Theoretical and Empirical Considerations of Eliciting Preferences and Model Estimation in Conjoint Analysis

by

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Abstract

The theoretical underpinnings associated with eliciting consumer preferences and statistical properties of alternative models in conjoint analysis are examined. Results show that model selection makes little difference in the context of sign and significance of coefficients. However, results show that tobit is a better predictor of ordinal ranking relative to the probit model.

Introduction

Conjoint analysis (CA) is widely used in marketing research to decompose an individual's total utility for a composite product into "part-worth" utilities for the product's constituent attributes. In recent years, CA applications have also emerged in the agricultural economics (AE) literature. Most AE studies have used CA to either examine consumer preferences for food products or to examine resource usage and willingness-to-pay for recreational services.

A summary of CA studies appearing in the AE literature is presented in Table 1. Studies evaluating consumer/decision makers' acceptance of new food and agricultural products include Gineo (1990), Prentice and Benell (1992), Halbrendt et al (1991), Halbrendt et al (1992), Yoo and Ohta (1995), Hobbs (1996), Sylvia and Larken (1995), Sy et al. (1997), Harrison et al. (1998), Gillespie et al. (1998), and Holland and Wessells (1998). Baker and Crosbie (1993) analyze food safety attributes. The new product acceptance (NPA) studies typically assume that a respondent's total utility for a hypothetical product is a function of various product attributes. CA is used to estimate "part worth" utilities, which measure the partial effect of a particular attribute level on the respondent's total utility for hypothetical products. Part worth estimates are typically used to simulate total utilities for products not evaluated by respondents, where simulated values are subsequently ranked to determine the optimal hypothetical products, or the product yielding the highest level of total utility.

The second category of CA studies seeks to estimate a respondent's willingness to pay (WTP) for a bundle of attributes associated with some recreational site or activity (e.g., a hunting trip). These include studies by Mackenzie (1990), Gan and Luzar (1993), Mackenzie (1993), Lin et al. (1996), Roe et al. (1996), Stevens et al. (1997), Miquel et al. (2000), and Boyle et al. (2001). These studies are quite similar to the contingent valuation (CV) literature, which also seek to estimate WTP for nonmarket goods. The major difference between CA studies and traditional CV is the way price is treated during the elicitation procedure. The CV approach requires respondents to place dollar valuations (i.e., price valuations) on attribute bundles as attribute levels are varied. In contrast, the CA approach requires respondents to rate/rank attribute bundles as price (e.g. hunting-trip cost) and other attribute levels are varied (Mackenzie, 1990). WTP values are calculated directly from the marginal rates of substitution between price and non-price attributes estimated from conjoint data.

In most cases, both NPA and WTP studies estimate utility models for the entire sample, which introduces the problem of controlling for heterogeneity of preferences across respondents. Heterogeneity across respondents can be attributed to two sources. First, product ratings/ranking scales are inherently subjective. Some respondents may use the entire scale specified by the researcher, while other respondents will use only a portion of the scale. Respondents also tend to "anchor" or "center" on a particular product, and use it as the basis for evaluating all other products. This introduces variation in the ratings/ranking scale as respondents choose different anchoring points. Two methods are typically used to address this problem. In some cases, the average rating or ranking for each respondent is used to control for the anchoring problem (Green and Srinivasan, 1978; Mackenzie, 1993). In other cases, interaction terms between product attributes and socioeconomic/demographic variables are introduced to adjust for the heterogeneity across individuals (Holland and Wessells, 1998).

Although not widely used in the AE literature, individual CA models may also be estimated. Examples include Baker and Crosbie, 1993; and Harrison et al., 2001. Estimating individual-level utility functions has the advantage of avoiding aggregation bias because parameters are allowed to vary across individuals. However, other problems are introduced. Individual-level estimation requires that enough information be collected from each respondent to estimate his/her utility function (Holland and Wessells, 1998). This problem is compounded by the fact that most studies call for a relatively large number of attributes to be tested. This means that respondents must evaluate numerous products to collect the information needed to estimate all parameters. In some cases, degrees of freedom may be insufficient to provide confidence in the statistical properties of parameter estimates.

