Bayesian Analysis of Consumer Choices with Taste, Context, Reference Point and Individual Scale Effects

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Abstract

This paper adopts an approach to consumer choice based on the concepts of random utility maximization, building on the general theoretical framework of Lancaster and on the conceptual and econometric innovations of McFadden. Recent research in this area explores models that account for context effects, as well as methods for characterizing heterogeneity, response variability and decision strategy selection by consumers. This makes it possible to construct much richer empirical models of individual consumer behavior. A Bayesian approach provides a useful way to estimate and interpret models for which this is difficult to accomplish by conventional maximization/minimization algorithms. The application reported in the paper involves analysis of reference dependence and product labeling as context effects and the assessment of heterogeneity and response variability.

Key Words: Individual-level analysis, random utility, cognitive factors, Bayesian model

JEL Codes: D11, D12, C11, C25

Introduction

The theory of demand for product attributes outlined by Lancaster (1966) provides the foundation for economic analyses of individual's choices when faced with different attributes, as with the random utility model (RUM). The specifications by McFadden and Richter (1970) of the RUM, centering on individual decision-making, have explicit behavioral interpretations. With the accumulation of researchers' understanding and the number of available analytical tools, the RUM has become a very popular microeconometric model based on individual-level behavior as well as a model that supports individual-level parameter estimation (e.g., Allenby and Rossi 1999). The RUM has become increasingly popular in assessing individuals' preferences underlying demand, especially in cases where discrete choice decisions are made, such as whether to purchase a (new) product or deciding which product to purchase from a finite set of alternatives.

One intriguing and useful feature of the RUM is its ability to integrate information from other disciplines in the search for a better understanding of consumers' choices. This can be seen in the marriage of economics and psychology pioneered by Kahneman and Tversky (1979). This influential paper challenged recognized economic assumptions by demonstrating the impact of psychological factors on individual choices. These influences may explain features of human decision-making through the concepts of context, attitude, and perceptions. These may be incorporated in the RUM, for example, by interactions with an individual's demographic characteristics. In summarizing related works, Kahneman (2003) suggests that the economic concept of a rational consumer cannot be appropriately defined without consideration of psychological perspectives. In other words, a consumer will be rational only within the bounds of certain constraints. McFadden (2001) and Ben-Akiva et al. (2002) have noted that seemingly irrational behavior, in terms of the traditional economic definitions of rationality, may indeed be rational when psychological and contextual situations or anomalies are accounted for. McFadden (1999, 2001) summarized factors, which will be discussed in detail later in this paper, that may be important drivers in decision-making but have not been well recognized in empirical economic studies. In this paper, we use the general term "cognitive factors" following the "cognitive revolution" in psychology (Kahneman 2003) to describe these "non-economic" factors.

The consideration of both cognitive and economic factors, in the context of new modeling approaches, is being seen in some very recent studies focusing on individual demand/choice analysis, such as List (2004) and Hu et al. (2004). These developments, although still rare in the literature, have advanced the notion of measuring the structure of preferences and demand from broader perspectives. This paper attempts to contribute to the understanding of these developments. The first goal is to provide an overview of innovations to RUM derived from psychological-based studies. The potential impacts of cognitive factors on choices and ways to incorporate these effects in the RUM approach are discussed. A case study using data obtained from a stated preference choice experiment is presented in order to illustrate how, through a flexible estimation procedure, some aspects of human decision-making that are novel to economists can be incorporated within the RUM model in order to draw a more vivid picture of the structure of individual demand. Following the presentation of the case study, challenges that still exist in theoretical, conceptual, and empirical analysis using RUM will be discussed. The paper concludes with a discussion of implications for current and future studies of individual demand behavior.

Advances in RUM

The key feature of the RUM is the distinction between a deterministic and a stochastic component in specifying preference relationships. In the deterministic component, specific economic and demographic factors[1] are assumed to provide a systematic explanation of choices. The stochastic component of the preference function collects impacts from factors that cannot be observed or derived from the information contained in the data. Incorporating impacts from cognitive factors into the decision-making process may invoke structural change in the analysis and introduce fuzziness to the modeling process. For example, Erdem and Keane (1996) included perception errors and dynamic uncertainties in the deterministic component making an element of this stochastic as well. However, since the basic underlying structure of preferences is not random, one can still use the RUM to capture a complex decision structure (Ben-Akiva et al. 2002). We illustrate two aspects of innovations which bear on the following questions: what

[1] Such factors can be either directly observed from the data or latent. This point is illustrated later in the paper.

are the cognitive factors in decision-making that have to be considered, and how might these impacts be incorporated into the RUM framework.

