Intermediate Media Effects

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Abstract

Media exposures can have effects that do not always lead to the immediate purchase of a brand. Some media are effective at initiating search and trial, while others are more effective at promoting purchase once search and trial have taken place. The idea of intermediate communication effects have long been posited in textbooks and academic literature, but their practical existence has not been shown in quantitative models. This paper proposes a hierarchical Bayesian model for identifying media response segments in cross-sectional data that differ in their likelihood of purchase, and shows that effects are obscured in aggregate analyses that attempt to directly relate media exposure to purchase. Data from a national brand-tracking study are used to illustrate our model, where we find large intermediate media effects.

Keywords: Hierarchical Bayes, structural heterogeneity, variable selection, mediation analysis

1. Introduction

Managers are often faced with the task of justifying advertising budgets across a variety of media such as television, radio, and direct mail. One reason for the presence of positive budget allocations to various media is the qualitatively distinct effects they have in the process of consumer decision making. A television ad, for example, may not be sufficiently persuasive to motivate prospects to make an immediate purchase. It could, however, prompt them to seek additional product information (e.g., Consumer Reports), which could then lead to purchase. In this case, the impact of the advertisement is mediated through an intervening action. Attempts to define advertising effectiveness as the direct link to purchase would understate its actual effect by overstating its role.

In the context of high involvement products, consumers are believed to follow a systematic, sequential process whereby they move from consideration to choice (Assael 1993). This process can be characterized as being structurally heterogeneous. That is, consumers at different stages of the buying decision differ in the type and degree to which marketing activities influence their behavior. Consider the case of individuals engaged in the process of buying a new car. When first entering the market, they may conduct an extensive information search to identify all available products and their corresponding attribute sets. At this point, they may place a high value on advertising that helps facilitate this information search (e.g. magazine advertisements, television). However, as preferences develop and a consideration set is formed, they may become increasingly sensitive to marketing actions that allow them to better distinguish among the products within that set. Media, such as direct mail, may exert a greater influence on their likelihood of purchase.

Firms often conduct periodic studies to measure the effects of various marketing variables on aspects of consumer choice, including media exposure and consumer purchase intentions. These studies are typically cross-sectional in nature and do not track specific individuals through time, making it difficult to investigate the effects of media at the individual-level. We propose a method that simultaneously pools respondent data into segments that differ in the likelihood of purchase and its association to intended intermediate actions and media exposure. We incorporate the technique of Bayesian variable selection (McCulloch and George 1993) in the model to help identify associations among the many variables typically present in these studies.

We apply our method to data from a national brand-tracking study for a luxury brand of automobile. We find that an aggregate analysis of the data reveals nearly no effect of media on purchase likelihood. In contrast, results from our model indicate that media effects are large and that associations change dramatically as the likelihood of purchase increases. Thus, we find evidence supporting a sequential decision process in which media effects are qualitatively distinct (i.e., not substitutable). Analysis that fails to account for the intermediate stages in a purchase decision is shown to under-estimate the effectiveness of media.

The remainder of the paper is organized as follows. Section 2 presents a Bayesian model for estimating media effects using a structurally heterogeneous likelihood with a prior specification that facilitates variable selection. A simulation study is presented in Section 3 to demonstrate key features of the proposed method. Section 4 describes the data used to investigate media effects, and results are presented in Section 5. Section 6 contains a discussion of the results, and Section 7 offers concluding remarks and discusses limitations of our analysis.

2. Model

Models of the consumer decision process are a fixture of modern marketing textbooks (Boone and Kurtz 2007; Kotler and Keller 2005; Blackwell, Engel, and Miniard 2001; Howard and Sheth 1969). Consumers are believed to move sequentially through several distinct stages of behavior beginning with the recognition of a need and terminating with choice and post-purchase evaluation. Advertising and consumer behavior textbooks are also replete with examples of models that relate advertising to consumer outcomes through a hierarchical or sequential process (e.g., Vakratsas and Ambler 1996; Assael 1993). The AIDA framework (E. St. Elmo Lewis 1898; Strong 1925) is one of the earliest and best known examples, where advertising impacts choice through a specific, sequential process: from attention to interest to desire to action. Lavidge and Steiner (1961) extend this process to include knowledge, liking, preference, conviction, and ultimately, purchase. Recent work has attempted to generalize these early advertising effects models by couching them in terms of cognition, affect, experience, and action (Vakratsas and Ambler 1999; Holbrook and Batra 1987). Although they differ in form, most models adhere to the general notion that consumers first learn, and then know, feel and do.

Process based models of consumer behavior and advertising are particularly important in the context of high-involvement goods and services where substantial, prolonged consideration occurs prior to purchase. An initial stage of information search is typically posited as a set of considered brands is formed, and then additional information is sought as preferences are developed, brands are ranked and choices are made. If consumers do engage in a staged decision process, it is likely that their sensitivities to advertising and other, experiential, activities differ according to their relative stage in that process.

The analysis of media effects in the presence of a staged decision process requires models that allow for response segments affected by different variables. Models that acknowledge the presence of response segments with different behavior patterns and associated variables are known as models with structural heterogeneity. Structural heterogeneity models have been used in marketing to study the order in which different consumers process attributes in purchasing grocery items (Kamakura, Kim and Lee 1996), the evaluation of credit card offers and its relationship to a consumer's current balance (Yang and Allenby 2000), and the presence of conjunctive versus disjunctive screening rules in conjoint analysis (Gilbride and Allenby 2004). Structural heterogeneity models employ a finite mixture of likelihoods, in contrast to standard heterogeneity models that assume one likelihood function is sufficient for describing all respondents.

Our model of intermediate media effects relates an intent-to-purchase measure (y) to a series of intended intermediate actions (x) and media exposure variables (z). The intermediate action variables describe aspects of the decision process used to identify the response segments:

$$y_i \mid x_i, \left\{ \phi_k, \beta_k, \sigma_k^2 \right\} \sim \sum_{k=1}^{K} \phi_k N\left(x_i' \beta_k, \sigma_k^2 \right) \quad (1)$$

where k is an index for the response segments with relative size ϕ_k and $\sum_k \phi_k = 1$. Equation (1) implies that an arbitrarily selected respondent belongs to one of K response segments, each of which is related to the intermediate actions through segment-specific regression coefficients β_k and error variance σ^2_k. Our model differs from a traditional finite mixture model (Kamakura and

Russell 1989) by allowing the error variance to be segment-specific. We illustrate the importance of this assumption in our simulation study below.

Equation (1) is used to identify the K response segments using a hierarchical Bayes model that augments the parameter space with latent indicator variables, s_i, used to simplify calculations (see Rossi, Allenby and McCulloch 2005 chapter 5). At each iteration of the Markov chain used to estimate the parameters in equation (1), latent indicator variables $\{s_i\}$ are drawn from multinomial distributions. These latent variables are used to assign each observation to a response segment k = 1,…, K. Given these indicator variables, the regression coefficients $\{\beta_k, \sigma_k^2\}$ are estimated using a series of independent models for each of K datasets A_k, k=1,…,K where $A = A_1 \cup A_2 \cup \ldots \cup A_K$ denotes the entire set of data. Details of the estimation procedure are provided in the appendix.

The media exposure variables (z) are related to intended intermediate action variables (x) through an auxiliary multivariate regression model for each response segment:

$$x_i \mid z_i, \Gamma_k, \Sigma_k, (s_i = k) \sim N(\Gamma_k z_i, \Sigma_k) \tag{2}$$

where the regression coefficients (Γ_k) and error covariance matrix (Σ_k) are segment-specific. Our model assumes that the response segments (k) are determined entirely by the relationship between intermediate actions (x) and purchase intention (y) in equation (1). Equation (2) is only used to characterize these segments. An advantage of this approach over one that uses both equation (1) and (2) to define the segments is that it does not require the presence of media effects (Γ) for a staged decision process to exist. Some media may be ineffective at driving some of the intermediate actions, and this lack of relationship (i.e., elements of Γ equal to zero) should not be used as a basis for identifying the latent segments. Instead, our approach identifies response segments and implied stages of a purchase decision through intended intermediate actions, and then identifies media that are associated with, and are assumed to drive, these actions.

