

## **Consideration set of automobiles: Purchase feedback and exclusivity in formation**

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### **ABSTRACT**

Using a self-reported measure of consideration set, the current paper investigates consideration of automobiles at the manufacturer level that took place in a US market. The empirical questions posed are (1) the inter-temporal impact of the type of prior car purchased on consideration at the subsequent purchase period and (2) probabilistic dependence in consideration of different alternatives with the inter-temporal effect being accounted for. Empirical analyses document strong inter-temporal effects of prior purchase: the purchase of a particular manufacturer reinforces consideration of the manufacturer again, but reduces likelihood of other manufacturers being considered at the next purchase occasion. It is also found that buyers tend to focus on few manufacturers and correlations in manufacturer consideration are by and large negative. Consideration can be characterized as exclusive at the manufacturer level: the six major American and Japanese automakers examined tend not to be considered jointly.

Keywords: Consideration set, automobile market, multivariate probit, Bayesian estimation, Markov chain Monte Carlo

## INTRODUCTION

The concept of consideration set has attracted a substantial amount of academic attention in the marketing and economics literature. In the theory of consideration (see, for example, Howard & Sheth, 1969), a consumer filters brands available in the marketplace and forms a subset of them, called a consideration (or choice) set, that meet certain buying criteria and from which to choose. Numerous articles have developed a theoretical model for explaining the composition of consideration set and identified the role it plays in consumer's decision making process for choice. Roberts & Nedungadi (1995) declared three perspectives on consideration set formation: (a) cost-benefit approach, (b) learning approach, and (c) information processing approach. For a review of findings and issues in the area, see Roberts & Lattin (1997).

There is a large body of empirical applications of consideration to scanner panel datasets (e.g., Andrews & Srinivasan, 1995). This stream of research aims at incorporating the stage of consideration into choice models and uncovering unobserved consideration sets from data, because requesting consumers to articulate alternatives considered before making a purchase is extremely difficult and infeasible, if not impossible, for frequently purchased consumer packaged goods due to low-involvement nature of purchases. Numerous studies have documented empirical support that generally, consumers do not engage in full search of all brands in a given category.

Previous empirical studies often made an assumption that consideration of one alternative is independent of consideration of others. Roberts & Lattin (1991) have pointed out that the probabilistic independence assumption leads to independence of brand utilities, so that interaction between brands in the formation of consideration set cannot be explored. Using data on 26 Australian ready-to-eat cereal brands, Lattin & Roberts (1992) tested the probabilistic independence assumption on consideration. Their test for the three muesli brands did reject independence of consideration: the majority of consumers tend to consider either none or all the three brands. They concluded that while probabilistic independence might be a reasonable assumption in relatively unstructured markets, it might not be a good one in a strongly differentiated market.

Notably, most empirical research on the shape of consideration set have not fully addressed impacts of consumer variables, including socio-demographics and behavioral traits. In particular, a buyer's prior purchase behavior has not received much attention. A notable exception is van Nierop et al. (2010), who proposed a two-stage model composed of a multivariate probit for consideration and a multinomial probit for brand choice given consideration. Although they modeled an unobserved consideration set as evolving over purchase occasions, they did not model the possible impact of previous purchase on observed consideration at the next purchase occasion.

The current article investigates consideration of automobiles in a US market using data on consumers' self-reported measure of consideration set. While automobiles are a major purchase, involving a good deal of perceived risk, empirical work on consideration sets for automobiles is rather scant (DeSarbo & Jedidi, 1995 is an exception). Utilizing four cohorts of survey data, the present study provides a detailed descriptive analysis of consideration behavior in the automobile category, focusing on the pattern of manufacturer incidence. Preference for one manufacturer is likely to correlate with that for another because of perceived similarity or dissimilarity, making it unlikely that consideration is independent across alternatives. Using a reduced-form multivariate probit model of consideration, this paper addresses two main research

questions: (1) the impact of prior ownership on the composition of consideration set at the following purchase occasion, in other words, whether there is any purchase feedback mechanism that influences the formation of consideration set; and (2) association among auto manufacturers in terms of consideration, which sheds some lights on the shape of consideration set.