Cognitive Factors Affecting Choice

Following the seminal work of Kahneman and Tversky (1979) recognizing the importance of cognitive effects in making economic decisions, the impacts of cognitive factors on human decision-making have received rigorous and systematic investigation in psychology-based studies (Kahneman and Tversky 2000). The general conclusion from these studies is that spontaneous intuition frequently guides decision making. This is quite different from the "rationality" assumption of economics. However, incorporating these cognitive factors into economic analysis may not be straightforward (Kahneman 2003).

McFadden (1999) provided a succinct summary of four (overlapping) categories of cognitive factors of importance in decision-making, based on the nature of their impacts on decisions. These are context effects, reference point effects, availability effects, and superstition effects. Context effects refer to the impacts from the environment or format in which the decision task is presented. Reference point effects commonly involve decisions under uncertainty and are defined over a series of benchmarks that influence the decision process. Reference point effects may arise when decision-makers, holding different levels of benchmarks, treat differently decision tasks with different types and degrees of uncertainty. Availability effects arise in situations in which a decision-maker's processing of choice tasks is distorted or erroneous and therefore leads to seemingly irrational choices. Finally, superstition effects occur when decision-makers attach unwarranted cues or results to certain events. Innovations based on RUM have focused on the modeling of the impact of these factors on individual choice studies (Manski 2000).

Capturing Cognitive Impacts in RUM

Impacts of cognitive factors are expected to be deeply rooted in the decision process, as represented in Figure 1, modified from McFadden (2001). In this simple input-output diagram, cognitive factors are postulated to affect every step of human decision making, including how information on products is obtained and processed; how decisions are reached after processing;

and how these decisions may affect individuals' subsequent decisions of that individual. Within the context of RUM, such impacts can have several aspects. We briefly outline these aspects below.

- Formation of feasible choice sets (Swait et al. 2002; Manrai 1998; Gilbride and Allenby 2005)
- Taste variability (Hu et al. 2004; Elrod and Keane 1995; Ben-Akiva et al. 2001; McFadden and Train 2000)
- Decision strategy switching (Swait et al. 2002; Yang and Allenby 2000; Gilbride and Allenby 2005)
- Dynamics and intra-person dependence (Erdem and Keane 1996; Train 2003; Louviere 2001)
- Inter-person dependence or social interaction (Manski 2000; Brock and Durlauf 2003; Baerenklau 2005)

Recent developments in individual choice analysis have also occurred in empirical estimation methods. Conventionally, RUMs are estimated by parametric maximum likelihood estimation (MLE), which have tended to dominate since the 1930s (Bera and Bilias 2002). With improvements in computational speed, there is a growing body of literature that replaces the assumptions of a particular functional form or error distribution by smoothness assumptions in estimation, based on flexible nonparametric (Pagan and Ullah 1999) or semiparametric (Horowitz 1998) methods. These methods are especially powerful when the sample size is relatively small and it is difficult to obtain asymptotic properties of the estimates. Alternative parametric methods to MLE, such as the method of moments (MOM) as advocated by McFadden (1989), have also gained attention. The MOM approach, by trading off potential efficiency, may relax the conditions required by MLE for consistency estimation and may therefore reduce numerical difficulties that often trouble MLE (Bera and Bilias 2002).

Approaches such as MLE, MOM and other methods which are only valid based on asymptotic assumptions require approximation techniques to draw statistical properties of estimates and to conduct hypothesis tests. Contrary to these approaches (often referred to as frequentist approaches), Bayesian estimation is based directly on properties of the true distribution of the unknown parameters, given necessary assumptions of priors, so that no approximation is required. Given this property, Bayesian approaches have been increasingly applied in marketing studies. Fong (2004) provides a listing of such studies. When a RUM model that incorporates many impacts from cognitive factors becomes sufficiently complex, programming and estimating using MLE or MOM can be demanding. The Bayesian approach provides an alternative way to achieve the goals of estimation. This is demonstrated in the case study presented below.

The Empirical Study

In this case study, we analyze consumer's demand for GM/nonGM bread products in the framework of the RUM. Various factors related to context, demographic characteristics, reference point effects, and other unobserved cognitive factors are included in the model. We demonstrate that the extensions of the RUM can successfully capture these impacts. The model used is very flexible and we expect that the approach used here can be further extended.