Models that attempt to draw a direct relationship between media exposure and purchase likelihood can be seen to miss important relationships in the data by considering the partial derivatives of media exposure on purchase intention using equations (1) and (2):

$$\frac{\partial y}{\partial z_j} = \sum_{k=1}^{K} \sum_{r=1}^{R} \frac{\partial y}{\partial x_{rk}} \frac{\partial x_{rk}}{\partial z_j} = \sum_{k=1}^{K} \sum_{r=1}^{R} \beta_{kr} \gamma_{krj} \tag{3}$$

where r = 1,…,R indexes the elements of the intermediate action vector (x) and γ_{krj} is the (r,j) element of Γ_k. An immediate result from equation (3) is that specific elements of β_k and Γ_k both need to be non-zero for their product to be non-zero. Thus, attempting to explore a direct link between purchase intention (y) and media exposure (z) may result in a finding of no effect, even when media do affect some aspects of intermediate behavior (i.e., $\gamma_{krj} \neq 0$). Modeling the intermediate effect of media can potentially provide a much richer description of media effects.

The proposed model is highly parameterized due to the response segments (k) and the segment-specific coefficient matrices Γ_k, each of which are of dimension R × M where R is the number of intermediate action variables (i.e., dim(x)) and M is the number of different media (i.e., dim(z)). We deal with the issue of model dimensionality using Bayesian variable selection developed by George and McCulloch (1993) for univariate regression (equation 1) and by Brown et al. (1998) for multivariate regression (equation 2). Bayesian variable selection is implemented by assuming a prior distribution for the model coefficients that places mass close to zero, corresponding to the situation in which the variable is not selected. Thus, posterior estimates based on these priors are centered away from zero if the data provides fairly strong support of a non-zero effect. Otherwise, the posterior is centered near zero.

The prior distribution used in equation (1) is:

$$\pi\left(\beta_r \mid \kappa\right) = \left(1-\kappa\right) N\left(0, c^2\right) + \kappa N\left(0, d^2\right) \tag{4}$$

Thus, when $\kappa = 0$, the prior for β_r is described by $N\left(0, c^2\right)$, and when $\kappa = 1$, the prior is described by $N\left(0, d^2\right)$. By setting *c* small and *d* large, the prior is flat except for a spike in mass near zero. Posterior estimates based on this prior have the effect of shrinking small values of β to zero (the prior), and leaving larger values of β alone. As discussed by George and McCulloch (1993) we choose a value of c = 0.001 and d = 5.0 so that effect-sizes below 0.05 are shrunk to zero. The specification for the multivariate regression model follows Brown et al. (1998) and is discussed in more detail in the appendix.

3. Simulation Study

A simulation study is used to demonstrate the ability of our Bayesian estimation method to recover parameters from the finite mixture model in equation (1) using cross-sectional data. A problem with using predictive validation to establish the model is that segment membership for new observations are unknown. Moreover, the mathematical identity in equation (3) indicates that holdout predictions based on an aggregate model that does not consider intermediate effects will predict, on average, about the same as one that recognizes the presence of latent response segments. Since the latent segments are not observed, predictions based on equation (1) require integration over the finite mixture distribution. In contrast, models calibrated with panel data can use a few holdout observations per respondent to conduct predictive experiments conditional on respondent-specific parameters, including the latent assignment parameter s_k and regression coefficients β_k.

We show that inferences about the latent parameters in the normal mixture model (Equation 1) can be successfully conducted using two simulation studies. In the first study we assess the performance of our estimator versus an aggregate model when data are generated by a model with no latent segment structure. In the second study we investigate our ability to successfully determine the number of latent segments and segment-specific parameters.

For the first study, 1000 observations were generated according to a homogeneous linear regression model $y_i = x_i'\beta + \varepsilon_i$ with $\varepsilon_i \sim N(0,1)$ and analyzed using a standard Bayesian regression model with diffuse priors, and our normal mixture model with two latent segments. Results are presented in Table 1 and include estimates of the posterior mean, posterior standard deviation (in parenthesis), and a 95% credible interval (in brackets).

[Table 1]

Results indicate that both methods are able to successfully recover the true simulation parameters. The normal mixture model estimation routine is able to recognize the absence of heterogeneous segments in the population and successfully shut down draws from one of the two mixing distributions. This is illustrated by the trace plots presented in figure 1. The vertical axis displays the values of the segment size parameters ϕ across iterations of the Markov chain used for parameter estimation described in the appendix. After an initial burn-in period, the estimated size of one of the latent distributions goes to zero while the weight for the other converges to one. Thus, the estimation procedure is sensitive to absence of latent segments, and will find just one segment in data generated with K = 1.

[Figure 1]

The second simulation study generated 1000 observations using equation (1) with three latent segments (K = 3). Parameter estimates with their corresponding true values are presented in Table 2. Given the linear nature of the model described above, the parameter estimates using a standard regression model are a convex combination of parameter estimates for the normal mixture model, reflecting the marginal effect of x on y. Estimates based on the normal mixture model correctly identify the existence of the three segments, and successfully recover the true parameters.

[Table 2]

Figure 2 illustrates the ability of the Bayesian estimation procedure to successfully identify the number of latent mixing distributions when we incorrectly assume that four latent segments are present (K = 4). As illustrated by the trace plot in figure 2, the procedure correctly shuts down one of the series. In the analysis reported below, we employ an approach where we over-specify the number of latent segments in the data, and let the estimation routine shut down redundant segments by estimating small segment weights (i.e., $\phi_k = 0$) where appropriate.

[Figure 2]

Finally, Table 3 illustrates the results by allowing a common error variance across segments, which results in a finite mixture model. Here, we estimate a common variance (σ^2 = 1.8) across all segments and demonstrate this to be problematic, as illustrated in the results. This assumption leads to incorrect segment weights and parameter estimates (2 of 3 segment weights and 6 of 15 parameters converge to wrong values). Table 3 provides the posterior mean, standard deviation and 95% credible intervals for all the parameters. Entries in bold indicate the presence of the simulated true value in the 95% credible interval of the parameter estimates. Thus, the assumption of common error variance across segments needs to be relaxed to correctly identify the segments and parameter values.

[Table 3]

4. Data

We investigate the presence of intermediate media effects using data from a national brand-tracking study of a leading luxury automobile. Study participants completed an extensive questionnaire designed to elicit their attitudes and opinions toward the focal brand, their likelihood of purchasing a vehicle (y), intended intermediate actions (x) such as taking a test drive in the next six months, and their exposure to the focal brand through a variety of distinct media sources (z) such as television, radio, Internet and direct mail. A total of 6178 observations were available for analysis.

Descriptive statistics for the data are reported in Table 4. Likelihood of purchase (y) and intermediate action (x) variables were collected on an eleven point scale, with zero indicating "not at all," and ten indicating "extreme" likelihood of purchase or action within the next six months. Media exposure variables (z) were self-reported recall measures of the number of exposures to the brand via the indicated media during the prior six months. The summary statistics reported in Table 4 suggest there is sufficient variation in the data for analysis. In addition, the data contain a broad set of media variables under partial control of management.

The goal of our analysis is to determine the effect of these media on intended actions and purchase likelihood.

[Table 4]

5. Results

We begin analysis using an aggregate model that assumes one response segment (K = 1) and then compare estimates to a model with multiple segments (K > 1). Table 5 reports coefficient estimates for the one segment model in which intended actions (x) and media exposure (z) are directly related to likelihood of purchase. The left side of Table 5 is for the model of purchase intention regressed on intended actions alone (i.e., y | x), and the right side of the table is for the model that includes the media variables (i.e., y | x, z). Reported are posterior means, standard deviations, and the 95% credible interval. Entries in bold correspond to variables with at least 95% of their posterior mass centered away from zero.

