Modeling Yeah- and Nay-Saying to Alternatives in Conjoint Experiments

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Abstract

Using a series of hurdle choice models, this study considers both nay-saying and yeah-saying to alternatives offered in a conjoint experiment. These behaviors are characterized by respondents persistently choosing the no-choice alternative or choosing at least one of the non-empty options offered in a survey. Results show that jointly consider nay-saying and yeah-saying in a two-hurdle model drastically improves model fit; welfare implications based on hurdle models are also different from those based on models without hurdle specification.

Keywords: conjoint experiment, hurdle choice model, yeah and nay-saying

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One of the potential biases associated with data collected by survey approaches may be related to no-responses, or answers of “don’t know” in the survey. These biases have drawn sizable attention from researchers and may somehow be triggered one way or the other as described in Krosnick et al. (2002). In the literature of economic valuation and marketing particularly, the issue of no-response is frequently centered on survey participants answering “don’t know” to the key willingness to pay question, or making no choice among product/service alternatives offered in the survey. A number of studies have been devoted to understanding the non-participation issue and have made important recommendations on how to handle the consequences of such behavior (e.g., Wang 1997; Haab and McConnell 1996; Schweitzer 1994). Nevertheless, almost all these studies focus on non-participation in the context of total number of participations, dichotomous contingent choices, or various direct willingness to pay questions. Given the fast expanding body of literature concerned with the application of conjoint experiment in areas such as food safety, recreational demand, transportation research and health studies, there is a strong need to understand non-participation behavior in conjoint experiments.

A conjoint experiment typically records repeated choices made by each individual in the sample. Von Haefen, Massey and Adamowicz (2005) is one of the first studies that directly examined non-participation in a conjoint experiment by allowing the non-participation decision to be captured by a different behavior mechanism that may have been characterized by respondents’ demographic information. According to their definition, non-participation in a conjoint experiment is typically featured by respondents persistently selecting the no-choice option or indicating no-action in all choice situations in a survey.

In other words, one may view this as if the respondents are rejecting or saying “nay” to all product/service options offered in all choice scenarios. However, a natural question that comes along this line of reasoning is: what about respondents who are saying “yeah” to at least one product/service option offered in all choice scenarios? Do these respondents truly prefer one of the options offered in a choice situation, or are there other reasons they do so? If one suspects that nay-saying may generate potential biases in understanding choice behavior and suggested welfare implications, would it be reasonable to be concerned about yeah-saying choices? Previous studies have shown that yeah-saying bias, if present, may affect the analysis results (Adamowicz et al. 1998 and Boxall et al. 1996). Nevertheless, past studies have not examined yeah-saying behavior in the context of conjoint experiment.

In this article we propose a method that recognizes and explicitly models yeah- and nay-saying behavior. The proposed model is general and we do not intend to lay reference to any particular behavioral interpretation on why yeah- or nay-saying choices may occur, although attaching identifiable behavioral assumptions/restrictions may be proven to be valuable and further support the evidence offered here (Roebeling, Ruijs and Kragt 2006).

We adopt a hurdle model that can be applied in analyzing individuals' repeated choices in a conjoint experiment. The methodology follows the general framework in von Haefen, Massey and Adamowicz (and therefore denoted as VMA). Our evidence from analyzing the nay-saying behavior is consistent with these authors. Nevertheless, we made two major extensions of this framework. First, we show that the hurdle model may not only be used to address the issue of nay-saying to alternatives, it can be applied equally well to accommodate yeah-saying. In our application of the method to a dataset involving consumers' conjoint choices of canola oil, the yeah-saying hurdle approach outperforms the nay-saying hurdle approach in both the conditional and mixed logit choice model specifications. Second, since these two types of behavior may likely coexist in any given dataset, we incorporate them into the same model that employs the two hurdles simultaneously: one for the nay-saying behavior and one for the yeah-saying behavior. Our results suggest that the two-hurdle model drastically improves model fit. A fixed coefficient two-hurdle model performs better than a mixed logit model without considering possible hurdles.

Welfare implications (marginal willingness to pay) are also calculated based on these models. Results indicate that these measures differ moderately between models that consider or ignore either of the two or both hurdles. Welfare measures between fixed coefficient and mixed logit models are slightly different and almost no difference can be detected between two different ways of calculating these measures under the mixed logit models. The following section explains the hurdle models adopted and how they fit into the context of a conjoint experiment. Data employed are described in the next section.

Parameter estimation results, model fit comparison, and implied welfare measures under various models are discussed following the data description. The last section of this article summarizes the conclusions, and points out implications that may be drawn from this study and future research potentials.

Model

A majority of the literature analyzing individuals' discrete choice behavior, including that under a conjoint experiment, is built upon random utility theory (RUT) constructed by McFadden. Suppose each individual in the sample can be denoted by *i*, then the choice of *i* in a typical conjoint experiment may be represented by vector $\mathbf{C_i}$. Respondents are often asked to complete a series of choice questions in various situations referred to as choice sets. In each choice set, respondents are asked to choose one and only one option from several options offered. Under this scheme, each element of $\mathbf{C_i}$ can be used to identify the choices made by individual *i* in each of the choice sets. In designing the choice sets, an important feature is to allow consumers to express preference on alternatives not being offered in a choice set and this is commonly achieved by including a "no-choice" option that is not described by product/service features but by a description taking either of the following two forms: a) I do not wish to choose any of the options offered here or b) I would stay with the product/service I currently get/choose. This is known in the conjoint experiment literature as the exhaustive requirement (Louviere, Hensher and Swait 2000) which is also consistent with the 1993 NOAA panel's recommendation in the context of a contingent valuation study.