Data and Variables

Data for this study were obtained from a computer-based Canada-wide survey of consumers' purchasing intentions for pre-packaged sliced bread that could potentially include genetically modified (GM) ingredients. The survey was conducted in January 2003. A total of 437 respondents completed the portion of the survey that is of interest to this case study. The survey uses a choice-based conjoint approach in which respondents were directed into a series of choice tasks. Each choice task presents three bread products distinguished by their attributes and respondents were asked to choose one of these as an answer to the question "Which product would you most like to buy?" The first two products are described by various levels of the following attributes: brand name (2 levels), price (4 levels), bread type (4 levels), and GM content (3 levels). The third product alternative does not contain any attributes and is labeled as "buy none of them." Each respondent was assigned to a scenario in which one of three possible GM labeling contexts was applied to the products: mandatory labeling (where all products that contained GM ingredients were labeled as "contain GM ingredients"); voluntary labeling (where all products that did not contain GM ingredients were labeled as "contain no GM ingredients");

and a base case where no specific labeling requirement was in place (where any type of labels might appear). A fractional factorial design was applied to the attributes and labeling contexts to generate 8 choice tasks for each participant.

Reference point effects in this study are defined as the impact from deviations of respondent's perceived attribute levels upon entering the survey and the attribute levels in the actual choices that they made in the course of the survey. At the beginning of the survey, amongst several questions about their usual bread purchase, each respondent was asked to record the price that they usually pay for a loaf of bread in a grocery store, and to indicate whether they believed that the bread they normally purchase contained any GM ingredients. In terms of the products that were chosen in the survey, an increase of price in a chosen alternative relative to the perceived usual price level constitutes a price loss, while a decrease is taken as a price gain. For a respondent who indicated that GM ingredients were not present in their normal bread choice, we postulate that the appearance of GM ingredients in an alternative forms a loss, and the absence of GM ingredients in a chosen alternative represents a gain.

The reference point effect measures were interacted with their corresponding attributes in the model. That is, the price attribute is interacted with the price gain/loss information and the GM attribute is similarly interacted with reference point information. According to prospect theory, we anticipate that respondents will respond positively to a price gain and negatively to a price loss with a proportionally higher sensitivity to price loss. Given the credence property of the GM attribute, there is no clear expectation of whether respondents will respond according to prospect theory predictions based on our definition of gain and loss. Thus we rely on the empirical result for interpretation in this case. Information on the respondent's demographic and GM-related attitudes was also collected in the survey. Table 1 gives a list of the variables used in this case study.

Model

The empirical model is based on a logit representation of RUM[2]. The model we propose provides an example of a solution to the question raised by Louviere et al. (2002) on how to separate the effects of different aspects of cognitive factors. We assume that depending on personal characteristics and attitudes, respondents vary in terms of their sensitivity to reference point effects. These can be captured by a random coefficient specification of reference point effect variables, and these random coefficients are denoted in a vector β_n^r. Variables that were selected to explain this deviation are collected in a vector K_n including respondents' age, income, and an objective measure of their knowledge on GM related issues. The impact of other cognitive factors that may contribute to the variation in respondent's reactions to reference point effects are represented in the random component of these coefficients. The utility of individual *n* choosing product *i* in the *t*-th choice occasion can be written as:

$$U_{nit} = f\left(\beta^f, \beta_n^r(\gamma) \mid X_{nit}^f, X_{nit}^r, K_n\right) + \varepsilon_{nit} \qquad (1)$$

where β^f is a vector of fixed coefficients, and X_{nit}^f and X_{nit}^r are variables corresponding to fixed and random coefficients respectively. Parameter vector γ incorporates coefficients associated with factors in *K* and the magnitude of the random component of β_n^r. ε_{nit} is an unobserved noise term of the overall indirect utility function.

The scale of the choice problem is denoted as μ_{nit}, and this is parameterized as a function of a vector of variables S_{nt} representing the impacts from labeling contexts, task complexity, and individual demographic factors. A fixed-effect individual-scale specification, denoted as s_i, was also adopted to collect impacts from other factors that were not directly included in the model. Since the scale is proportional to the inverse of the overall variance of the model, to ensure that the scale function only returns positive scale measures, an exponent function was used to define μ_{nit}:

$$\mu_{nit} = \exp\left(\theta' S_{nt} + s_i\right) \qquad (2)$$

where θ is a vector of parameters associated with S_{nt}. Individual scales s_i can be specified as normally distributed across consumers in the sample. Assuming a linear function of U_{nit} in terms

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[2] Fitting a probit model is straightforward and does not add any further complexity because the Bayesian approach we use does not require simulation of a probit model.

of product attributes, the logit probability of individual *n* choosing product *i* in the *t*-th choice occasion can be written as:

$$P_{nit}\left(\Lambda = i \mid \Theta\right) = \int \cdots \int \frac{\exp\left(\mu_{nit}\left(\beta^{f'} X^{f}_{nit} + \beta^{r'}_{n} X^{r}_{nit}\right)\right)}{\sum_{j} \exp\left(\mu_{nit}\left(\beta^{f'} X^{f}_{njt} + \beta^{r'}_{n} X^{r}_{njt}\right)\right)} f\left(\beta^{r}_{n}\right) f\left(s\right) d\beta^{r}_{n} ds \quad (3)$$

where Λ is the outcome of choice; Θ represents all unknown parameters to be estimated in the model; $f\left(\beta^{r}_{n}\right)$ is the joint density function of vector β^{r}_{n}; and $f\left(s\right)$ is the density function of individual-level scales s_i[3].