The main reason for CA's recent popularity is its flexibility in studying a wide range of multi-attribute decisions. Despite its widespread use in the AE literature, there is little consensus among researchers on the best method for eliciting respondent preferences in conjoint surveys. Moreover, a consensus regarding the appropriate econometric method for estimating part-worth utilities is also absent in the literature. Most of the CA studies we have examined use interval rating scales to elicit preferences, but use a variety of methods to estimate CA parameters. Most use ordinary least squares regression (OLS). Alternatives include ordered probit or logit models, and two-limit tobit models (Table 1). The objectives of this paper are to 1) clarify the theoretical underpinnings associated with the elicitation of consumer preferences in conjoint analysis, and 2) examine the statistical properties associated with using alternative methods of model estimation.

Theoretical and Empirical Considerations

An important consideration in CA research is how an individual's preferences are elicited, which determines the metric and nonmetric properties of the dependent variable. The most commonly used methods are rank ordering and interval rating scales. Both methods require subjects to evaluate multiple (or sometimes pairwise) combinations of multi-attribute choices using some type of experimental design (i.e., fractional factorial or various types of split block designs). The rank order method requires the respondent to rank all choices in order of preference, with little regard for the intensity of an individual's preference across choices. The interval rating scale requires the respondent to assign a numerical value to each choice, given pre-determined intervals for the rating scale. Of course, deciding which method is best depends on research objectives and methodological context of the particular study. In general, the rating method is usually preferred when the experimental design requires respondents to evaluate a large number of choices, since ranking a large number of choices is relatively difficult for most respondents and may lead to inconsistent rankings. On the other hand, when a small number of choices are evaluated, rankings provide an unambiguous preference ordering since respondents cannot express indifference (i.e., intensity) between choices.

The rating method is more commonly used because of its flexibility in handling larger experimental designs, and because it captures at least ordinal significance of a respondent's preferences (Mackenzie, 1990). If a rating scale is used to elicit preferences, then OLS or tobit are the most common approaches for estimating part-worth values (Table 1). However, some researchers argue that ordered logit/probit models are best suited for estimating part-worths, since a discrete (ordinal) dependent variable makes the use of OLS or tobit inappropriate (Mackenzie, 1990 and 1993; Sy et al., 1997; Holland and Wessells, 1998).

Other authors argue that rating scales may also contain useful cardinal information that ordered probit/logit fails to incorporate (Roe et al. 1999, Stevens et al., 1997; Harrison et al., 2001). Estimating bounded ratings with OLS yields truncated residuals and asymptotically biased estimates. The biased parameter problem of OLS can be avoided by using a two-limit tobit model for estimating part-worth values while retaining cardinal information. However, two-limit tobit assumes a continuous (i.e., cardinal) dependent variable, which leads to questions regarding the distributional properties of the error terms if the true nature of individual preferences is discrete (ordinal). This leads to the central questions of this paper. Is cardinal information embodied in the rating scale? What are the empirical implications of treating rating scales as cardinal measures when estimating conjoint models?

Several studies have examined the issue of cardinality and ordinality of preferences. In separate studies, Mackenzie (1993), Roe et al. (1996), and Stevens et al. (1997) evaluated the effects of recoding rating data so as to eliminate ties and preserve the ordinal ranking of the data. These studies compare parameter estimates and the predictability of tobit with ordered probit / logit models. Results from these studies have been mixed. Mackenzie (1993) found evidence that the rating scale does embody intensity of preferences. The other two studies found that elicitation and estimation assuming ordinal preferences is more theoretically appealing, and found empirical evidence that suggests ordered probability models are better frameworks for analysis. More recently, Boyle et al. (2001) examined the issue of cardinality by analyzing both rating and ranking scales for independent subsamples of respondents. They found that tobit and ordered probit models result in the same attributes being significant and having the same sign. They conclude that assumptions regarding ordinality and cardinality are irrelevant for their sample. However, they did not examine how well the models predicted individuals' preference orderings. This paper seeks additional evidence regarding assumptions of cardinality when using rating scales to examine respondent preferences.

