heuristic strategy is a way to make decisions quickly and simply, rather than making choices based on how to get the optimal results when people make decisions. Tversky and Kahneman defined the heuristics as simple judgmental principles. *"People rely on a limited number of heuristic principles which reduce complex tasks of assessing probabilities and predicting values to simpler operations"* (Tversky and Kahneman 1974. p. 1124)." Hensher, Rose, and Greene viewed choice heuristics as simple preference constructions. "*Individuals use to simplify preference construction and hence make choices, or to make the representation of what matters relevant, regardless of the degree of complexity as perceived by the decision maker and/or analyst"* (Hensher, Rose and Greene 2015. p.937). Heuristic decision rules do not guarantee agents' utility maximization. Heuristics can often introduce systematic errors. Nevertheless, in real life, the reason why people apply heuristic rules is to avoid deliberate and effortful computations (Kahneman 2003b), to minimize time-consuming (Leong and Hensher 2012), or to reduce cognitive efforts (Leong and Hensher 2012; Caputo, Scarpa and Nayga 2017).

Choice heuristics have been defined in various ways by researchers. But the basic idea is in line with Tversky's choice theory that is known as elimination-by-aspects. According to the elimination-by-aspects, individual alternatives consist of a combination of attributes, and alternatives that do not contain an attribute that is a crucial contributor to a decision maker' utility are removed from the choice set. The elimination process continues until one option finally remains in the choice set (Tversky 1972)

The elimination heuristics were recently applied in several ways (Leong and Hensher 2012). The first concept is to classify alternatives based on whether they contain attributes that contribute to agents' utility function, which is related to ANA. This concept assumes that if a specific attribute of alternatives contributes to an agent's utility, the agent evaluates that attribute, otherwise the agent does not pay attention to the attribute. The attributes carefully evaluated by the agent are estimated in econometric models but are restricted to zero for attributes that are not a contributor to the utility. Attendance or inattention for a certain attribute can be determined by directly asking the decision makers or by inferring the agent's implicit decision process using a latent class framework. The latter case is the approach our paper adopts, which is mainly applied when the decision rule was not observed or could not be monitored (Scarpa et al. 2009; Collins, Rose and Hensher 2013; Hensher, Collins and Greene 2013; Hess et al. 2013; Lagarde 2013; Kragt 2013; Weller et al. 2014; Hole et al. 2013; Sandorf, Campbell and Hanley 2017; Heidenreich et al. 2018; Thiene, Franceschinis and Scarpa 2018; Balbontin, Hensher and Collins 2019).

Second, the elimination-by-aspects were dealt with in the perspective of reference points or value learning (Balbontin, Hensher and Collins 2017; Tonsor 2018; Caputo, Lusk and Nayga 2019; Balbontin, Hensher and Collins 2019). This method is to decide whether to remove an alternative from the choice set based on the agent's a reference point (threshold level). In other words, this approach is based on the cut-off levels for attributes, and the gains or losses caused by choosing an alternative are measured using a reference point (Balbontin, Hensher and Collins 2019). The reference point may be respondent-specific levels (Tonsor 2018) or could be adjusted across the processing rules and choice situations (Leong and Hensher 2012).

Third, Adamowicz (1994) and Adamowicz and Swait (2013) examined habitual and variety-seeking choices. The habitual choice indicates a decision rule that agents choose always the same item, while the variety-seeking choice is a choice strategy that an agent chooses a different product from the last product purchased (Adamowicz 1994; Adamowicz and Swait 2013). These decision principles are also kinds of the elimination-by-aspects.

In addition, some studies have taken a position that inattention behavior is also rational because attaining and evaluating information are also costly. This perspective has arisen since Sims (2003). The literature on rational inattention (RI) approach has addressed the lack of attention of decision makers under imperfect information circumstances in the aspect of rational behavior (Joo 2019; Fosgerau, Melo and Shum 2019; Matějka and Mckay 2015). They introduce information costs into the random utility function based on Luce’s choice model (1959).

There were many efforts to establish a heuristic strategy in DCM literature, and many studies employed stated preference data collected from choice experiments. However, choice heuristics also can be applicable to consumers' actual choice environments as they may not always account for all attributes of alternative products in a market. In real life, shoppers may judge alternatives and make a choice one intuitively. The decisions may be simple without deliberate and effortful computations. Because they want to not only maximize their utility but also reduce information processing costs (Louviere, Hensher and Swait, 2000). In other words, the heuristic decision rules may be found in non-hypothetical market data by applying a latent class structure.

The ultimate goal of this study is to explore heuristic choice behavior using actual market data (panel households' frankfurters purchase record), instead of relying on hypothetical data (stated choice data). Previous ANA literature adopted stated choice data to investigate heterogeneity in the decision-making process in the context of the RUM framework. We also utilize the latent class structure of the discrete choice model based on the RUM. Unlike previous studies, however, our study attempts to apply some choice heuristics to scanner data that came from the IRI marketing data set. We focus on consumer behavior at the household level, while many economic studies that use market data for analysis at the store level. The present study applied the same econometric approach that often used in CE, at the household level, which allows comparing with literature relied on CE methods.

This study contributes to better understanding of consumers' choice, applying a latent class framework of discrete choice models. If no significant ANA choice is found in our analysis, it will provide evidence that all attributes of products are fully considered when shoppers buy hotdog products in the real market. Otherwise, attributes may not always be central factors for some consumers in an actual market. And it supports previous ANA discussions based on CE methods.

2.2 The IRI Marketing Data

The Information Resources, Inc. (IRI) marketing data was employed to explore choice heuristics in the present paper. The IRI marketing data introduced by Bronnenberg, Kruger, and Mela (2008) is a scanner dataset representing consumers' actual purchases in stores. It includes information about 30 different product categories sold weekly in a particular store across 47 markets from 2001 to 2012. In addition, the IRI data provides its panel households' weekly purchasing records within two different markets (Eau Claire, WI, and Pittsfield, MA), as well as their socio-economic characteristics. The IRI data is a popular source in the field of industrial organization, marketing, and household economics.

To deeply investigates consumer' choice heuristics at the level of the household, this study focuses on hotdog sausage choice behavior at a grocery store in Eau Claire, WI, in 2012. We picked Eau Claire, WI, as the population of Eau Claire, WI, is higher than Pittsfield, MA. The U.S. census 2010 reported that the populations for Eau Claire, WI, and Pittsfield, MA were 65,8823 and 44,737, respectively. The reason for using only one year's data is to keep product availability to the consumers as consistent as possible. If multiple years of data were used, an analyst should consider the entry of a new product and the exit of an existing product. For simplicity, this study analyzed only the products sold in 2012. Given the nature of the scanner data, we only have information about products bought by consumers, it is not easy to consider the entry of new products and the exit of products. This means that we may not know the characteristics of alternative products if they were not bought by households so that it is hard to construct choice sets. A grocery store with the highest number of hotdog sausage purchases in Eau Clare, WI. was chosen as the target store. We could not identify what local store was selected because the IRI data did not provide specific store information such as store names and addresses. There are seven grocery stores and three drug stores where panel households visited for hotdog sausage products in Eau Clare, WI. The chosen store is the most popular grocery store for hotdogs for the IRI panel households.

Our study constructs choice sets for discrete choice analysis based on 531 households' hotdog sausage purchase records and information on product attributes to build choice sets for discrete choice analysis. The number of choice situations varies by household. Unlike choice experiments in which researchers often set the same number of choice tasks faced by respondents, it is common for households to have different numbers of choice situations in real life. For example, some households buy hot dogs five times for 52 weeks (one year), while others buy 13 times. As such, the fact that the number of events of hotdog sausage purchases may vary across households produces an unbalanced panel structure (see Table B.1 in Appendix). Our study analyzes this information using the data aggregated weekly.

Household panel data shows how much of household *i*'s purchases and expenditure for hotdog product *j* in a specific week. It also includes households' socio-economic characteristics, for example, household income, family size, household head's age, education achievement, and occupation. For households' annual income level, 22.60% of 531 households earned less than \$25,000. 34.84% is for \$25,000 to \$54,999, and 31.07% is for \$55,000 to \$99,999, and 11.30% earned more than \$100,000. For family size, two people households accounted for more than half (50.47%). For the age of household head, the highest portion was 39.36% for those aged 65 or higher, followed by 28.06% for 55-64 years old and 18.46% for 45-54 years old. For education achievement, some high school and graduated high school were 29.19% and 25.42% respectively. According to the occupation information, private household workers were the highest at 29.00%. This information can be identified with a unique panel id in household panel data.

Table 2.1 Socio-Economic Characteristics of Household Panel

		Socio-Economic Characteristics	Frequency	Percent (%)	Cumulative Freq.
Household	1	Less than $ 9,999	31	5.84	31
Income per year	2	$10,000 to $11,999	9	1.69	40
(Pre-Tax)	3	$12,000 to $14,999	14	2.64	54
	4	$15,000 to $19,999	30	5.65	84
	5	$20,000 to $24,999	36	6.78	120
	6	$25,000 to $34,999	70	13.18	190
	7	$35,000 to $44,999	79	14.88	269
	8	$45,000 to $54,999	36	6.78	305
	9	$55,000 to $64,999	55	10.36	360
	10	$65,000 to $74,999	24	4.52	384
	11	$75,000 to $99,999	86	16.20	470
	12	$100,000 and greater	60	11.30	530
		No information	1	0.19	531
Family	1	One person	89	16.76	89
Size	2	Two people	268	50.47	357
	3	Three people	71	13.37	428
	4	Four people	58	10.92	486
	5	Five people	33	6.21	519
	6	Six people	8	1.51	527
	7	Seven people or more	4	0.75	531
Age of	1	18-24 years old	0	0.00	0
Household	2	25-34 years old	23	4.33	23
Head	3	35-44 years old	52	9.79	75
	4	45-54 years old	98	18.46	173
	5	55-64 years old	149	28.06	322
	6	65 or higher	209	39.36	531
Education	0	N/A	1	0.19	1
Household	1	Some grade school or less	7	1.32	8
Head	2	Completed grade school	13	2.45	21
	3	Some high school	155	29.19	176
	4	Graduated high school	135	25.42	311

	5	Technical school	114	21.47	425
	6	Some college	53	9.98	478
	7	Graduated from college	23	4.33	501
	8	Post graduate work	4	0.75	505
	99	No information	26	4.90	531
Occupation of Household Head	1	Professional or technical	98	18.46	98
	2	Manager or administrator	45	8.47	143
	3	Sales	49	9.23	192
	4	Clerical	37	6.97	229
	5	Craftsman	4	0.75	233
	6	Operative (machine operator)	19	3.58	252
	7	Laborer	4	0.75	256
	8	Cleaning, food, health service worker	49	9.23	305
	9	Private household worker	154	29.00	459
	10	Retired	36	6.78	495
	99	No information	36	6.78	531
Total			531	100.00	

The IRI data provides a data set of product characteristics with the universal product code (UPC). The UPC helps researchers identify the characteristics of each product. In the case of hotdog sausage products, for example, we can tell what brands are, how they are packaged, what kind of meat they use, what their size is. The UPCs were used to match individual product attribute information with hotdog sausage products purchased by household panels.[9] The IRI data provides eight different attribute groups for hotdog products, including brands, package sizes (oz), product sizes, meat types, flavors, fat contents, package types, and process. For simplicity, this study utilizes six attribute groups of brands, package sizes (oz), product sizes, meat types, flavors, and fat contents.

[9] Specifically, we combined the two datasets using colupc (the collapsed UPC). The colupc allow us to identify unique products.

The observed panel households sausage purchases indicate that households in Eau Claire, WI, usually bought hotdog sausage products from a major grocery store in 2012. Limiting household choice behavior at a specific store has both pros and cons. One of the advantages of narrowing the scope of the analysis is that researchers are able to more closely look at and scrutinize household buying behavior from a micro-perspective. That is, it can be observed that the household i selected j product among the J available alternatives of hotdog products at store s, evaluating attributes of each alternative product. In addition to the analyzing detailed decision-making process, the biggest advantage of focusing on one store in performing the empirical analysis is that it allows us to reduce the number of available alternatives J. This means analysts control a smaller choice set. If researchers allow the choice of all the households observed at multiple stores, the model should reflect that the products available to decision-makers depend on stores they visited. The research may be able to construct a nested logit model to deal with this issue, but this may extend the complexity of the analysis rather than focusing on our research questions. Hence, this study focuses on purchasing events that happened at a grocery store in Eau Claire, WI, to test whether households use a heuristic approach that ignores attributes when buying hotdog sausages.

2.3 Conceptual Framework

2.3.1 Multinomial Logit Model (MNL)

To explore shoppers' heuristic choices in purchasing hotdog sausage products, in terms of the ANA concept, this research utilizes latent class frameworks of the discrete choice models. In particular, we employ latent class multinomial logit models (LC-MNLs) and latent class random parameter logit models (LC-RPLs) based on the RUM framework that is often used in the standard ANA literature.

Suppose that consumer *i* chooses an alternative hotdog item *j* in choice situation *t*. Under the RUM, agent *i*'s random utility U_{itj} obtained by consuming the product *j* in choice situation *t* and can be expressed as:

$$U_{itj} = V_{itj} + \varepsilon_{itj} \tag{1}$$

Where V_{itj} is a deterministic part and ε_{itj} is an unobservable part. We assume that the stochastic component, ε_{itj}, be identically and independently distributed (IID) with a type I extreme value distribution. This assumption yields the multinomial logit formulation for the probability of decision maker *i*'s choosing alternative *j* in choice circumstance *t* (McFadden 1974; Train 2009; Hensher, Rose and Greene 2015).

$$P_{itj} = \frac{\exp\,(V_{itj})}{\sum_{j \in J} \exp\,(V_{itj})} \tag{2}$$

In the standard multinomial logit model (MNL), the observed component of the utility involved with alternative *j*, V_{itj}, is specified as:

$$V_{itj} = \beta' X_{itj} \quad (3)$$

Where X_{itj} is a vector of the K attributes of alternative *j* in choice situation *t* faced by agent *i*. And parameter estimates, β, indicate the marginal utility of attribute *k* of alternative *j*.

With the above specification for the modeled component in the equation (3), the choice probability yields equation (4) for a single situation and equation (5) for a panel data, respectively.

$$P_{itj} = P_{(y_{itj}=j)} = \frac{\exp(\beta' X_{itj})}{\sum_{j \in J} \exp(\beta' X_{itj})} \quad (4)$$

$$P_{ij} = P_{(y_{ij}=j)} = \prod_{t=1}^{T} \frac{\exp(\beta' X_{itj})}{\sum_{j \in J} \exp(\beta' X_{itj})} \quad (5)$$

Under this MNL framework, parameter estimates, β, is an invariant across individuals and assume homogeneous preferences.

2.3.2 Random Parameters Logit Model (RPL)

In contrast to the MNL, random parameters logit (RPL) models assume that some of the parameters are random and the random parameter distributions are continuous over the samples. This feature accounts for systematical preference heterogeneity across individual agents by decomposing the mean and standard deviation of random parameters (Hensher, Rose and Greene 2015). The RPL also is free of the independence of irrelevant alternatives (IIA) assumption and allows correlation in unobserved factors over time.

The indirect utility function and the random utility function can be summarized as equation (6) and (7), respectively.

$$V_{itj} = \beta'_i X_{itj} \tag{6}$$

$$U_{itj} = \beta'_i X_{itj} + \varepsilon_{itj} \tag{7}$$

Where X_{itj} is a vector of the K attributes of alternative *j* in choice situation *t* faced by agent i. And β_i, is a vector of parameters of these variables for individual agent *i* representing the person's preferences. The parameters vary over agents in the population with density, $f(\beta)$. ε_{itj} is the stochastic error term that is assumed to be IID with the type I extreme value.

Under the systematic portion of the utility function in the equation (6), the choice probability takes the logit probability, and this is the same as the equation (4), except β_i. The probability is conditional on β_i since β_i is unobservable by analysts (Train 2009).

$$L_{itj}(\beta_i) = \frac{\exp(\beta'_i X_{itj})}{\sum_{j\in J} \exp(\beta'_i X_{itj})} \tag{8}$$

The unconditional choice probability can be obtained by taking integral of the equation (8) over all possible variables of β_i, which is given as equation (9) for a cross-section and equation (10) for a panel data (Train 2009; Hensher, Rose and Greene 2015).

$$\pi_{itj} = \int \left[\frac{\exp(\beta'_i X_{itj})}{\sum_{j\in J} \exp(\beta'_i X_{itj})}\right] f(\beta_i)\, d\beta_i \tag{9}$$

$$\pi_{ij} = \int \left[\prod_{t=1}^{T} \frac{\exp(\beta'_i X_{itj})}{\sum_{j\in J} \exp(\beta'_i X_{itj})}\right] f(\beta_i)\, d\beta_i \tag{10}$$

2.3.3 Latent Class Structure

The underlying theory of the latent class model approach posits that individual behavior depends not only on observable attributes but also on latent heterogeneity that varies with factors that are unobserved by analysts. The latent class modeling assumes that the population is comprised of a finite number of groups, Q, and each segment is predefined (Hensher, Collins and Greene 2013). The latent class structure can be applied to both the MNL and the RPL. The latent class multinomial logit model (LC-MNL) assumes that decision makers have heterogeneous preferences across classes, but homogeneous preferences within each class as in the conventional MNL (McKendree, Tonsor and Wolf 2018). The LC-MNL is more flexible than the MNL but somewhat less flexible than the RPL, in which the mixing distribution, $f(\beta)$, is discrete in the LC-MNL whereas the MNL has a uniform distribution and the RPL is based on the continuous distributions of parameters across individuals (Greene and Hensher, 2003; Train 2009). The LC-MNL consists of two MNL formation components. The first portion is for the probability of individual choice and the second part is for the prior probability of the class assignment. The choice behavior within the class of q is estimated by a logit model for discrete choice of alternative *j* among *J* alternatives, by individual *i,* observed in choice circumstance *t*, (Hensher and Greene 2010).

$$P_{it|q(j)} = Prob(y_{it} = j\,|class = q) = \frac{\exp(\beta'_q X_{itj})}{\sum_{k \in J} \exp(\beta'_q X_{itj})} \tag{11}$$

For the given class assignment *(class=q)*, the contribution of individual *i* to the likelihood is the joint probability of the sequence (Hensher and Greene 2010), given in (12)

$$P_{i|q(j)} = \prod_{t=1}^{T} P_{it|q(j)} \tag{12}$$

The prior probability for class q for individual *i* also has the MNL form as equation (13).

$$P_{(class=q)} = H_{iq} = \frac{\exp(\theta'_q Z_i)}{\sum_{q=1}^{Q} \exp(\theta'_q Z_i)}, \quad q = 1, 2, \dots, Q \text{ and } \theta_Q = 0, \tag{13}$$

Where Z_i denotes a set of observable characteristics of individuals that enter the model for class membership. Note that the Q^{th} parameter vector, θ_Q, is normalized to zero to secure identification of the model (Hensher and Greene 2010).

