

Estimating Recommendation and Repurchase Thresholds with a Joint Heterogeneity Response Model

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ABSTRACT

Recommendation and repurchase intentions are the two most important dimensions of customer loyalty. Latent satisfaction thresholds at the individual level, if obtained, can function as an additional valid and effective criterion to satisfaction ratings in determining customer behavior. Hence, customer segmentation based on these thresholds can help firms optimize their resources to improve customer retention. This paper proposes a joint heterogeneity response model to simultaneously calibrate the individual-level recommendation and repurchase thresholds through a joint specification over the heterogeneity. We conduct a simulation study to examine the parameter recovery and model comparison between our proposed model and two competing models. We apply our model to the satisfaction survey data of automotive customers. The results outperform the other three alternative models and show more insight into uplifting customer loyalty using a segmentation scheme based on estimated recommendation and repurchase thresholds. In addition to the heterogeneous distribution of thresholds, our results uncover the effects of customer characteristics on the thresholds.

1. INTRODUCTION

It is very common in satisfaction surveys for customers with the same satisfaction rating to express different loyalty intentions. For instance, amongst customers whose satisfaction ratings are all eight, some would recommend the brand while others would not, and some intend to repurchase, while others do not. One explanation is related to stochastic aspects of behavior which cannot be observed by researchers. The other explanation is that customers may have different thresholds that are not fully captured by satisfaction ratings (Bryant and Cha 1996; Mittal and Kamakura 2001). Customers choose to recommend or repurchase only when their satisfaction ratings are higher than their recommendation or repurchase thresholds. Amongst customers, even those with the same satisfaction ratings, individuals with higher thresholds are less likely to recommend or repurchase the brand than customers with lower thresholds.

Satisfaction surveys provide firms with the satisfaction ratings of customers, but not their satisfaction thresholds. Firms do not know what level of satisfaction would lead to customer loyalty intention or behavior. However, previous research has found that customer satisfaction does not necessarily result in higher customer loyalty (Jones and Sasser 1995; Reichheld 1996). Because the focus of most firms' satisfaction programs is on customer loyalty, it is not enough merely to know customer satisfaction levels. Instead, companies need to identify customer satisfaction thresholds and use these as indicators of the intrinsic retainability of customers (Mittal and Kamakura 2001). By obtaining individual thresholds from an existing satisfaction survey, firms can allocate resources more optimally by designing different loyalty programs for different market segments based on threshold levels.

Satisfaction thresholds are unobserved and therefore need to be estimated with a robust and advanced data analysis approach. This paper investigates simultaneously recommendation and repurchase intentions, the most frequently used multiple dimensions of customer loyalty (Andreassen 2001; Brady, Cronin, and Brand 2002; Olsen and Johnson 2003). We construct a joint heterogeneity response model to calibrate the individual-level recommendation and repurchase thresholds. To implement the estimation we use a hybrid algorithm from the Gibbs sampler and Metropolis-Hastings method for MCMC simulation. This paper compares the proposed model with two competing models and one benchmark: (1) bivariate response model, (2) separate response model, and (3) Mittal and Kamakura (2001) model. The results show that the joint heterogeneity response model performs better than the rest alternative models.

We apply our model to satisfaction survey data of automotive customers. The results show the heterogeneous distribution of the two thresholds and the effects of customer characteristics on these thresholds. This paper also finds that the segmentation of customers based on recommendation and repurchase thresholds differs significantly in response to satisfaction changes.

This paper contributes to marketing literature from the following perspectives. We develop a joint heterogeneity response model to cope with situations when regular hierarchical multivariate probit model (Chib and Greenberg 1998; Hall and Hamilton 2004; Manchanda, Ansari and Gupta 1999; Rossi, Allenby, and McCulloch 2005) can not be applied. Multivariate probit model requires at least some covariates to be different for the same individual across multiple choice categories. However, if there is only one satisfaction rating

as a covariate regardless of recommendation or repurchase response categories, the typical multivariate probit model would fail. Furthermore, our proposed model provides not only individual-specific but also category-specific parameter estimates, the latter of which can not be possibly estimated in multivariate probit models. To deal with insufficient data when there is only one observation per individual, we develop a hierarchical Bayesian (HB) method with data augmentation for the proposed joint heterogeneity model when the traditional approaches fail. The advantage of our proposed approach is shown in both simulation study and real data situations.