The inclusion of the no-choice option raises the empirical distinction between yeah- and nay-saying to the alternatives offered in choice sets. If a dummy variable can be created where it equals zero when a no-choice option is chosen and equals one when any of the non-empty product/service alternatives offered is chosen, then a typical outcome of the series of choices an individual makes may be a mixture of zeros and ones such that $\mathbf{C_i} = \{1,0,0,1,1,0,... \mid J\}$, where J is the total number of choices (or choice sets) individual i sees in a conjoint experiment. Without losing generality, J is assumed to be constant across individuals. A nay-saying choice pattern may be captured by choices $\mathbf{C_i} = \mathbf{C_i^0} = \{0,0,0,0,0,0,... \mid J\}$ and similarly, a yeah-saying behavior may be represented by $\mathbf{C_i} = \mathbf{C_i^1} = \{1,1,1,1,1,1,... \mid J\}$. Certainly, choice patterns consistent with these styles may not suggest a different choice behavior than other types of choices, but it is likely that individuals making choices $\mathbf{C_i^1}$ and $\mathbf{C_i^0}$ behave systematically different to other individuals in the sample.

Following RUT, the indirect utility associated with alternative j in the n-th choice set by individual i can be written as:

(1) $U_{ijn} = \mathbf{X_{ijn}}\boldsymbol{\beta} + e_{ijn}$

where $\mathbf{X_{ijn}}$ is a vector of the attributes associated with option j faced by i in choice set n; $\boldsymbol{\beta}$ is a vector of corresponding unknown coefficient to be estimated; and e_{ijn} is a noise term that gives the random nature of utility U_{ijn} from the perspective of a researcher. If e_{ijn} is assumed iid in Gumbel distribution, the choice probability P_{ijn} can be represented by the logit model:

(2) $$P_{ijn} = \frac{\exp(\mathbf{X_{ijn}}\boldsymbol{\beta})}{\sum_{k=1}^{J}\exp(\mathbf{X_{ikn}}\boldsymbol{\beta})}$$

The likelihood of the series of choices represented in $\mathbf{C_i}$ can then be written as:

(3) $$P_{\mathbf{C_i}} = \prod_{n}^{N}\prod_{j}^{J}(P_{ijn})\wedge y_{ijn}$$

where y_{ijn} is a dummy variable indicating actual choices: $y_{ijn} = 1$ if *j* is chosen by *i* in choice set *n*; otherwise $y_{ijn} = 0$. Following the same idea, the likelihood of $\mathbf{C_i^1}$ and $\mathbf{C_i^0}$ being realized respectively is:

(4.1) $$P_{\mathbf{C_i^0}} = \prod_{n}^{N} P_{i0n}$$

(4.2) $$P_{\mathbf{C_i^1}} = \prod_{n}^{N} P_{i\mathbf{1}n}$$

The expression $P_{i\mathbf{1}n}$ denotes the likelihood of *i* choosing one of the non-empty options offered in choice set *n*. Since there is typically more than one non-empty product/service options besides the no-choice option in a choice set, indicator 1 is vectorized. Similarly P_{i0n} represents the likelihood of choosing the no-choice option in choice set *n*.

VMA reviewed the relevant literature that has proposed methods to particularly deal with the potential bias introduced by nay-saying behavior. These authors conclude that a hurdle model may offer a more direct treatment of non-participation by allowing different data generating mechanisms in the model. Following VMA, a hurdle structure can be specified to capture the nay-saying as well as yeah-saying probabilities separately from the choice models. If one assumes that the hurdle probabilities for nay-saying and yeah-saying can be represented by λ and τ respectively and further assumes that these probabilities take the convenient logit form, then one may specify:

$$(5.1) \quad \lambda_i = \frac{\exp(\mathbf{Z_i}\boldsymbol{\gamma}_\lambda)}{1+\exp(-\mathbf{Z_i}\boldsymbol{\gamma}_\lambda)}$$

$$(5.2) \quad \tau_i = \frac{\exp(\mathbf{Z_i}\boldsymbol{\gamma}_\tau)}{1+\exp(-\mathbf{Z_i}\boldsymbol{\gamma}_\tau)}$$

where $\mathbf{Z_i}$ is a vector of individual characteristics variables that may explain the behavior of yeah- and/or nay-saying to the options in a conjoint experiment; $\boldsymbol{\gamma}$ is a vector of unknown coefficients to be estimated and distinguished by corresponding subscripts in different hurdles.