[Table 5]

The results indicate a fairly strong relationship between intended actions and purchase likelihood, but that the media variables add little to improve model fit. The media coefficients are estimated to be small in magnitude, with almost all estimates being near zero (except for "Contact with Dealer Sales Rep"). We find that the Bayesian measure of model fit, the log marginal density, improves slightly from -13,990 to -13,983, and the R^2 measure does not change measurably with the inclusion of the media variables.

Table 6 reports parameter estimates for the normal mixture model in equation 1, which improves the log marginal density from -13,983 to -13,924. We find support for four latent segments of respondents (K = 4). We find at least one intermediate action variable to be associated with each of the segments, and that the magnitude of the coefficients to be much larger than that reported for the model with K = 1. We also find differences in the variance of the error terms, σ^2_k, for each of the segments, justifying the need for the proposed model relative to simpler specifications such as a finite mixture model. Finally, we report the average value of purchase intention for each segment at the bottom of the table. This statistic is computed across iterations of the Markov chain: at each iteration, the latent indicator variables $\{s_i\}$ are used to classify observations to the latent segments and the average purchase intention (y) is calculated. The latent segments are ordered in the table so that segment 1 has the smallest average purchase intention, and segment 4 has the largest. A more detailed examination of the results is offered in the discussion section below.

[Table 6]

Figure 3 displays the trace plot of the draws of weights, ϕ_k, k=1 ,…, 4. These plots indicate that the Markov chain used to estimate the parameters converges quickly to the posterior distribution, and that initial conditions are quickly dissipated in this model.

[Figure 3]

Table 7 reports parameter estimates for the auxiliary regression of the intended intermediate actions (x) on media exposure (z). Displayed are results for the second segment, k = 2. In contrast to the parameter estimates in the aggregate model (K = 1), we find much larger coefficient estimates. Consider, for example, the effect of a brochure on the intermediate actions. The brochure coefficients are found to have a large effect on the intended actions, with an increase of just one exposure associated with an increase on the intention scale of approximately 0.50 for all actions. Thus, we find that the effects of media on intended intermediate actions are larger than their direct effects on purchase likelihood. As illustrated in equation (3), direct effects can be masked in the presence of intermediate effects. Coefficient estimates for other auxiliary regressions, i.e., Γ_k, are not reported but are available from the authors.

[Table 7]

Finally, Table 8 reports average values of brand beliefs about the brand for each of the four segments. These averages were calculated at each iteration of the Markov chain using the latent assignment variables $\{s_i\}$, and then averaged over the iterations of the chain. The segments are found to be unassociated with respondent beliefs about the brand and their overall impression. Similar results are found (but not reported) for a variety of other variables in the survey such as demographic descriptors. The results reported in Table 8 indicate that commonly collected variables in brand-tracking studies are not capable of identifying the latent response segments.

[Table 8]

6. Discussion

Our analysis indicates that the effect of media (z) on purchase intention (y) is moderated by a set of intended intermediate actions (x) that can be used to describe stages of a purchase decision. We find large effect-sizes of media on intended actions, and intended actions on purchase likelihood, once we control for heterogeneous response segments. Our analysis indicates that it is useful to study media effects for each of the response segments separately.

Table 9 provides a breakdown of media effects by response segment. As illustrated in equation (3), a zero effect-size between an intended action and purchase intention (i.e., $\beta = 0$) will zero out any effect of media on purchase intention, regardless of its effect on intended action (i.e., γ). We therefore present results for each segment separately, and only include those effect-sizes for which we find a nonzero relationship between purchase intention and intended intermediate action (i.e., $\beta = \partial y/\partial x > 0$ and $\gamma = \partial x/\partial z > 0$). The top of Table 9 displays the effect-sizes for segment 1, followed by segments 2 and 3, and the effect-sizes for segment 4 appears at the bottom of the table. Three effect-sizes are reported on the right side of the table: $\partial y/\partial x$, $\partial x/\partial z$ and the combined effect of $\partial y/\partial z$. These effects are computed at each iteration of the Markov chain, and then averaged over the iterations to integrate out the probabilistic assignment of observations to segments. As discussed earlier, the segments are ordered in terms of their average value of purchase likelihood.

[Table 9]

Respondents with a high likelihood of belonging to segment 1 are identified as having a strong association between purchase intention and the intended action of going to the dealer. They report having the lowest values of purchase intention, averaging just 0.40 on the eleven-point scale, indicating little chance of making a purchase in the next six months. Variation in this intended action across segment members is positively associated with the number of times they report being exposed to a brochure for the automobile, and the number of times they received a recommendation. We note that for this segment, and all segments, the overall and intermediate effect-sizes are large compared to the aggregate effect-sizes reported in Table 5.

Respondents in segment 2 have a higher likelihood of purchase, and are identified as having a strong association between purchase intention and the intent to seek information directly, which in turn is influenced by a variety of media vehicles including direct mail, brochures, taking a test-drive, recommendations and independent articles. Respondents in the second segment are therefore broader in their information search as compared to the first segment, and do not rely entirely on the dealer for information.

Respondents in segment 3 have a relatively high average likelihood of purchase, and are characterized by their specific purchase likelihoods and intentions to go to the dealer and read their mail. Individuals in this segment are influenced by calls from the dealer and the dealer website. In addition, the intent to go to the dealer is also influenced by exposures to the manufacturer's brand website, while the intent to read mail is also influenced by magazine advertisements. Thus, an increase in magazine exposures is associated with a greater intent to read mail in the next six months, and this intended action is associated with higher purchase intentions. We note that the error variance for this segment is estimated to be large ($\hat{\sigma}^2 = 2.6$), as reported in Table 6. Models that assume a constant variance across segments (i.e., a finite mixture model) would not capture these empirical results.

Respondents in segment 4 have the highest average likelihood of purchase of 6.2, and are associated with the intended action of making a recommendation to a friend in the next six months. This intent to make a recommendation is associated with the quantity of media exposure through four vehicles: direct mail, brochure, the brand website and recommendation that have been made to them. We find that these respondents are less sensitive to media that provide product information (e.g., independent articles, television advertising, etc.) than, for example, respondents in the first segment. Rather, they appear to have already formed preferences and, as such, are impacted by marketing communication that helps facilitate the actual transaction. The only consumer action they can take that would increase their likelihood of purchase is to recommend the vehicle to a friend, thereby increasing their commitment to the same.

In general, we find the effect-sizes to be largest for individuals with low purchase intentions (i.e., segments 1 and 2). As purchase intention increases, media effect-sizes are seen to decrease in magnitude. Thus, it is plausible that an aggregate analysis of attempt to measure the direct effect of media exposure on purchase intention misses important associations early in the process of decision making.

7. Conclusion

This paper presents evidence of intermediate media effects using a hierarchical Bayes model for cross-sectional data. The model employs a mixture of likelihoods pertaining to latent segments of individuals that are structurally distinct and related to a set of intended action variables. Media variables are associated with these segments in an auxiliary specification. We deal with the high dimension of variables using Bayesian variable selection, and we find evidence of large effect-sizes that are segment-specific. We associate the latent segments with phases of a purchase decision using the average value of each segment's intent to purchase. We find that media effects are largest in segments with relatively low purchase intention and smallest in segments with high purchase intention. The low purchase intention segment comprises individuals who have not yet made up their minds to purchase, and are found to be highly influenced by media exposure. Moreover, we find that an aggregate analysis that directly relates media exposure to purchase likelihood shows effect-sizes to be near zero.

The existence of differentiated media effects is discussed widely in marketing and advertising textbooks. There is a long history of extended models of behavior in marketing, beginning with motivating conditions, moving to desired attributes and benefits, and ending with a purchase in the marketplace. Our model facilitates analysis across these components with the introduction of latent segments of respondents with qualitatively different responses. In contrast to numerous published articles that point to ineffective effects and the lack of a hierarchical decision structure (e.g., Weilbacher 2001; Vakratsas and Ambler 1999; Palda 1966), our analysis finds empirical support for the presence of a multi-staged purchase process for a high-involvement product.