In addition, this paper investigates simultaneously the two satisfaction thresholds at the individual level. There is little extant research linking customer recommendation and repurchase thresholds through covariates and error terms. Finally, this paper proposes a new segmentation scheme based on the estimated thresholds rather than stated satisfaction. This segmentation approach shows different insights into the relationship between customer satisfaction and loyalty.

2. REVIEW OF RELATED LITERATURE

Recommendation Threshold vs. Repurchase Threshold

Recommendation intention and repurchase intention are two specific facets of loyalty. In the absence of theories comparing repurchase and recommendation intentions, Soderlund (2006) reveals that satisfaction does not have the same effect on repatronage intention and recommendation (word-of-mouth) intention. Previous research suggests that the impact of satisfaction on intention is related to a customer's perceptions of the control of intent on

behavior (Soderlund and Ohman 2003). Recommendation behavior and repurchase behavior are subject to different perceptions of control by a customer. Repurchase behavior is related to spending money, while recommendation behavior is related to talking to other people. It may be easy to talk about a brand, but difficult to repurchase, especially in the case of durable goods.

Loyal Customer Thresholds vs. Disloyal Customer Thresholds

A few studies on the relation between satisfaction and repurchase intention have revealed that higher satisfaction does not guarantee higher repurchase rates (Jones and Sasser 1995; Reichheld 1996). According to research on automotive customers, 85–90% of customers self-report that they are satisfied, but only 30–40% of customers have repurchase intentions (Reichheld 1996). The relationship between satisfaction and intention is more complicated than is usually assumed. Customer loyalty is found to be one of several factors that moderate this relationship. Some studies (Garbarino and Johnson 1999; Mittal and Katrichis 2000) suggest that loyal customers might use a different process when evaluating satisfaction levels. Loyal customers are more relational to a particular brand and are long-term oriented, while disloyal customers are less relational and are transaction and short-term oriented (Yi and La 2004). In addition, loyal customers have a more stable satisfaction level and a higher tolerance for experience and expectation disconfirmation.

Factors Influencing Thresholds

Despite the huge potential for both the theoretical and practical application thereof, few studies have directly investigated the factors influencing satisfaction thresholds, with the exception of Mittal and Kamakura (2001). Their study on automotive customers finds that

consumers with different characteristics have different repurchase thresholds. The directions of characteristics' effects on thresholds are shown in Table 1. The American Customer Satisfaction Index (ACSI), a national, cross-industry, cross-company measure of satisfaction, also shows that customers with different demographic and socioeconomic characteristics may have different satisfaction thresholds (Bryant and Cha 1996).

Table 1

FACTORS INFLUENCING THRESHOLDS

Author(s)	Factor(s)	Direction
Bryant and Cha (1996)	Demographic and socioeconomic characteristics	N/A
Yi and La (2004)	Accumulated brand knowledge	Negative
Soderlund (2006)	Pre-purchase knowledge	Positive
Rust and Oliver (2000)	Expectation	Positive
Mittal and Kamakura (2001)	Gender (Female)	Negative
	Education Level (Collage graduate and above)	Positive
	Age (60 years or older)	Negative
	Variety-seeking ability	Positive

Accumulated brand knowledge can be one of the factors negatively affecting the difference in satisfaction thresholds (Yi and La 2004). That is, brand familiarity may lead to lower thresholds. Customer pre-purchase knowledge about the product may be another factor influencing the threshold. Soderlund (2006) shows that customers with higher expertise manifest accurate links between service performance and behavioral intentions. Only when service performance is good will customers with high expertise express high levels of satisfaction and behavioral intentions. This implies that expert customers have lower tolerance to dissatisfying performance and higher thresholds than uninformed customers.

Variety-seeking tendencies have an impact on repurchase thresholds (Mittal and Kamakura 2001). Customers with higher searching ability are more likely to be cognizant of

superior alternatives. Therefore, given the same satisfaction level, they may tend to have higher thresholds than those with lesser competence.

Finally, expectations may change satisfaction thresholds. Rust and Oliver (2000) point out that a service program that exceeds customer expectations to a surprising degree will lift these expectations and make it more difficult for customers to repurchase in the future. This indicates that expectation may have a direct impact on customer repurchase thresholds. However, expectations are updated as consumers learn from experiences in the market (Johnson, Anderson, and Fornell 1995), suggesting the dynamic nature of satisfaction thresholds.