The choice probability of a nay-saying single hurdle model[1] can therefore be written as:

$$(6) \quad NP_i = \begin{cases} \lambda_i * 1 & \text{if} \quad \mathbf{C_i} = \mathbf{C_i^0} \\ (1-\lambda_i)\dfrac{P_{\mathbf{C_i}}}{1-P_{\mathbf{C_i^0}}} & \text{if} \quad \text{otherwise} \end{cases}$$

This is the same as in VMA. Based on this expression, the extension to the yeah-saying hurdle model is straightforward:

$$(7) \quad YP_i = \begin{cases} \tau_i * 1 & \text{if} \quad \mathbf{C_i} = \mathbf{C_i^1} \\ (1-\tau_i)\dfrac{P_{\mathbf{C_i}}}{1-P_{\mathbf{C_i^1}}} & \text{if} \quad \text{otherwise} \end{cases}$$

When the above two hurdle specifications are considered simultaneously under one choice model, the choice probability has three parts and is given as follows:

(8) $$NYP_i = \begin{cases} \lambda_i * 1 & \text{if} \quad \mathbf{C_i} = \mathbf{C_i^0} \\ \tau_i * 1 & \text{if} \quad \mathbf{C_i} = \mathbf{C_i^1} \\ (1-\lambda_i)(1-\tau_i)\dfrac{P_{\mathbf{C_i}}}{1 - P_{\mathbf{C_i^0}} - P_{\mathbf{C_i^1}}} & \text{if} \quad \text{otherwise} \end{cases}$$

The overall log-likelihood of the hurdle models is simply the log of the individual choice probabilities summed over the number of individuals in the sample. The development of the mixed logit model (Train 1998) has gained great attention from researchers in recent years. The mixed logit model is not only able to reveal unobserved heterogeneity in choice models, it often provides a better fit to the data compared to the fixed coefficient conditional logit model. A mixed logit model can be specified by replacing the basic choice likelihood $P_{\mathbf{C_i}}$ by $P'_{\mathbf{C_i}} = \int P_{\mathbf{C_i}} f(\boldsymbol{\beta}) d\boldsymbol{\beta}$, which is the fixed coefficient choice likelihood integrated out of the entire distribution of the random coefficients. Once $P_{\mathbf{C_i}}$ is replaced by $P'_{\mathbf{C_i}}$, all hurdle mixed logit models can be obtained in identical ways as their fixed coefficient versions. To assist estimation, a simulated maximum likelihood approach can be taken to estimate the mixed logit models.

Data

The canola oil survey was administered by mails between 2003 and 2004 in four regions of Japan: Tokyo, Kanagawa, Saitama, and Chiba. Respondents were randomly selected by their phone book registry and a total of 1050 questionnaires were mailed. Out of the 430 returned surveys that at least answered portions of the questionnaire, 367 completed all conjoint experiment questions and are useable in this study. Descriptive statistics of demographic characteristics of the respondents show that the sample is representative based on a typical survey of retail food items. Table 1 describes the attributes and their levels used in the conjoint experimental design, and the survey was focused on credence attributes of canola oil. Each respondent was presented with eight choice sets and within each choice set, three options were offered. Among the three options, the first two are described by actual attributes listed in table 1. The last option is the no-choice option where the individuals can choose this option and indicate that they "would not like to choose either one of the first two products in this occasion". To obtain a preliminary idea of the issue of yeah- and nay-saying to the options offered in each choice set, figure 1 gives the distribution of the number of times a respondent chose the no-choice option. Zero implies yeah-saying and eight suggests nay-saying.

Contrary to the two datasets used in VMA, where a large proportion of the respondents were non-participants, in this canola oil survey, only 31 individuals out of the 367 (roughly 8%) respondents exhibited the pattern of nay-saying. On the other extreme however, 72 individuals consistently chose a non-empty product offered in each choice set, consisting about 20% of the sample. This large proportion of yeah-saying individuals makes it logical to investigate whether these choices are featured by different underlying choice behavior. The rest of the respondents were distributed rather evenly in terms of the number of no-choice options chosen, except for the category representing individuals who chose the no-choice option seven out of eight times in the survey. These characteristics indicate that in a survey on food purchase and marketing, it may not be as imperative as in a survey regarding environmental goods/services (as both datasets in

VMA) to treat the nay-saying as a separate group with distinctive choice patterns; rather, at least equal effort should be directed to examine the yeah-saying behavior. Differences in natures between different surveys may invoke different need for modeling methods. The gain of using a hurdle and ultimately the model selection may rely largely on the characteristics of the data in interest.

Results

Results of this study are presented in two sections: direct parameter estimation results from various models and the welfare implications associated with these models.

Model Estimation Results

Table 2 gives the model estimation results. Given that there is relatively much information presented in table 2, discussion in this subsection takes the following order: First, the fixed-coefficient conditional logit model without hurdle specification is discussed. Although different models have slightly different predictions on the significance of the coefficients of the product attribute variables in the indirect utility function; i.e., $\boldsymbol{\beta}$,[2] the result of this base-line logit model helps to bring a general view of the empirical meaning of this study. Second, various models are compared under the fixed-coefficient conditional logit base-line choice model. Third, a similar comparison is conducted within the scope of a mixed logit base-line choice model. Lastly, results of comparisons between models across all categories are highlighted.