Similar to empirical findings in the choice literature, two types of purchase feedback mechanisms are detected that affect the formation and shape of consideration set at the subsequent purchase moment. First, there is little evidence of variety seeking in consideration: the purchase of one manufacturer weakens consideration of other manufacturers. Second, loyalty transfers to the consideration stage: the last purchase reinforces consideration of the same manufacturer. These findings illustrate a dynamic relationship between choice and consideration: future consideration, and so choice, is affected by the prior choice.

Estimated correlations in consideration of manufacturers are mostly negative, except for Japanese manufacturers. Combined with the finding that a large portion of sampled buyers confined their consideration to one or two manufacturers, negative correlations imply that considerations sets for automobiles are characterized by exclusivity: instead of having a broad range of manufacturers not to miss out on a better buy, prospective buyers seem to minimize cognitive effort by considering alternatives from few number of manufacturers.

The rest of this article is organized as follows. In the next section, the statistical model and estimation procedure are presented. Then, data collection and variables used in the empirical analyses are detailed. Subsequently, estimation results are highlighted regarding the inter-temporal effect of prior purchase and correlations in manufacturer consideration. Discussions of empirical findings are followed. The paper concludes with discussion of limitations.

## THE FULL PROBABILITY MODEL

From a data-analytic perspective, consideration of brands yields a datum of multiple binary responses per cross-sectional unit. In a typical survey study that collects information on consideration sets of (potential) buyers, interviewees might be asked either to check off any from the list of available alternatives provided by an interviewer or to recall which models they seriously considered as a possible choice. Consideration of each alternative could be modeled as a binary response variable, and the primary focus of studies for consideration would be on revealing statistical relationships among these binary incidences. A vector of incidences, however, is not amenable to multivariate data reduction techniques, since these qualitative variables in themselves are barely likely to be an outcome of a multivariate normal on which most of those methodologies are predicated. More importantly, to study the influence of observed characteristics of either alternatives or decision makers, a formal modeling approach is required that articulates a data generating process for observed multiple (multivariate) binary consideration variables.

Suppose that consumer  $n \in \{1, \dots, N\}$ , looking forward to purchasing a new car in a certain size/class, forms a consideration set composed of a subset of  $J$  models. The consideration set can be symbolized as a  $J$ -tuple of binary variables  $[y_{n1}, \dots, y_{nJ}]$ , where  $y_{nj}$  indicates whether the consumer considers model  $j \in \{1, \dots, J\}$ . It is assumed that dichotomous variable  $y_{nj}$  is tied to unobserved latent preference  $z_{nj}$  for model  $j$ : that is, alternative  $j$  will be a member of the consideration set if and only if preference for the model exceeds zero:

$y_{nj} = I(z_{nj} > 0)$ , where  $I(\cdot)$  is an indicator function. The continuous latent preference is expressed as  $z_{nj} = \alpha_j + \gamma_j' \mathbf{x}_n + \varepsilon_{nj}$ , where  $\alpha_j$  is an intercept for model  $j$ ,  $\mathbf{x}_n$  is a  $K$ -dimensional vector of observed consumer characteristics, and  $\gamma_j$  is a corresponding response vector that measures impacts of demographics on preference for model  $j$ . The system of  $J$  preference equations can be written in vector form  $\mathbf{z}_n = \boldsymbol{\alpha} + \boldsymbol{\Gamma}' \mathbf{x}_n + \boldsymbol{\varepsilon}_n$ , where  $\mathbf{z}_n = [z_{n1}, \dots, z_{nJ}]'$ ,  $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_J]'$ ,  $\boldsymbol{\Gamma}' = [\gamma_1, \dots, \gamma_J]'$ , and  $\boldsymbol{\varepsilon}_n = [\varepsilon_{n1}, \dots, \varepsilon_{nJ}]'$ . One of the main estimation tasks is to include the type of last car purchased into  $\mathbf{x}_n$  and examine corresponding elements of  $\boldsymbol{\Gamma}$  to see whether ownership of a particular model affects consideration of other models as well as the focal model.