Ultimately, the likelihood for consumer *i* is the expectation (over classes) of the class-specific contributions and is described by equation (14) (Hensher and Greene 2010).

$$P_{ij} = \sum_{q=1}^{Q} H_{iq} \, P_{i|q(j)} \tag{14}$$

This study also tries to jointly address attribute inattention and preference heterogeneity by employing the latent class random parameter logit model (LC-RPL). By allowing for random variation in the parameter estimates for attributes, we consider heterogeneity in preferences (Sandorf, Campbell and Hanley 2017). Accounting for the fact that preferences vary across agents within a latent segment q, β_{iq}, helps us explore choice heuristics by seeing different segments and on heterogeneous preferences within a specific segment through the continuous mixing distributions, $f(\beta)$.

Like the LC-MNL, the LC-RPL also has two components, the probability of agents' choice and the prior probability of the class assignment. The segment probability that consumer *i* belongs to class q is the same as equation (13). The conditional probability of consumer i choosing alternative product *j* out of *J* alternatives within class q can be described by:

$$L_{it|q(j)}\left(\beta_{iq}\right) = Prob(y_{it} = j \,|class = q) = \frac{\exp\,(\beta'_{iq} X_{itj})}{\sum_{j \in J} \exp\,(\beta'_{iq} X_{itj})} \qquad (15)$$

The unconditional choice probability within a class can be obtained by taking integral of the equation (15) over β_q given as equation (16) for a cross-section and equation (17) for a panel structure (Thiene et al. 2018; Train 2009; Hensher, Rose and Greene 2015).

$$\pi_{it|q(j)} = \int \left[\frac{\exp\,(\beta'_{iq} X_{itj})}{\sum_{j \in J} \exp\,(\beta'_{iq} X_{itj})}\right] f\left(\beta_{iq}\right) d\beta_{iq} \qquad (16)$$

$$\pi_{i|q(j)} = \int \left[\prod_{t=1}^{T} \frac{\exp\,(\beta'_{iq} X_{itj})}{\sum_{j \in J} \exp\,(\beta'_{iq} X_{itj})}\right] f\left(\beta_{iq}\right) d\beta_{iq} \qquad (17)$$

Finally, the likelihood for consumer *i* is the expectation (over classes) of the class-specific contributions and is expressed as:

$$\pi_{ij} = \sum_{q=1}^{Q} H_{iq}\, \pi_{i|q(j)} \qquad (18)$$

2.4 Empirical Application

We begin with a simple MNL for homogeneous attribute processing and move to LC-MNL models to investigate consumers' heuristic decision-making process when buying frankfurter products. A RPL and LC-RPL models are also employed to reflect preference heterogeneity within a class. This study further examines if the LC-RPL models provide a better fit than the LC-MNL models. As a base model for embedding choice heuristics into the discrete choice model, the LC-DCMs (LC-MNL and LC-RPL) start with the two segments for the most extreme type of two attribute processing rules: total attribute preservation and total attribute non-attendance. The LC-DCM then is extended by adopting choice heuristics of attribute non-attendance cases where may occur between the two extreme modes of attribute processing protocols. Using the revealed preference data from the IRI marketing data sets the present study estimates the MNL and the RPL models for the full attribute attendance as the base models, and adopts the LC-MNL and the LC-RPL models for multiple attribute processing rules.

2.4.1 Attributes and Choice set

This study examines attribute inattention decision making strategies, focusing on consumer choices of hotdog sausage products at one of the food stores in Eau Clare, WI, in 2012. We do not know exactly what store was selected because the IRI data did not provide specific store information such as store names and addresses. There are seven grocery stores and three drug stores where panel household visited for hotdog sausage products in Eau Clare, WI. A grocery store with the highest number of hotdog sausage purchases in Eau Claire, WI, from 2008 to 2012 was chosen as the target store for this study.

Table 2.2 Attributes and their levels used

Attribute group	Level	Description
Price	28 different prices between \$1.37 and \$10.49	• Average price for each alternative item in 2012
Brand	Oscar Mayer	• Oscar Mayer and Oscar Mayer Selects
(vs. Other)	Ball Park	• Ball Park
	Other	• Other brands except Oscar Mayer and Ball Park
Package size	*Small*	• Less than 16 oz
(vs. Small)	Medium	• 16 oz ≤ Size < 24 oz
	Large	• 24 oz and larger
Product size	Jumbo	• Jumbo size
(vs. Other)	Other	• Other product sizes
Meat type	Beef (only beef)	• Beef and Angus Beef
(vs. Other)	Other	• Pork, Turkey, Chicken, Mixed meats, and so on.
Flavor	Regular	• Regular, Classic, Original, and Old Fashioned
(vs. Other)	Other	• Smoked, Cheese, Jalapeno, Cheddar, and so on.
Fat Contents	Low fat	• Low fat, Extra lean, Fat free
(vs. Regular)	Regular	• Original, No information about fat contents

Revealed preference data do not have information about unpurchased items but only contain records about chosen products. Thus, we are not able to figure out the real choice sets consumers faced. To address this issue, we built a choice set of products bought by panel households more than once in 2012. A total of 166 unique hotdog sausage products were sold in Eau Claire, WI in 2012. For attributes of hotdog sausage products, we consider six attribute groups of product characteristics provided by the IRI scanner data sets. This includes the brands, package sizes (oz), product sizes, meat types, flavors, and fat contents. For simplicity, recategorizing each attribute within attribute groups and regenerating products based on combinations of attributes produces a total of 28 unique hotdog sausage products at the selected grocery (see Table 2.2).[10]

[10] We examined the correlation between attributes by seeing two-way frequency tables. All the attributes are independent except for the correlation of the small package size and the regular flavor. There is no regular hotdog sausage product with a small package. That is, the hotdog products that have regular flavor attributes are available with a medium or a large package.

Table 2.3 Descriptive Statistics of the IRI Data Used for Discrete Choice Models

Variable	Description	Num of Samples	Mean	Std. Dev.	Minimum	Maximum
panel_id	Id of household panel	37,744	3,305,744.00	218,073.00	3,100,529.00	3,842,948.00
t	t^{th} purchase event	37,744	2.86	2.62	1.00	18.00
nt	Purchase Occasion	37,744	4.73	3.91	1.00	18.00
inchh	Household income	37,660	7.92	3.16	1.00	12.00
fam_size	Family size	37,744	2.54	1.22	1.00	7.00
hh_age	Age of Household head	37,744	4.77	1.24	2.00	6.00
hh_edu	Education level of Household head	37,744	10.96	24.41	0.00	99.00
hh_occ	Occupation of Household head	37,744	13.43	26.09	1.00	99.00
choice	Choice or not	37,744	0.04	0.19	0.00	1.00
hotdog	Alternatives	37,744	14.50	8.08	1.00	28.00
price	Prices	37,744	4.02	1.92	1.37	10.49
brand1	Oscar Mayer	37,744	0.43	0.50	0.00	1.00
brand2	Ball Park	37,744	0.18	0.38	0.00	1.00
brand3	Other	37,744	0.39	0.49	0.00	1.00
oz1	Small package	37,744	0.36	0.48	0.00	1.00
oz2	Medium package	37,744	0.50	0.50	0.00	1.00
oz3	Large package	37,744	0.14	0.34	0.00	1.00
size1	Other size product	37,744	0.89	0.31	0.00	1.00
size2	Jumbo size product	37,744	0.11	0.31	0.00	1.00
meat1	Other	37,744	0.57	0.49	0.00	1.00
meat2	Beef	37,744	0.43	0.49	0.00	1.00
flavor1	Other	37,744	0.14	0.35	0.00	1.00
flavor2	Regular	37,744	0.86	0.35	0.00	1.00
fat1	Regular	37,744	0.71	0.45	0.00	1.00
fat2	Low fat	37,744	0.29	0.45	0.00	1.00

We assume that 28 alternatives are always available for all consumers and that there is no entry of a new product and no exit of an existing product. Thus, the number of alternative products is 28 in our analysis, indicating that individual *i* choose a hotdog product among 28 alternatives in our econometric models. In addition to product attributes, price is also an important factor influencing consumer choice. The amount paid by consumers depends on hotdog products. Furthermore, even if consumers purchase the same hotdog product, the amount paid may vary depending on when the purchase was made or whether a coupon is applied. Since the price of respective hotdog sausage product is not constant for one year, we take the average of the prices of each alternative sold in 2012 and set them as the price of each alternative.

2.4.2 Decision Making Rules

This study attempts to investigate four representative choice heuristics as decision making processes. The first decision making strategy is full attribute attendance (FAA), which is for total attribute attendance. The decision-making principle of the FAA correspondent to the standard assumption of discrete choice analysis that agents evaluate all attributes of alternative products and choose one. For the FAA, the systematical component of the utility function is specified as:

$$V_{itj} = P'_{tj}\alpha + \sum_{c\in C} X'_{tjc}\beta_c \tag{19}$$

The second decision making rule is to only consider the price of products. We call this rule as price attendance (PA) in this study. The PA principle indicates that agents assess only the price of alternative products and ignore other attributes. For the PA, the systematical part of the utility function is specified as:

$$V_{itj} = P'_{tj}\alpha \tag{20}$$

The third rule we consider here is price attribute non-attendance (PANA), which is the opposite of the second one. The principle of PANA assumes that all attributes of alternative products are evaluated by agents, except the price. For the PA, the indirect utility function is specified as:

$$V_{itj} = \sum_{c \in C} X'_{tjc} \beta_c \quad (21)$$

The last decision-making protocol examined in this study is a purely random (PR) choice, which assumes that decision makers do not account for any attribute of alternatives and randomly select one among alternatives. The PR is known as total attribute non-attendance because it is opposite to the total attendance. The modeled component and the utility function are specified as the following, respectively.

$$V_{itj} = 0 \quad (22)$$

$$U_{itj} = V_{itj} + \varepsilon_{itj} \quad (23)$$

In addition to the above four decision rules, there could be a lot of additional possible combinations of attributes for decision rules. For example, when decision making is made based on six attribute groups (c is 1 to 6) along with the price of the product, a decision rule that considers five attribute groups but does not consider one attribute group may be considered. Alternatively, another decision rule may be that the three attribute groups enter the decision criteria, but the other three attribute groups may be ignored. However, this study examines only the four representative rules. Given our number of 531 sample households, if it considers many multiple classes for various heuristics, each class might become too thin and lead to impractical estimation of the models. For instance, we tried to put nine different decision rules in our discrete choice model and the estimation results were not good due to the small sample for some specific choice heuristic decision rules.[11] For this reason, four representative decision-making rules that include the FAA and three choice heuristics were examined in this study.

2.4.3 Model Specifications

Model 1 is our base model for the choice of agents who take into account all attributes following the traditional assumption. The systematical part of the random utility is specified as the equation (19). To do this we estimate the choice probability of model 1 and leave it to compare with other choice strategies.

Model 2 is a simple extension of the model 1, which allow heterogeneous preferences of agents across segments using discrete distributions of parameters. Similar to the model 1, the systematical component of the model 2 is the same as the equation (19). However, the model 2 is based on the two-segment latent class structure, so that the marginal utility of the consumer for each attribute varies by segment. The indirect utility of decision maker *i*'s choosing alternative *j* can be described as:

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c\in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ P'_{tj}\alpha_2 + \sum_{c\in C} X'_{tjc}\beta_{c2} & \text{if } q = 2 \end{cases} \tag{24}$$

Model 3, 4, and 5 try to explore, the PR, the PA, and the PANA, respectively, based on the two-segment latent class structure of LC-MNL and LC-RPL. These models compare choice

[11] For example, we tried to examine nine different decision rules using the latent class structure, but the estimation result was not good due to some thin segments.

heuristic and the FAA strategy. The model 3 investigates the FAA and the PR and the indirect utility function is determined by:

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c \in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ 0 & \text{if } q = 2 \end{cases} \tag{25}$$

In the equation (25), the probability that decision maker *i* buy alternative *j* at choice situation *t* is $\frac{1}{J}$ because of all coefficients of zero (i.e., $\alpha_2 = \beta_{1,k} = 0$).

The model 4 is for the FAA and the PA and the indirect utility is given as equation (26).

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c \in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ P'_{tj}\alpha_2 & \text{if } q = 2 \end{cases} \tag{26}$$

The model 5 investigates the FAA and the PANA and the indirect utility function is specified as equation (27).

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c \in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ \sum_{c \in C} X'_{tjc}\beta_{c2} & \text{if } q = 2 \end{cases} \tag{27}$$

Model 6 investigates three different choice strategies, the FAA, the PA, and the PR, by employing three-segments model of LC-MNL and LC-RPL. The indirect utility is specified as:

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c \in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ P'_{tj}\alpha_2 & \text{if } q = 2 \\ 0 & \text{if } q = 3 \end{cases} \tag{28}$$

Model 7 explores four different decision principles, the FAA, the PANA, the PA, and the PR, through four-segments discrete choice models. The indirect utility can be described as below:

$$V_{itj} = \begin{cases} P'_{tj}\alpha_1 + \sum_{c\in C} X'_{tjc}\beta_{c1} & \text{if } q = 1 \\ \sum_{c\in C} X'_{tjc}\beta_{c1} & \text{if } q = 2 \\ P'_{tj}\alpha_3 & \text{if } q = 3 \\ 0 & \text{if } q = 4 \end{cases} \tag{29}$$

2.4.4 Likelihood Ratio Tests

The likelihood ratio tests (LR tests) for each model were carried out to ensure if it is valid to adopt the LC-RPL to reflect heterogeneous preference for each model. Our null hypothesis is that the standard deviation is zero, which implies that preference heterogeneity is not well represented by the LC-RPL as the standard deviations are not significantly different from zero.

$$H_0: Std.Dev = 0 \qquad \text{vs.} \qquad H_1: Std.Dev \neq 0$$

If we reject the null hypothesis, the LC-RPL relaxes the assumption of homogeneous preference within the same attribute processing rule and enables more flexible analysis. On the other hand, if we fail to reject the null hypothesis, the LC-RPL is not significantly different from the LC-MNL. That is, the LC-RPL is not superior to the LC-MNL.

2.5 Results

Our estimation results are shown in Table 2.4, 2.5, 2.6, and 2.7. NLOGIT 7.0 version was used for estimations of all models in our paper. Table 2.4 and 2.5 report the results by the MNL and LC-MNL, for homogeneous preference within a certain attribute processing rule. Table 2.6 and 2.7 show the results based on the RPL-based models, which assume heterogeneous preference within a certain attribute processing rule.

2.5.1 Estimation Results

For the model 1, the MNL and the RPL outcomes show that a negative marginal utility of the price variable, -0.182 and -0.415, respectively, which correspond to the basic demand theory as expected. The coefficient estimates for other attributes of hotdog sausage products have the same sign in both the MNL and the RPL, and they are statistically significant. The consumers are likely to get disutility from the brands of Oscar Mayer and Ball Park, Jumbo size, the meat type of only beef, and low-fat contents, compared to the opposite characteristics of hotdog products. On the other hand, medium and large products are likely to have a positive marginal utility, compared to small packages (under 16 oz). In addition, regular flavor hotdog sausage products showed a relatively positive marginal utility over other flavored products such as cheese, smoked, or jalapeno.

Model 2 is a simple extensive version of the model 1 by introducing the latent class structure. It allows heterogeneous preferences of agents across segments using discrete distributions of parameters. Heterogeneous preferences are differently reflected depending on segments of LC-MNL. On the other hand, in the two-segment model of LC-RPL, they are differently expressed depending on segments as well as have variations within the segment. The

LC-MNL estimation result of the model 2 shows the probabilities of the first and second segments are 71.0% and 29.0%, respectively. In the model 2, consumers who are likely to belong to the first class have the same sign as the result of the model 1, except the attributes of Oscar Mayer. The price coefficient estimate is -0.566. The positive contributors to the utility are Oscar Mayer, medium and large size packages, and regular flavor. But Jumbo size, only beef, and low-fat attributes may reduce consumers' utility. In the second segment, the coefficient estimate of the price is +0.164, implying that higher price contributes to the consumers' utility. Consumers who are likely to fit the second segment may believe that the hotdogs with higher prices have better quality than lower priced items. They are likely to have a positive marginal utility of large packaged products and a negative marginal utility of regular flavored products.