The constant for the no-choice option is negative. This suggests that Japanese consumers in general would like to have the option of purchasing canola oil and if not, a negative impact to utility may incur. The attributes of being high in Oleic acid and containing Vitamin E are negative. These effects are compared to the omitted category "low in saturated fat". The negative coefficients indicate that consumers would prefer the low saturated fat attribute more than the two relatively newer types of nutritional claims. Similarly, a non-significant coefficient for the variable representing high in Alpha-Linoleic acid shows that consumers did not in general differentiate this attribute with the low in fat attribute. It has been found in numerous other studies that genetic modification is often regarded as an attribute that, when present, will decrease product values. The same effect can be seen here as well, in that the coefficient associated with the GM attribute is negative. Consumers would prefer a bottle of canola oil more if it is produced by organic oilseeds. The functional food attribute was also welcomed by consumers as reflected by its positive coefficient in the model. The surveyed Japanese consumers did not appear to like canola oil imported from other countries. Finally, the price coefficient is negative and significant.

Based on the same conditional logit base-line choice models, various hurdle models are also estimated. Comparing magnitude of parameters across models is not sensible because of the scale issue, thus, the discussion is focused on signs of parameters and model fit. A series of consumers' demographic information is used in the specification of the hurdle probability. In the nay- and yeah-saying hurdle probabilities, these variables are identified by the suffixes "-Nay" and "-Yeah" respectively. The nay-saying hurdle model improves the standard conditional logit model by a significant margin based on the nonparametric information criteria (AIC and BIC). This is consistent with the findings in VMA. According to this model, individuals who are male, younger, less educated, and/or lower household income, were significantly more likely to consistently choose the no-choice option in the survey. These significant variables suggest that a distinctive choice pattern may be adopted by different individuals. Size of household and the number of children in household were not significant factors determining the nay-saying behavior.

Compared to the nay-saying hurdle model, the yeah-saying hurdle model improves the model fit by a much larger degree. This is likely consistent with the data. Given the choice patterns displayed in figure 1, augmenting choice probabilities with the yeah-saying hurdle does provide a better understanding of the data reflected by further improved model fit. Male, younger, and less educated individuals might be more likely to get involved with consistently choosing at least one of the non-empty products offered in each choice set. Different to the nay-saying group, yeah-saying consumers tend to have less children at home and/or have more family income. The last model, which contains both nay- and yeah-saying hurdles, has the best model fit among all four models. This result likely comes from the fact that this model allows and considers more types of choice patterns contained in the data, and therefore provides a better description of overall consumer preferences. The impact of demographic variables to either nay- or yeah-saying is consistent to that given under the two, one-hurdle models separately.

In the specification of the mixed logit models, all coefficients are assumed to have a normal distribution across sampled consumers, except that of the price variable. This is mainly to maintain the calculation of the marginal values explained in the next subsection separately from the "dividing by zero" problem (Layton and Brown 2000 and Hu, Veeman and Adamowicz 2005). Models with a random price coefficient (lognormally distributed) have been analyzed and no conclusion in the current analysis was affected. The mixed logit model offers great improvement in fit. The mixed logit without hurdle specification improves the conditional logit fit by almost 15% in AIC score. Estimated standard deviations of various coefficients are labeled with "SD-" as the prefix. These standard deviation estimates are also robust across various models, with minor differences. These parameters suggest that Japanese consumers are heterogeneous in terms of their preferences to the studied attributes of canola oil.

When the nay-saying hurdle was included, the model obtained further gain in fit. However, also consistent with VMA, the relative gain in moving from a non-hurdle model to a nay-saying hurdle model is less drastic under the mixed logit context than under the conditional logit context. When the yeah-saying hurdle is considered instead, the model again fits the data better than when nay-saying was included, and when both hurdles are explicitly modeled in the two-hurdle model, the fit is further improved. Summarizing the above observations, the best model fit is achieved with the two-hurdle mixed logit base-line choice model. Compared to the most naïve conditional logit model without hurdles, this last model drastically improves the overall model fit and enhances understanding and interpretation of the underlying data greatly.

If all models in table 2 are compared simultaneously, one can observe at least two additional interesting trends. First, within each pair of models, although the mixed logit consistently outperforms the conditional logit model, the difference between model fits is diminishing along with the different ways of including hurdles. Moving from the models without hurdles to models with nay-saying, yeah-saying, and both hurdles, the relative improvement in AIC scores from employing a mixed logit decreased from 15% improvement to 10%, to 6% and finally to 3%. Second, comparing the mixed logit model without hurdles and the two-hurdle model without random coefficients, the latter has a 12% improvement on AIC score. This difference highlights the trade-off between a statistically demanding procedure and a structurally tailored model. This may have some implications on model selection in the repeated conjoint experiment literature.

Welfare Implications

Models' implications on welfare measures are calculated through the marginal values of attributes. Marginal values are given as the opposite of the ratio between the coefficient of an attribute and that of the price. This enables one to assess the values associated with each attribute among Japanese consumers, holding other attributes separate. In addition, since these marginal values are ratios between two parameters, the issue of different scales in different models is eliminated. Table 3 presents the implied values of the eight canola oil attributes. All quantities are in thousands Japanese Yen, which is about 8.5 US dollars. The standard deviations of the marginal values are calculated following the Krinsky and Robb (1986) approach with 3000 simulation iterations.