Methods and Data

The analysis assumes that respondent ratings are a linear function of product attributes. The model takes the following general form:

(1) $U = \beta A + e$

where U is the total utility measured by a rating scale, β is a row vector of part worth values, A is a column vector of product attributes, and e is the error term. Two data sets are used to evaluate the effects of estimating the part worth values (β's) using ordinary least squares regression, two-limit tobit, and ordered probit. Both data sets were collected in order to examine consumer/buyer preferences for new hypothetical products using an interval rating scale. The OLS models assume that rating scales measure intensity of individual preferences without censoring. The tobit model also assumes cardinality of preferences, but accounts for the censored nature of the rating scale. The ordered probit model assumes the rating scale measures only the ordinality of preferences. Models are compared by examining the signs of parameter estimates, statistical significance of parameter estimates, and the predicted validity of choice rankings. Predictive validity is examined by comparing actual ratings included in the sample with predicted ratings.

Data Set 1

The first data set was collected as part of a study to examine consumer preferences for new food products derived from Southern crawfish. An exploratory survey consisting of 10 local grocery stores and national supermarket chains in South Louisiana was performed to identify the most relevant attributes and levels for the crawfish prototype products. Information was collected pertaining to the characteristics of existing products similar in design to the prototype products. Based on survey results, the attributes and levels selected for the study were three breaded product forms consisting of crawfish minced-based nuggets, patties, and poppers; three package sizes consisting of a 12, 24, and 48 pack; three reheating methods expressed as a baked, fried, or microwaved product; and three price levels set at 10, 20, and 50 cents per ounce. The attributes were pre-tested with a small group of 12 subjects to determine if they were expressed in a manner easy for a consumer to understand. All subjects indicated the attributes were consistent with their perceptions of these type products.

With four three-level attributes selected for this study (product form, package size, reheating method, and price), a full factorial experimental design would involve 81 (3x3x3x3) hypothetical product combinations. Subjects would have difficulty rating all 81 product profiles, so a fractional factorial design was used to reduce the number of profiles to 9 product combinations. The Bretton-Clark Designer (1988) program was used to select the sample of 9 product combinations. This program minimizes the confounding of attribute main effects by selecting a subsample of orthogonal product combinations.

The questionnaire contained the 9 hypothetical product profiles arranged on a single page. The questionnaire was administered using a personal interview method, where groups of respondents were allowed to inspect all three product forms in combination with the appropriate package size, reheat method, and price (as prescribed by the fractional design). All 9 profiles were displayed on a table in a large room. Each subject was allowed to walk around the table to visually inspect and handle the products. After careful examination, the respondent was asked to rate each product profile on a scale from 1 to 10, where 1 is the least preferred and 10 is the most preferred bundle of attributes. The survey took place over a period of four days and included three one-hour sessions per day. The sample was composed of 111 consumers participating in a Food Science sensory panel test of crawfish minced-based products. Survey respondents were recruited by telephone in and around the city of Baton Rouge, Louisiana. Only respondents indicating they ate crawfish regularly were asked to participate in the survey. The conjoint survey was conducted prior to the sensory panel tests so as to avoid biasing the respondent's preference for a particular product form.