Bayes' theorem states that the posterior distribution of the parameters is proportional to the product of likelihood of the data and the prior (Geweke 1989). This implies that:

$$F^{p}\left(\Theta \mid \Lambda\right) \propto \prod_{n} \prod_{t} P_{nit}\left(\Lambda \mid \Theta\right) F\left(\Theta\right) \quad (4)$$

where $F^{p}\left(\cdot\right)$ and $F\left(\cdot\right)$ are posterior and prior density functions respectively. In order to complete the expression in (4), priors of unknown parameters are specified as:

$\beta^{f} = \left(\beta^{f_1}, \beta^{f_2}, ...\right) \sim$ independent normal $N(0, \sigma_{\beta^{f}})$

$\beta^{r}_{n} \sim$ multivariate normal $MN\left(\eta_{\beta^{r}}, \sigma_{\beta^{r}}\right)$

$\eta_{\beta^{r}} = \gamma' K_{n}$

$\gamma \sim$ normal $N\left(0, \sigma_{\gamma}\right)$

$\sigma_{\beta^{r}} \sim$ inverse Wishart $IW\left(I_{q}, q\right)$

$\mu_{nit} \sim$ log normal $LN\left(\eta_{\mu}, \sigma_{i\mu}\right)$

$\eta_{\mu} = \theta' S_{nt}$

$\theta \sim$ normal $N\left(0, \sigma_{\theta}\right)$

$\sigma_{i\mu} \sim$ gamma $G\left(a, b\right)$

[3] It is arguable that a joint density of vector β^{r}_{n} and s can be specified. However, given that these two sets of random parameters follow very different distributions (see the discussion on these distributions later in the paper), they are assumed to be distributed independently.

where q is the number of random coefficients in vector β_n^r. To ensure that the posterior distribution does not depend critically on the assumptions of prior distributions, diffuse priors were used: I_q is an identity matrix with dimension of q; standard deviations σ_{β^f}, σ_γ, and σ_θ were large (1E+3)); and the gamma distribution $G(a,b)$ was specified as $a = 0.1$ and $b = 10$, such that the implied prior for variance $\sigma_{i\mu}$ was also large (10).

A Markov Chain Monte Carlo (MCMC) updating procedure was adopted as the sampling approach. The sampling procedures followed Geweke (1989) and Carlin and Louis (2000). The use of this procedure in analyzing discrete choice models followed Allenby and Rossi (1999) and Train (2001). In principal, the chain starts with draws of unknown parameters from their prior distributions. Conditional on these parameters, choice probabilities (proportional to the likelihood of the observed choice data) are calculated, and combined with parameter prior distributions, to form draws from the posterior distributions. Inferences of parameters are obtained from their posterior distributions. This Bayesian procedure relies on large numbers of sampling iterations. In the case study reported in this paper, after initial convergence (5,000 iterations), the model was allowed to update 10,000 times before the final results were summarized.

Results

The estimation results are reported in Tables 2 through 5. Other models with more restrictive formats were also estimated, including models with no random coefficient specification, no scale function specification, or with a scale function specification but with no individual-specified scale parameter. However, the deviance information criterion (DIC) suggests that the most complex model has the highest power in explaining the data[4]. Table 2 gives the estimated coefficients with fixed coefficients. These coefficients are all significant based on the 95% confidence interval of their corresponding posterior distribution. The results imply that in general, and holding other factors constant, the sampled respondents wished to buy bread and preferred bread with national brand names; they preferred multi-grain bread rather

[4] We recognize that the DIC slightly favors the more complex model. However, the improvement in DIC was large for the most complex model compared with other simpler models. This leads us to conclude that the most complex model is indeed better in terms of the fitting the data.

than white, partially whole wheat or whole wheat bread; preferred bread without GM ingredients; and preferred lower prices.