The computation of welfare measures within the context of a mixed logit model is slightly more complicated. Two methods have been adopted in the literature. One approach simply takes the mean estimate of the coefficients and plugs them directly into the Krinsky and Robb procedure. The other approach, advocated by Hu, Adamowicz and Veeman (2005) is to consider the standard deviation estimates of the mean attribute coefficients. These authors formulated a procedure that first simulates a coefficient by its mean and standard deviation estimates within the mixed logit model and uses the averaged coefficient in the Krinsky and Robb routine. This study examines both methods and when applying the Hu, Adamowicz and Veeman approach, the iteration within a mixed logit model takes 500 iterations. The two approaches are labeled as mixed logit I and II in the table respectively.

In the context of a hurdle model, marginal values can be calculated by simply taking the estimated coefficients in the indirect utility function. A different approach is to recognize the existence of the hurdles and incorporate the hurdle likelihood into the welfare calculation. For each of the three hurdle models (nay-saying, yeah-saying, and two-hurdle), table 3 presents the marginal values when the hurdle(s) are or are not considered. Following VMA, when hurdle likelihoods are considered, the suggested marginal values are discounted by one over the likelihood of a respondent not belonging to the extremes (either nay- or yeah-saying).[3] All marginal values reported in table 3 show that these values, under different models, are consistent in their signs but the magnitude differs moderately.

The two simulation approaches of calculating welfare measures under mixed logit models show very little difference in this application. The mixed logit models in general produce larger marginal values (in an absolute sense) than the conditional logit models. The yeah-saying hurdle model gives the lowest marginal values compared to other models regardless whether the hurdle is considered. The nay-saying hurdle models suggest larger attribute values than those under models without hurdle specifications, while the yeah-saying and the two-hurdle models imply lower marginal values. For the three hurdle models, when hurdle likelihoods are considered in the welfare calculation, the suggested marginal values are smaller, and in general they differ moderately to those predicted by models without hurdle specifications. The change to marginal value predictions brought by considering or not considering hurdle likelihoods is the largest in the two-hurdle model.

Summary and Discussion

This study considers modeling discrete choices generated from conjoint experiments by particularly focusing on whether choices may be captured by different preference patterns. Built upon previous studies on survey non-participation, this article extends the understanding of choices to two types of behaviors: the non-participation behavior categorized as nay-saying to alternatives in a conjoint experiment and the yeah-saying behavior characterized by always agreeing to select at least some options offered. The modeling approach adopted in this study considers these types of choices through a series of hurdle models.

It is found that when decision-hurdles are introduced into choice modeling, the models perform significantly better than when no such hurdles are specified. Although consistent with previous studies, the nay-saying hurdle model offers improvement in model fit, a better model is identified as the yeah-saying hurdle model, and the most comprehensive two-hurdle model that jointly considers the two types of behavior brings the largest increase in model fit of all three hurdle models. The welfare implications are demonstrated by marginal values suggested under each model. Compared to those without hurdle specifications, the three hurdle models also give moderately different predictions on the value of various attributes.

In the application of the empirical models in this study, a noticeable observation is surrounding the mixed logit model. The mixed logit has been proven as a powerful tool in discrete choice modeling and in many published studies involving moderate modeling effort, the mixed logit model often outperforms other competing models considered. In this study however, we show that the two-hurdle model without random coefficients is strongly preferred to the mixed logit model without hurdles, and since the two-hurdle model does not require simulating any likelihood functions, it takes only a fraction of the computer time to estimate a mixed logit model (without hurdles). Although it is true that the random parameter version of the two-hurdle model offers slightly better fit than the fixed coefficient specification, the small gain is at the cost of significantly increased estimation effort. Given this evidence, we would like to view the mixed logit model as a tool that can be superimposed to other models that seek better representation of the choice behavior by directly targeting the fundamental structure of the data.

The above discussion also highlights the importance of having an ex ante understanding of the structure of data. For example, as presented in figure 1 only, it can be seen that there are individuals involved in other types of choice patterns, such as choosing the no-choice option for 1, 2,…, seven times out of eight. We have studied the two extreme situations which may be generated by the most distinctive patterns in choices but, this neither indicates that including other choice categories in figure 1 is not feasible, nor does it guarantee the two-hurdle model will still hold as the best alternative. Indeed, hurdles may be specified on any particular switch variables that may differentiate individuals' behavior into various groups. The switch variables may be linked to the survey design (such as different data collection methods), time taken to complete a survey, or many other factors. Given these potential switching identifiers, a further advance of the modeling effort may involve a randomized hurdle model or an individual-level hurdle model that associates each individual with a unique hurdle. No matter what may be considered, a likely valuable consideration would be to achieve, as close as possible, an understanding of the structure of the data along with the empirical modeling effort.

Notes

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[1] In this article, only single hurdle models are considered. VMA demonstrated that a hurdle model and a non-hurdle model may generate different estimation and welfare results but there exists little difference between single- and double-hurdle models in various conditions.

[2] All models predict consistently in terms of the signs of $\boldsymbol{\beta}$.

[3] All marginal values are based on sample enumeration: values for each person is calculated and averaged across the sample and the averaged measures are reported in table 3.