With the assumption that  $\boldsymbol{\varepsilon}_n$  is distributed independently and identically a mean-zero  $J$ -dimensional normal with unrestricted covariance matrix  $\boldsymbol{\Omega}$ , the probability model for latent preferences and observed consideration is a multivariate probit (Chib & Greenberg, 1998; Edwards & Allenby, 2003):  $\mathbf{z}_n | \mathbf{x}_n, \boldsymbol{\alpha}, \boldsymbol{\Gamma}, \boldsymbol{\Omega} \sim \text{ind. Normal}(\boldsymbol{\alpha} + \boldsymbol{\Gamma}' \mathbf{x}_n, \boldsymbol{\Omega})$ . Since the random errors are unrestricted, any force beyond observed traits that induces buyers to consider some models together or to disregard some models while considering others would be reflected in the covariance matrix  $\boldsymbol{\Omega}$  through positive or negative off-diagonals. Apparently, in the case of no correlations among random errors (i.e., under the probabilistic independence), there is no need for modeling  $J$  incidences jointly, and analysts would proceed to estimate parameters  $j$  by  $j$ .

The model parameters  $\boldsymbol{\Omega}^{-1}$ ,  $\boldsymbol{\alpha}$ , and  $(\gamma_1, \dots, \gamma_J)$  are estimated via Bayesian framework, which requires to specify priors. Non-informative, independent, and conditionally conjugate priors are elicited for the parameters:  $\boldsymbol{\Omega}^{-1} \sim \text{Wishart}(11, 11\mathbf{I})$  ( $E(\boldsymbol{\Omega}^{-1}) = \mathbf{I}$ ),  $\boldsymbol{\alpha} \sim \text{Normal}(0, 100\mathbf{I})$ , and  $\gamma_j \sim \text{i.i.d. Normal}(0, 100\mathbf{I})$ . Following the standard strategy for estimating qualitative dependent variable models (Albert & Chib, 1993; Tanner & Wong, 1987), the current paper augments observed-data likelihood of binary outcomes with unobserved continuous latent preferences. Then, all the conditional posteriors are standard from which sampling is straightforward. To remove scale-invariance of a multivariate probit model,  $\boldsymbol{\Omega}$  need to be set to a correlation matrix. Following Edwards & Allenby (2003), the Markov chain Monte Carlo (MCMC) sampler draws parameters from the joint posterior induced by the unidentified complete-data likelihood and then post-process these draws to achieve identification.

## THE DATA AND VARIABLES USED

Data collected from 4 independent mail surveys that were commissioned in February of 2000, 2002, 2004, and 2006 are analyzed to study consideration of automobiles. The surveys all followed exactly the same data collection procedure. Each survey was sent to 3,000 new automobile buyers in Buffalo, NY area. Respondents were asked to articulate up to 6 the car models they seriously considered as a possible choice for their new car. The indication of manufacturer (brand) and line-up was obtained as a response (e.g., Chevrolet Cavalier was considered). Referring to affiliation of brands, the authors construct consideration of major 6 manufacturers: Chrysler, Ford, GM, Honda, Nissan, and Toyota. The data contain also information on the brand and line-up of the last new car purchased by the respondent. That information is converted to construct dummies for purchase of the 6 major manufacturers. The

original dataset contains respondents who had purchased and considered other countries-of-origin, but the proportion is minor. Therefore, the authors retain only observations with last purchase and consideration of one of the six American and Japanese makers.