Data Set 2

The second data set was collected as part of a study to examine retailer preferences of alternative ostrich meat products. A two-limit tobit analysis conducted with this data set was previously published by Gillespie et al. The relevant attributes were determined through personal interviews with meat retailers in Baton Rouge, Louisiana. Based upon these interviews, four attributes and their respective levels were selected: portion size, which included non-portioned, four-ounce, and six-ounce portions; product type, which included ground, processed, and filet; whether or not the product was branded; and purchase price from the processor in dollars per pound: $4.00, $8.00, and $12.00. With four attributes, three of which had three levels and one of which had two, a full factorial experimental design would involve 3×3×3×2 = 54 hypothetical product combinations. As with the crawfish study, a fractional factorial design was used to reduce the number of profiles to nine. Unlike the crawfish study, no holdout profile was included. The questionnaire was administered via mail survey to retailers in Arkansas, Louisiana, Mississippi and Texas. Respondents were asked to rate each profile from 0 to 10, where 0 was the least preferred and 10 was the most preferred product. Of the 1,985 surveys sent to restaurants and retailers, 200 were returned as undeliverable, reducing the effective mailing to 1,785. Of the 326 surveys returned, 195 had completed conjoint sections. Of these, 133 were retail outlets.

Results

The parameter estimates and diagnostic statistics for data sets 1 and 2 are presented in Tables 2 and 3, respectively. Unless noted otherwise, the level of significance chosen for the analysis is

α=.05. Most of the β estimates associated with data set 1 are significant. Exceptions include the microwave reheating method and the package size. Interpretation of the estimates are straight forward for the OLS and tobit models. For instance, the OLS estimate associated with the nugget form indicates the average respondent's total utility increases by 0.7097 when the hypothetical product takes the form of a nugget. The tobit estimates are interpreted in a similar manner, except that part worth estimates must be adjusted by accounting for the probability that the dependent variable (U) falls in the 1-10 range. The OLS and tobit models yield similar coefficients with respect to both sign and magnitude. The tobit estimates are generally associated with higher t-values, indicating improved efficiency compared to the OLS model. Both OLS and tobit models are significant at the α=.01 level.

The interpretation of the probit model estimates are not as straightforward. For instance, the estimate associated with the nugget form in the probit model indicates the probability index function increases by 0.2827 when the hypothetical product takes the form of a nugget. This does not imply the average respondent's utility increases by 0.2827. Rather, the probit model assumes that utility increases in a discrete fashion, only when the threshold levels given by the μ_i estimates have been reached. Hence, the concept of a part worth value (i.e., a direct partial effect on utility) is not valid in the probit framework. Consequently, a comparison across the three models is not valid in the context of examining the magnitude of the βs. On the other hand, the signs of the estimates across the three models are the same, indicating that either model predicts direction of respondent preferences consistently. However, comparing signs may also be problematic. The significant coefficients for the OLS and tobit models imply an unambiguous increase/decrease in utility. Coefficients for the probit model indicate only that the attribute contributes positively or negatively to the probability index function, which may or may not be sufficient to increase/decrease total utility. This is the key difference associated with assuming ordinality or cardinality of respondent preferences, and the key difference between the OLS, tobit, and probit frameworks.

Spearman rank correlation coefficients are also calculated for each model. The spearman rank correlation is calculated between observed and predicted values for each individual. This allows for analysis of each model's ability to predict the ordering of respondent preferences. The averages across all individuals for the respective models are presented in Table 2. The correlations for the OLS , tobit, and probit models are 0.393, 0.392, and 0.368, respectively. This indicates that OLS provides slightly better predictions relative to the tobit model. Both OLS and tobit perform better than the probit model in this regard.

Most of the β estimates associated with data set 2 are significant, with the exception of the four-ounce portion and ground form. As with the crawfish model, the OLS and tobit models yield similar coefficients with respect to both sign and magnitude. With the ordered probit model, the same variables are significant and are of the same sign as with the OLS and tobit models. The OLS, tobit, and ordered probit models each are significant at the α=0.01 level.

As with the crawfish model, spearman rank correlation coefficients are calculated between observed and predicted values for each individual, with averages across individuals presented in Table 3. The correlations for the OLS, tobit, and ordered probit models are 0.364, 0.364, and 0.286, respectively, indicating that both the OLS and tobit models perform better than the ordered probit model in that regard. Both OLS and tobit predicted ratings are more highly correlated with actual ratings than those produced by the ordered probit model.