In the LC-RPL estimation outcome of the model 2 the probabilities of segments 1 and 2 are 52.8% and 47.2%, respectively. The probability of the class 1 is smaller than the LC-MNL result. In the model 2, consumers who are likely to belong to the first segment have the same sign as the result of the model 1, except the attributes of Oscar Mayer. [12] The price coefficient estimate is -0.798. Attributes of Oscar Mayer and regular flavor are likely to positively impact on consumers' utility, whereas Ball Park, jumbo size, only beef, and low-fat attributes may reduce the utility. For the second segment, the coefficient estimate of the price is +0.174. For consumers who are likely to be in the second segment, medium and large packaged products are likely to increase consumers' utility but brands of Oscar Mayer and Ball Park, jumbo size, regular flavored, and low-fat products may decrease the utility.

[12] The coefficient estimates of medium and large packages were not statistically significant in the LC-RPL for the model 2.

Table 2.4 Estimation Results by LC-MNL models

Attribute	Model 1 - FAA Coefficient (S.E)	Model 2 class 1 FAA Coefficient (S.E)	class 2 FAA Coefficient (S.E)	Model 3 class 1 FAA Coefficient (S.E)	class 2 PR Coefficient (S.E)	Model 4 class 1 FAA Coefficient (S.E)	class 2 PA Coefficient (S.E)	Model 5 class 1 FAA Coefficient (S.E)	class 2 PANA Coefficient (S.E)
Price	-0.182 ***	-0.566 ***	0.164 *	-0.265 ***	-	-0.050	-1.305 ***	-0.563 ***	-
	(0.041)	(0.075)	(0.089)	(0.096)	-	(0.045)	(0.092)	(0.077)	-
Brand (vs. Other)									
Oscar Mayer	-0.283 ***	0.603 ***	-3.621 ***	-0.316 **	-	-0.486 ***	-	0.639 ***	-3.657 ***
	(0.068)	(0.094)	(0.372)	(0.137)	-	(0.091)	-	(0.101)	(0.380)
Ball Park	-0.920 ***	-0.830	-0.002	-1.156 ***	-	-1.091 ***	-	-1.199 ***	0.343
	(0.096)	(0.167)	(0.267)	(0.162)	-	(0.139)	-	(0.179)	(0.238)
Package size (vs. Small, under 16 oz)									
Medium	0.990 ***	0.507 ***	2.651	0.724 ***	-	1.623 ***	-	0.490 ***	2.267 ***
(B/w 16 and < 24 oz)	(0.081)	(0.099)	(0.415)	(0.134)	-	(0.149)	-	(0.105)	(0.318)
Large	0.688 ***	0.687 **	2.788 ***	0.903 *	-	1.053 ***	-	0.642 *	2.995 ***
(Larger than 24 oz)	(0.204)	(0.341)	(0.483)	(0.546)	-	(0.249)	-	(0.345)	(0.382)
Product size (vs. Other)									
Jumbo	-0.488 ***	-0.534 ***	0.220	-0.390 **	-	-1.144 ***	-	-0.519 ***	-0.078
	(0.098)	(0.122)	(0.380)	(0.186)	-	(0.192)	-	(0.124)	(0.312)
Meat type (vs. Other)									
Beef	-0.598 ***	-0.168	0.004	-1.873 ***	-	-0.293 ***	-	-0.120	-0.191
(only beef)	(0.092)	(0.159)	(0.171)	(0.355)	-	(0.100)	-	(0.162)	(0.142)
Flavor (vs. Other)									
Regular	0.508 ***	1.455 ***	-1.516 ***	0.029	-	0.262 **	-	1.498 ***	-1.610 ***
(Regular, Class, Orinial, Old Fashioned)	(0.099)	(0.171)	(0.214)	(0.201)	-	(0.113)	-	(0.175)	(0.235)
Fat Contents (vs. Regular)									
Low fat	-0.948 ***	-1.049 ***	0.162	-1.732 ***	-	-1.221 ***	-	-1.090 ***	0.310
	(0.085)	(0.094)	(0.529)	(0.174)	-	(0.144)	-	(0.096)	(0.390)
Prob(Class)	-	0.710 ***	0.290 ***	0.671 ***	0.329 ***	0.662 ***	0.338 ***	0.678 ***	0.322 ***
		(0.028)	(0.028)	(0.043)	(0.043)	(0.033)	(0.033)	(0.027)	(0.027)
Log likelihood function	-4,102.795		-3,771.704		-4,061.829		-3,968.360		-3,771.126
Restricted Log likelihood function	-		-4,491.812		-4,491.812		-4,491.812		-4,491.812
Inf.Cr.AIC	8,223.6		7,581.4		8,143.7		7,958.7		7,578.3
AIC/N	6.101		5.624		6.041		5.904		5.622
Number of obs.	1,348		1,348		1,348		1,348		1,348

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

Table 2.5 Estimation Results by LC-MNL models (Continues)

Attribute	Model 6 class 1 FAA Coefficient (S.E)	class 2 PA Coefficient (S.E)	class 3 PR Coefficient (S.E)	Model 7 class 1 FAA Coefficient (S.E)	class 2 PANA Coefficient (S.E)	class 3 PA Coefficient (S.E)	class 4 PR Coefficient (S.E)
Price	-0.196 ***	-1.341 ***	-	-0.813 ***	-	-1.390	-
	(0.061)	(0.092)	-	(0.202)	-	(0.121)	-
Brand (vs. Other)							
Oscar Mayer	-0.657 ***	-	-	2.263 ***	-2.780 ***	-	-
	(0.117)	-	-	(0.292)	(0.293)	-	-
Ball Park	-1.706 ***	-	-	-0.746	-0.415 **	-	-
	(0.256)	-	-	(0.553)	(0.192)	-	-
Package size (vs. Small, under 16 oz)							
Medium	1.984 ***	-	-	1.698 ***	2.562 ***	-	-
(B/w 16 and < 24 oz)	(0.257)	-	-	(0.254)	(0.545)	-	-
Large	2.078 ***	-	-	3.083 ***	2.726 ***	-	-
(Larger than 24 oz)	(0.367)	-	-	(0.871)	(0.581)	-	-
Product Size (vs. Other)							
Jumbo	-1.799 ***	-	-	-1.004 ***	-0.680 **	-	-
	(0.345)	-	-	(0.298)	(0.270)	-	-
Meat type (vs. Other)							
Beef	-0.465 ***	-	-	1.113 ***	-0.271 **	-	-
(only beef)	(0.118)	-	-	(0.401)	(0.134)	-	-
Flavor (vs. Other)							
Regular	-0.062	-	-	3.738	-1.026 ***	-	-
(Regular, Class, Orinial, Old Fashioned)	(0.149)	-	-	(0.913)	(0.167)	-	-
Fat Contents (vs. Regular)							
Low fat	-2.714 ***	-	-	-0.908 ***	-0.990 **	-	-
	(0.482)	-	-	(0.159)	(0.475)	-	-
Prob(Class)	0.508 ***	0.334 ***	0.158 ***	0.288 ***	0.341 ***	0.270 ***	0.101 ***
	(0.038)	(0.032)	(0.032)	(0.029)	(0.029)	(0.030)	(0.029)
Log likelihood function			-3,929.742				-3,669.666
Restricted Log likelihood function			-4,491.812				-4,491.812
Inf.Cr.AIC			7,883.5				7,381.3
AIC/N			5.848				5.476
Number of obs.			1,348				1,348

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

In the estimation results from the model 1 and 2, we examined how consumer preferences change as they reflect preference heterogeneity. This paper does not consider heterogeneity in attribute processing rules in the model 1 and 2. To explore choice heuristics, we now analyze the estimation results of models that accommodate heterogeneity in decision rules.

Model 3 is for adding the PR as a decision-making rule. The class 1 is for the FAA and the class 2 is for the PR. Given the definition of the PR, all parameters of attributes were restricted to zero within the second segment. The coefficients in the first segment were estimated by the LC-MNL and the LC-RPL. The LC-MNL result of the model 3 reports the portions of the first and second classes are 67.1% and 32.9%, respectively. In the first class for the FAA, all the coefficient estimates of attributes are the same sign as the model 1. The coefficient of the price is -0.265. In the LC-RPL estimation outcome of the model 3, the probabilities of the first and second classes are 63.8% and 36.2%, respectively. Similar to the LC-MNL result, the LC-RPL result of the model 3 shows that the mean value of coefficient estimate of each attribute in the class for the FAA are the same sign in the model 1 excluding large package.

Model 4 is for examining the PA decision rule. The class 1 is for the FAA and the class 2 is for the PA. Following the definition of the PA, the price coefficient within the class 2 was freely estimated while other coefficients were restricted to zero. The LC-MNL result of the model 4 reports the probabilities of the first and second classes are 66.2% and 33.8%, respectively. In the first class for the FAA, all the coefficient estimates of attributes are the same sign as the model 1. The coefficient of the price is -0.050, which is insignificant. In the LC-RPL estimation outcome of the model 4, the portions of the first and second classes are 66.7% and 33.3%, respectively. The LC-RPL result for the model 3 reports the same sign of attribute coefficients within the class for the FAA as the model 1, similar to the LC-MNL outcome.

Table 2.6 Estimation Results by LC-RPL models

Attribute	Model 1	Model 2		Model 3		Model 4		Model 5	
	-	class 1	class 2	class 1	class 2	class 1	class 2	class 1	class 2
	FAA	FAA	FAA	FAA	PR	FAA	PA	FAA	PANA
	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)	Coefficient (S.E)
Random Parameters									
Price	-0.415 ***	-0.798 ***	0.174 ***	-0.111	-	-0.058	-1.331 ***	-0.684 ***	-
	(0.056)	(0.128)	(0.056)	(0.111)	-	(0.045)	(0.094)	(0.123)	-
Brand (vs. Other)									
Oscar Mayer	-0.802 ***	1.044 ***	-1.278 ***	-0.104	-	-0.503 ***	-	1.197 ***	-1.644 ***
	(0.162)	(0.113)	(0.092)	(0.153)	-	(0.091)	-	(0.111)	(0.140)
Ball Park	-1.313 ***	-0.548 ***	-1.011 ***	-1.191 ***	-	-1.064 ***	-	-0.581 ***	-0.948 ***
	(0.177)	(0.150)	(0.095)	(0.170)	-	(0.138)	-	(0.157)	(0.100)
Package size (vs. Small, under 16 oz)									
Medium	1.391 ***	-0.138	1.865 ***	0.587 ***	-	1.657 ***	-	-0.066	1.906 ***
(B/w 16 and < 24 oz)	(0.136)	(0.122)	(0.156)	(0.146)	-	(0.152)	-	(0.115)	(0.155)
Large	0.598	0.835	0.719 ***	-0.032	-	1.151 ***	-	0.753	1.578 ***
(Larger than 24 oz)	(0.379)	(0.529)	(0.254)	(0.666)	-	(0.248)	-	(0.514)	(0.171)
Product Size (vs. Other)									
Jumbo	-0.924 ***	-0.392 ***	-0.785 ***	-0.188	-	-1.073 ***	-	-0.408 ***	-0.823 ***
	(0.161)	(0.137)	(0.242)	(0.209)	-	(0.186)	-	(0.134)	(0.216)
Meat type (vs. Other)									
Beef	-1.286 ***	-0.878 ***	-0.048	-2.292 ***	-	-0.279 ***	-	-0.622 ***	-0.108
(only beef)	(0.212)	(0.258)	(0.102)	(0.480)	-	(0.099)	-	(0.238)	(0.084)
Flavor (vs. Other)									
Regular	1.662 ***	1.532 ***	-0.219 *	0.317	-	0.213 *	-	1.584 ***	-0.542 ***
(Regular, Class, Orinial, Old Fashioned)	(0.271)	(0.393)	(0.118)	(0.223)	-	(0.113)	-	(0.331)	(0.096)
Fat Contents (vs. Regular)									
Low fat	-1.090 ***	-1.159 ***	-0.710 ***	-1.814 ***	-	-1.206 ***	-	-1.230 ***	-0.297 **
	(0.108)	(0.087)	(0.133)	(0.178)	-	(0.144)	-	(0.086)	(0.150)
Distns. of RPs. Std.Devs									
Price	0.394 ***	0.144	0.018	0.005	-	0.001	0.001	0.082	-
	(0.043)	(0.162)	(0.426)	(0.020)	-	(0.018)	(0.066)	(0.185)	-
Brand (vs. Other)									
Oscar Mayer	3.511 ***	0.005	0.008	0.007	-	0.018	-	0.005	0.000
	(0.303)	(1.417)	(2.077)	(0.071)	-	(0.069)	-	(1.381)	(3.005)
Ball Park	1.445 ***	0.001	0.001	0.009	-	0.002	-	0.001	0.001
	(0.208)	(2.737)	(2.728)	(0.126)	-	(0.115)	-	(3.213)	(2.736)
Package size (vs. Small, under 16 oz)									
Medium	1.783 ***	0.003	0.008	0.015	-	0.016	-	0.003	0.000
(B/w 16 and < 24 oz)	(0.287)	(1.502)	(2.496)	(0.078)	-	(0.076)	-	(1.434)	(2.569)
Large	1.964 ***	0.029	0.009	0.018	-	0.038	-	0.010	0.014
(Larger than 24 oz)	(0.315)	(2.621)	(0.914)	(0.113)	-	(0.089)	-	(2.624)	(0.921)
Product Size (vs. Other)									

Jumbo	0.774 ***	0.003	0.013	0.004	-	0.006	-	0.002	0.008
	(0.191)	(0.956)	(2.697)	(0.092)	-	(0.138)	-	(0.949)	(2.432)
Meat type (vs. Other)									
Beef	2.614 ***	0.012	0.011	0.001	-	0.001	-	0.002	0.006
(only beef)	(0.236)	(1.248)	(0.777)	(0.135)	-	(0.070)	-	(0.968)	(0.813)
Flavor (vs. Other)									
Regular	2.509 ***	0.005	0.005	0.109	-	0.000	-	0.018	0.000
(Regular, Class, Orinial, Old Fashioned)	(0.288)	(2.576)	(0.737)	(0.087)	-	(0.081)	-	(2.132)	(0.739)
Fat Contents (vs. Regular)									
Low fat	0.894 ***	0.001	0.020	0.007	-	0.028	-	0.007	0.297
	(0.164)	(0.849)	(1.903)	(0.121)	-	(0.119)	-	(0.797)	(0.150)
Prob(Class)	-	0.528 ***	0.472 ***	0.638 ***	0.362 ***	0.667 ***	0.333 ***	0.556 ***	0.444 ***
		(0.046)	(0.046)	(0.045)	(0.045)	(0.033)	(0.033)	(0.039)	(0.039)
Log likelihood function	-3,505.367		-3,841.051		-4,061.843		-3,968.256		-3,824.832
Restricted Log likelihood function	-4,491.812		-4,491.812		-4,491.812		-4,491.812		-4,491.812
Inf.Cr.AIC	7,046.7		7,756.1		8,161.7		7,978.5		7,717.7
AIC/N	5.228		5.754		6.055		5.919		5.725
Number of obs.	1,348		1,348		1,348		1,348		1,348

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

Table 2.7 Estimation Results by LC-RPL models (Continues)

Attribute	Model 6 class 1 FAA Coefficient (S.E)	class 2 PA Coefficient (S.E)	class 3 PR Coefficient (S.E)	Model 7 class 1 FAA Coefficient (S.E)	class 2 PANA Coefficient (S.E)	class 3 PA Coefficient (S.E)	class 4 PR Coefficient (S.E)
Random Parameters							
Price	-0.214 ***	-1.341 ***	-	-0.764 ***	-	-1.863 ***	-
	(0.061)	(0.092)	-	(0.190)	-	(0.173)	-
Brand (vs. Other)							
Oscar Mayer	-0.673 ***	-	-	1.204 ***	-2.669 ***	-	-
	(0.118)	-	-	(0.154)	(0.306)	-	-
Ball Park	-1.710 ***	-	-	-0.980 ***	-1.461 ***	-	-
	(0.257)	-	-	(0.277)	(0.289)	-	-
Package size (vs. Small, under 16 oz)							
Medium	2.029 ***	-	-	0.062	1.562 ***	-	-
(B/w 16 and < 24 oz)	(0.264)	-	-	(0.156)	(0.261)	-	-
Large	2.201 ***	-	-	0.742	1.639 ***	-	-
(Larger than 24 oz)	(0.370)	-	-	(0.830)	(0.267)	-	-
Product Size (vs. Other)							
Jumbo	-1.830 ***	-	-	-0.932 ***	-0.956 ***	-	-
	(0.347)	-	-	(0.209)	(0.336)	-	-
Meat type (vs. Other)							
Beef	-0.431 ***	-	-	-0.773 **	-0.518 ***	-	-
(only beef)	(0.116)	-	-	(0.372)	(0.118)	-	-
Flavor (vs. Other)							
Regular	-0.100	-	-	1.451 ***	-1.105 ***	-	-
(Regular, Class, Orinial, Old Fashioned)	(0.149)	-	-	(0.421)	(0.109)	-	-
Fat Contents (vs. Regular)							
Low fat	-2.701 ***	-	-	-1.462 ***	-1.919 ***	-	-
	(0.475)	-	-	(0.153)	(0.700)	-	-
Distns. of RPs. Std.Devs							
Price	0.002	0.001	-	0.187	0.000	0.001	-
	(0.021)	(0.067)	-	(0.121)	(0.000)	(11.829)	-
Brand (vs. Other)							
Oscar Mayer	0.000	-	-	0.007	0.003	-	-
	(0.080)	-	-	(1.990)	(7.855)	-	-
Ball Park	0.011	-	-	0.011	0.003	-	-
	(0.169)	-	-	(6.927)	(8.391)	-	-
Package size (vs. Small, under 16 oz)							
Medium	0.000	-	-	0.003	0.003	-	-
(B/w 16 and < 24 oz)	(0.088)	-	-	(1.847)	(3.227)	-	-
Large	0.013	-	-	0.011	0.016	-	-
(Larger than 24 oz)	(0.096)	-	-	(3.297)	(1.039)	-	-
Product Size (vs. Other)							