Several consumer traits are controlled for: gender (Male), marital status (Married), the presence of children in the family (Kids), employment status (Employed), age ( $\text{Age} \leq 30$ ,  $31 \leq \text{Age} \leq 40$ ,  $41 \leq \text{Age} \leq 50$ ,  $51 \leq \text{Age} \leq 60$ , and  $60 < \text{Age}$ ), education (High School Education, College Education, and Graduate Education), and the level of household income (from 1 Below \$4,999 to 13 More than \$100,000). Information on the size/class of the purchased new car is available and 6 dummies are created to capture mean difference in consideration rate. Descriptive statistics of the data are reported in Table 1. GM commands the highest share of consideration and Nissan the lowest. Similarly, GM captures the highest market share and Nissan the lowest. The portion of first-time buyers in the sample is rather small (around 4%).

Table 2 derives distribution of the number of manufacturers considered. On average, the respondents considered 1.733 manufacturers. The majority of the respondents considered only one manufacturer (consideration sets of size 1). More than 80% of the respondents confined their attention to 1 or 2 manufacturers. These indicate low likelihood of considering autos from many different manufacturers. Around 40% of the sample considered only the same manufacturer that they purchased the last time (around 74% of those who have a consideration set of size 1), a figure far greater than 17% reported in Lapersonne et al. (1995) for French automobiles. This is understandable because their brand level investigation is more disaggregate than the current study.

## ESTIMATION RESULTS

### Model Comparison

The Markov chain was iterated 20,000 times. The initial 10,000 repetitions were discarded as burn-in draws. The last 10,000 Gibbs draws are retained for posterior inference. Convergence of the chain was examined by looking into time-series plots and histograms of posterior draws. To gauge explanatory power of last purchase, which is the main variable of interest in this study, the authors calibrate two restricted versions as well: one with manufacturer-specific constants  $\alpha$  only and the other with covariates but no last purchase. At the posterior means, marginal probability of considering a manufacturer is evaluated. Likelihood ratio index of the model with all but last purchase relative to one with  $\alpha$  only is termed LRI1. Likelihood ratio index of the model with all the variables relative to the model lacking last purchase is termed LRI2. LRI3 denotes likelihood ratio index that contrasts the model containing all the variables with the model including only  $\alpha$ . The results are shown at the bottom of Table 3. The inspection of LRI1 reveals that static demographics appear not to be very effective at capturing much variation in consideration (it is below .10). LRI2, however, exhibits a sizable improvement over no use of last purchase. These in-sample fit statistics show that the manufacturer of last auto has a non-ignorable impact in predicting which manufacturers will be considered.



## The Effect of Demographics

The posterior means of  $\alpha$  and  $\gamma$  are reported in Table 3 with indication of “significance” (hereafter, an estimate will be labelled as significant if the posterior has at least 95% of its mass away from zero, that is, if posterior probability mass of being greater than zero is at least .95). Male consumers are more likely to consider GM, but less likely Toyota than females. Marital status does not have influence over consideration of different manufacturers. Buyers with kids are more likely to consider GM than those with no kids. Employed consumers are more likely to consider Chrysler relative to the nonemployed. Higher income buyers are less likely to consider Ford than those with lower level income. Somehow consistent patterns are found in the impacts of age and education. There is a strong negative relationship between age and consideration of Japanese makers (the coefficient on  $60 < \text{Age}$  for Toyota is significant at the .10 level). Conversely, a strong positive relationship is found between higher education and consideration of Japanese autos. As per mean difference across sizes/classes within a manufacturer, Chrysler has a higher consideration rate in Minivan relative to other classes; Ford has a higher rate in small SUV but lower rate in midsize; GM has a higher rate in midsize and SUV; Honda has a higher rate in subcompact and small SUV; Nissan has a higher rate in midsize; and no significant difference in consideration rate across classes is found for Toyota. The coefficients on time dummies show that Chrysler and Ford seem to lose consideration rate over time; however, GM and Japanese manufacturers gain more consideration. The results on size/class effects and time trends may not readily generalize to the whole US population because the data pertain only to one geographic market.