There are a number of limitations of our research that need to be acknowledged. First, our analysis is based on cross-sectional data that is commonly encountered in brand-tracking studies. Because we do not track specific respondents through time, we cannot concretely establish the existence of a multi-staged process with our data. Our results are correlational in nature, and while we find evidence in support of a staged decision process, our analysis does not offer conclusive proof of its existence. Second, our results may be dependent on the specific product category for which we have data. Additional analysis using our model is needed to establish similar results in other categories. Finally, our analysis cannot make statements about the duration and movement of respondents across the latent segments. We leave these issues for future research.

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Appendix

The empirical application discussed in this article is a cross-sectional dataset with i = 1, …, 6178 consumers. There are R = 1, ..., 6 intended consumer action variables (x) and M = 1, ..., 18 media exposure variables (z). Let K denote the number of latent segments present in the data. Let ϕ_k denote the weights associated with each of the K latent segments and s_i denote the underlying latent indicator variable. The following steps describe the Gibbs sampler used to obtain the estimates of the model parameters, for a more detailed discussion of the different components refer to, Richardson and Green (1997), George and McCulloch (1993) and Brown et al. (1998).

1) Generate ϕ

The segment weights ϕ have a Dirichlet distribution with prior parameters $\rho_1, \ldots, \rho_K$:

$$[\phi_k \mid s_i, k] \sim D(\rho_1 + n_1, \rho_2 + n_2, \ldots, \rho_K + n_K)$$

where, $n_k = \#\{i : s_i = k\}$ is the number of subjects assigned to group k. In our analysis we set $\rho_1 = \rho_1 = \ldots = \rho_K = 2$, given the large sample size for the data used, this prior specification results in a very mild influence on the posterior.

2) Generate β_k , σ_k^2

The segment specific parameters for each of the k = 1, …, K segments are estimated using Bayesian variable selection procedure suggested by George and McCulloch (1993, 1997). Variable selection is accomplished using the R × R matrix, D_{τ_k} , formed as diag[τ_k]. Here, τ_k is a vector of length equal to j = 1…R (number of covariates (x)) and $\tau_{kj} \in$ {c, d}, where c is a small constant and d is a large constant, we set c = 0.001 and d = 5. When τ_{kj} = c, the prior on β_{kj} is concentrated around 0, and when τ_{kj} = d, a diffuse prior is used on β_{kj}, pertaining to exclusion and inclusion of predictor j respectively from the final model.

The full conditionals for β_k, σ_k^2 and τ_k for each of the K segments, are given below.

i) $$[\beta_k \mid \tau_k, \sigma_k^2, y, X] \sim Normal\left(\left[\sigma_k^{-2} X'X + \left(D_{\tau_k} I D_{\tau_k}\right)^{-1}\right]^{-1} \sigma_k^{-2} X'y, \; \left[\sigma_k^{-2} X'X + \left(D_{\tau_k} I D_{\tau_k}\right)^{-1}\right]^{-1} \right)$$

ii) $$[\sigma_k^2 \mid \beta_k, y, X] \sim Inverted\,Gamma\left(\frac{\upsilon + n_k}{2}, \frac{|y - X'\beta_k|^2 + \upsilon\psi}{2} \right)$$

iii) $[\tau_{kj} \mid \beta_k, \tau_{-kj}] = \Pr(\tau_{kj} = d)$, is Bernoulli with probability

$$\frac{[\beta_k \mid \tau_{kj} = d]}{[\beta_k \mid \tau_{kj} = d] + [\beta_k \mid \tau_{kj} = c]}$$

the above expression involves evaluation of multivariate normal densities. For further details refer to George and McCulloch (1993) and Gilbride et al. (2006).

3) Generate Γ_k

The segment specific parameters Γ_k for each of the k = 1, …, K segments are estimated using Bayesian multivariate variable selection procedure suggested by Brown et al. (1998), which is an extension of the univariate regression procedure of George and McCulloch (1993, 1997). With n_k observations x_i (R × 1) conditional on z_i (M × 1) we have a generalized multivariate regression model. The parameters to be estimated are Γ_k which is of dimensionality (R × M) and the variance-covariance matrix Σ_k. The prior distribution for Γ_k and Σ_k can be written as $[\Gamma_k \mid \Sigma_k][\Sigma_k]$.

Multivariate variable selection is accomplished using a latent binary R-vector λ. The j^{th} element of λ, λ_j is either a 0 or a 1. A 0 implies that the covariance matrix of the corresponding row of Γ_k is very small and 1 implies that it is large, pertaining to the exclusion or inclusion of predictor j respectively.

We use prior distributions as proposed in Brown et al. (1998):

$$[\Sigma_k] \sim \textit{Inverted Wishart}(\Omega_0, V)$$

$$[\Gamma_k | \Sigma_k] \sim N(D_\lambda C_\lambda D_\lambda, \Sigma_k)$$

Here D_λ is diagonal matrix and C_λ is a correlation matrix, the j^{th} element of D_λ^2 is either m_{0j}, a small constant, when $\lambda_j = 0$ or m_{1j}, a large constant, when $\lambda_j = 1$. George and McCulloch (1997) provide further discussion on the different choices of m_{0j}, m_{1j} and C_λ. We set $m_{0j} = 0.001$ and $m_{1j} = 5$ for our analysis and C_λ as the identity matrix.

An efficient algorithm for sampling from a multivariate regression can be carried out using the procedure suggested in Rossi, Allenby and McCulloch 2005 (chapter 2).

$$[\Gamma_k | \lambda_j, \Sigma_k, X, Z] \sim \textit{Normal}(\tilde{\gamma}_k, \Sigma_k \otimes (Z'Z + \Lambda_k)^{-1})$$

i) $\tilde{\gamma}_k = vec(\tilde{\Gamma}_k)$, $\tilde{\Gamma}_k = (Z'Z + \Lambda_k)^{-1}(Z'Z\hat{\Gamma}_k + \Lambda_k \bar{\Gamma}_k)$,

$\hat{\Gamma}_k = (Z'Z)^{-1} Z'X$, $\Lambda_k = D_\lambda C_\lambda D_\lambda$

ii) $[\Sigma^k | \Gamma_k, X, Z, S] \sim \textit{Inverted Wishart}(\Omega_0 + n_k, V_0 + S)$

$S = (X - Z\tilde{\Gamma}_k)'(X - Z\tilde{\Gamma}_k) + (\tilde{\Gamma}_k - \bar{\Gamma}_k)'\Lambda_k(\tilde{\Gamma}_k - \bar{\Gamma}_k)$

iii) $[\lambda_{kj} | \Gamma_k, \lambda_{-kj}]$, the prior on λ_k is multivariate Bernoulli with probability similar to that given in the univariate case and involves evaluation of multivariate normal densities.