Table 3 displays the estimated coefficients of variables in the scale function. Only the variable "task", an indication of fatigue, is significant. This is negative, indicating that as more tasks are completed, the variance (inverse of scale) of respondents' choices started to increase. This could be explained as the effect of fatigue: when respondents are tired of completing the survey tasks, they may begin to make choices with more variability, rather than choosing the most attractive option, leading to an increase in choice variances. This can be classified as a context effect. Although the other two context variables (the labeling context and demographic factors) are not significant in the model, the standard deviation of the fixed effect random scale parameter is significantly different from zero[5], indicating that there might be other factors that affect the variances of respondents' choice that we failed to capture by the variables currently included in the scale function. These could be cognitive, demographic, or other factors that cannot be measured. The inclusion of fixed effect random scales is necessary to capture the remaining impacts.

Due to limited space, Table 4 reports estimates of individual scales of only ten randomly selected respondents. Two of these ten scale measures are negative and significant. Since the scale is proportional to the inverse of the standard deviation between choices respondents made, holding other factors constant, Table 4 indicates that choices for respondents 2 and 6 in are relatively more volatile than the other respondents. In other words, our model predicts less well the choice behavior of these two respondents relative to the others. Figure 2 sorts and plots the distribution of the scale estimates s_i of the entire sample of 437 respondents. It can be seen from the broken line that these individual scale estimates are centered around zero, because the mean effects are assumed to be represented by the covariates specified in the model. The solid line gives the "actual" individual scales after exponentiation of the estimated s_i.

[5] A series of individual scale parameters was also obtained. However, due to the limited space, these parameters are not included in Table 2.

Table 5 contains the random parameter estimates associated with the reference point effects. Respondent income is significant in explaining the effect of price loss, and age and income are significant in explaining the effects of gain in GM ingredients. These estimates indicate that wealthier respondents are less sensitive to price loss. Conventional economic theory does not consider reference point (changes of an attribute from a benchmark) effects, but our case study indicates that inclusion of price reference points will better predict responses to price changes. For the GM attribute, relative to younger respondents, older respondents were less sensitive to the "gain" when GM attributes were declared to be absent in the chosen product if this attribute was perceived to be present in the normal purchase. However, higher income respondents enjoyed more utility than lower income respondents from the unexpected absence of GM ingredients. All four estimated standard deviations of the random reference point effects are significant, which indicates that there are still heterogeneities in the sampled consumers associated with these reference points that are not captured by the covariates currently used in the model. These heterogeneities can be labeled as "unobserved" in this situation. The covariances between the four random reference point effects measures resulting from the underlying multivariate-normal distribution are not significant and therefore are not reported in Table 5.

To examine the impact, on average, of reference point effects, we took an average respondent (with median age, income, and GM-knowledge level) and calculated the four coefficients associated with gains and losses. These coefficients are reported as "overall reference point effects" in Table 5. It is clear that for a representative respondent a gain in price introduced positive utility, while a loss in price brought negative utility; it is also clear that the magnitude of the impact of loss in price is larger than the gain in price. Thus there is clear evidence of asymmetry in gains and losses in terms of price changes. However, while the unanticipated absence of GM ingredients in bread increased utility, the unanticipated presence of GM ingredients also caused utility to increase. This may be due to the feature that the identified presence of GM ingredients increased the number of product varieties that respondents could potentially choose from, therefore increasing utility overall. It may also be that those characteristics of the individuals who do not believe there is GM in bread, which are not captured by the included demographic variables, cause utility to increase in this case.

Conclusions and Implications

The importance of cognitive factors in a respondent's decision-making process is the major focus of the paper. In an empirical study, we attempt to incorporate impacts from both cognitive and demographic factors in an empirical model. Instead of modeling and testing each impact separately, the joint incorporation of these factors into a RUM is pursued. We show how such impacts can be modeled by the construction of additional variables in the indirect utility expression (reference point effect measures), by specifying random structures in a respondent's valuation of various factors (with observed and unobserved effects), and by parameterizing the overall variability of choices (with explained and random scales). Significant estimates that are consistent with expectations support the model and the approach.

The analysis implies that results from behavioral studies can be incorporated into economic studies, adding to the insights provided by such models. Added features that reflect the bounds on decision-making behavior can provide significant insights into issues related to consumer preferences and decision-making. Basic tools derived from the RUM can be useful for this type of analysis. Variations and adjustments can be made to the basic model to produce desirable modeling tools in various situations and for a variety of purposes. However, viewing the consumer's decision-making process as a system indicates that factors that are explored in the paper may be internally correlated. Identifying and measuring the various impacts of cognitive factors on the economic theory of consumer behavior is a continuing and important direction for future research.

References

Allenby, G. and P. Rossi (1999) "Marketing Models of Consumer Heterogeneity" *Journal of Econometrics* 89: 57-78.

Andrews, R. L. and A. K. Manrai (1998) "Simulation Experiments in Choice Simplification: The Effects of Task and Context on Forecasting Performance" *Journal of Marketing Research* 25: 198-209.