## Purchase Feedback Mechanisms

One of main findings in this study is that the purchase of a particular manufacturer will increase (decrease) probability of considering the same (other) manufacturer at the next purchase occasion relative to first-time buyers. For instance, respondents who purchased Ford are more likely to consider Ford again and less likely to consider GM, Honda, Nissan, and Toyota than first-time buyers. All the own-effects (i.e., the impact on consideration of the same manufacturer) are positive and significant. Most of the significant cross-effects (i.e., the impact on consideration of the other) are negative. Some exceptions are the positive impacts of Honda or Toyota purchase on consideration of Nissan; the estimate of impact of Honda purchase on Toyota consideration is positive and significant at the .10 level.

To quantify these effects, the authors calculate marginal effect of prior purchase on consideration probability. Since the variables are qualitative, a change in probability of considering model  $j$  due to the purchase of manufacturer  $k$  is computed by:

$$\Pr(y_j = 1 | \text{purchase of manufacturer } k) - \Pr(y_j = 1 | \text{first-time buyer}),$$

where probability is assessed at the sample mean of the other covariates. Dummy variables for purchase of manufacturer  $k \neq j$  are set to zero. The authors calculate the difference in probability, multiplied by 100 to give interpretation of percent change, over the entire posterior draws and report the posterior mean effect in Table 4. All the own-effects of Japanese ownership are larger than those of Big 3: Honda has the strongest own effect of 53% point increment in consideration probability; Toyota and Nissan show 52% point increment. The strongest cross-effect is that of GM purchase on consideration of Ford, which is a 18% point reduction. Other stronger effects are as follows: Honda purchase reduces probability of considering Ford

and GM by 16% and 17% points, respectively; Toyota purchase decreases probability of considering GM by 16% points; and GM purchase diminishes chance of considering Honda by 14% points. In contrast, Honda and Toyota purchases increase consideration probability of Nissan by 7% and 9% points, respectively. Honda purchase boosts probability of considering Toyota by 9%, which is significant at the .10 level.

### **Correlations among Brand Preferences**

As pointed out, the statistical model does not pose probabilistic independence of consideration across alternatives. The residual  $\varepsilon$  captures the impact of unobserved factors on latent preference (and thus consideration) once intertemporal effect of prior purchase as well as other demographics are accounted for. Correlations among residuals relate to the inclusion or exclusion of correlated brands. The posterior mean of  $\Omega$  is displayed in Table 5. Most of the correlation estimates are negative. For instance, GM residuals are negatively correlated with all the others. One exception is a significantly positive one between Nissan and Ford. The other is relatively higher positive correlations among residuals of 3 Japanese. The correlation between Honda and Toyota preferences is especially strong at around .49. On balance, mostly negative correlations imply that consideration of autos at the manufacturer level is exclusive in terms of composition, except for Japanese makers, which seem to have relatively higher likelihood of being considered together than other combinations.

## **DISCUSSIONS**

### **Feedback from Prior Purchase**

The analyses so far document that the very last choice affects the formation of consideration set at the next purchase task. The negative cross-effects imply little variety seeking in consideration: likelihood of considering a different one than the last manufacturer purchased decreases relative to first-time buyers. Conversely, the positive own-effects translate into loyalty in consideration: likelihood of considering the same manufacturer last purchased increases relative to first-time buyers. Combined, these two purchase feedback mechanisms suggest that facing a new purchase situation, buyers build consideration around the manufacturer last chosen, thereby rendering it more likely to end up with the choice of the same manufacturer. In other words, last purchase triggers some sort of loyalty at the consideration phase, which precedes and transfer to loyalty to the manufacturer at the choice stage. Consideration and choice are intertwined and path-dependent: prior choice limits consideration, which sets the scope of the next choice, which in turn shapes the boundary for consideration. To the extent that these effects are central to consumer behavior of automobile consideration and choice, it is crucial for an auto maker to attract first-time buyers to its family models with aggressive marketing policies who will then reward it with ongoing loyalty (Sudhir, 2001).