4) Generate s_i

The multinomial probabilities for the latent variable s_i, where $s_i = k$ if subject i belongs to segment k (for k = 1, …, K) is given by:

$$p(s_i = k \mid \phi_k, \sigma_k, \beta_k, y_i, x_i) \propto \frac{\phi_k}{\sigma_k} \exp\left(-\frac{(y_i - x_i \beta_k)^2}{\sigma_k^2} \right)$$

Figure 1
Trace Plot of Segment Weights for Regression Model
(Simulate Data)

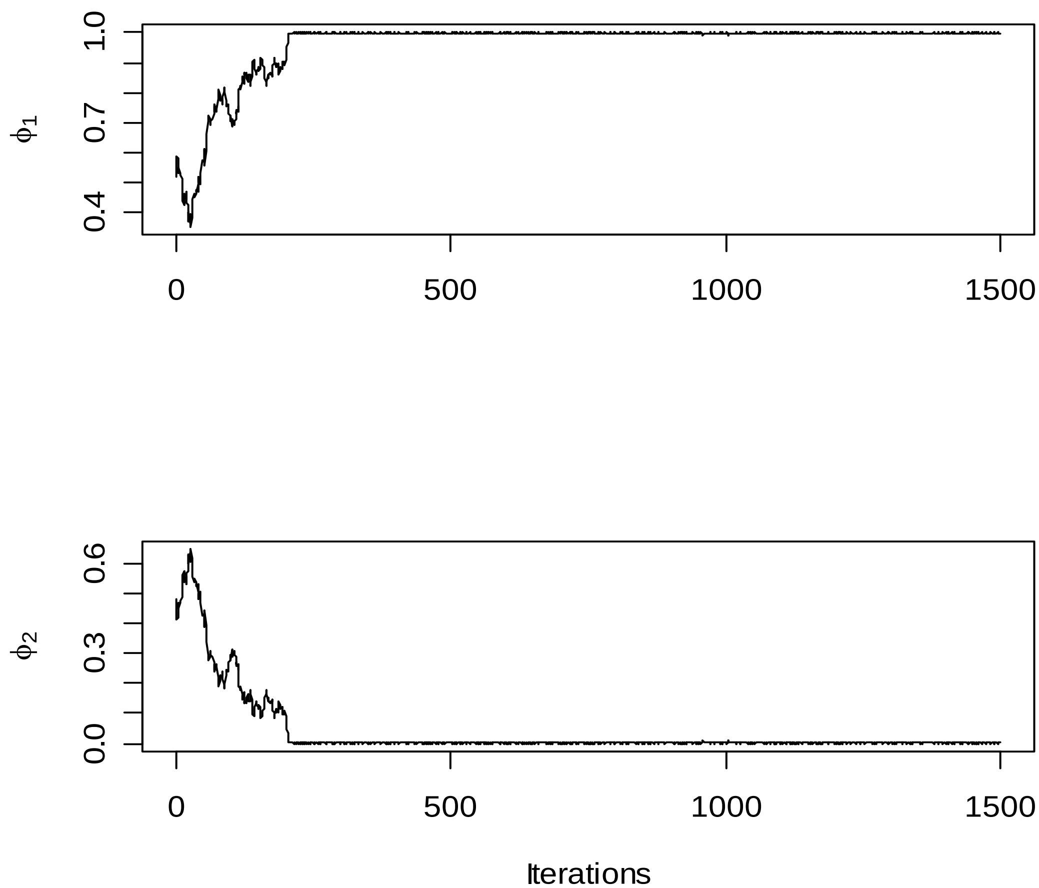

Figure 2
Trace Plot of Segment Weights for a Three-Component Mixture Model with K = 4
(Simulated Data)