Baerenklau, K. (2005) "Toward an Understanding of Technology Adoption: Risk, Learning, and Neighborhood Effects" *Land Economics* 81(1): 1-20.

Ben-Akiva, M., D. Bolduc, and J. Walker (2001) "Specification, Identification, & Estimation of the Logit Kernel (or Continuous Mixed Logit) Model" Working Paper, MIT.

Ben-Akiva, M., D. McFadden, K. Train, J. Walker, C. Bhat, M. Bierlaire, D. Bolduc, A. Boersch-Supan, D. Brownstone, D. Bunch, A. Daily, A. De Palma, D. Gopinath, A. Karlstrom, and A. A. Munizaga (2002) "Hybrid Choice Models: Progress and Challenges" *Marketing Letters* 13(3): 163-175.

Bera A. K. and Y. Bilias (2002) "The MM, ME, ML, EL, EF and GMM Approaches to Estimation: a Synthesis" *Journal of Econometrics* 107: 51-86.

Brock, W. A. and S. N. Durlauf (2003) "Multinomial Choice with Social Interactions" Working Paper, National Bureau of Economic Research, USA.

Carlin, B. P. and T. A. Louis (2000) *Bayes and Empirical Bayes Methods for Data Analysis*. Chapman and Hall.

Elrod, T. and M. P. Keane (1995) "A Factor-Analytic Probit Model for Representing the Market Structure in Panel Data" *Journal of Marketing Research* 32: 1-16.

Erdem, T., and M. P. Keane (1996) "Decision-Making Under Uncertainty: Capturing Choice Dynamics in Turbulent Consumer Goods Markets" *Marketing Science* 15(1): 1-21.

Fong, D. H. K. (2004) "Some Recent Bayesian Applications in Marketing" *ISBA Bulletin* 11(1): 6-8.

Geweke, J. (1989) "Bayesian Inference in Econometric Models Using Monte Carlo Integrations" *Econometrica* 57(6): 1317-1339.

Gilbride, T. J. and G. M. Allenby (2005) "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules" *Marketing Science* (*forthcoming).*

Heckman, J. (1981) "*Statistical Models for the Analysis of Discrete Panel Data*" in Structural Analysis of Discrete Data, Manski, C. and D. McFadden (eds.), MIT Press, Cambridge, 1981.

Horowitz, J. (1998) *Semiparametric Methods in Econometrics*. New York: Springer-Verlag.

Hu, W., W. Adamowicz, and M. Veeman (2004) “Decomposing Unobserved Choice Variability In the Presence of Consumers’ Taste Heterogeneity” Working Paper, University of Alberta.

Kahneman, D. (2003) “Maps of Bounded Rationality: Psychology for Behavioral Economics” *American Economic Review* 93(2): 1449-1475.

Kahneman, D. and A. Tversky (1979), “Prospect Theory: An Analysis of Decision under Risk” *Econometrica* 47: 263-291.

Kahneman, D. and A. Tversky (2000) *Choices, Values, and Frames*. Cambridge: Cambridge University Press.

Lancaster, K. (1966) “A New Approach to Consumer Theory” *Journal of Political Economy* 74: 132-157.

List, J. A. (2004) “Neoclassical Theory Versus Prospect Theory: Evidence from the Marketplace” *Econometrica* forthcoming.

Louviere, J. (2001) “What if Consumer Experiments Impact Variances as well as Means? Response Variability as a Behavioral Phenomenon” *Journal of Consumer Research* 28(3): 506-511.

Louviere, J., D. Street, R. Carson, A. Ainslie, J. R. Deshazo, T. Cameron, D. Hensher, R. Kohn, and T. Marley (2002) “Dissecting the Random Component of Utility” *Marketing Letters* 13(3): 177-193.

Manski, C. F. (2000) “Economic Analysis of Social Interactions” *Journal of Economic Perspectives* 14(3): 115-136.

McFadden, D. (1989) “A Method of Simulated Moments for Estimation of Discrete Response Models without Numerical Integration” *Econometrica* 57(5): 995-1026.

McFadden, D. (1999) “Rationality for Economists?” *Journal of Risk and Uncertainty* 19: 73-105.

McFadden, D. (2001) “Economic Choices” *American Economic Review* 91(3): 351-378.

McFadden, D. and M. K. Richter (1970) “On the Extension of a Probability to the Boolean Algebra Generated by a Family of Events” Working Paper, University of California, Berkeley.

McFadden, D. and K. Train (2000) “Mixed MNL Models of Discrete Response” *Journal of Applied Econometrics* 15: 447-470.