Jumbo	0.003	-	-	0.015	0.017	-	-
	(0.194)	-	-	(1.788)	(3.989)	-	-
Meat type (vs. Other)							
Beef	0.000	-	-	0.013	0.004	-	-
(only beef)	(0.085)	-	-	(1.229)	(1.103)	-	-
Flavor (vs. Other)							
Regular	0.000	-	-	0.019	0.010	-	-
(Regular, Class, Orinial, Old Fashioned)	(0.088)	-	-	(2.014)	(0.822)	-	-
Fat Contents (vs. Regular)							
Low fat	0.019	-	-	0.034	0.006	-	-
	(0.270)	-	-	(1.466)	(9.438)	-	-
Prob(Class)	0.507 ***	0.334 ***	0.159 ***	0.403 ***	0.313 ***	0.078 ***	0.207 ***
	(0.038)	(0.032)	(0.032)	(0.046)	(0.031)	(0.022)	(0.038)
Log likelihood function			-3,929.801				-3,744.895
Restricted Log likelihood function			-4,491.812				-4,491.812
Inf.Cr.AIC			7,903.6				7,567.8
AIC/N			5.863				5.614
Number of obs.			1,348				1,348

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

Model 5 examines the PANA decision making rule. The class 1 is for the FAA and the class 2 is for the PANA. The PANA leads the price coefficient to be restricted to zero within the class 2. The LC-MNL result of the model 5 reports the probabilities of the first and second classes are 67.8% and 32.2%, respectively. In the first class for the FAA, all the coefficient estimates of attributes are the same sign as the first segment of the model 2. The coefficient estimate of the price in the class 1 was -0.563. As the price is not considered in the class 2, the disutility of the price to consumers became larger in the class 1. In the segment for the FAA, the marginal utility of price is -0.563 while that of Oscar Mayer has a positive value of 0.639. For consumers who are not paying attention to the price in the class 2, it is noticeable that the marginal utility of Oscar Mayer was -3.657 and statistically significant. That means consumers who don't pay attention to price don't like Oscar Mayer, compared to other brands. This is because hotdog sausage products with the Oscar Mayer brand may be cheaper than other brand products, and the hotdog products labeled the Oscar Mayer are attractive to shoppers who are sensitive to the price while they are not likely to appeal to customers who do not account for the price. This could be the same as the LC-RPL result. The LC-RPL result of the model 5 reveals that the coefficient estimate of the price was -0.684 and that of Oscar Mayer brand was +1.197 within the first class. On the other hand, the coefficient estimate of Oscar Mayer was -1.644 within the second class. The portion of the first and second classes are 55.6% and 44.4%, respectively, in the LC-RPL.

Model 6 is for examining the PA and PR decision making rule. This model is a combination of the model 3 and 4. The class 1, 2, and 3 are for the FAA, the PA, and the PR, respectively. The LC-MNL result of the model 6 reports the portions for each segment are 50.8%, 33.4%, and 15.8%, respectively. In the first class for the FAA, the coefficient of the price is -0.196, which is statistically significant. For the segment for the PA, the price coefficient is -1.341. In the LC-RPL estimation outcome of the model 6, the probabilities for each segment are 50.7%, 33.4%, and 15.9%, respectively. Those are not much different from the LC-MNL estimation.

Model 7 explores the PAAN, PA, and PR decision rule, simultaneously. The model 7 is a combination of the model 3, 4, and 5. The class 1, 2, 3, and 4 are for the FAA, the PANA, the PA, and the PR, respectively. The LC-MNL estimation result of the model 7 reports that the probabilities for each segment are 28.8%, 34.1%, 27.0%, and 10.1%, respectively. For the FAA class, the coefficient estimates of the price and Oscar Mayer brand are -0.813 and +2.263, respectively. Consumers in the FAA class are likely to gain bigger utility from choosing Oscar Mayer products. In addition, they are likely to obtain higher utility from medium and large packages, only beef products. On the other hand, they may lose some utility by choosing Ball Park brand, jumbo size, and low-fat products. This is similar to the findings found in model 2 and 5. But, people within the FAA are likely to gain higher utility from only beef. For the PANA class, the Oscar Mayer brand is likely to reduce consumers' utility. In the LC-RPL result of the model 7, the portions for each class are 40.3%, 31.3%, 7.8%, and 20.7% respectively. Those are very different from the LC-MNL outcome. In particular, it is noticeable that the portion of the segment for the PA was greatly reduced. For the sign of the coefficients of attributes, the LC-RPL result is similar to the LC-MNL, excluding the characteristic of only beef for meat-type within the segment for the FAA. The coefficient estimate of only beef is -0.773 in the FAA class, -0.518 in the PANA class. This implies that price-sensitive consumers are likely to have smaller utility by selecting hotdog products that are made of only beef.

2.5.2 WTP estimates

Willingness-to-pays (WTPs) in Table 2.8 and 2.9 are computed from the MNL and LC-MNL models. We focus on WTP estimates in the FAA segment for each model since the choice heuristics examined in this study, the PA, the PANA, and the PR, do not provide the denominator and the numerators that are required to calculate WTPs. The delta method was employed to get the standard errors for all WTP estimates in NLOGIT 7.0.

The WTP estimates derived by the model 1 are shown in the column 2 of Table 2.8. The WTPs for Oscar Mayer and Ball Park brands are -\$1.55 and -\$5.05, respectively. This implies that on average consumers do not prefer these two branded products to other brands and that Ball Park products are relatively less preferred to Oscar Mayer's. The WTPs for medium and large packages are \$5.44 and \$3.77, respectively, suggesting that they are preferred to a small package. Therefore, consumer preference for package sizes is the highest in medium, followed by large packages. The WTPs for jumbo size, meat type of only beef, were calculated to -\$2.68, -\$3.28, and -\$5.20, respectively, inducing that those attributes were less preferred by households. On the other hand, the WTP for a flavor of regular is \$2.79. Hence, consumers prefer the regular flavor to other flavored hotdog products such as cheese, smoked, and jalapeno.

The WTP estimates calculated by the model 2 are shown in the columns 3 and 4 of Table 2.8. For households belonging to the class 1, the WTP for Oscar Mayer is \$1.06, while the WTP for Ball Park is still negative. For households who are in the class 2, the WTP for Oscar Mayer is \$22.02, which is very high. The WTP for medium packages is -\$16.12, negative value. This is not only different from the class 1 of the same model, but also the opposite of the model 1. Consumers who are likely to belong to the class 2 less prefer the bigger packages to small.

Table 2.8 Willingness to pay estimates by LC-MNL models

Attribute	Model 1	Model 2		Model 3		Model 4		Model 5	
	-	class 1	class 2	class 1	class 2	class 1	class 2	class 1	class 2
	FAA	FAA	FAA	FAA	PR	FAA	PA	FAA	PANA
	WTP	WTP	WTP	WTP	WTP	WTP	WTP	WTP	WTP
	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)
Brand (vs. Other)									
Oscar Mayer	-1.55 ***	1.06 ***	22.02 *	-1.19 ***	-	-9.83	-	1.13 ***	-
	(0.45)	(0.22)	(11.70)	(0.38)	-	(8.98)	-	(0.23)	-
Ball Park	-5.05 ***	-1.47 ***	0.01	-4.36 ***	-	-22.03	-	-2.13 ***	-
	(1.24)	(0.36)	(1.62)	(1.62)	-	(20.25)	-	(0.45)	-
Package size (vs. Small, under 16 oz)									
Medium	5.44 ***	0.90 ***	-16.12 *	2.73 ***	-	32.79	-	0.87 ***	-
(B/w 16 and < 24 oz)	(1.27)	(0.21)	(8.62)	(0.92)	-	(30.23)	-	(0.23)	-
Large	3.77 ***	1.21 **	-16.96	3.40 ***	-	21.26	-	1.14 **	-
(Larger than 24 oz)	(0.62)	(0.48)	(10.69)	(0.98)	-	(16.37)	-	(0.49)	-
Product Size (vs. Other)									
Jumbo	-2.68 ***	-0.94 ***	-1.34	-1.47 ***	-	-23.10	-	-0.92 ***	-
	(0.60)	(0.19)	(1.98)	(0.43)	-	(20.32)	-	(0.20)	-
Meat type (vs. Other)									
Beef	-3.28 ***	-0.30	-0.02	-7.06 **	-	-5.92	-	-0.21	-
(only beef)	(1.16)	(0.31)	(1.04)	(3.56)	-	(6.78)	-	(0.31)	-
Flavor (vs. Other)									
Regular	2.79 ***	2.57 ***	9.22 *	0.11	-	5.29	-	2.66 ***	-
(Regular, Class, Orinial, Old Fashioned)	(1.03)	(0.52)	(5.30)	(0.79)	-	(6.19)	-	(0.55)	-
Fat Contents (vs. Regular)									
Low fat	-5.20 ***	-1.85 ***	-0.98	-6.53 ***	-	-24.67	-	-1.94 ***	-
	(1.27)	(0.32)	(3.11)	(2.42)	-	(22.44)	-	(0.35)	-
Prob(Class)	-	0.710 ***	0.290 ***	0.671 ***	0.329 ***	0.662 ***	0.338 ***	0.678 ***	0.322 ***
		(0.028)	(0.028)	(0.043)	(0.043)	(0.033)	(0.033)	(0.027)	(0.027)

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. We use the delta method to get the standard errors in NLOGIT 7.0. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

Table 2.9 Willingness to pay estimates by LC-MNL models (Continues)

Attribute	Model 6 class 1 FAA WTP (S.E)	class 2 PA WTP (S.E)	class 3 PR WTP (S.E)	Model 7 class 1 FAA WTP (S.E)	class 2 PANA WTP (S.E)	class 3 PA WTP (S.E)	class 4 PR WTP (S.E)
Brand (vs. Other)							
Oscar Mayer	-3.36 ***	-	-	2.78 ***	-	-	-
	(1.03)	-	-	(0.69)	-	-	-
Ball Park	-8.71 ***	-	-	-0.92	-	-	-
	(2.94)	-	-	(0.76)	-	-	-
Package size (vs. Small, under 16 oz)							
Medium	10.13 ***	-	-	2.09 ***	-	-	-
(B/w 16 and < 24 oz)	(3.40)	-	-	(0.61)	-	-	-
Large	10.61 ***	-	-	3.79 ***	-	-	-
(Larger than 24 oz)	(2.50)	-	-	(0.41)	-	-	-
Product Size (vs. Other)							
Jumbo	-9.18 ***	-	-	-1.24 ***	-	-	-
	(2.62)	-	-	(0.36)	-	-	-
Meat type (vs. Other)							
Beef	-2.37 **	-	-	1.37 ***	-	-	-
(only beef)	(1.14)	-	-	(0.20)	-	-	-
Flavor (vs. Other)							
Regular	-0.32	-	-	4.60 ***	-	-	-
(Regular, Class, Orinial, Old Fashioned)	(0.71)	-	-	(1.37)	-	-	-
Fat Contents (vs. Regular)							
Low fat	-13.85 ***	-	-	-1.12 ***	-	-	-
	(4.29)	-	-	(0.41)	-	-	-
Prob(Class)	0.508 ***	0.334 ***	0.158 ***	0.288 ***	0.341 ***	0.270 ***	0.101 ***
	(0.038)	(0.032)	(0.032)	(0.029)	(0.029)	(0.030)	(0.029)

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. We use the delta method to get the standard errors in NLOGIT 7.0. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

The two-class models that examine the PR, the PA, and the PANA bring about WTP estimates in the columns 5, 7, and 9 of Table 2.8, respectively. In the model 3 for the PR, the WTP estimates have the same sign as the model 1. The largest WTP attribute was $ 3.40 in a large package. In the model 4 for the PA, we could not have a significant WTP as the coefficient of the price which enters the denominator in the calculation of WTP was not significant. In the WTP results of the model 5 for the PANA, the regular flavor attribute has the highest value of $2.66, followed by the large package of $1.14 and the Oscar Mayer brand of $1.13. As in the model 2, the Oscar Mayer brand is characterized by a positive WTP in the model 5.

The three-class model explores the PR and the PA produces WTP estimates for the FAA in the column 2 of Table 2.8. The WTP estimations from the model 6 report that households belonging to the FAA have high values for larger packages. The WTPs were $10.61 for large and $10.13 medium packages. Other attributes appear to have negative WTP, which seems to be less favored by consumers.

The four-class model for examining the PR, the PA, and the PANA yields WTP estimates for the FAA decision-makers in the column 5 of Table 2.9. In the model 7, 28.8% of consumers applied the FAA. Consumers in this segment were found to have the highest WTP in regular flavor ($4.60). The WTP for Oscar Mayer brand was $2.78, which implies that these consumers prefer Oscar Mayer to other brand products. They also prefer hotdog products consisting of only beef compared to other meat types. This feature is similar to the results found in models 2 and 5.

WTPs described in Table 2.10 and 2.11 are calculated from the RPL and LC-RPL models. The WTP estimates computed by model 1 are shown in the column 2 of Table 10. The regular flavor reports the WTP of $4.01, compared to others. This is the highest value among attributes considered in this model. The WTPs for Oscar Mayer and Ball Park brands are -$1.93 and -$3.17, respectively. This implies that on average consumers less prefer these two branded products to other brands. The WTPs for medium and large packages are \$3.35 and \$1.44, respectively. Thus, consumers are likely to prefer bigger packages to small ones. However, the WTPs for meat type of only beef, low-fat contents, and jumbo size were calculated to -\$3.10, -\$2.63, and -\$2.23, respectively, which are negative. This indicates that consumers do not prefer these kinds of attributes, to the opposite attributes within each group.

The WTP estimates derived by model 2 are in the columns 3 and 4 of Table 2.10. For households belonging to the class 1, the WTP for Oscar Mayer is \$1.31, while that for Ball Park is negative (-\$0.69). They prefer Oscar Mayer but do not Ball Park. In addition, the WTPs for large packages and regular flavors have positive values, indicating being preferred. For consumers belonging to the class 2, the WTPs for Oscar Mayer and Ball Park are \$7.34 and \$5.81 , respectively, which are the largest values within the second class. They prefer the jumbo size and low-fat products while disliking medium packages. People in the class 1 and those in the class 2 have opposite preferences for other attributes excluding Oscar Mayer.

The two-class models for examining the PR, the PA, and the PANA bring about WTP estimates in the columns 5, 7, and 9 of Table 2.10, respectively. Similar to the LC-MNL of the model 3, we could not get a significant WTP due to the insignificant price coefficient in the FAA of the model 3 and 4. The WTP estimates in the FAA segment of the model 4 shows the same rankings of consumers preference on attributes in the first class of the model 2. The attributes with the largest WTP values were regular flavors (\$2.31), followed by Oscar Mayer (\$1.75) and large packages (\$1.10).