Conclusions

Results of runs with both data sets show that β estimates are consistent in terms of sign and statistical significance across all three models. This is consistent with the findings of Boyle et.al (2001), which also examined the consistency of parameter estimates between the tobit and probit models. Hence, it appears that model selection makes little difference in this context. However, it should be noted that even with the assumption of cardinality, the OLS estimates are theoretically biased relative to the tobit model. This implies that there is little justification for choosing OLS over tobit, given the censored nature of the dependent variable.

On the other hand, there may be justification for choosing the tobit model over the probit. Results show the tobit model is superior to probit in predicting the ordinal rankings of respondents in the two data sets analyzed in this study. This result is important for NPA research, since the primarily goal is to determine attribute combinations that result in agricultural and food products most likely to be accepted by the market. It should be noted that the predictive superiority of the tobit model found in this study is contrary to the findings by Roe et al. (1996). They found a "ratings difference" tobit model to be inferior to an ordered logit specification. However, their "ratings difference" approach assumes utility is measured by the difference between hypothetical attribute profiles and a status quo bundle of attributes. Hence, these mixed results lead to the conclusion that predictive validity of conjoint is closely tied to the construction of the dependent variable and the manner in which preferences are elicited.

Results from the analysis imply several directions for future research. First, additional research is needed regarding the appropriateness of rating, rating difference, and ranking scales in NPA and WTP studies. For instance, it may be appropriate to use additional variants of the rating scale to better capture the possibility that respondents do reveal cardinal preferences. It may also be possible to develop statistical tests to better evaluate the cardinal/ordinal properties of the data. Finally, although links between utility theory and CA have been developed in the WTP literature, additional work is needed that links utility theory with the NPA applications.

Table 1: Summary of Agricultural Economics Literature Using Conjoint Analysis.

Year	Journal	Author(s)	Scale	Type of Study	Estimation Procedure
1990	NJARE	Gineo	RK[1] (1-9)	N P A[3]	OLS, Logit
1990	NJARE	Mackenzie	RT[2] (1-10)	W T P[4]	Rank-order Logit
1991	SJAE	Halbrendt, et al	RT (0-10)	N P A	OLS
1992	ABIJ[5]	Halbrendt et al.	RT (0-10)	N P A	WLS
1992	CJAE	Prentice & Benell	RT (0-10)	N P A	OLS
1993	JAAE	Gan & Luzar	RT (1-10)	W T P	Ordered Logit
1993	AJAE	Mackenzie	RT (1-10)	W T P	Ordered Probit
1993	JARE	Baker & Crosbie	RT (1-11)	N P A	OLS
1995	IJPE	Yoo & Ohta	RK (1-16)	N P A	Multinomial Logit
1995	CJAE	Sylvia & Larkin	RT(-10-+10)	N P A	Tobit, GLS
1996	JEM	Roe et al.	RT, RTs Dif[6]	W T P	Double-hurdle Tobit, Logit
1996	ABIJ	Lin et al.	RK (1-16)	W T P	Order Logit, Two-limit Tobit
1996	ABIJ	Hobbs	RT (1-9)	N P A	OLS
1997	ARER	Stevens et al.	RT, RTs Dif	W T P	Tobit, Logit
1997	AJAE	Sy et al.	RT (0-10)	N P A	Ordered Probit
1998	ARER	Holland & Wessells	RK (1-9)	N P A	Rank-order Logit
1998	ABIJ	Gillespie et al.	RT (0-10)	N P A	Tobit
1998	JFS	Dennis	RK (0-17)	N P A	Ordered Probit
1998	JFS	Reddy & Bush	RT (0-7)	W T P	OLS
1998	JAAE	Harrison et al.	RT (1-10)	N P A	OLS
1999	JEM	Stevens et al.	RT (1-10)	N P A	Ordered Logit
2000	JAE.	Miquel et al.	RK	W T P	Random Effects Probit
2001	AJAE	Boyle et al.	RT, RK, CH[7]	N P A	Double-hurdle Tobit, Ordered Probit, Rank-order Logit, Probit