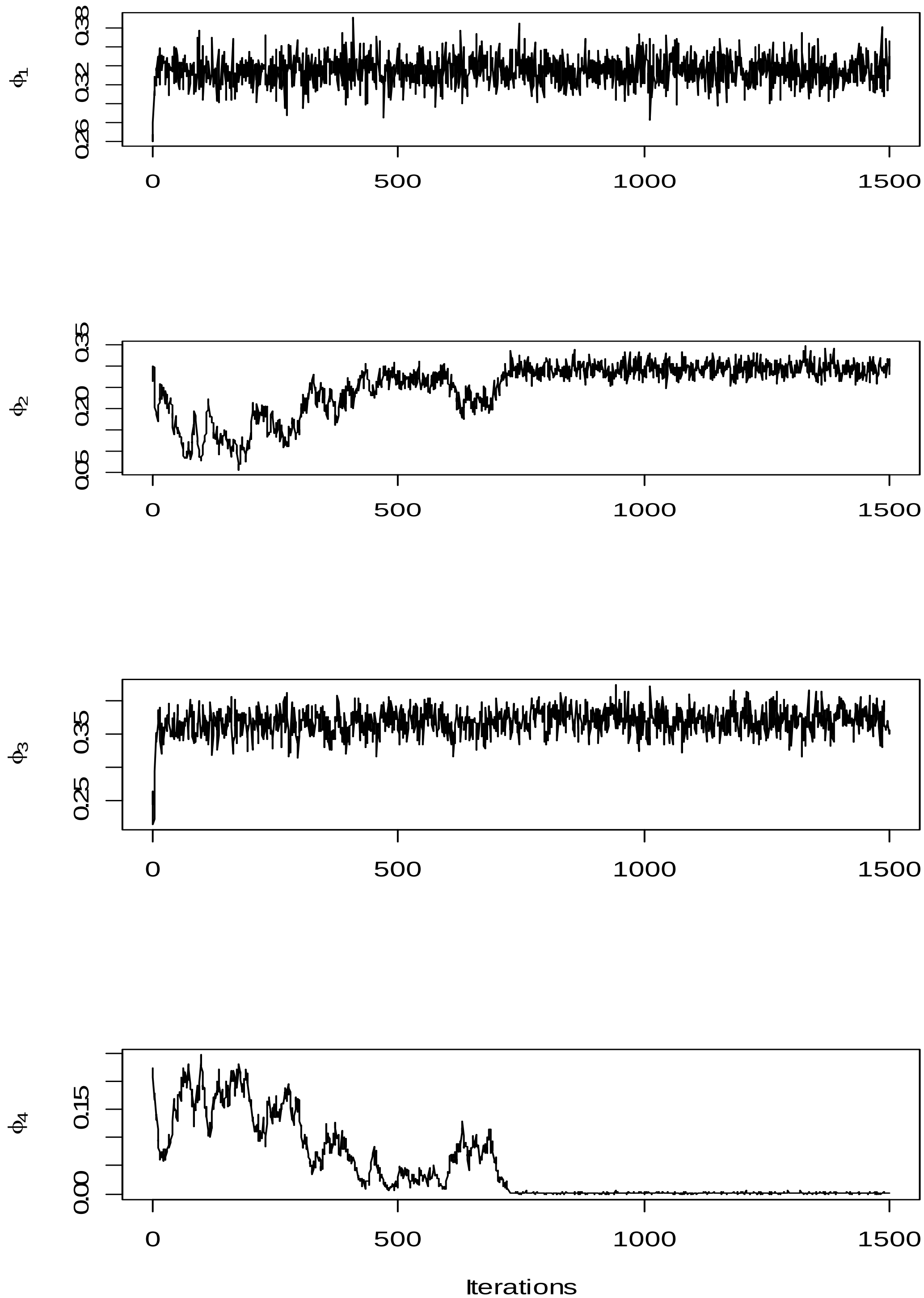

Figure 3
Trace Plot of Segment Weights for Automobile Data with K = 4

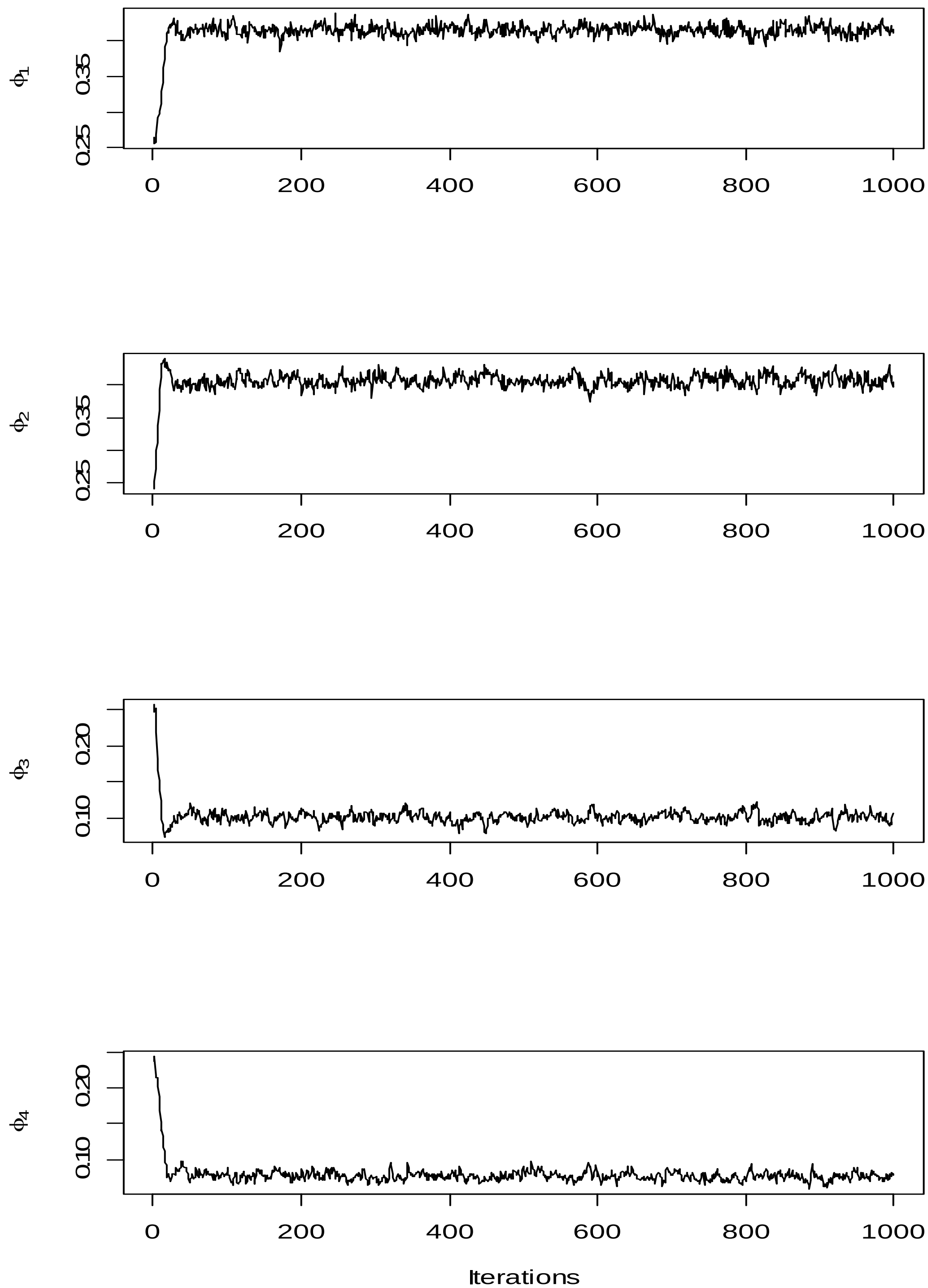

Table 1
Coefficient Estimates for Regression Model
(Simulated Data)

Variable	Regression $y = X\beta + \varepsilon$	Normal Mixture Model (K = 2)	
		Segment 1	Segment 2
X0	**0.67** (0.12) [0.44, 0.90] True Val: **0.80**	**0.67** (0.13) [0.41, 0.94]	0.00
X1	**2.52** (0.03) [2.47, 2.58] True Val: **2.50**	**2.52** (0.03) [2.46, 2.58]	0.00
X2	**1.80** (0.02) [1.76, 1.85] True Val: **1.80**	**1.80** (0.03) [1.75, 1.85]	0.00
X3	**0.39** (0.08) [0.24, 0.54] True Val: **0.40**	**0.38** (0.09) [0.21, 0.55]	0.00
X4	**2.72** (0.01) [2.69, 2.74] True Val: **2.7**	**2.72** (0.01) [2.69, 2.75]	0.00
Sigma	1.05 (0.10) [0.78, 1.12] True Val: 1.0	1.1 (0.11) [0.79, 1.23]	0.0
Weights	n/a	1.0	0.0

Parameter estimates are the posterior means, posterior standard deviation (in parenthesis) and 95% credible interval (in brackets).

Table 2
Coefficient Estimates for Normal Mixture Model
(Simulated Data)

Variable	Regression $y = X\beta + \varepsilon$	Normal Mixture Model (K = 3)		
		Segment 1	Segment 2	Segment 3
X0	1.35 (1.00) [-0.63, 3.31]	**2.69** (0.42) [1.86, 3.51] True Val: **2.6**	**1.67** (0.34) [1.00, 2.30] True Val: **1.3**	**0.19** (0.26) [-0.31, 0.71] True Val: **0.4**
X1	1.43 (0.24) [0.96, 1.91]	**3.46** (0.10) [3.27, 3.66] True Val: **3.5**	**0.33** (0.08) [0.16, 0.49] True Val: **0.4**	**0.80** (0.06) [0.69, 0.92] True Val: **0.8**
X2	2.75 (0.19) [2.38, 3.11]	**4.31** (0.08) [4.16, 4.45] True Val: **4.3**	**1.83** (0.06) [1.71, 1.95] True Val: **1.9**	**1.54** (0.05) [1.44, 1.64] True Val: **1.5**
X3	2.31 (0.65) [1.05, 3.58]	**1.76** (0.27) [1.23, 2.29] True Val: **1.8**	**1.96** (0.20) [1.57, 2.34] True Val: **2.2**	**2.13** (0.17) [1.79, 2.46] True Val: **2.0**
X4	2.12 (0.12) [1.88, 2.36]	**2.68** (0.05) [2.58, 2.77] True Val: **2.7**	**1.32** (0.04) [1.25, 1.40] True Val: **1.3**	**2.50** (0.03) [2.43, 2.56] True Val: **2.5**
Sigma	8.72 (0.2) [8.43, 9.03]	**2.06** (0.08) [1.91, 2.21] True Val: 2.0	**1.35** (0.06) [1.23, 1.47] True Val: 1.45	**1.25** (0.05) [1.16, 1.35] True Val: 1.20
Weights	n/a	0.34 (0.01) [0.31, 0.36] True Val: 0.34	0.29 (0.02) [0.26, 0.33] True Val: 0.33	0.37 (0.02) [0.34, 0.40] True Val: 0.34

Parameter estimates are the posterior means, posterior standard deviation (in parenthesis) and 95% credible interval (in brackets).

Table 3
Coefficient Estimates using Finite Mixture Model
(Simulated Data)

Variable	Fixed Variance Model (K = 3)		
	Segment 1	Segment 2	Segment 3
X0	**2.56** (0.36) [1.82, 3.24] True Val: 2.6	**1.66** (0.57) [0.57, 2.82] True Val: 1.3	0.23 (0.36) [-0.50, 0.91] True Val: 0.4
X1	**3.54** (0.09) [3.36, 3.72] True Val: 3.5	0.79 (0.14) [0.52, 1.05] True Val: 0.4	0.42 (0.09) [0.24, 0.59] True Val: 0.8
X2	**4.31** (0.07) [4.17, 4.45] True Val: 4.3	**1.72** (0.07) [1.52, 1.93] True Val: 1.9	1.87 (0.07) [1.73, 2.01] True Val: 1.5
X3	**1.66** (0.24) [1.20, 2.13] True Val: 1.8	**1.85** (0.38) [1.17, 2.53] True Val: 2.2	**2.25** (0.22) [1.81, 2.67] True Val: 2.0
X4	**2.72** (0.04) [2.63, 2.80] True Val: 2.7	2.15 (0.07) [2.01, 2.28] True Val: 1.3	1.42 (0.04) [1.34, 1.49] True Val: 2.5
Weights	**0.32** (0.02) [0.29, 0.39] True Val: 0.34	0.23 (0.03) [0.17, 0.28] True Val: 0.33	0.44 (0.03) [0.39, 0.48] True Val: 0.34

Parameter estimates are the posterior means, posterior standard deviation (in parenthesis) and 95% credible interval (in brackets).