Table 2.10 Willingness to pay estimates by LC-RPL models

	Model 1	Model 2		Model 3		Model 4		Model 5	
	-	class 1	class 2	class 1	class 2	class 1	class 2	class 1	class 2
Attribute	FAA	FAA	FAA	FAA	PR	FAA	PA	FAA	PANA
	WTP	WTP	WTP	WTP	WTP	WTP	WTP	WTP	WTP
	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)	(S.E)
Brand (vs. Other)									
Oscar Mayer	-1.93 ***	1.31 ***	7.34 ***	-0.94	-	-8.67	-	1.75 ***	-
	(0.42)	(0.23)	(2.56)	(0.92)	-	(6.76)	-	(0.33)	-
Ball Park	-3.17 ***	-0.69 ***	5.81 ***	-10.77	-	-18.33	-	-0.85 ***	-
	(0.61)	(0.26)	(1.96)	(10.70)	-	(14.34)	-	(0.32)	-
Package size (vs. Small, under 16 oz)									
Medium	3.35 ***	-0.17	-10.71 ***	5.31	-	28.54	-	-0.10	-
(B/w 16 and < 24 oz)	(0.54)	(0.15)	(3.63)	(4.85)	-	(22.40)	-	(0.17)	-
Large	1.44 *	1.05 **	-4.13	-0.29	-	19.82	-	1.10 *	-
(Larger than 24 oz)	(0.85)	(0.50)	(2.61)	(6.31)	-	(12.85)	-	(0.56)	-
Product Size (vs. Other)									
Jumbo	-2.23 ***	-0.49 ***	4.51 *	-1.70	-	-18.48	-	-0.60 ***	-
	(0.40)	(0.14)	(2.33)	(1.07)	-	(13.70)	-	(0.15)	-
Meat type (vs. Other)									
Beef	-3.10 ***	-1.10 **	0.27	-20.73	-	-4.81	-	-0.91 *	-
(only beef)	(0.77)	(0.49)	(0.54)	(24.35)	-	(4.89)	-	(0.51)	-
Flavor (vs. Other)									
Regular	4.01 ***	1.92 ***	1.26	2.87	-	3.67	-	2.31 ***	-
(Regular, Class, Orinial, Old Fashioned)	(0.88)	(0.74)	(0.98)	(4.74)	-	(4.07)	-	(0.83)	-
Fat Contents (vs. Regular)									
Low fat	-2.63 ***	-1.45 ***	4.08 ***	-16.41	-	-20.76	-	-1.80 ***	-
	(0.44)	(0.30)	(1.47)	(16.99)	-	(16.02)	-	(0.40)	-
Prob(Class)	-	0.528 ***	0.472 ***	0.638 ***	0.362 ***	0.667 ***	0.333 ***	0.556 ***	0.444 ***
		(0.046)	(0.046)	(0.045)	(0.045)	(0.033)	(0.033)	(0.039)	(0.039)

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. We use the delta method to get the standard errors in NLOGIT 7.0. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

Table 2.11 Willingness to pay estimates by LC-RPL models (Continues)

Attribute	Model 6 class 1 FAA WTP (S.E)	class 2 PA WTP (S.E)	class 3 PR WTP (S.E)	Model 7 class 1 FAA WTP (S.E)	class 2 PANA WTP (S.E)	class 3 PA WTP (S.E)	class 4 PR WTP (S.E)
Brand (vs. Other)							
Oscar Mayer	-3.14 ***	-	-	1.58 ***	-	-	-
	(0.90)	-	-	(0.47)	-	-	-
Ball Park	-7.99 ***	-	-	-1.28 **	-	-	-
	(2.53)	-	-	(0.52)	-	-	-
Package size (vs. Small, under 16 oz)							
Medium	9.48 ***	-	-	0.08	-	-	-
(B/w 16 and < 24 oz)	(2.97)	-	-	(0.20)	-	-	-
Large	10.29 ***	-	-	0.97	-	-	-
(Larger than 24 oz)	(2.25)	-	-	(0.85)	-	-	-
Product Size (vs. Other)							
Jumbo	-8.55 ***	-	-	-1.22 ***	-	-	-
	(2.27)	-	-	(0.25)	-	-	-
Meat type (vs. Other)							
Beef	-2.02 ***	-	-	-1.01	-	-	-
(only beef)	(0.94)	-	-	(0.73)	-	-	-
Flavor (vs. Other)							
Regular	-0.47	-	-	1.90 *	-	-	-
(Regular, Class, Orinial, Old Fashioned)	(0.63)	-	-	(0.99)	-	-	-
Fat Contents (vs. Regular)							
Low fat	-12.62 ***	-	-	-1.91 ***	-	-	-
	(3.64)	-	-	(0.60)	-	-	-
Prob(Class)	0.507 ***	0.334 ***	0.159 ***	0.403 ***	0.313 ***	0.078 ***	0.207 ***
	(0.038)	(0.032)	(0.032)	(0.046)	(0.031)	(0.022)	(0.038)

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% level, respectively. The Standard errors are presented in parentheses. We use the delta method to get the standard errors in NLOGIT 7.0. Hyphens (-) indicate 0, which was restricted by the definition of each choice rule.

The column 2 of Table 2.11 reports WTP estimates for the FAA in the three-class model results for examining the PR and the PA. The WTP estimates resulted from the model 6 report that households belonging to the FAA have high values for larger packages. The WTPs were $10.29 for large and $9.48 for medium packages. Other attributes appear to have negative WTP, which seems to be less favored by consumers. This is the same sign in the LC-MNL result.

The four-class model for examining the PR, the PA, and the PANA yield WTP estimates for the FAA decision-makers for the FAA in the column 5 of Table 2.11. In the model 7, 40.3% of consumers applied the FAA. Consumers in this segment were found to have the highest WTP in regular flavors ($1.90). They also prefer Oscar Mayer to other brand products as the WTP for Oscar Mayer brand positive ($1.58).

The ranking of WTPs for the attributes of hotdog products considered in this study varies greatly with models. Therefore, analysts need to carefully specify their models and choose appropriate estimation methods depending on the purpose of research. The contribution of this study is to show that heterogeneity in decision making rules needs to be considered in the use of discrete choice models.

2.5.3 Model Fits and LR Test Results

For the LC-MNL methods, the lowest absolute value of the log-likelihood function was reported in the model 7 (-3,669.666), and followed by the model 5 (-3,771.126) and 2 (-3,771.704). In addition, AIC of the model 7 was the smallest as 7,381.3. The AIC for the model 5 and 1 were 7,578.3 and 7,581.4, respectively. In the LC-RPL applications, the model 1 resulted in the value of the log-likelihood function closest to zero of -3,505.367, which is the not case for choice heuristics. And the model 7 and 5 reported the log-likelihood functions of -3,744.895 and -

3,824.832, respectively, which include the PANA choice rule. In terms of AIC, the AIC value for the model 1 was the lowest (7,046.7), followed by the model 7 (7,567.8) and the model 5 (7,717.7).

The results of the LR tests are shown in Table 2.12. First of all, in the case of the model 1 and 2 that do not account for choice heuristics but for the FAA, the LR test results reveal that the RPL and the LC-RPL could capture preference heterogeneity. The test statistics for model 1 and 2 are 1,194.86 and 138.69, respectively, which are significantly larger than the respective critical value at 95%. Hence, we rejected the null hypothesis.

Next, this study moves to the two-segment models for choice heuristics (the model 3, 4, and 5). The results of LR tests report the LC-RPL is not dominant against the LC-MNL in model 3 and 4 as we failed to reject the null hypothesis. However, the LC-RPL could jointly reflect preference and attribute processing heterogeneity in model 5 because the null hypothesis was rejected. In the case of the model 3 for the PR and the model 4 for the PA, coefficient estimates of most attributes are enforced to zero by the definition of the PR and PA. On the other hand, the model 5 for the PANA allows coefficients of most attributes to be freely estimated by econometric models, except the price. Given the nature of the constraints for each model, the LC-RPL may be effective when there are many freely estimated coefficients. The LR test result for the model 6 shows that we rejected the null hypothesis. In addition to the model 6, the test for the model 7 is the same. Therefore, we could jointly reflect preference and attribute processing heterogeneity in model 6 and 7.

To sum up, our study showed that heterogeneity in preference and heterogeneity in attribute processing rules could be jointly accommodated in the analysis of decision making by employing the LC-RPL. However, in the case of decision rules where many attributes are ignored, the heterogeneous preference may not be well represented in the LC-RPL model.

Table 2.12 LR Test Results

Model specifications	Number of Classes	Class 1	Class 2	Class 3	Class 4	MNL/ LC-MNL LL Fn (Number of parameters)	RPL / LC-RPL LL Fn (Number of parameters)	LR Test Statistics	P-Value
Model 1	1	FAA	-	-	-	-4,102.795 (9)	-3,505.367 (18)	1,194.856	0.000
Model 2	2	FAA	FAA	-	-	-3,771.704 (20)	-3,841.051 (38)	138.694	0.000
Model 3	2	FAA	PR	-	-	-4,061.829 (20)	-4,061.843 (38)	0.028	1.000
Model 4	2	FAA	PA	-	-	-3,968.360 (20)	-3,968.256 (38)	0.208	1.000
Model 5	2	FAA	PANA	-	-	-3,771.126 (20)	-3,824.832 (38)	107.413	0.000
Model 6	3	FAA	PA	PR	-	-3,929.742 (30)	-3,929.801 (57)	0.118	0.000
Model 7	4	FAA	PANA	PA	PR	-3,669.666 (40)	-3,744.895 (76)	150.457	0.000

Note: FAA, PA, PANA, and PR indicate full attribute attendance, only price attendance, price non-attendance, and pure random choice, respectively. The numbers of parameters are presented in parentheses. The critical values of LR test at 95% are 16.919 for the model 1, 28.869 for the model 2-5, 40.113 for the model 6, and 50.998 for the model 7. The MNL / LC-MNL do not have random parameter while RPL / LC-RPL do have.

2.6 Conclusions

The present study investigated households' choice heuristics in the hotdog sausage market from the perspective of the discrete choice framework. We applied the IRI marketing data sets into the latent class structure of the discrete choice models (LC-MNL and LC-RPL) to explore choice heuristics based on different attribute processing at the level of the household.

This study makes several contributions. First, our paper attempts to incorporate heterogeneity in decision making rules into a discrete choice analysis based on revealed preference data. Second, many previous choice analyses have tested choice heuristics in terms of ANA by applying stated choice data. On the other hand, our paper differs in that it applied revealed preference data instead of hypothetical CE data. Also, we have the advantage of indirect comparison with existing studies because we applied the similar estimation methods to previous literature based on stated preference data.

The estimation results of this study showed that marginal utilities of attributes and WTP estimates for attributes are sensitive to not only model specifications but also estimation methods. It requires analysts to carefully specify the systematical component of a random utility model and to select estimation models. Our empirical analysis suggests that accounting for heterogeneous decision rules could provide better model fit than in considering only full attribute preservation rule. This is consistent with previous literature. Accordingly, researchers need to consider the heterogeneous decision rules as an alternative to the classic assumption that all attributes are considered in choice situations by decision makers in order to better understand consumer choice.

The limitations of our research can be summarized as follows, and we would like to suggest some future studies that are related to our paper. First, this paper did not examine all ANA scenarios. We have only tested choice heuristics, focusing on some of the simplest extreme ANA scenarios. Given our number of 531 sample households, if various heuristics were considered there should be many multiple classes for those decision rules and each class might become too thin so that it may lead to impractical estimation of the models. For this reason, four representative decision-making rules that include the FAA and three choice heuristics were examined in this study. The investigation of other scenarios that can happen between the extreme decision rules could be carried out in future research. It is expected that Hensher, Rose and Greene (2012)'s a 2^K multinomial logit model may be applied to investigate all combination of attention or inattention with attributes. Second, the present study examined choice heuristics focusing on consumers' food choices at one store. Hence, further research is required to investigate consumer choice heuristics on a larger scale. For example, investigating choice heuristics across multiple stores in a town or at the national level may provide stronger empirical evidence. To do this, store-specific effects should be considered. Researchers should also keep in mind that the choice sets vary from store to store. A nested model may be applicable. Third, our analysis was based on the assumption that 28 alternatives are available to all customers who purchase a hotdog product in the selected grocery store. However, given the entry of new products and the exit of existing ones in a market, this assumption may be somewhat strong. Therefore, if an econometric model could reflect the change of choice set over time, it is expected to be a more realistic analysis. Lastly, the socio-economic characteristics of households could be further considered to obtain policy implications for food consumption.

2.7 References

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Appendix A - Supplement Material for Chapter 1

Table A.1. Descriptive Structure of the FooDS Data for Discrete Choice Models by months

Year	Month	Number of samples	Percent (%)	Number of observations	Nnumber of respondents
2013	6	81,243	14.02	9,027	1,003
	7	82,296	14.20	9,144	1,016
	8	82,782	14.28	9,198	1,022
	9	81,243	14.02	9,027	1,003
	10	86,994	15.01	9,666	1,074
	11	82,701	14.27	9,189	1,021
	12	82,377	14.21	9,153	1,017
	Subtotal	579,636	100.00	64,404	7,156
2014	1	81,324	8.2	9,036	1,004
	2	82,782	8.35	9,198	1,022
	3	84,159	8.48	9,351	1,039
	4	82,296	8.30	9,144	1,016
	5	82,539	8.32	9,171	1,019
	6	83,592	8.43	9,288	1,032
	7	82,377	8.30	9,153	1,017
	8	81,972	8.26	9,108	1,012
	9	84,645	8.53	9,405	1,045
	10	82,296	8.30	9,144	1,016
	11	81,810	8.25	9,090	1,010
	12	82,134	8.28	9,126	1,014
	Subtotal	991,926	100.00	110,214	12,246
2015	1	82,296	8.27	9,144	1,016
	2	81,000	8.14	9,000	1,000
	3	84,240	8.47	9,360	1,040
	4	81,972	8.24	9,108	1,012
	5	86,184	8.66	9,576	1,064
	6	83,754	8.42	9,306	1,034
	7	86,103	8.66	9,567	1,063
	8	82,782	8.32	9,198	1,022
	9	81,243	8.17	9,027	1,003
	10	82,296	8.27	9,144	1,016
	11	81,729	8.22	9,081	1,009
	12	81,162	8.16	9,018	1,002
	Subtotal	994,761	100.00	110,529	12,281
2016	1	81,000	8.02	9,000	1,000

	2	87,885	8.70	9,765	1,085
	3	83,430	8.26	9,270	1,030
	4	81,162	8.04	9,018	1,002
	5	82,863	8.20	9,207	1,023
	6	83,835	8.30	9,315	1,035
	7	81,243	8.04	9,027	1,003
	8	85,698	8.48	9,522	1,058
	9	85,941	8.51	9,549	1,061
	10	83,916	8.31	9,324	1,036
	11	81,405	8.06	9,045	1,005
	12	91,692	9.08	10,188	1,132
	Subtotal	1,010,070	100.00	112,230	12,470
2017	1	85,779	8.58	9,531	1,059
	2	92,502	9.25	10,278	1,142
	3	82,458	8.25	9,162	1,018
	4	60,750	6.08	6,750	750
	5	83,430	8.35	9,270	1,030
	6	84,969	8.50	9,441	1,049
	7	83,025	8.31	9,225	1,025
	8	83,106	8.31	9,234	1,026
	9	91,125	9.12	10,125	1,125
	10	85,050	8.51	9,450	1,050
	11	84,564	8.46	9,396	1,044
	12	82,782	8.28	9,198	1,022
	Subtotal	999,540	100.00	111,060	12,340
2018	1	82,377	19.95	9,153	1,017
	2	83,025	20.10	9,225	1,025
	3	83,106	20.12	9,234	1,026
	4	81,324	19.69	9,036	1,004
	5	83,187	20.14	9,243	1,027
	Subtotal	413,019	100.00	45,891	5,099
Total		4,988,952		554,328	61,592

Table A.2 The Frequency of the Price Variables across the Food Types in the FooDS data

Price	Burger	Steak	Chop	Ham	Breast	Wing	Bean	Pasta	None
$0.00	-	-	-	-	-	-	184,776	-	554,328
$0.50	-	-	-	-	-	-	-	-	-
$0.75	-	-	-	-	-	184,776	-	-	-
$1.15	-	-	-	184,776			-	-	-
$1.75	-	-	-	-	184,776	184,776	-	-	-
$2.00	184,776	-	-	-	-	-	184,776	-	-
$2.25	-	-	184,776	-	-	-	-	-	-
$2.50	-	-	-	-	-	-	-	184,776	-
$2.65	-	-	-	184,776	-	-	-	-	-
$3.25	184,776	-	-	-	184,776	184,776	-	-	-
$3.50	-	-	-	-	-	-	184,776	-	-
$3.75	-	-	184,776	-	-	-	-	-	-
$4.00	-	-	-	-	-	-	-	184,776	-
$4.15	-	-	-	184,776	-	-	-	-	-
$4.75	-	-	-	-	184,776	-	-	-	-
$5.00	184,776	184,776	-	-	-	-	-	-	-
$5.25	-	-	184,776	-	-	-	-	-	-
$5.50	-	-	-	-	-	-	-	184,776	-
$6.50	-	184,776	-	-	-	-	-	-	-
$8.00	-	184,776	-	-	-	-	-	-	-
Total	554,328	554,328	554,328	554,328	554,328	554,328	554,328	554,328	554,328

Table A.3 WTP Estimates, RRS, and OOS Prediction Accuracy Rates by models

Model	Heterogeneity	Log-Likelihood	AIC	IS WTP ($) STEAK	BREAST	BURGER	CHOP	HAM	WING	BEAN	PASTA	RRS (%)	OOS Pred. Accuracy (%)
MNL1	Base Model	-11,844.204	23,706.408	6.68	5.42	4.65	3.77	2.33	2.33	1.98	3.19	-	32.59
				(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)	(0.12)	(0.13)		(1.68)
RRS1	Base Model	-11,364.791	22,749.582	6.14	5.18	4.55	3.94	2.49	2.41	1.77	3.19	36.7	31.64
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(2.13)
RRS2	Gender	-11,362.085	22,746.177	6.13	5.17	4.54	3.93	2.49	2.41	1.76	3.19	36.7	32.69
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
RRS2	AGE	-11,354.922	22,731.840	6.11	5.14	4.51	3.92	2.47	2.38	1.74	3.16	36.6	32.69
				(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
RRS2	EDU	-11,362.552	22,747.108	6.14	5.17	4.55	3.94	2.49	2.41	1.76	3.19	38.0	32.69
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
RRS2	HSIZE	-11,363.158	22,748.310	6.14	5.17	4.54	3.94	2.49	2.41	1.76	3.19	36.8	32.69
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
RRS2	HINC	-11,362.682	22,747.372	6.13	5.16	4.54	3.93	2.49	2.40	1.76	3.18	37.2	32.69
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
RRS2	SCTIME	-11,363.116	22,748.230	6.14	5.17	4.54	3.94	2.49	2.41	1.76	3.19	36.8	32.69
				(0.15)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.04)	(1.72)
MNL2	Gender	-11,772.485	23,580.965	6.76	5.50	4.74	3.86	2.41	2.41	2.03	3.20	-	32.62
				(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.17)	(0.18)	(0.20)		(1.73)
RRS3		-11,322.504	22,683.010	6.29	5.29	4.68	4.06	2.60	2.52	1.85	3.21	35.8	32.78
				(0.23)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.22)	(0.03)	(1.75)
MNL2	AGE	-11,747.170	23,530.343	7.07	5.85	5.03	3.97	2.64	2.73	2.32	3.51	-	32.76
				(0.21)	(0.23)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)		(1.75)
RRS3		-11,300.629	22,639.255	6.67	5.74	5.09	4.27	2.94	2.98	2.23	3.63	34.8	32.86
				(0.28)	(0.26)	(0.26)	(0.25)	(0.25)	(0.25)	(0.25)	(0.26)	(0.04)	(1.78)
MNL2	EDU	-11,790.312	23,616.622	6.85	5.60	4.72	3.89	2.40	2.40	2.12	3.30	-	32.49
				(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.18)	(0.20)		(1.61)
RRS3		-11,321.358	22,680.718	6.30	5.33	4.62	4.05	2.56	2.48	1.86	3.28	36.2	32.82
				(0.22)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.03)	(1.70)
MNL2	HSIZE	-11,801.875	23,639.745	7.06	5.81	5.01	4.08	2.64	2.71	2.26	3.50	-	32.56
				(0.21)	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)		(1.66)
RRS3		-11,338.327	22,714.645	6.41	5.44	4.81	4.16	2.72	2.70	1.96	3.42	36.0	32.64
				(0.25)	(0.23)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)	(0.25)	(0.04)	(1.73)
MNL2	HINC	-11,756.283	23,548.562	6.97	5.72	4.85	4.02	2.48	2.47	2.16	3.40	-	32.84
				(0.19)	(0.19)	(0.18)	(0.19)	(0.19)	(0.18)	(0.19)	(0.20)		(1.58)
RRS3		-11,290.143	22,618.283	6.42	5.41	4.71	4.15	2.59	2.50	1.84	3.32	35.5	33.06
				(0.22)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.20)	(0.21)	(0.03)	(1.71)
MNL2	SCTIME	-11,814.439	23,664.880	6.50	5.24	4.52	3.71	2.27	2.29	1.92	3.13	-	32.64
				(0.18)	(0.18)	(0.17)	(0.18)	(0.19)	(0.18)	(0.18)	(0.20)		(1.69)
RRS3		-11,338.058	22,714.113	6.02	5.00	4.42	3.85	2.41	2.35	1.73	3.10	36.5	32.76
				(0.22)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.22)	(0.04)	(1.79)

Note: RRS, In-sample (IS) willingness-to-pay (WTP) for each food type, Out-of-sample (OOS) prediction accuracy are the averages of values from 60 individual model estimations. Numbers described in parentheses are also the mean values of 60 individual standard errors for willingness to pay for each food type. We use the delta method to get the standard errors in NLOGIT 7.0. Numbers presented in parentheses for RRS and OOS Predictive Accuracy are the standard deviations.