Pagan, A. and A. Ullah (1999) *Nonparametric Econometrics*. Cambridge: Cambridge University Press.

Swait, J., W. Adamowicz, M. Hanemann, A. Diederich, J. Krosnick, D. Layton, W. Provencher, D. Schkade, and R. Tourangeau (2002) "Context Dependence and Aggregation in Disaggregate Choice Analysis" *Marketing Letters* 13(3): 195-205.

Train, K. (2001) "A Comparison of Hierarchical Bayes and Maximum Simulated Likelihood for Mixed Logit" Working Paper, Department of Economics, University of California, Berkeley.

Train, K. (2003) *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.

Yang, S. and G. M. Allenby (2000) "A Model for Observation, Structural, and Household Heterogeneity in Panel Data" *Marketing Letters* 11(2): 137-149.

Table 1. Model Variable Descriptions

Variable Name	Variable Description
Price	A continuous variable representing actual price
Buyno	Alternative specific constant representing the utility associated with choosing to buy none of the bread
Storeb	=1 if the bread has a store brand, otherwise=0
White	=1 if the bread is white bread, otherwise =0
Partial	=1 if the bread is partial whole wheat, otherwise =0
Whole	=1 if the bread is whole wheat, otherwise=0
GMO	=1 if the bread has GM ingredients, otherwise =0
NOGMO	=1 if the bread does not contain GM ingredients, otherwise =0
PG	=1 if the alternative involves a gain in price, otherwise =0
PL	=1 if the alternative involves a loss in price, otherwise =0
GMG	=1 if the alternative involves a gain in GM ingredients, otherwise =0
GML	=1 if the alternative involves a loss in GM ingredients, otherwise =0
Age	A continuous variable representing respondents' age
Income	A continuous variable representing respondents' income
Know	A dummy variable representing whether a respondent has answered all of five GM knowledge questions correctly
Mand	=1 if the context is a mandatory labelling, otherwise =0
Volun	=1 if the context is a voluntary labelling, otherwise =0
Task	A continuous variable representing the task number
Male	=1 if the respondent is a male, otherwise =0
College	=1 if the respondent received some post-secondary education, otherwise =0

Table 2. Estimates of Fixed Coefficients

coefficient	mean	95% confidence interval	
		lower	upper
Price	-0.7324*	-1.1460	-0.2984
Buyno	-5.1670*	-6.5810	-3.6820
Storeb	-0.2766*	-0.4499	-0.1247
White	-1.5610*	-2.0380	-1.1680
Partial	-1.0190*	-1.4070	-0.6957
Whole	-0.4324*	-0.7885	-0.1482
GMO	-2.8290*	-3.8810	-2.0460
NOGMO	0.4103*	0.1182	0.7623
Model DIC	*5593.03*		

* significant based on the 95% confidence interval.

Table 3. Estimated Scale Function Parameters

parameter	mean	95% confidence interval	
		lower	upper
Mand	-0.1202	-0.4195	0.1876
Volun	0.1062	-0.1806	0.4327
Task	-0.0777*	-0.1129	-0.0447
Male	-0.1134	-0.3544	0.1294
College	-0.0458	-0.3119	0.2148
Stand. Dev. Of random Scales Across Sample	1.1030*	0.8111	1.5190

* significant based on the 95% confidence interval.

Table 4. A Sample of Individual Scale Parameters (logarithm of actual scale)

Individual	mean	95% confidence interval	
		lower	upper
1	1.0930	-0.3510	2.5100
2	-1.3550*	-2.6270	-0.2623
3	-0.9081	-2.1660	0.0596
4	-0.3990	-1.5420	0.5304
5	0.7347	-0.9371	2.3580
6	-1.0900*	-2.3920	-0.0611
7	-0.9529	-2.4140	0.8992
8	0.1535	-1.2240	1.2930
9	0.2380	-1.1230	1.3740
10	-0.2533	-1.5860	0.8282

* significant based on the 95% confidence interval.