### **Exclusivity in Consideration Set Composition**

While investigating context effects on consideration sets with the introduction of new products, Lehmann & Pan (1994) argued that alternatives positioned closely to each other would be easier to process (evaluate) and hence receive more consideration (attention) than those

positioned less closely to each other. Conversely, it is equally likely that a consumer chooses to have a portfolio of models that are reasonably dispersed in a perceptual space (attribute space) in order not to miss out on an alternative likely to have a high value of utility (Roberts & Lattin 1997). Table 2 revealed that buyers tended to consider only few manufacturers. The correlation estimates suggest that the 6 manufacturers are likely to form distinct branches of the market. These two findings combine to imply that automobile buyers in this study tend to achieve minimal dispersion in an attribute space of alternatives that are to be examined at the consideration stage. One may presume that a prospective buyer who seeks to purchase a particular class, say, SUV, confines attention to only, for instance, GM, and then proceeds to make a choice out of several brands and line-ups of the same affiliation (e.g., Buick Rendezvous, Chevy Suburban, or GMC Envoy), without also considering some SUVs from other manufacturers. Hence, to the extent that consideration is exclusive at the manufacturer level, it would be imperative for auto makers, in particular with weaker market presence, to invest more in communication programs in order to break into competitive clutters, because a necessary condition for sale is to be included into a consideration set. It should also be pointed out that feedback from prior purchase too contributes to the degree of exclusivity in consideration sets in a dynamic fashion, because the purchase of one manufacturer reduces chance of considering other manufacturers, thereby leading to a consideration set of smaller size over time.

## CONCLUSIONS AND LIMITATIONS

The present paper has investigated consideration of automobiles with self-reported measure of consideration sets. Recognizing the paucity of empirical research on the shape of consideration sets in the automobile category, this study attempted to produce substantive findings on consumer behavior of consideration for autos. The authors provided evidence for dynamic (inter-temporal) effect of prior purchase on consideration at the manufacturer level by documenting little variety seeking but ample loyalty at the consideration stage of purchase decision making process. It has also been presented a static snapshot of the shape of consideration set, which can be characterized by exclusive.

Unfortunately, the independent variables used for empirical analyses did not appear to capture much variation in consideration, as indicated by lower values of likelihood ratio index. It is, therefore, concerned that unobserved heterogeneity in preference for manufacturers might have compounded with the impacts of last purchase (i.e., state-dependency). Future research will benefit from a better way of controlling for heterogeneity across buyers (or acquiring richer information on preference) to refine estimates of the impact of prior purchase on consideration.

In a similar vein, future research need to obtain a more extensive set of consumer characteristics that include search ability and opportunity, the use of various information media, prior experience, expertise/knowledge, etc. With those variables, a statistical model must be more valuable in predicting consideration behavior. The current study has dealt with consideration of autos at the manufacturer level by aggregating purchases of different auto sizes/classes. Analyzing consideration within each size/class may yield knowledge of competitive interaction among models which can be readily translated into marketing actions. In that case, it would be desirable to decompose alternative-specific constant into a bundle of characteristics, which helps better understand impacts of engineering and styling aspects of autos on consideration behavior. Finally, the statistical model developed here is only descriptive. Policy experiments and normative inputs could be made with an econometric model derived



from a theoretical framework where a consumer's decision making problem in the forming of consideration set is explicitly defined.

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Table 1: Descriptive Statistics

Variable		Mean	(SD)
Consideration	Chrysler	.269	(.444)
	Ford	.400	(.490)
	GM	.593	(.491)
	Honda	.175	(.380)
	Nissan	.103	(.304)
	Toyota	.193	(.394)
Last Purchase	Chrysler	.152	(.360)
	Ford	.250	(.433)
	GM	.425	(.495)
	Honda	.043	(.204)
	Nissan	.039	(.194)
	Toyota	.045	(.208)
Demographics	First-time buyers	.044	
	Male	.547	(.498)
	Married	.694	(.461)
	Kids	.488	(.500)
	Employed	.752	(.432)
	Age≤30	.124	(.330)
	31≤Age≤40	.169	(.375)
	41≤Age≤50	.259	(.438)
	51≤Age≤60	.223	(.416)
	60<Age	.223	(.417)
	High School Education	.251	(.434)
	College Education	.494	(.500)
	Graduate Education	.248	(.432)
Income	7.917	(2.856)	
N		2440	

Sample mean or proportion is reported. Statistics on size/class dummies are suppressed to save space.