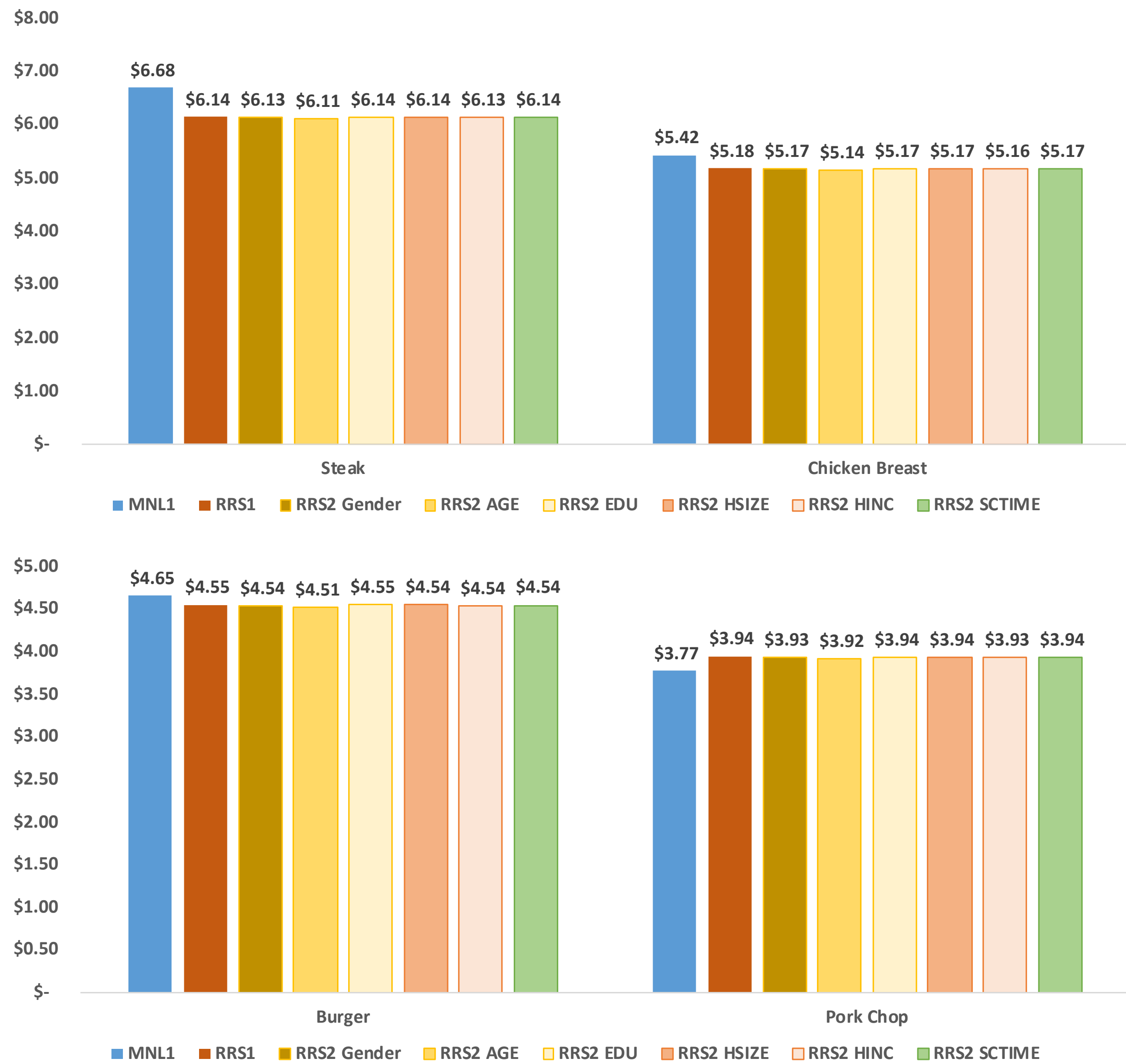
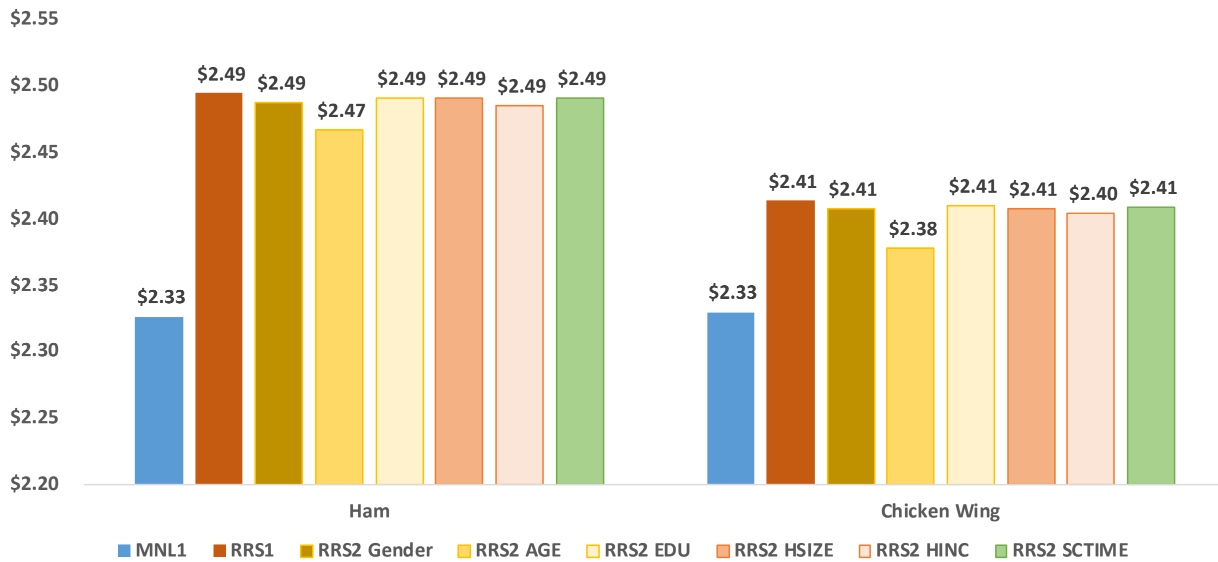


Figure A.1 WTP estimates by the MNL 1, RRS 1, and RRS 2



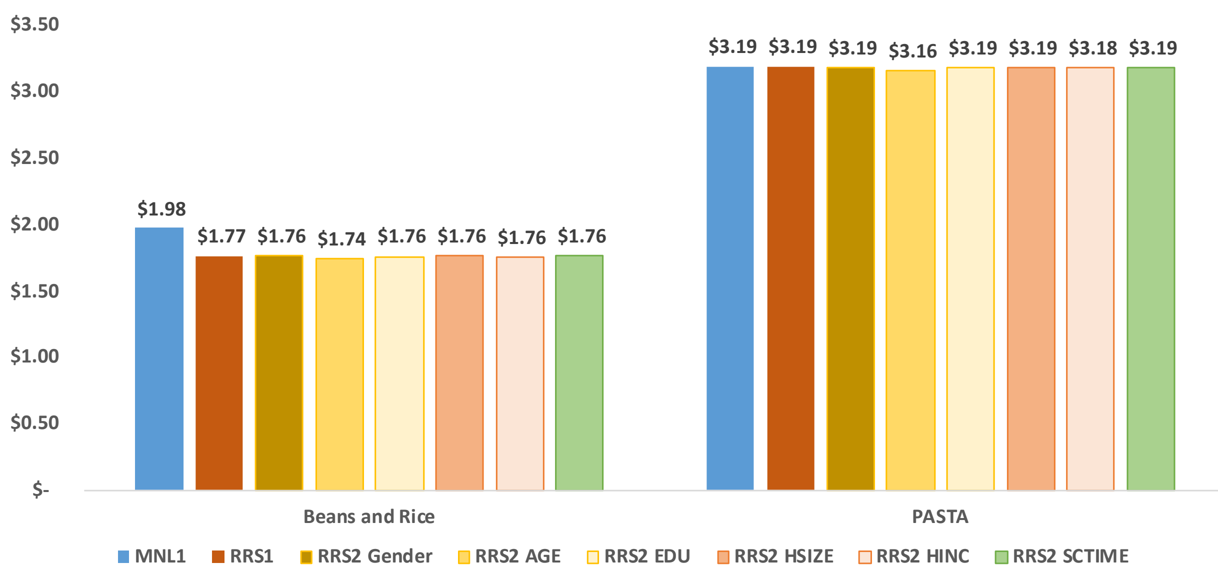


Figure A.2 WTP estimates by the MNL 1, RRS 1, and RRS 2 (Continues)

Table A.4 OOS Prediction Results based on Base Models (MNL 1 and RRS 1)

		MNL 1 Prediction				RRS 1 Prediction			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	986	32.80	2020	67.20	975	32.44	2,031	67.56
	7	1,047	34.42	1995	65.58	948	31.16	2,094	68.84
	8	1,057	34.54	2003	65.46	947	30.95	2,113	69.05
	9	1,034	34.40	1972	65.60	999	33.23	2,007	66.77
	10	1,092	33.99	2121	66.01	938	29.19	2,275	70.81
	11	1,034	33.79	2026	66.21	974	31.83	2,086	68.17
	12	1,010	33.20	2032	66.80	931	30.60	2,111	69.40
2014	1	975	32.44	2031	67.56	974	32.40	2,032	67.60
	2	1,023	33.43	2037	66.57	1,037	33.89	2,023	66.11
	3	1,092	35.07	2,022	64.93	1,089	34.97	2,025	65.03
	4	940	30.90	2,102	69.10	920	30.24	2,122	69.76
	5	1,055	34.58	1,996	65.42	1,059	34.71	1,992	65.29
	6	1,030	33.37	2,057	66.63	1,040	33.69	2,047	66.31
	7	1,001	32.91	2,041	67.09	971	31.92	2,071	68.08
	8	1,017	33.53	2,016	66.47	997	32.87	2,036	67.13
	9	1,055	33.68	2,077	66.32	1,041	33.24	2,091	66.76
	10	963	31.66	2,079	68.34	885	29.09	2,157	70.91
	11	1,014	33.53	2,010	66.47	976	32.28	2,048	67.72
	12	990	32.64	2,043	67.36	927	30.56	2,106	69.44
2015	1	1,021	33.56	2,021	66.44	1,025	33.69	2,017	66.31
	2	944	31.50	2,053	68.50	949	31.66	2,048	68.34
	3	943	30.28	2,171	69.72	967	31.05	2,147	68.95
	4	951	31.36	2,082	68.64	938	30.93	2,095	69.07
	5	1,019	31.98	2,167	68.02	1,017	31.92	2,169	68.08
	6	980	31.65	2,116	68.35	980	31.65	2,116	68.35
	7	989	31.04	2,197	68.96	971	30.48	2,215	69.52
	8	1,054	34.44	2,006	65.56	987	32.25	2,073	67.75
	9	974	32.40	2,032	67.60	861	28.64	2,145	71.36
	10	1,015	33.37	2,027	66.63	996	32.74	2,046	67.26
	11	933	30.85	2,091	69.15	803	26.55	2,221	73.45
	12	965	32.20	2,032	67.80	933	31.13	2,064	68.87
2016	1	1,045	34.87	1,952	65.13	1,056	35.24	1,941	64.76
	2	1,113	34.26	2,136	65.74	1,120	34.47	2,129	65.53
	3	1,051	34.05	2,036	65.95	1,076	34.86	2,011	65.14
	4	988	32.97	2,009	67.03	994	33.17	2,003	66.83
	5	962	31.44	2,098	68.56	953	31.14	2,107	68.86
	6	928	29.97	2,168	70.03	928	29.97	2,168	70.03
	7	820	27.28	2,186	72.72	765	25.45	2,241	74.55

	8	955	30.15	2,213	69.85	919	29.01	2,249	70.99
	9	870	27.38	2,307	72.62	808	25.43	2,369	74.57
	10	955	30.76	2,150	69.24	916	29.50	2,189	70.50
	11	973	32.37	2,033	67.63	917	30.51	2,089	69.49
	12	1,142	33.66	2,251	66.34	1,098	32.36	2,295	67.64
2017	1	969	30.59	2,199	69.41	959	30.27	2,209	69.73
	2	1,121	32.78	2,299	67.22	1,118	32.69	2,302	67.31
	3	962	31.53	2,089	68.47	947	31.04	2,104	68.96
	4	713	31.82	1,528	68.18	701	31.28	1,540	68.72
	5	1,071	34.69	2,016	65.31	1,076	34.86	2,011	65.14
	6	1,124	35.78	2,017	64.22	1,133	36.07	2,008	63.93
	7	1,017	33.14	2,052	66.86	926	30.17	2,143	69.83
	8	1,041	33.92	2,028	66.08	1,012	32.97	2,057	67.03
	9	1,163	34.55	2,203	65.45	1,076	31.97	2,290	68.03
	10	1,003	31.93	2,138	68.07	955	30.40	2,186	69.60
	11	1,011	32.37	2,112	67.63	960	30.74	2,163	69.26
	12	1,033	33.76	2,027	66.24	994	32.48	2,066	67.52
2018	1	965	31.72	2,077	68.28	960	31.56	2,082	68.44
	2	992	32.32	2,077	67.68	1,002	32.65	2,067	67.35
	3	979	31.90	2,090	68.10	979	31.90	2,090	68.10
	4	981	32.63	2,025	67.37	970	32.27	2,036	67.73
	5	967	31.42	2,111	68.58	992	32.23	2,086	67.77
Average		1,002	32.59	2,072	67.41	3,074	100.00	973	31.64