[1]RK = Ranking
[2]RT = Rating
[3]N P A = New Product Acceptance Study
[4]W T P = Willingness-To-Pay Study
[5]ABIJ = Agribusiness: An International Journal
[6] RTs Dif = Ratings Difference
[7]CH = Choose One

Table 2: Conjoint Estimations of Crawfish Meat Data Set - Model Comparisons

Attributes	**Conjoint Estimates**				
	OLS	**Two-Limit**	**Ordered Probit**		
Intercept	1.1377* (2.24)	0.6464 (1.03)	0.1464 (0.610)	**μ's**	
Patty Form	-0.3203* (2.73)	-0.4109* (-3.03)	-0.1365* (-2.976)	μ_1	0.422* (9.40)
Nuggget Form	0.7097* (6.06)	0.8411* (6.21)	0.2827* (5.799)	μ_2	0.761* (14.22)
Popper Form	-0.3894* (-3.49)	-0.4302* (-3.18)	-0.1462* (-2.998)	μ_3	1.081* (18.44)
Fried Reheat	-0.2903* (-2.48)	-0.3783* (-2.79)	-0.1288* (-2.816)	μ_4	1.405* (22.59)
Baked Reheat	0.3403* (2.91)	0.4003* (2.95)	0.1383* (2.913)	μ_5	1.695* (26.07)
Micro Reheat	-0.0500 (-.43)	-0.0220 (-0.162)	-0.0095 (-0.2079)	μ_6	2.053* (30.07)
Price	-5.0116* (-10.28)	-6.0464* (-10.68)	-2.044* (-10.26)	μ_7	2.456* (33.78)
Package Size	0.0071 (1.36)	0.0099 (1.56)	0.0033 (1.49)	μ_8	2.954* (37.26)
AvgRate	1.00* (10.15)	1.1452* (9.52)	0.3830* (7.87)		
R^2	0.2103				
χ^2 Log-L, F	38.96**	142.43**	227.38**		
Spearman Coef.	0.393	0.392	0.368		

* indicates statistical significance at 95 percent (i.e., α=05) level or higher.
** indicates statistical significance at 99 percent (i.e., α=01) level or higher.

Table 3: Conjoint Estimations of Ostrich Meat Data Set - Model Comparisons

Attributes	**Conjoint Estimates**				
	OLS	**Two-Limit**	**Ordered Probit**		
Intercept	-0.1156 (-0.46)	-2.6360* (-6.49)	-0.7543* (-7.09)	**μ's**	
4-Ounce Portion	0.0365 (0.30)	0.0119 (0.07)	0.0021 (0.05)	μ_1	0.173* (7.32)
6-Ounce Portion	0.2787* (2.32)	0.4239* (2.34)	0.1014* (2.27)	μ_2	0.416* (12.15)
Ground Form	0.1156 (0.96)	0.1322 (0.73)	0.0386 (0.89)	μ_3	0.663* (16.36)
Processed Form	-0.4407* (-3.66)	-0.6810* (-3.74)	-0.1682* (-3.67)	μ_4	0.870* (19.57)
Branded Product	-0.3038* (-4.22)	-0.4313* (-4.02)	-0.1024* (–4.64)	μ_5	1.238* (24.80)
Price = $8.00	-0.2658* (-2.21)	-0.3027 (-1.68)	-0.0846 (-1.85)	μ_6	1.482* (27.95)
Price = $12.00	-0.9384* (-7.79)	-1.4582* (-7.93)	-0.3529* (-8.10)	μ_7	1.619* (29.47)
AvgRate	-0.9965* (20.33)	1.4605* (18.56)	0.3573* (16.47)	μ_8	2.183* (35.85)
				μ_9	2.327* (37.18)
R^2	0.3323				
χ^2 Log-L, F	71.66**	442.28**	449.10**		
Spearman Coef.	0.364	0.364	0.286		

* indicates statistical significance at 95 percent (i.e., α=05) level or higher.
** indicates statistical significance at 99 percent (i.e., α=01) level or higher.

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