Satisfaction-Intention Linkage

Recently, satisfaction programs have once again attracted the attention of researchers and practitioners. Rather than maximizing satisfaction ratings alone, most customer satisfaction programs pay attention to the satisfaction-retention relationship (Anderson and Mittal 2000).

Traditionally, the relationship between satisfaction and repurchase intention is considered to be a symmetric and linear function. For example, Ralston (1996) suggests that in the service industry, a one-unit increase in overall satisfaction results in a 6% increase in the likelihood of repurchase. However, many recent studies in various industries have found that the linkage function is asymmetric and nonlinear (Anderson, Fornell, and Lehmann 1994; Ngobo 1999; Mittal and Kamakura 2001). Generally, the nonlinear form comes from the fact that the satisfaction level has a greater impact on repurchase intention at its two extremes (very low or very high satisfaction), whereas the impact of the satisfaction level at the middle range is relatively flat. These studies also show that the satisfaction-intention linkages in

different industries or firms may exhibit deviations from the general pattern.

Combining segmentation with satisfaction-retention analysis will be useful for practitioners. This is because both the retention curve and cost of increasing the satisfaction level may vary with customer segments (Anderson and Mittal 2000). Some related studies show that retention is much more sensitive to variations in satisfaction ratings of certain customer segments than of others (Garbarino and Johnson 1999; Mittal and Kamakura 2000). In these studies, demographic variables (Mittal and Kamakura 2000) and customer type (relationship with firm) (Garbarino and Johnson 1999) are used to segment the customer base.

In this paper, we use recommendation and repurchase thresholds as the segmentation criterion to examine the differences in loyalty intention curves of various segments. Our research shows that the customers in different segments differ remarkably in response to satisfaction changes. It indicates that customers with different levels of thresholds should be treated distinctively in CRM programs.

3. MODEL DEVELOPMENT

Our goals are to estimate individual-level thresholds and the effects of customer characteristics on these thresholds from multiple response categories. We develop a joint heterogeneity response model with HB approach to simultaneously calibrate the individual-level recommendation and repurchase thresholds.

Previous research has found that demographic characteristics may influence customer self-reported satisfaction ratings (Bryant and Cha 1996; Mittal and Kamakura 2001). We

incorporate customer characteristic factors into our model to adjust the observed satisfaction ratings. Assuming the probability of customer i having a recommendation intention equal to the probability of her satisfaction being greater than the recommendation threshold, we have

$$(1) \quad \Pr\{ Y_{1i}=1 \} = \Pr\{ w_{1i} > 0 \} = \Pr\{ \beta_{1i}X_i - r_{1i} + \varepsilon_{1i} > 0 \},$$

where $Y_{1i} = 1$ denotes that customer i has a recommendation intention, $Y_{1i} = 0$ denotes that she has no recommendation intention, w_{1i} is a latent variable, X_i is the customer's observed satisfaction level, β_{1i} denotes the coefficient capturing the effects of stated satisfaction on recommendation, r_{1i} is her unadjusted recommendation threshold, and ε_{1i} stands for the error term following standard normal distribution. It should be noted that, due to the identification issue, r_{1i} and β_{1i} can not be separately identified. Hence, in the following sections, the thresholds are only referred as the relative ratio adjusted by β_{1i} .

Similarly, we can model the repurchase threshold as

$$(2) \quad \Pr\{ Y_{2i}=1 \} = \Pr\{ w_{2i} > 0 \} = \Pr\{ \beta_{2i}X_i - r_{2i} + \varepsilon_{2i} > 0 \},$$

where Y_{2i} represents whether customer i has a repurchase intention, w_{2i} is a latent variable, β_{2i} is the coefficient of stated satisfaction in the event of repurchase, r_{2i} denotes customer i 's unadjusted repurchase threshold, and ε_{2i} represents the error term following standard normal distribution.