Table 1. Variables Used in Conjoint Design

Attributes and Levels	Nature	Representation in Choice Model
4 levels of nutrition claims	4 possible contents: low in saturated fat, high in Oleic acid, high in Vitamin E, high in Alpha-Linoleic acid	Low is saturated fat is omitted in estimation
2 levels of genetic modification	Present or absent	Enter as a dummy variable
2 levels of organic food	Present or absent	Enter as a dummy variable
2 levels of functional food	Present or absent	Enter as a dummy variable
2 levels of imported or not	Present or absent	Enter as a dummy variable
4 levels of prices	All in Japanese Yen	Enter as a continuous variable

Table 2. Estimation Results

	Models without Hurdles			
	Logit		Mixed Logit	
Variable	Coeff	Std. Err.	Coeff	Std. Err.
Constant for No-Choice (NC)	-0.974	0.140	-1.941	0.193
Oleic Acid (OLA)	-0.082	0.080	-0.266	0.092
Vitamin E (VE)	-0.297	0.080	-0.392	0.079
Alpha-Linoleic Acid (ALA)	0.036	0.081	0.044	0.099
Genetically Modified (GM)	-1.879	0.080	-3.304	0.172
Organic (Org)	0.313	0.084	0.399	0.070
Functional (Fun)	0.700	0.058	0.914	0.068
Imported (Imp)	-0.832	0.066	-1.406	0.088
Price	-1.304	0.244	-1.923	0.281
SD-NC			-1.960	0.103
SD-OLA			-0.019	0.095
SD-VE			-0.003	0.084
SD-ALA			-0.352	0.094
SD-GM			1.818	0.161
SD-Org			-0.374	0.110
SD-Fun			-0.184	0.073
SD-Imp			0.620	0.093
LL	-2608.839		-2191.787	
AIC	5279.827		4500.965	
BIC	5270.827		4483.965	

	Models with Nay-Saying Hurdles			
	Logit		Mixed Logit	
	Coeff	Std. Err.	Coeff	Std. Err.
Constant for No-Choice (NC)	-1.473	0.157	-2.277	0.188
Oleic Acid (OLA)	-0.200	0.094	-0.344	0.103
Vitamin E (VE)	-0.298	0.081	-0.355	0.084
Alpha-Linoleic Acid (ALA)	-0.043	0.095	-0.066	0.104
Genetically Modified (GM)	-2.042	0.087	-3.253	0.161
Organic (Org)	0.330	0.092	0.336	0.103
Functional (Fun)	0.728	0.061	0.915	0.073
Imported (Imp)	-1.004	0.073	-1.466	0.094
Price	-1.442	0.255	-1.866	0.279
Constant-Nay	-0.842	0.167	-0.926	0.225
Male-Nay	0.702	0.271	0.752	0.262
Age-Nay	-0.641	0.148	-0.779	0.284
Household Size-Nay	0.069	0.141	0.078	0.112
Number of Children-Nay	-0.183	0.218	-0.171	0.112
Education-Nay	-0.662	0.165	-0.505	0.208
Income-Nay	-1.083	0.283	-1.231	0.389
SD-NC			-0.994	0.134
SD-OLA			0.214	0.095
SD-VE			-0.002	0.087
SD-ALA			-0.128	0.100
SD-GM			1.897	0.160
SD-Org			-0.408	0.121
SD-Fun			-0.225	0.079
SD-Imp			0.835	0.098
LL	-2411.583		-2159.180	
AIC	4993.651		4484.088	
BIC	4977.651		4460.088	

Table 2. Estimation Results (Continued)

	Models with Yeah-Saying Hurdles			
	Logit		Mixed Logit	
	Coeff	Std. Err.	Coeff	Std. Err.
Constant for No-Choice (NC)	-0.701	0.154	-1.202	0.186
Oleic Acid (OLA)	-0.118	0.106	-0.220	0.116
Vitamin E (VE)	-0.286	0.088	-0.427	0.094
Alpha-Linoleic Acid (ALA)	0.122	0.099	0.157	0.121
Genetically Modified (GM)	-2.347	0.103	-3.916	0.312
Organic (Org)	0.447	0.091	0.531	0.091
Functional (Fun)	0.759	0.070	0.914	0.079
Imported (Imp)	-1.055	0.071	-1.448	0.107
Price	-1.413	0.267	-2.026	0.319
Constant-Yeah	-0.548	0.075	-0.646	0.062
Male-Yeah	0.331	0.081	0.368	0.082
Age-Yeah	-0.333	0.046	-0.347	0.040
Household Size-Yeah	-0.059	0.055	-0.101	0.048
Number of Children-Yeah	-0.171	0.054	-0.133	0.076
Education-Yeah	-0.518	0.068	-0.420	0.072
Income-Yeah	0.250	0.081	0.383	0.076
SD-NC			-1.461	0.143
SD-OLA			-0.269	0.082
SD-VE			0.125	0.082
SD-ALA			-0.399	0.110
SD-GM			1.799	0.308
SD-Org			-0.265	0.130
SD-Fun			-0.225	0.100
SD-Imp			0.286	0.142
LL	-2060.122		-1905.330	
AIC	4230.729		3976.388	
BIC	4214.729		3952.388	