Table 4
Descriptive Statistics for Automobile Data
(N = 6178)

Variable	Mean	Std. deviation
Dependent variable (y)*		
Likelihood of purchase	3.10	3.44
Intermediate Variables (x)*		
Go to a retailer	2.26	3.20
Seek info directly	2.58	3.33
Seek info from objective Source	2.66	3.36
Recommend to a Friend	3.48	3.68
Read mail	4.36	3.79
Take a test Drive	2.32	3.21
Media Exposure Variables (z)		
Magazine Advertisement	3.65	6.25
News Advertisement	3.81	8.70
Radio Advertisement	3.80	12.24
Television Advertisement	7.15	12.65
Sponsor Advertisement	0.69	2.53
Internet Advertisement	0.86	3.96
Direct Mailing	0.35	1.69
Brochure	0.44	2.03
Focal Brand's Website	0.45	2.43
Test-drive at Dealership	0.12	0.91
Contact with Dealer Sales Rep	0.16	0.82
Call from Dealership	0.08	0.70
Dealership Website	0.23	1.16
Demonstration from Associate	0.43	2.83
Recommendation from Associate	0.62	3.32
Independently published article	0.71	2.33
Independent Website	0.40	2.43
Display in Public Place	1.32	5.05

* y and x variables measured on a 0-10 scale

Table 5
Regression Coefficient Estimates
Automobile Data

Variables (Dependent variable y: Likelihood of purchase)	Estimates (y | x)		Estimates (y | x, z)	
Intermediate Variables (x)	Posterior Mean (std. dev.)	95% Credible Interval	Posterior Mean (std. dev.)	95% Credible Interval
Go to a retailer	**0.29** (0.02)	[0.24, 0.33]	**0.27** (0.02)	[0.22, 0.32]
Seek info directly	**0.16** (0.02)	[0.11, 0.21]	**0.16** (0.02)	[0.11, 0.20]
Seek info from objective Source	0.03 (0.02)	[-0.02, 0.07]	0.02 (0.02)	[-0.02, 0.06]
Recommend to a Friend	**0.20** (0.01)	[0.17, 0.22]	**0.19** (0.01)	[0.17, 0.22]
Read mail	**0.14** (0.01)	[0.12, 0.17]	**0.14** (0.01)	[0.12, 0.16]
Take a test Drive	0.01 (0.02)	[-0.04, 0.05]	0.02 (0.02)	[-0.03, 0.06]
Media Exposure Variables (z)				
Magazine Advertisement			0.0 (0.01)	[-0.01, 0.01]
News Advertisement			0.01(0.00)	[0.00, 0.02]
Radio Advertisement			0.0 (0.00)	[0.00, 0.01]
Television Advertisement			0.01 (0.00)	[0.00, 0.01]
Sponsor Advertisement			-0.01 (0.01)	[-0.04, 0.02]
Internet Advertisement			0.00 (0.01)	[-0.02, 0.02]
Direct Mailing			0.04 (0.03)	[-0.01, 0.10]
Brochure			-0.03 (0.02)	[-0.08, 0.02]
Focal Brand's Website			0.02 (0.02)	[-0.02, 0.05]
Test-drive at Dealership			0.03 (0.05)	[-0.06, 0.12]
Contact with Dealer Sales Rep			**0.20** (0.05)	[0.10, 0.30]
Call from Dealership			0.00 (0.05)	[-0.10, 0.10]
Dealership Website			-0.04 (0.03)	[-0.10, 0.02]
Demonstration from Associate			0.01 (0.01)	[-0.02, 0.03]
Recommendation from Associate			0.01 (0.01)	[-0.01, 0.03]
Independently published article			0.02 (0.02)	[-0.01, 0.05]
Independent Website			0.01 (0.02)	[-0.02, 0.04]
Display in Public Place			0.00 (0.01)	[-0.01, 0.02]
Intercept	0.63 (0.05)	[0.54, 0.72]	0.57 (0.05)	[0.48, 0.66]
Sigma	5.76 (0.11)		5.4 (0.10)	
Model Fit (R^2)	0.54		0.54	
Log Marginal Density	-13990		-13983	

Table 6
Normal Mixture Model Estimates with K = 4
Automobile Data

Variable	Segment 1	Segment 2	Segment 3	Segment 4
Go to a Dealer	**0.89** (0.04) [0.82, 0.98]	0.00 (0.01) [-0.01, 0.01]	**0.11** (0.05) [0.02, 0.19]	0.02 (0.03) [-0.03, 0.08]
Seek info directly	0.04 (0.03) -0.01 0.09	**1.00** (0.01) [0.99, 1.01]	-0.01 0.05 [-0.10, 0.08]	-0.01 (0.03) [-0.07, 0.05]
Seek info from obj. source	-0.01 (0.03) [-0.06, 0.04]	0.00 (0.00) [-0.01, 0.01]	0.06 (0.04) [-0.03, 0.14]	-0.01 (0.03) [-0.08, 0.06]
Recommend to a Friend	-0.03 (0.02) [-0.06, 0.00]	0.00 (0.00) [0.00, 0.00]	0.05 (0.03) [0.00, 0.10]	**0.91** (0.02) [0.87, 0.96]
Read mail	0.01 (0.01) [-0.02, 0.04]	0.00 (0.00) [0.00, 0.00]	**0.14** (0.02) [0.09, 0.19]	0.04 (0.03) [-0.01, 0.09]
Take a test Drive	-0.04 (0.03) [-0.12, 0.02]	0.00 (0.00) [-0.01, 0.01]	-0.02 (0.04) [-0.10, 0.06]	0.04 (0.03) [-0.02, 0.09]
Intercept	-0.07 (0.06) [-0.19, 0.03]	0.00 (0.01) [-0.01, 0.01]	**2.96** (0.12) [2.72, 3.19]	**0.33** (0.11) [0.13, 0.57]
Sigma	0.56 (0.09)	0.20 (0.1)	2.6 (0.04)	0.76 (0.09)
Weights	0.08 (0.01)	0.42 (0.02)	0.41 (0.01)	0.10 (0.01)
Mean (y)	**0.4** (0.001)	**3.9** (0.18)	**4.6** (0.04)	**6.2** (0.11)
Log Marginal Density	-13924			

Parameter estimates are the posterior means, posterior standard deviation (in parenthesis) and 95% credible interval (in brackets).