Table 5. Estimated Parameters Associated with Reference Point Effects

parameters		mean	95% confidence interval	
			lower	upper
Constant in PG		0.0935	-0.2407	0.4655
	PG-Age	-0.1996	-1.3810	0.7752
	PG-Income	0.1104	-0.6333	0.8027
	PG-Know	0.0601	-0.3686	0.4516
Std. Dev. PG		0.4286*	0.1069	0.9787
Constant in PL		-0.9919*	-1.3170	-0.6571
	PL-Age	0.7776	-1.0270	2.5350
	PL-Income	1.5040*	0.4264	2.6860
	PL-Know	-0.1391	-0.9227	0.6480
Std. Dev. PL		0.8021*	0.4685	1.2700
Constant in GMG		0.5935	-1.1860	1.9860
	GMG-Age	-3.4250*	-6.4540	-0.0207
	GMG-Income	2.0230*	0.2472	4.2860
	GMG-Know	-0.1405	-1.1140	0.8643
Std. Dev. GMG		1.0380*	0.2205	2.5610
Constant in GML		-1.3090	-0.0610	2.3830
	GML-Age	0.3732	-1.5050	0.7236
	GML-Income	-0.3958	-0.5582	1.4110
	GML-Know	0.4372	-1.4200	0.5068
Std. Dev. GML		4.3700*	1.8000	8.3040
Overall PG		0.1386		
Overall PL		-0.9209		
Overall GMG		0.9299		
Overall GML		1.7258		

* significant based on the 95% confidence interval.

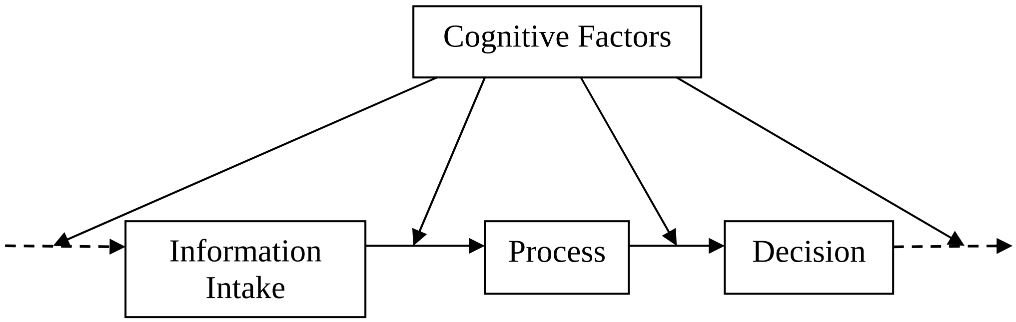

Figure 1. Impacts of Cognitive Factors on Decision Process
(Diagram modified from McFadden (2001))

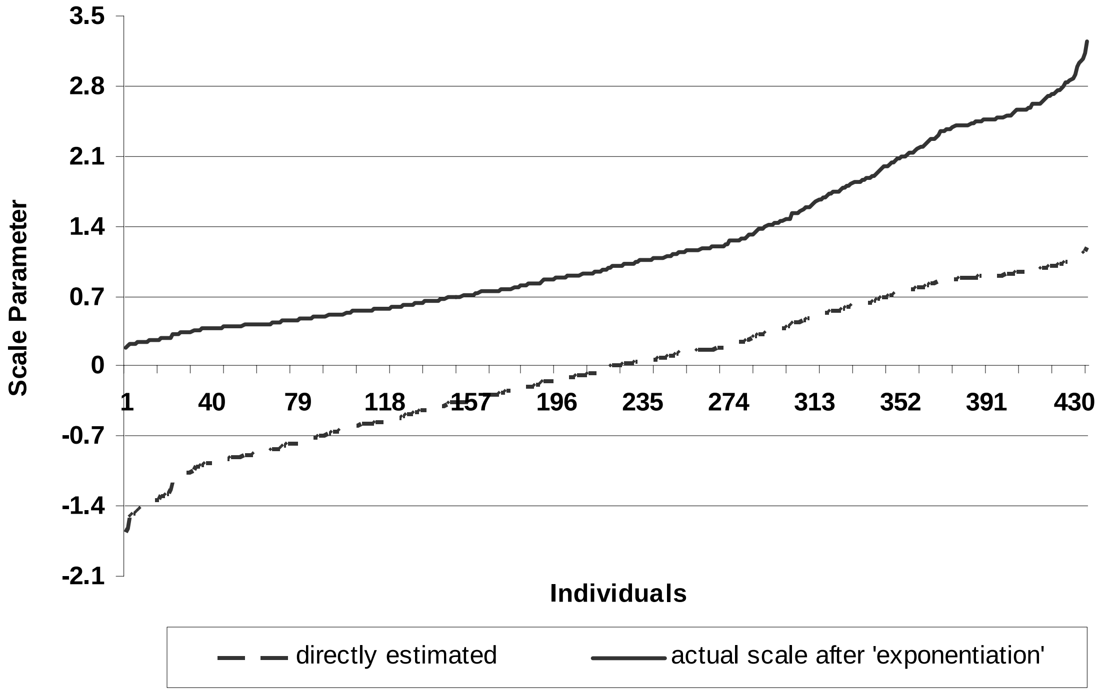

Figure 2. Plot of Individual Scale Parameters