Table 2: Distribution of the Number of Manufacturer Considered

Number	Frequency	(Percent)
1	1237	(50.70)
2	735	(30.12)
3	367	(15.04)
4	85	(3.48)
5	15	(.61)
6	1	(.04)
Only the same manufacturer as the last car	921	(39.48)
No more than 2 manufacturers	1972	(80.82)
Mean	1.733 (SD=.888)	
N	2440	

Table 3: Impact of Consumer Characteristics on Consideration of Manufacturers

Variable	Chrysler	Ford	GM	Honda	Nissan	Toyota
Constant ( $\alpha$ )	<b>-0.463</b>	.112	<b>-0.436</b>	<b>-1.057</b>	<b>-1.593</b>	<b>-1.046</b>
<i>Demographics</i>						
Male	.094	-0.006	<b>.109</b>	-0.033	-0.008	<b>-.125</b>
Married	-.048	-0.007	.070	-0.040	-.139	.049
Kids	.046	.068	<b>.141</b>	-.075	-.077	.027
Employed	<b>.292</b>	-0.001	.041	-.135	.087	-.109
31≤Age≤40	.023	.064	-0.069	-.100	-.197	.047
41≤Age≤50	-.163	.060	-0.062	-.153	<b>-.221</b>	.078
51≤Age≤60	-.166	.019	-.117	<b>-.348</b>	<b>-.207</b>	-0.010
60<Age	-.087	-0.048	-0.047	<b>-.423</b>	<b>-.462</b>	-0.200
College Education	-.109	.102	.073	<b>.251</b>	<b>.179</b>	.131
Graduate Education	-.122	-0.019	<b>-.176</b>	<b>.560</b>	<b>.423</b>	<b>.558</b>
Income	-.011	<b>-.024</b>	-0.016	.022	.010	.006
<i>Last Purchase</i>						
Chrysler	<b>.999</b>	-0.052	.033	<b>-.330</b>	-0.001	<b>-.311</b>
Ford	<b>-.364</b>	<b>1.098</b>	-0.063	<b>-.513</b>	<b>-.331</b>	<b>-.450</b>
GM	<b>-.220</b>	<b>-.506</b>	<b>1.278</b>	<b>-.561</b>	-.206	<b>-.502</b>
Honda	-.246	<b>-.474</b>	<b>-.475</b>	<b>1.463</b>	<b>.360</b>	.261
Nissan	-.164	<b>-.268</b>	<b>-.340</b>	-0.014	<b>1.654</b>	.023
Toyota	-.082	<b>-.382</b>	<b>-.429</b>	.030	<b>.441</b>	<b>1.439</b>
<i>Auto Size/Class</i>						
Subcompact	<b>-.482</b>	-.143	<b>.275</b>	<b>.542</b>	.165	.102
Midsize	<b>-.411</b>	<b>-.253</b>	<b>.383</b>	.174	<b>.361</b>	.157
Minivan	<b>.707</b>	-0.033	<b>-.216</b>	<b>.409</b>	.082	.012
Small SUV	.147	<b>.218</b>	.143	<b>.424</b>	-.147	.135
SUV	-.002	.027	<b>.324</b>	.131	.110	-.145
<i>Year</i>						
Year 2002	.072	<b>-.182</b>	.052	-.099	-.023	.131
Year 2004	<b>-.148</b>	<b>-.426</b>	<b>.140</b>	<b>.275</b>	.167	<b>.258</b>
Year 2006	<b>-.306</b>	<b>-.293</b>	<b>.229</b>	<b>.200</b>	<b>.312</b>	<b>.471</b>
LRI1	.095	.028	.040	.083	.068	.069
LRI2	.110	.181	.186	.114	.140	.113
LRI3	.194	.204	.219	.188	.198	.174

Estimates in bold have at least 95% of their posterior mass away from zero.