	Models with Both Yeah and Nay-Saying Hurdles			
	Logit		Mixed Logit	
	Coeff	Std. Err.	Coeff	Std. Err.
Constant for No-Choice (NC)	-1.283	0.173	-1.732	0.167
Oleic Acid (OLA)	-0.273	0.113	-0.363	0.129
Vitamin E (VE)	-0.262	0.096	-0.379	0.092
Alpha-Linoleic Acid (ALA)	0.008	0.109	-0.031	0.111
Genetically Modified (GM)	-2.600	0.113	-3.968	0.228
Organic (Org)	0.468	0.104	0.500	0.095
Functional (Fun)	0.799	0.073	0.931	0.077
Imported (Imp)	-1.307	0.089	-1.591	0.110
Price	-1.533	0.283	-1.995	0.235
Constant-Nay	-0.816	0.216	-0.697	0.088
Male-Nay	0.861	0.273	0.753	0.148
Age-Nay	-0.742	0.324	-0.560	0.138
Household Size-Nay	0.043	0.097	0.007	0.063
Number of Children-Nay	-0.158	0.163	-0.184	0.075
Education-Nay	-0.395	0.259	-0.525	0.162
Income-Nay	-1.144	0.367	-0.954	0.170
Constant-Yeah	-0.645	0.163	-0.554	0.065
Male-Yeah	0.430	0.088	0.453	0.063
Age-Yeah	-0.354	0.064	-0.323	0.029
Household Size-Yeah	-0.077	0.066	-0.087	0.047
Number of Children-Yeah	-0.143	0.135	-0.147	0.065
Education-Yeah	-0.356	0.124	-0.397	0.085
Income-Yeah	0.299	0.132	0.263	0.075
SD-NC			-0.345	0.146
SD-OLA			0.018	0.107
SD-VE			0.107	0.074
SD-ALA			-0.107	0.129
SD-GM			2.265	0.201
SD-Org			-0.241	0.068
SD-Fun			-0.287	0.085
SD-Imp			0.562	0.129
LL	-1928.119		-1836.715	
AIC	4015.060		3887.496	
BIC	3992.060		3856.496	

Table 3. Marginal Attribute Values in Thousands Japanese Yen

	Models without Hurdles					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.76	0.13	-1.02	0.12	-1.02	0.12
Oleic Acid (OLA)	-0.07	0.10	-0.14	0.06	-0.14	0.06
Vitamin E (VE)	-0.24	0.11	-0.21	0.06	-0.21	0.06
Alpha-Linoleic Acid (ALA)	0.03	0.05	0.02	0.05	0.02	0.05
Genetically Modified (GM)	-1.50	0.40	-1.75	0.28	-1.75	0.28
Organic (Org)	0.25	0.11	0.21	0.06	0.21	0.06
Functional (Fun)	0.56	0.15	0.49	0.09	0.49	0.09
Imported (Imp)	-0.67	0.18	-0.74	0.12	-0.74	0.12
	Nay-Saying Hurdle Models Without Considering the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-1.04	0.14	-1.23	0.14	-1.24	0.15
Oleic Acid (OLA)	-0.14	0.08	-0.19	0.07	-0.19	0.07
Vitamin E (VE)	-0.21	0.08	-0.19	0.06	-0.20	0.06
Alpha-Linoleic Acid (ALA)	-0.03	0.07	-0.04	0.06	-0.04	0.06
Genetically Modified (GM)	-1.46	0.29	-1.78	0.29	-1.79	0.30
Organic (Org)	0.24	0.09	0.18	0.07	0.19	0.07
Functional (Fun)	0.52	0.12	0.50	0.09	0.50	0.09
Imported (Imp)	-0.72	0.15	-0.80	0.13	-0.81	0.14
	Nay-Saying Hurdle Models that Consider the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.95	0.13	-1.12	0.13	-1.13	0.13
Oleic Acid (OLA)	-0.13	0.08	-0.17	0.06	-0.17	0.07
Vitamin E (VE)	-0.19	0.07	-0.18	0.05	-0.18	0.05
Alpha-Linoleic Acid (ALA)	-0.03	0.06	-0.03	0.05	-0.03	0.06
Genetically Modified (GM)	-1.33	0.27	-1.62	0.26	-1.63	0.28
Organic (Org)	0.22	0.08	0.17	0.06	0.17	0.06
Functional (Fun)	0.48	0.11	0.46	0.08	0.46	0.08
Imported (Imp)	-0.65	0.14	-0.73	0.12	-0.74	0.13
	Yeah-Saying Hurdle Models Without Considering the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.50	0.08	-0.60	0.09	-0.60	0.09
Oleic Acid (OLA)	-0.09	0.09	-0.11	0.07	-0.11	0.07
Vitamin E (VE)	-0.21	0.08	-0.22	0.06	-0.22	0.06
Alpha-Linoleic Acid (ALA)	0.09	0.07	0.08	0.06	0.08	0.06
Genetically Modified (GM)	-1.72	0.38	-1.97	0.34	-1.98	0.35
Organic (Org)	0.33	0.10	0.27	0.06	0.27	0.06
Functional (Fun)	0.56	0.13	0.46	0.08	0.46	0.08
Imported (Imp)	-0.77	0.17	-0.73	0.14	-0.74	0.14