Table 7
Γ Matrix Estimates for Segment 2
Automobile Data

Variable	*Go to a Dealer*	*Seek onfo directly*	*Seek info obj. source*	*Recommend to a Friend*	*Read mail*	*Take a test drive*
Magazine Ad	0 (0.01)	0 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.02 (0.01)	0 (0.01)
	[-0.02, 0.02]	[-0.02, 0.02]	[-0.03, 0.01]	[-0.02, 0.04]	[0, 0.05]	[-0.03, 0.02]
Newspaper Ad	0.01 (0.01)	0 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0 (0.01)
	[-0.01, 0.03]	[-0.01, 0.02]	[-0.01, 0.03]	[-0.01, 0.03]	[-0.01, 0.03]	[-0.01, 0.02]
Radio Ad	-0.01 (0)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0 (0.01)	-0.01 (0.01)
	[-0.02, 0]	[-0.02, 0]	[-0.02, 0]	[-0.02, 0.01]	[-0.02, 0.01]	[-0.02, 0]
TV Ad	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)	0 (0.01)
	[-0.01, 0.01]	[-0.01, 0.01]	[-0.01, 0.01]	[-0.02, 0.01]	[-0.01, 0.01]	[-0.01, 0.01]
Sponsorship Event	0.04 (0.04)	0.02 (0.04)	0.03 (0.04)	0.09 (0.04)	0.09 (0.04)	0.04 (0.04)
	[-0.03, 0.11]	[-0.04, 0.1]	[-0.04, 0.11]	[0, 0.16]	[0, 0.18]	[-0.03, 0.12]
Internet Ad	0.04 (0.03)	0.03 (0.03)	0.04 (0.03)	0.03 (0.04)	0.01 (0.04)	0.03 (0.03)
	[-0.03, 0.09]	[-0.02, 0.12]	[-0.01, 0.13]	[-0.03, 0.13]	[-0.05, 0.1]	[-0.02, 0.11]
Direct Mail	**0.17** (0.08)	**0.21** (0.08)	**0.17** (0.08)	**0.22** (0.09)	**0.21** (0.09)	**0.14** (0.08)
	[0.04, 0.35]	[0.07, 0.39]	[0.04, 0.33]	[0.07, 0.39]	[0.03, 0.4]	[003, 0.33]
Brochure	**0.58** (0.08)	**0.59** (0.08)	**0.58** (0.08)	**0.57** (0.08)	**0.53** (0.09)	**0.49** (0.09)
	[0.4, 0.73]	[0.41, 0.75]	[0.41, 0.74]	[0.4, 0.73]	[0.33, 0.7]	[0.29, 0.64]
Company Website	0.04 (0.04)	0.05 (0.04)	0.04 (0.04)	0.03 (0.04)	0.02 (0.04)	0.04 (0.04)
	[-0.01, 0.15	[-0.01, 0.15]	[-0.01, 0.15]	[-0.03, 0.13]	[-0.04, 0.12]	[-0.01, 0.14]
Test Drive	**0.61** (0.28)	**0.46** (0.27)	**0.46** (0.25)	**0.45** (0.23)	**0.4** (0.24)	**0.62** (0.29)
	[0.27, 1.38]	[0.11, 1.23]	[0.13, 1.14]	[0.12, 1.1]	[0.03, 1.01]	[0.27, 1.44]
Dealer Sales Contact	0.06 (0.03)	0.06 (0.03)	0.05 (0.03)	0.05 (0.03)	0.04 (0.03)	0.06 (0.03)
	[0.01, 0.11]	[0.01, 0.12]	[0, 0.1]	[-0.01, 0.11]	[-0.02, 0.11]	[0, 0.11]
Call from Dealership	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.03)	-0.04 (0.04)	-0.04 (0.03)
	[-0.1, 0.03]	[-0.01, 0.03]	[-0.1, 0.02]	[-0.11, 0.03]	[-0.11, 0.03]	[-0.1, 0.03]
Dealer Website	0.08 (0.09)	0.09 (0.1)	0.08 (0.09)	0.04 (0.09)	0.03 (0.09)	0.07 (0.09)
	[-0.07, 0.28]	[-0.07, 0.3]	[-0.07, 0.27]	[-0.12, 0.24]	[-0.12, 0.23]	[-0.09, 0.26]
Demo from Friend	0.02 (0.02)	0.03 (0.02)	0.01 (0.02)	0 (0.03)	0 (0.03)	0.03 (0.02)
	[-0.02, 0.06]	[-0.02, 0.08]	[-0.04, 0.05]	[-0.06, 0.04]	[-0.06, 0.06]	[-0.01, 0.08]
Recommendation from Friend	**0.1** (0.02)	**0.12** (0.02)	**0.11** (0.02)	**0.12** (0.02)	**0.1** (0.03)	**0.12** (0.02)
	[0.07, 0.15]	[0.08, 0.16]	[0.08, 0.15]	[0.07, 0.17]	[0.04, 0.15]	[0.08, 0.16]
Independent Article	**0.18** (0.06)	**0.19** (0.06)	**0.23** (0.07)	**0.19** (0.07)	**0.19** (0.07)	**0.16** (0.06)
	[0.09, 0.36]	[0.1, 0.38]	[0.13, 0.43]	[0.09, 0.39]	[0.09, 0.37]	[0.08, 0.33]
Independent Website	0.06 (0.02)	0.07 (0.02)	0.07 (0.02)	0.04 (0.03)	0.04 (0.03)	0.06 (0.02)
	[0.01, 0.1]	[0.02, 0.11]	[0.02, 0.11]	[-0.01, 0.09]	[-0.01, 0.09]	[0.01, 0.11]
Public Display	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)	0.03 (0.02)	0.04 (0.02)	0.02 (0.01)
	[-0.01, 0.05]	[-0.01, 0.04]	[-0.01, 0.04]	[0, 0.06]	[0, 0.07]	[-0.01, 0.05]
Intercept	**0.95** (0.06)	**1.02** (0.07)	**1.08** (0.07)	**1.64** (0.08)	**2.28** (0.08)	**1.03** (0.07)
	[0.82, 1.08]	[0.88, 1.15]	[0.94, 1.21]	[1.48, 1.79]	[2.12, 2.46]	[0.88, 1.16]

Parameter estimates are the posterior means, posterior standard deviation (in parenthesis) and 95% credible interval (in brackets).

Table 8
Mean Brand Beliefs and Overall Brand Impression for the Four Segments

Variables	Segment 1	Segment 2	Segment 3	Segment 4
Overall Impression of the Brand	7.60 (0.01)	7.89 (0.09)	7.84 (0.02)	8.01 (0.06)
Performance	4.49 (0.01)	4.43 (0.07)	4.43 (0.01)	4.53 (0.05)
Durability	7.50 (0.01)	7.90 (0.08)	7.82 (0.02)	7.97 (0.06)
Security	7.33 (0.01)	7.68 (0.08)	7.61 (0.02)	7.77 (0.06)
Excitement	6.21 (0.01)	6.62 (0.09)	6.46 (0.02)	6.68 (0.06)
Design	6.57 (0.01)	6.95 (0.09)	6.79 (0.02)	7.00 (0.06)
Innovation	6.80 (0.01)	7.16 (0.08)	7.07 (0.02)	7.23 (0.06)
Manufacturing Quality	7.67 (0.01)	8.01 (0.08)	7.88 (0.02)	8.05 (0.05)

Mean and standard deviation (in parenthesis)

Table 9
Summary of Effect-sizes for Normal Mixture Model
Automobile Data

	Mean Intended Purchase (y)	Intended Action Variables (x)	Media Exposure Variables (z)	Effect-sizes		
				$\partial y/\partial x$	$\partial x/\partial z$	$\partial y/\partial z$
Segment 1 (ϕ_1= 0.08)	**0.4** (0.001)	Go to a Dealer	Brochure	**0.89** (0.04)	**0.48** (0.22)	**0.43** (0.19)
			Recommendation from a Friend		**0.29** (0.15)	**0.25** (0.13)
Segment 2 (ϕ_2= 0.42)	**3.9** (0.18)	Seek info directly	Direct Mail	**1.00** (0.01)	**0.21** (0.08)	**0.21** (0.08)
			Brochure		**0.59** (0.08)	**0.58** (0.08)
			Test Drive		**0.46** (0.27)	**0.46** (0.21)
			Recommendation from a Friend		**0.12** (0.02)	**0.12** (0.02)
			Independent article		**0.19** (0.06)	**0.20** (0.06)
Segment 3 (ϕ_3= 0.41)	**4.6** (0.04)	Go to a Dealer	Company Website	**0.11** (0.05)	**0.10** (0.03)	0.01 (0.01)
			Call from Dealership		**0.57** (0.15)	**0.07** (0.03)
			Dealer Website		**0.10** (0.03)	0.01 (0.005)
		Read Mail	Magazine Advertisement	**0.14** (0.02)	**0.05** (0.02)	0.01 (0.002)
			Call from Dealership		**0.36** (0.14)	**0.06** (0.02)
			Dealer Website		**0.07** (0.03)	0.01 (0.004)
Segment 4 (ϕ_4= 0.10)	**6.2** (0.11)	Recommend to a Friend	Direct Mail	**0.91** (0.02)	**0.08** (0.04)	**0.08** (0.03)
			Brochure		**0.08** (0.04)	**0.07** (0.03)
			Company Website		**0.09** (0.04)	**0.08** (0.03)
			Recommendation from a Friend		**0.07** (0.04)	**0.07** (0.03)

Mean and standard deviation (in parenthesis)