Table A.5 OOS Prediction Results based on MNL 1 and RRS 2

		MNL 1 Prediction				RRS 2 Prediction			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	986	32.80	2020	67.20	975	32.44	2,031	67.56
	7	1,047	34.42	1995	65.58	948	31.16	2,094	68.84
	8	1,057	34.54	2003	65.46	947	30.95	2,113	69.05
	9	1,034	34.40	1972	65.60	999	33.23	2,007	66.77
	10	1,092	33.99	2121	66.01	938	29.19	2,275	70.81
	11	1,034	33.79	2026	66.21	974	31.83	2,086	68.17
	12	1,010	33.20	2032	66.80	931	30.60	2,111	69.40
2014	1	975	32.44	2031	67.56	974	32.40	2,032	67.60
	2	1,023	33.43	2037	66.57	1,037	33.89	2,023	66.11
	3	1,092	35.07	2,022	64.93	1,089	34.97	2,025	65.03
	4	940	30.90	2,102	69.10	920	30.24	2,122	69.76
	5	1,055	34.58	1,996	65.42	1,059	34.71	1,992	65.29
	6	1,030	33.37	2,057	66.63	1,040	33.69	2,047	66.31
	7	1,001	32.91	2,041	67.09	971	31.92	2,071	68.08
	8	1,017	33.53	2,016	66.47	997	32.87	2,036	67.13
	9	1,055	33.68	2,077	66.32	1,041	33.24	2,091	66.76
	10	963	31.66	2,079	68.34	885	29.09	2,157	70.91
	11	1,014	33.53	2,010	66.47	976	32.28	2,048	67.72
	12	990	32.64	2,043	67.36	927	30.56	2,106	69.44
2015	1	1,021	33.56	2,021	66.44	1,025	33.69	2,017	66.31
	2	944	31.50	2,053	68.50	949	31.66	2,048	68.34
	3	943	30.28	2,171	69.72	967	31.05	2,147	68.95
	4	951	31.36	2,082	68.64	938	30.93	2,095	69.07
	5	1,019	31.98	2,167	68.02	1,017	31.92	2,169	68.08
	6	980	31.65	2,116	68.35	980	31.65	2,116	68.35
	7	989	31.04	2,197	68.96	971	30.48	2,215	69.52
	8	1,054	34.44	2,006	65.56	987	32.25	2,073	67.75
	9	974	32.40	2,032	67.60	861	28.64	2,145	71.36
	10	1,015	33.37	2,027	66.63	996	32.74	2,046	67.26
	11	933	30.85	2,091	69.15	803	26.55	2,221	73.45
	12	965	32.20	2,032	67.80	933	31.13	2,064	68.87
2016	1	1,045	34.87	1,952	65.13	1,056	35.24	1,941	64.76
	2	1,113	34.26	2,136	65.74	1,120	34.47	2,129	65.53
	3	1,051	34.05	2,036	65.95	1,076	34.86	2,011	65.14
	4	988	32.97	2,009	67.03	994	33.17	2,003	66.83
	5	962	31.44	2,098	68.56	953	31.14	2,107	68.86
	6	928	29.97	2,168	70.03	928	29.97	2,168	70.03
	7	820	27.28	2,186	72.72	765	25.45	2,241	74.55

	8	955	30.15	2,213	69.85	919	29.01	2,249	70.99
	9	870	27.38	2,307	72.62	808	25.43	2,369	74.57
	10	955	30.76	2,150	69.24	916	29.50	2,189	70.50
	11	973	32.37	2,033	67.63	917	30.51	2,089	69.49
	12	1,142	33.66	2,251	66.34	1,098	32.36	2,295	67.64
2017	1	969	30.59	2,199	69.41	959	30.27	2,209	69.73
	2	1,121	32.78	2,299	67.22	1,118	32.69	2,302	67.31
	3	962	31.53	2,089	68.47	947	31.04	2,104	68.96
	4	713	31.82	1,528	68.18	701	31.28	1,540	68.72
	5	1,071	34.69	2,016	65.31	1,076	34.86	2,011	65.14
	6	1,124	35.78	2,017	64.22	1,133	36.07	2,008	63.93
	7	1,017	33.14	2,052	66.86	926	30.17	2,143	69.83
	8	1,041	33.92	2,028	66.08	1,012	32.97	2,057	67.03
	9	1,163	34.55	2,203	65.45	1,076	31.97	2,290	68.03
	10	1,003	31.93	2,138	68.07	955	30.40	2,186	69.60
	11	1,011	32.37	2,112	67.63	960	30.74	2,163	69.26
	12	1,033	33.76	2,027	66.24	994	32.48	2,066	67.52
2018	1	965	31.72	2,077	68.28	960	31.56	2,082	68.44
	2	992	32.32	2,077	67.68	1,002	32.65	2,067	67.35
	3	979	31.90	2,090	68.10	979	31.90	2,090	68.10
	4	981	32.63	2,025	67.37	970	32.27	2,036	67.73
	5	967	31.42	2,111	68.58	992	32.23	2,086	67.77
Average		1,002	32.59	2,072	67.41	973	31.64	2,101	68.36

Table A.6 OOS Prediction Results based on MNL 2 and RRS 3 (GEN Interaction Terms)

		MNL 2 Prediction (GEN)				RRS 3 Prediction (GEN)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	985	32.77	2,021	67.23	988	32.87	2,018	67.13
	7	1,046	34.39	1,996	65.61	1,050	34.52	1,992	65.48
	8	1,078	35.23	1,982	64.77	1,084	35.42	1,976	64.58
	9	1,038	34.53	1,968	65.47	1,050	34.93	1,956	65.07
	10	1,096	34.11	2,117	65.89	1,107	34.45	2,106	65.55
	11	1,030	33.66	2,030	66.34	1,038	33.92	2,022	66.08
	12	1,016	33.40	2,026	66.60	1,018	33.46	2,024	66.54
2014	1	974	32.40	2,032	67.60	985	32.77	2,021	67.23
	2	1,048	34.25	2,012	65.75	1,043	34.08	2,017	65.92
	3	1,091	35.04	2,023	64.96	1,058	33.98	2,056	66.02
	4	961	31.59	2,081	68.41	952	31.30	2,090	68.70
	5	1,061	34.78	1,990	65.22	1,078	35.33	1,973	64.67
	6	1,030	33.37	2,057	66.63	1,048	33.95	2,039	66.05
	7	999	32.84	2,043	67.16	1,003	32.97	2,039	67.03
	8	1,020	33.63	2,013	66.37	1,015	33.47	2,018	66.53
	9	1,050	33.52	2,082	66.48	1,066	34.04	2,066	65.96
	10	965	31.72	2,077	68.28	940	30.90	2,102	69.10
	11	1,022	33.80	2,002	66.20	1,026	33.93	1,998	66.07
	12	1,004	33.10	2,029	66.90	1,011	33.33	2,022	66.67
2015	1	1,027	33.76	2,015	66.24	1,020	33.53	2,022	66.47
	2	940	31.36	2,057	68.64	951	31.73	2,046	68.27
	3	954	30.64	2,160	69.36	984	31.60	2,130	68.40
	4	949	31.29	2,084	68.71	946	31.19	2,087	68.81
	5	1,015	31.86	2,171	68.14	1,024	32.14	2,162	67.86
	6	993	32.07	2,103	67.93	985	31.82	2,111	68.18
	7	1,017	31.92	2,169	68.08	1,013	31.80	2,173	68.20
	8	1,053	34.41	2,007	65.59	1,042	34.05	2,018	65.95
	9	971	32.30	2,035	67.70	993	33.03	2,013	66.97
	10	1,025	33.69	2,017	66.31	1,006	33.07	2,036	66.93
	11	950	31.42	2,074	68.58	954	31.55	2,070	68.45
	12	973	32.47	2,024	67.53	962	32.10	2,035	67.90
2016	1	1,015	33.87	1,982	66.13	1,056	35.24	1,941	64.76
	2	1,136	34.96	2,113	65.04	1,141	35.12	2,108	64.88
	3	1,056	34.21	2,031	65.79	1,068	34.60	2,019	65.40
	4	950	31.70	2,047	68.30	992	33.10	2,005	66.90
	5	960	31.37	2,100	68.63	957	31.27	2,103	68.73
	6	927	29.94	2,169	70.06	922	29.78	2,174	70.22
	7	816	27.15	2,190	72.85	824	27.41	2,182	72.59

	8	951	30.02	2,217	69.98	951	30.02	2,217	69.98
	9	852	26.82	2,325	73.18	883	27.79	2,294	72.21
	10	946	30.47	2,159	69.53	959	30.89	2,146	69.11
	11	967	32.17	2,039	67.83	968	32.20	2,038	67.80
	12	1,124	33.13	2,269	66.87	1,129	33.27	2,264	66.73
2017	1	963	30.40	2,205	69.60	967	30.52	2,201	69.48
	2	1,106	32.34	2,314	67.66	1,102	32.22	2,318	67.78
	3	952	31.20	2,099	68.80	948	31.07	2,103	68.93
	4	709	31.64	1,532	68.36	699	31.19	1,542	68.81
	5	1,024	33.17	2,063	66.83	1,078	34.92	2,009	65.08
	6	1,121	35.69	2,020	64.31	1,133	36.07	2,008	63.93
	7	1,031	33.59	2,038	66.41	1,036	33.76	2,033	66.24
	8	1,027	33.46	2,042	66.54	1,047	34.12	2,022	65.88
	9	1,162	34.52	2,204	65.48	1,171	34.79	2,195	65.21
	10	1,008	32.09	2,133	67.91	1,014	32.28	2,127	67.72
	11	1,028	32.92	2,095	67.08	1,013	32.44	2,110	67.56
	12	1,046	34.18	2,014	65.82	1,036	33.86	2,024	66.14
2018	1	964	31.69	2,078	68.31	972	31.95	2,070	68.05
	2	1,011	32.94	2,058	67.06	1,004	32.71	2,065	67.29
	3	980	31.93	2,089	68.07	990	32.26	2,079	67.74
	4	986	32.80	2,020	67.20	984	32.73	2,022	67.27
	5	969	31.48	2,109	68.52	976	31.71	2,102	68.29
Average		1,003	32.62	2,071	67.38	1,008	32.78	2,066	67.22

Table A.7 OOS Prediction Results based on MNL 2 and RRS 3 (AGE Interaction Terms)

		MNL 2 Prediction (AGE)				RRS 3 Prediction (AGE)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	992	33.00	2,014	67.00	979	32.57	2,027	67.43
	7	1,061	34.88	1,981	65.12	1,066	35.04	1,976	64.96
	8	1,064	34.77	1,996	65.23	1,055	34.48	2,005	65.52
	9	1,046	34.80	1,960	65.20	1,056	35.13	1,950	64.87
	10	1,080	33.61	2,133	66.39	1,085	33.77	2,128	66.23
	11	1,025	33.50	2,035	66.50	1,041	34.02	2,019	65.98
	12	1,021	33.56	2,021	66.44	1,033	33.96	2,009	66.04
2014	1	982	32.67	2,024	67.33	994	33.07	2,012	66.93
	2	1,001	32.71	2,059	67.29	1,025	33.50	2,035	66.50
	3	1,088	34.94	2,026	65.06	1,080	34.68	2,034	65.32
	4	960	31.56	2,082	68.44	940	30.90	2,102	69.10
	5	1,052	34.48	1,999	65.52	1,061	34.78	1,990	65.22
	6	1,035	33.53	2,052	66.47	1,041	33.72	2,046	66.28
	7	1,013	33.30	2,029	66.70	1,009	33.17	2,033	66.83
	8	1,022	33.70	2,011	66.30	1,023	33.73	2,010	66.27
	9	1,058	33.78	2,074	66.22	1,057	33.75	2,075	66.25
	10	968	31.82	2,074	68.18	948	31.16	2,094	68.84
	11	1,036	34.26	1,988	65.74	1,029	34.03	1,995	65.97
	12	990	32.64	2,043	67.36	977	32.21	2,056	67.79
2015	1	1,018	33.46	2,024	66.54	1,027	33.76	2,015	66.24
	2	949	31.66	2,048	68.34	964	32.17	2,033	67.83
	3	939	30.15	2,175	69.85	967	31.05	2,147	68.95
	4	938	30.93	2,095	69.07	944	31.12	2,089	68.88
	5	1,033	32.42	2,153	67.58	1,030	32.33	2,156	67.67
	6	986	31.85	2,110	68.15	1,005	32.46	2,091	67.54
	7	997	31.29	2,189	68.71	997	31.29	2,189	68.71
	8	1,051	34.35	2,009	65.65	1,047	34.22	2,013	65.78
	9	984	32.73	2,022	67.27	996	33.13	2,010	66.87
	10	1,029	33.83	2,013	66.17	1,030	33.86	2,012	66.14
	11	945	31.25	2,079	68.75	953	31.51	2,071	68.49
	12	973	32.47	2,024	67.53	961	32.07	2,036	67.93
2016	1	1,057	35.27	1,940	64.73	1,049	35.00	1,948	65.00
	2	1,125	34.63	2,124	65.37	1,132	34.84	2,117	65.16
	3	1,047	33.92	2,040	66.08	1,059	34.31	2,028	65.69
	4	967	32.27	2,030	67.73	1,024	34.17	1,973	65.83
	5	964	31.50	2,096	68.50	952	31.11	2,108	68.89
	6	908	29.33	2,188	70.67	925	29.88	2,171	70.12
	7	842	28.01	2,164	71.99	823	27.38	2,183	72.62

	8	954	30.11	2,214	69.89	963	30.40	2,205	69.60
	9	867	27.29	2,310	72.71	881	27.73	2,296	72.27
	10	942	30.34	2,163	69.66	948	30.53	2,157	69.47
	11	973	32.37	2,033	67.63	981	32.63	2,025	67.37
	12	1,131	33.33	2,262	66.67	1,127	33.22	2,266	66.78
2017	1	956	30.18	2,212	69.82	973	30.71	2,195	69.29
	2	1,119	32.72	2,301	67.28	1,133	33.13	2,287	66.87
	3	968	31.73	2,083	68.27	945	30.97	2,106	69.03
	4	725	32.35	1,516	67.65	706	31.50	1,535	68.50
	5	1,069	34.63	2,018	65.37	1,080	34.99	2,007	65.01
	6	1,141	36.33	2,000	63.67	1,158	36.87	1,983	63.13
	7	1,024	33.37	2,045	66.63	1,032	33.63	2,037	66.37
	8	1,063	34.64	2,006	65.36	1,071	34.90	1,998	65.10
	9	1,191	35.38	2,175	64.62	1,175	34.91	2,191	65.09
	10	1,029	32.76	2,112	67.24	1,033	32.89	2,108	67.11
	11	1,040	33.30	2,083	66.70	1,018	32.60	2,105	67.40
	12	1,053	34.41	2,007	65.59	1,053	34.41	2,007	65.59
2018	1	965	31.72	2,077	68.28	975	32.05	2,067	67.95
	2	1,000	32.58	2,069	67.42	1,011	32.94	2,058	67.06
	3	980	31.93	2,089	68.07	986	32.13	2,083	67.87
	4	983	32.70	2,023	67.30	968	32.20	2,038	67.80
	5	998	32.42	2,080	67.58	1,008	32.75	2,070	67.25
Average		1,007	32.76	2,067	67.24	1,010	32.86	2,064	67.14

Table A.8 OOS Prediction Results based on MNL 2 and RRS 3 (EDU Interaction Terms)

		MNL 2 Prediction (EDU)				RRS 3 Prediction (EDU)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	974	32.40	2,032	67.60	986	32.80	2,020	67.20
	7	1,042	34.25	2,000	65.75	1,055	34.68	1,987	65.32
	8	1,063	34.74	1,997	65.26	1,071	35.00	1,989	65.00
	9	1,010	33.60	1,996	66.40	1,029	34.23	1,977	65.77
	10	1,098	34.17	2,115	65.83	1,096	34.11	2,117	65.89
	11	1,038	33.92	2,022	66.08	1,046	34.18	2,014	65.82
	12	1,022	33.60	2,020	66.40	1,035	34.02	2,007	65.98
2014	1	980	32.60	2,026	67.40	981	32.63	2,025	67.37
	2	1,024	33.46	2,036	66.54	1,048	34.25	2,012	65.75
	3	1,095	35.16	2,019	64.84	1,092	35.07	2,022	64.93
	4	956	31.43	2,086	68.57	954	31.36	2,088	68.64
	5	1,047	34.32	2,004	65.68	1,058	34.68	1,993	65.32
	6	998	32.33	2,089	67.67	1,031	33.40	2,056	66.60
	7	970	31.89	2,072	68.11	1,002	32.94	2,040	67.06
	8	1,013	33.40	2,020	66.60	1,001	33.00	2,032	67.00
	9	1,019	32.54	2,113	67.46	1,057	33.75	2,075	66.25
	10	959	31.53	2,083	68.47	975	32.05	2,067	67.95
	11	1,030	34.06	1,994	65.94	1,020	33.73	2,004	66.27
	12	1,010	33.30	2,023	66.70	1,015	33.47	2,018	66.53
2015	1	993	32.64	2,049	67.36	1,029	33.83	2,013	66.17
	2	966	32.23	2,031	67.77	966	32.23	2,031	67.77
	3	931	29.90	2,183	70.10	972	31.21	2,142	68.79
	4	940	30.99	2,093	69.01	938	30.93	2,095	69.07
	5	996	31.26	2,190	68.74	1,025	32.17	2,161	67.83
	6	971	31.36	2,125	68.64	964	31.14	2,132	68.86
	7	984	30.89	2,202	69.11	1,006	31.58	2,180	68.42
	8	1,046	34.18	2,014	65.82	1,059	34.61	2,001	65.39
	9	997	33.17	2,009	66.83	1,001	33.30	2,005	66.70
	10	1,028	33.79	2,014	66.21	1,019	33.50	2,023	66.50
	11	941	31.12	2,083	68.88	982	32.47	2,042	67.53
	12	968	32.30	2,029	67.70	974	32.50	2,023	67.50
2016	1	1,040	34.70	1,957	65.30	1,057	35.27	1,940	64.73
	2	1,122	34.53	2,127	65.47	1,133	34.87	2,116	65.13
	3	1,019	33.01	2,068	66.99	1,079	34.95	2,008	65.05
	4	954	31.83	2,043	68.17	980	32.70	2,017	67.30
	5	928	30.33	2,132	69.67	957	31.27	2,103	68.73
	6	938	30.30	2,158	69.70	918	29.65	2,178	70.35
	7	858	28.54	2,148	71.46	836	27.81	2,170	72.19