Table 3. Marginal Attribute Values in Thousands Japanese Yen (Continued)

	Yeah-Saying Hurdle Models that Consider the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.40	0.06	-0.48	0.07	-0.48	0.08
Oleic Acid (OLA)	-0.07	0.07	-0.09	0.06	-0.09	0.06
Vitamin E (VE)	-0.17	0.07	-0.17	0.05	-0.17	0.05
Alpha-Linoleic Acid (ALA)	0.07	0.06	0.06	0.05	0.06	0.05
Genetically Modified (GM)	-1.38	0.30	-1.58	0.27	-1.59	0.28
Organic (Org)	0.26	0.08	0.21	0.05	0.22	0.05
Functional (Fun)	0.45	0.11	0.37	0.06	0.37	0.07
Imported (Imp)	-0.62	0.14	-0.59	0.11	-0.59	0.11
	Two-Hurdle Models Without Considering the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.85	0.12	-0.88	0.08	-0.87	0.08
Oleic Acid (OLA)	-0.18	0.10	-0.19	0.08	-0.19	0.07
Vitamin E (VE)	-0.18	0.08	-0.19	0.05	-0.19	0.05
Alpha-Linoleic Acid (ALA)	0.00	0.07	-0.02	0.06	-0.02	0.06
Genetically Modified (GM)	-1.75	0.36	-2.01	0.20	-2.01	0.20
Organic (Org)	0.32	0.10	0.25	0.06	0.25	0.06
Functional (Fun)	0.54	0.12	0.47	0.07	0.47	0.07
Imported (Imp)	-0.88	0.18	-0.81	0.11	-0.81	0.11
	Two-Hurdle Models that Consider the Hurdles in Marginal Values					
	Conditional Logit		Mixed Logit I		Mixed Logit II	
	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.	Marginal Value	Std. Dev.
Constant for No-Choice (NC)	-0.57	0.08	-0.59	0.06	-0.59	0.06
Oleic Acid (OLA)	-0.12	0.07	-0.13	0.05	-0.13	0.05
Vitamin E (VE)	-0.12	0.05	-0.13	0.04	-0.13	0.04
Alpha-Linoleic Acid (ALA)	0.00	0.05	-0.01	0.04	-0.01	0.04
Genetically Modified (GM)	-1.18	0.25	-1.35	0.15	-1.36	0.15
Organic (Org)	0.21	0.07	0.17	0.04	0.17	0.04
Functional (Fun)	0.36	0.08	0.32	0.05	0.32	0.05
Imported (Imp)	-0.59	0.13	-0.54	0.08	-0.54	0.08

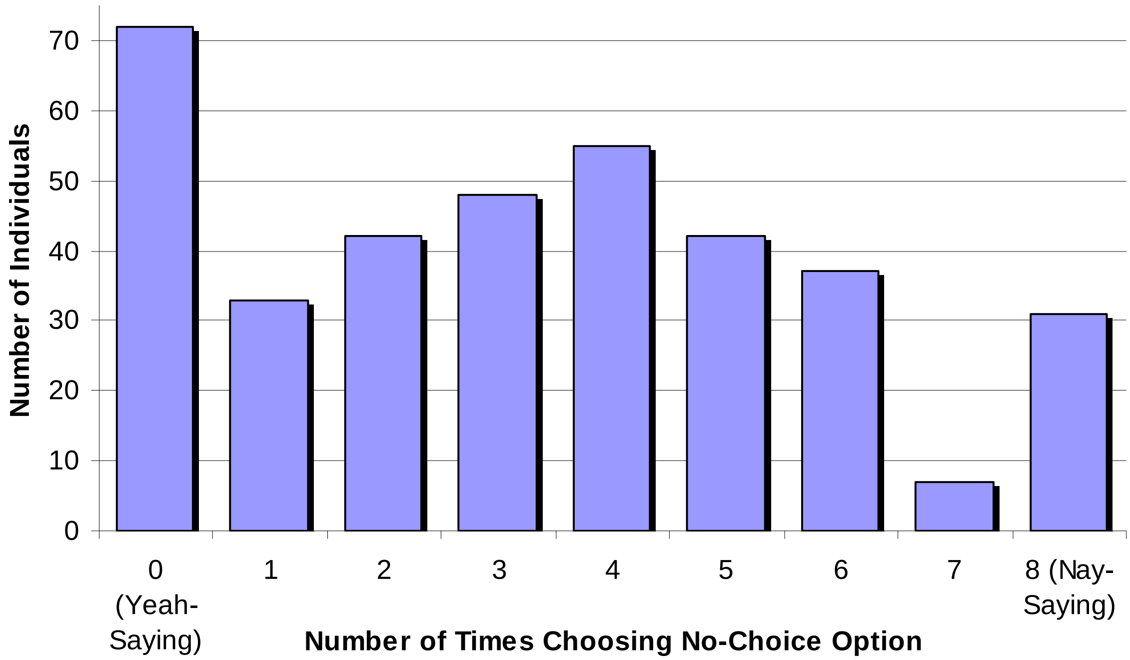

Figure 1. Frequency Distribution of the No-Choice Option Being Selected

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