Female, not married, no kids, unemployment, age less than 31, no college education, first-time buyers, other classes, and Year 2000 are not included and serve as the base categories for comparison.

LRI1 contrasts the model with all but last purchase relative to the model with intercept only.

LRI2 contrasts the model with all the covariates relative to the model without last purchase.

LRI3 contrasts the model with all the covariates relative to the model with intercept only.

Table 4: Marginal Effect on Consideration Probability

→ Last Purchase	Consideration					
	Chrysler	Ford	GM	Honda	Nissan	Toyota
Chrysler	<b>37.7</b> (4.4)	-2.0 (4.7)	1.3 (4.8)	<b>-9.0</b> (4.1)	-.2 (2.8)	<b>-8.8</b> (4.2)
Ford	<b>-10.3</b> (3.8)	<b>40.2</b> (4.3)	-2.5 (4.5)	<b>-12.9</b> (3.8)	<b>-4.2</b> (2.6)	<b>-12.0</b> (3.9)
GM	<b>-6.7</b> (3.7)	<b>-17.5</b> (4.3)	<b>42.7</b> (4.1)	<b>-13.8</b> (3.8)	-2.9 (2.5)	<b>-13.1</b> (3.8)
Honda	-7.1 (4.9)	<b>-16.4</b> (5.4)	<b>-17.4</b> (5.7)	<b>53.2</b> (5.6)	<b>6.9</b> (4.0)	8.9 (5.7)
Nissan	-4.9 (5.2)	<b>-9.7</b> (5.8)	<b>-12.8</b> (5.9)	-.4 (5.4)	<b>51.9</b> (5.7)	.8 (5.5)
Toyota	-2.5 (5.1)	<b>-13.5</b> (5.5)	<b>-15.9</b> (5.7)	.9 (5.2)	<b>8.9</b> (4.2)	<b>52.4</b> (5.5)

Estimates in bold have at least 95% of their posterior mass away from zero. Posterior standard deviations are given in parentheses.

Table 5: Estimated Correlation Matrix  $\Omega$ 

	Chrysler	Ford	GM	Honda	Nissan
Ford	.005 (.040)				
GM	<b>-.133</b> (.039)	<b>-.208</b> (.037)			
Honda	.071 (.046)	<b>-.228</b> (.041)	-.274 (.041)		
Nissan	<b>-.106</b> (.056)	<b>.113</b> (.051)	<b>-.108</b> (.050)	<b>.118</b> (.052)	
Toyota	-.009 (.045)	-.076 (.041)	<b>-.260</b> (.040)	<b>.492</b> (.037)	<b>.311</b> (.047)

Estimates in bold have at least 95% of their posterior mass away from zero. Posterior standard deviations are given in parentheses.

### Author Biographies

Jung Seek Kim is an associate professor of marketing in School of Business at Edinboro University of Pennsylvania. He received his Ph.D. in marketing from School of Management at the University of Texas at Dallas. His research interests lie in consumer information search, choice models, applied econometric modeling, and semiparametric Bayesian methods.

Brain T. Ratchford is Charles and Nancy Davidson Distinguished Professor of Marketing in School of Management at the University of Texas at Dallas. His research has been published in *Marketing Science*, *Management Science*, *Journal of Marketing Research*, *Journal of Consumer Research*, *Journal of Business*, *Journal of Retailing*, *International Journal of Research in Marketing*, *Journal of Interactive Marketing*, and *Managerial and Decision Economics*. He has served as the editor of *Marketing Science*.