	8	965	30.46	2,203	69.54	949	29.96	2,219	70.04
	9	884	27.82	2,293	72.18	891	28.05	2,286	71.95
	10	960	30.92	2,145	69.08	964	31.05	2,141	68.95
	11	966	32.14	2,040	67.86	974	32.40	2,032	67.60
	12	1,139	33.57	2,254	66.43	1,143	33.69	2,250	66.31
2017	1	965	30.46	2,203	69.54	961	30.33	2,207	69.67
	2	1,113	32.54	2,307	67.46	1,113	32.54	2,307	67.46
	3	934	30.61	2,117	69.39	924	30.29	2,127	69.71
	4	721	32.17	1,520	67.83	720	32.13	1,521	67.87
	5	1,063	34.43	2,024	65.57	1,077	34.89	2,010	65.11
	6	1,121	35.69	2,020	64.31	1,135	36.13	2,006	63.87
	7	1,035	33.72	2,034	66.28	1,017	33.14	2,052	66.86
	8	1,025	33.40	2,044	66.60	1,031	33.59	2,038	66.41
	9	1,163	34.55	2,203	65.45	1,164	34.58	2,202	65.42
	10	1,000	31.84	2,141	68.16	1,012	32.22	2,129	67.78
	11	1,013	32.44	2,110	67.56	1,025	32.82	2,098	67.18
	12	1,018	33.27	2,042	66.73	1,044	34.12	2,016	65.88
2018	1	966	31.76	2,076	68.24	989	32.51	2,053	67.49
	2	996	32.45	2,073	67.55	1,000	32.58	2,069	67.42
	3	976	31.80	2,093	68.20	981	31.96	2,088	68.04
	4	992	33.00	2,014	67.00	982	32.67	2,024	67.33
	5	938	30.47	2,140	69.53	988	32.10	2,090	67.90
Average		999	32.49	2,075	67.51	1,009	32.82	2,065	67.18

Table A.9 OOS Prediction Results based on MNL 2 and RRS 3 (HSIZE Interaction Terms)

		MNL 2 Prediction (HSIZE)				RRS 3 Prediction (HSIZE)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	983	32.70	2,023	67.30	978	32.53	2,028	67.47
	7	1,044	34.32	1,998	65.68	1,056	34.71	1,986	65.29
	8	1,055	34.48	2,005	65.52	1,044	34.12	2,016	65.88
	9	1,031	34.30	1,975	65.70	1,042	34.66	1,964	65.34
	10	1,094	34.05	2,119	65.95	1,095	34.08	2,118	65.92
	11	1,028	33.59	2,032	66.41	1,044	34.12	2,016	65.88
	12	1,014	33.33	2,028	66.67	1,028	33.79	2,014	66.21
2014	1	980	32.60	2,026	67.40	995	33.10	2,011	66.90
	2	1,005	32.84	2,055	67.16	1,015	33.17	2,045	66.83
	3	1,099	35.29	2,015	64.71	1,096	35.20	2,018	64.80
	4	945	31.07	2,097	68.93	934	30.70	2,108	69.30
	5	1,059	34.71	1,992	65.29	1,057	34.64	1,994	65.36
	6	1,024	33.17	2,063	66.83	1,024	33.17	2,063	66.83
	7	998	32.81	2,044	67.19	1,016	33.40	2,026	66.60
	8	1,014	33.43	2,019	66.57	1,002	33.04	2,031	66.96
	9	1,037	33.11	2,095	66.89	1,055	33.68	2,077	66.32
	10	959	31.53	2,083	68.47	944	31.03	2,098	68.97
	11	1,033	34.16	1,991	65.84	1,019	33.70	2,005	66.30
	12	985	32.48	2,048	67.52	989	32.61	2,044	67.39
2015	1	1,015	33.37	2,027	66.63	1,005	33.04	2,037	66.96
	2	956	31.90	2,041	68.10	937	31.26	2,060	68.74
	3	942	30.25	2,172	69.75	966	31.02	2,148	68.98
	4	949	31.29	2,084	68.71	933	30.76	2,100	69.24
	5	1,012	31.76	2,174	68.24	1,017	31.92	2,169	68.08
	6	976	31.52	2,120	68.48	977	31.56	2,119	68.44
	7	983	30.85	2,203	69.15	1,013	31.80	2,173	68.20
	8	1,048	34.25	2,012	65.75	1,046	34.18	2,014	65.82
	9	983	32.70	2,023	67.30	992	33.00	2,014	67.00
	10	1,026	33.73	2,016	66.27	1,010	33.20	2,032	66.80
	11	947	31.32	2,077	68.68	967	31.98	2,057	68.02
	12	967	32.27	2,030	67.73	976	32.57	2,021	67.43
2016	1	1,056	35.24	1,941	64.76	1,050	35.04	1,947	64.96
	2	1,112	34.23	2,137	65.77	1,123	34.56	2,126	65.44
	3	1,059	34.31	2,028	65.69	1,068	34.60	2,019	65.40
	4	962	32.10	2,035	67.90	991	33.07	2,006	66.93
	5	955	31.21	2,105	68.79	940	30.72	2,120	69.28
	6	924	29.84	2,172	70.16	891	28.78	2,205	71.22
	7	822	27.35	2,184	72.65	848	28.21	2,158	71.79

	8	964	30.43	2,204	69.57	946	29.86	2,222	70.14
	9	878	27.64	2,299	72.36	879	27.67	2,298	72.33
	10	938	30.21	2,167	69.79	937	30.18	2,168	69.82
	11	965	32.10	2,041	67.90	968	32.20	2,038	67.80
	12	1,131	33.33	2,262	66.67	1,128	33.24	2,265	66.76
2017	1	981	30.97	2,187	69.03	962	30.37	2,206	69.63
	2	1,101	32.19	2,319	67.81	1,115	32.60	2,305	67.40
	3	956	31.33	2,095	68.67	955	31.30	2,096	68.70
	4	718	32.04	1,523	67.96	703	31.37	1,538	68.63
	5	1,062	34.40	2,025	65.60	1,087	35.21	2,000	64.79
	6	1,110	35.34	2,031	64.66	1,123	35.75	2,018	64.25
	7	1,012	32.97	2,057	67.03	1,028	33.50	2,041	66.50
	8	1,039	33.85	2,030	66.15	1,048	34.15	2,021	65.85
	9	1,157	34.37	2,209	65.63	1,159	34.43	2,207	65.57
	10	1,012	32.22	2,129	67.78	1,012	32.22	2,129	67.78
	11	1,018	32.60	2,105	67.40	1,030	32.98	2,093	67.02
	12	1,043	34.08	2,017	65.92	1,040	33.99	2,020	66.01
2018	1	950	31.23	2,092	68.77	962	31.62	2,080	68.38
	2	999	32.55	2,070	67.45	1,009	32.88	2,060	67.12
	3	985	32.10	2,084	67.90	976	31.80	2,093	68.20
	4	981	32.63	2,025	67.37	972	32.34	2,034	67.66
	5	978	31.77	2,100	68.23	983	31.94	2,095	68.06
Average		1,001	32.56	2,073	67.44	1,003	32.64	2,070	67.36

Table A.10 OOS Prediction Results based on MNL 2 and RRS 3 (HINC Interaction Terms)

		MNL 2 Prediction (HINC)				RRS 3 Prediction (HINC)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	976	32.47	2,030	67.53	992	33.00	2,014	67.00
	7	1,036	34.06	2,006	65.94	1,061	34.88	1,981	65.12
	8	1,039	33.95	2,021	66.05	1,053	34.41	2,007	65.59
	9	1,022	34.00	1,984	66.00	1,044	34.73	1,962	65.27
	10	1,089	33.89	2,124	66.11	1,086	33.80	2,127	66.20
	11	1,083	35.39	1,977	64.61	1,090	35.62	1,970	64.38
	12	1,029	33.83	2,013	66.17	1,019	33.50	2,023	66.50
2014	1	975	32.44	2,031	67.56	991	32.97	2,015	67.03
	2	1,015	33.17	2,045	66.83	1,056	34.51	2,004	65.49
	3	1,077	34.59	2,037	65.41	1,088	34.94	2,026	65.06
	4	962	31.62	2,080	68.38	955	31.39	2,087	68.61
	5	1,056	34.61	1,995	65.39	1,065	34.91	1,986	65.09
	6	1,040	33.69	2,047	66.31	1,054	34.14	2,033	65.86
	7	1,002	32.94	2,040	67.06	1,008	33.14	2,034	66.86
	8	1,006	33.17	2,027	66.83	1,004	33.10	2,029	66.90
	9	1,043	33.30	2,089	66.70	1,048	33.46	2,084	66.54
	10	978	32.15	2,064	67.85	968	31.82	2,074	68.18
	11	1,037	34.29	1,987	65.71	1,033	34.16	1,991	65.84
	12	995	32.81	2,038	67.19	1,009	33.27	2,024	66.73
2015	1	1,032	33.93	2,010	66.07	1,044	34.32	1,998	65.68
	2	963	32.13	2,034	67.87	968	32.30	2,029	67.70
	3	976	31.34	2,138	68.66	1,002	32.18	2,112	67.82
	4	945	31.16	2,088	68.84	953	31.42	2,080	68.58
	5	1,048	32.89	2,138	67.11	1,067	33.49	2,119	66.51
	6	990	31.98	2,106	68.02	986	31.85	2,110	68.15
	7	995	31.23	2,191	68.77	1,004	31.51	2,182	68.49
	8	1,030	33.66	2,030	66.34	1,050	34.31	2,010	65.69
	9	999	33.23	2,007	66.77	1,013	33.70	1,993	66.30
	10	1,025	33.69	2,017	66.31	1,012	33.27	2,030	66.73
	11	973	32.18	2,051	67.82	973	32.18	2,051	67.82
	12	1,012	33.77	1,985	66.23	1,018	33.97	1,979	66.03
2016	1	1,062	35.44	1,935	64.56	1,080	36.04	1,917	63.96
	2	1,141	35.12	2,108	64.88	1,141	35.12	2,108	64.88
	3	1,035	33.53	2,052	66.47	1,059	34.31	2,028	65.69
	4	982	32.77	2,015	67.23	997	33.27	2,000	66.73
	5	956	31.24	2,104	68.76	946	31.90	2,084	68.10
	6	954	30.81	2,142	69.19	944	30.49	2,152	69.51
	7	858	28.54	2,148	71.46	842	28.01	2,164	71.99

	8	942	29.73	2,226	70.27	947	29.89	2,221	70.11
	9	885	27.86	2,292	72.14	883	27.79	2,294	72.21
	10	959	30.89	2,146	69.11	972	31.30	2,133	68.70
	11	945	31.44	2,061	68.56	967	32.17	2,039	67.83
	12	1,137	33.51	2,256	66.49	1,124	33.13	2,269	66.87
2017	1	981	30.97	2,187	69.03	977	30.84	2,191	69.16
	2	1,137	33.25	2,283	66.75	1,148	33.57	2,272	66.43
	3	959	31.43	2,092	68.57	938	30.74	2,113	69.26
	4	714	31.86	1,527	68.14	709	31.64	1,532	68.36
	5	1,066	34.53	2,021	65.47	1,083	35.08	2,004	64.92
	6	1,121	35.69	2,020	64.31	1,122	35.72	2,019	64.28
	7	1,024	33.37	2,045	66.63	1,032	33.63	2,037	66.37
	8	1,055	34.38	2,014	65.62	1,067	34.77	2,002	65.23
	9	1,171	34.79	2,195	65.21	1,183	35.15	2,183	64.85
	10	1,019	32.44	2,122	67.56	1,015	32.31	2,126	67.69
	11	1,047	33.53	2,076	66.47	1,043	33.40	2,080	66.60
	12	1,051	34.35	2,009	65.65	1,053	34.41	2,007	65.59
2018	1	981	32.25	2,061	67.75	995	32.71	2,047	67.29
	2	1,000	32.58	2,069	67.42	1,015	33.07	2,054	66.93
	3	989	32.23	2,080	67.77	989	32.23	2,080	67.77
	4	1,012	33.67	1,994	66.33	1,008	33.53	1,998	66.47
	5	951	30.90	2,127	69.10	958	31.12	2,120	68.88
Average		1,010	32.84	2,064	67.16	1,016	33.06	2,057	66.94

Table A.11 OOS Prediction Results based on MNL 2 and RRS 3 (SCTIME Interaction Terms)

		MNL 2 Prediction (SCTIME)				RRS 3 Prediction (SCTIME)			
		Correct		Incorrect		Correct		Incorrect	
		$A_{it} = 1$		$A_{it} = 0$		$A_{it} = 1$		$A_{it} = 0$	
Year	Month	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
2013	6	990	32.93	2,016	67.07	973	32.37	2,033	67.63
	7	1,037	34.09	2,005	65.91	1,045	34.35	1,997	65.65
	8	1,058	34.58	2,002	65.42	1,076	35.16	1,984	64.84
	9	1,024	34.07	1,982	65.93	1,049	34.90	1,957	65.10
	10	1,079	33.58	2,134	66.42	1,100	34.24	2,113	65.76
	11	1,045	34.15	2,015	65.85	1,049	34.28	2,011	65.72
	12	1,022	33.60	2,020	66.40	1,022	33.60	2,020	66.40
2014	1	974	32.40	2,032	67.60	977	32.50	2,029	67.50
	2	1,031	33.69	2,029	66.31	1,024	33.46	2,036	66.54
	3	1,092	35.07	2,022	64.93	1,078	34.62	2,036	65.38
	4	937	30.80	2,105	69.20	926	30.44	2,116	69.56
	5	1,066	34.94	1,985	65.06	1,075	35.23	1,976	64.77
	6	1,044	33.82	2,043	66.18	1,053	34.11	2,034	65.89
	7	1,009	33.17	2,033	66.83	1,018	33.46	2,024	66.54
	8	1,011	33.33	2,022	66.67	986	32.51	2,047	67.49
	9	1,048	33.46	2,084	66.54	1,070	34.16	2,062	65.84
	10	968	31.82	2,074	68.18	954	31.36	2,088	68.64
	11	1,037	34.29	1,987	65.71	1,021	33.76	2,003	66.24
	12	993	32.74	2,040	67.26	1,006	33.17	2,027	66.83
2015	1	1,020	33.53	2,022	66.47	1,023	33.63	2,019	66.37
	2	946	31.56	2,051	68.44	943	31.46	2,054	68.54
	3	940	30.19	2,174	69.81	958	30.76	2,156	69.24
	4	941	31.03	2,092	68.97	962	31.72	2,071	68.28
	5	1,024	32.14	2,162	67.86	1,035	32.49	2,151	67.51
	6	979	31.62	2,117	68.38	982	31.72	2,114	68.28
	7	997	31.29	2,189	68.71	1,001	31.42	2,185	68.58
	8	1,051	34.35	2,009	65.65	1,053	34.41	2,007	65.59
	9	976	32.47	2,030	67.53	983	32.70	2,023	67.30
	10	1,016	33.40	2,026	66.60	1,020	33.53	2,022	66.47
	11	954	31.55	2,070	68.45	951	31.45	2,073	68.55
	12	963	32.13	2,034	67.87	969	32.33	2,028	67.67
2016	1	1,047	34.93	1,950	65.07	1,052	35.10	1,945	64.90
	2	1,118	34.41	2,131	65.59	1,127	34.69	2,122	65.31
	3	1,044	33.82	2,043	66.18	1,062	34.40	2,025	65.60
	4	958	31.97	2,039	68.03	991	33.07	2,006	66.93
	5	964	31.50	2,096	68.50	958	31.31	2,102	68.69
	6	923	29.81	2,173	70.19	926	29.91	2,170	70.09
	7	826	27.48	2,180	72.52	830	27.61	2,176	72.39

	8	964	30.43	2,204	69.57	956	30.18	2,212	69.82
	9	870	27.38	2,307	72.62	875	27.54	2,302	72.46
	10	944	30.40	2,161	69.60	945	30.43	2,160	69.57
	11	969	32.24	2,037	67.76	954	31.74	2,052	68.26
	12	1,126	33.19	2,267	66.81	1,130	33.30	2,263	66.70
2017	1	972	30.68	2,196	69.32	964	30.43	2,204	69.57
	2	1,114	32.57	2,306	67.43	1,107	32.37	2,313	67.63
	3	963	31.56	2,088	68.44	949	31.10	2,102	68.90
	4	708	31.59	1,533	68.41	702	31.33	1,539	68.67
	5	1,073	34.76	2,014	65.24	1,091	35.34	1,996	64.66
	6	1,122	35.72	2,019	64.28	1,139	36.26	2,002	63.74
	7	1,025	33.40	2,044	66.60	1,039	33.85	2,030	66.15
	8	1,048	34.15	2,021	65.85	1,063	34.64	2,006	65.36
	9	1,165	34.61	2,201	65.39	1,177	34.97	2,189	65.03
	10	1,011	32.19	2,130	67.81	1,016	32.35	2,125	67.65
	11	1,037	33.21	2,086	66.79	1,023	32.76	2,100	67.24
	12	1,043	34.08	2,017	65.92	1,047	34.22	2,013	65.78
2018	1	981	32.25	2,061	67.75	977	32.12	2,065	67.88
	2	994	32.39	2,075	67.61	1,015	33.07	2,054	66.93
	3	993	32.36	2,076	67.64	980	31.93	2,089	68.07
	4	953	31.70	2,053	68.30	974	32.40	2,032	67.60
	5	981	31.87	2,097	68.13	986	32.03	2,092	67.97
Average		1,003	32.64	2,070	67.36	1,007	32.76	2,066	67.24

Appendix B - Supplement Material for Chapter 2

Table B.1 Sample Sizes by the Number of Choice Situations

Number of Choice Situation (t)	Number of Unique panel_id	Number of Sample
1	531	531
2	294	588
3	181	543
4	108	432
5	70	350
6	41	246
7	34	238
8	25	200
9	18	162
10	13	130
11	9	99
12	6	72
13	4	52
14	4	56
15	4	60
16	3	48
17	2	34
18	1	18