A second level of parameterization is developed to control the heterogeneity, where β_{1i} , β_{2i} , r_{1i} , and r_{2i} are expressed separately as four functions of customer characteristics:

$$(3) \quad \begin{cases} r_{1i} = Z_i\Delta'_1 + \eta_{1i} \\ \beta_{1i} = Z_i\Delta'_2 + \eta_{2i} \\ r_{2i} = Z_i\Delta'_3 + \eta_{3i} \\ \beta_{2i} = Z_i\Delta'_4 + \eta_{4i}, \end{cases}$$

$$\text{and } \begin{bmatrix} \eta_{1i} \\ \eta_{2i} \\ \eta_{3i} \\ \eta_{4i} \end{bmatrix} \sim \text{Multivariate Normal } (0, V), \quad V = \begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \sigma_{13}^2 & \sigma_{14}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \sigma_{23}^2 & \sigma_{24}^2 \\ \sigma_{31}^2 & \sigma_{32}^2 & \sigma_{33}^2 & \sigma_{34}^2 \\ \sigma_{41}^2 & \sigma_{42}^2 & \sigma_{43}^2 & \sigma_{44}^2 \end{bmatrix},$$

where Z_i is a vector of observed features and characteristics of customer i , $\Delta'_j, j = 1, 2, 3, 4$, denotes the transposed coefficients vector corresponding to r_{1i} , β_{1i} , r_{2i} , and β_{2i} . There may exist some unobserved variables, such as satisfaction with competing products and the customer's psychographic characteristics, affecting her recommendation and repurchase thresholds and satisfaction coefficients simultaneously. Hence, we assume that the error terms, η_{ji} , follow a multivariate Normal $(0, V)$ distribution, where V is the covariance matrix.

Through the correlated error terms in equation (3), a joint heterogeneity response model is developed by combining equations (1), (2), and (3).

To deal with the identification issue, the classical approach (McCulloch, Polson, and Rossi 2000) fixes the first element $(1, 1)$ of the covariance matrix, V , to one. In our model, the absolute value of parameters, β_{1i} , β_{2i} , r_{1i} , r_{2i} , and V , cannot be identified. However, we are interested in the relative value of those parameters due to two reasons. First, equation (1) and (2) will still hold if both r and β are multiplied by the same positive constant. Therefore, to keep this relationship between r and β , we need to restrict $\sigma_{11}^2 = \sigma_{22}^2$, and $\sigma_{33}^2 = \sigma_{44}^2$. For interpretation and identification purpose, r_1/β_1 and r_2/β_2 are better measures than $(\beta_1 X - r_1)$ and $(\beta_2 X - r_2)$ because the ratio format can be used to compare with the observed satisfaction ratings. Second, the unobserved factors may jointly affect both r_1 and r_2 . In order to identify this correlation between η_1 and η_3 , we also need to restrict $\sigma_{11}^2 = \sigma_{33}^2$. For the above reasons, the diagonal elements in the covariance matrix, V , are restricted to one. Hence, this

covariance matrix is the same as its correlation matrix, D , where $D = \begin{pmatrix} 1 & & & \\ d_{12} & 1 & & \\ d_{13} & d_{23} & 1 & \\ d_{14} & d_{24} & d_{34} & 1 \end{pmatrix}$.

Competing Model I: Bivariate Response Model

In the competing model I, based on the proposed model, we assume ε_{1i} and ε_{2i} in equation (1) and (2) to be correlated and follow a bivariate Normal distribution. That is,

$$(4) \quad \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{pmatrix} \sim \text{Bivariate Normal } (0, \Sigma),$$

where Σ is the covariance matrix. Following the approach in dealing with identification issue by Chib and Greenberg (1998), we restrict Σ to equal to its correlation matrix, denoted as

$$\Psi = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}, \text{ where } \rho \text{ is the correlation between the two error terms.}$$

Competing Model II: Separate Response Model

In the competing model II, we assume the recommendation and repurchase intentions to be independent. That is, for the recommendation model, we have

$$(5) \quad \Pr\{ Y_{1i} = 1 \} = \Pr\{ w_{1i} > 0 \} = \Pr\{ \beta_{1i} X_i - r_{1i} + \varepsilon_{1i} > 0 \},$$

$$(6) \quad \begin{cases} r_{1i} = Z_i \Delta_1' + \eta_{1i} \\ \beta_{1i} = Z_i \Delta_2' + \eta_{2i} \end{cases},$$

and $\begin{pmatrix} \eta_{1i} \\ \eta_{2i} \end{pmatrix} \sim \text{Multivariate Normal } (0, V')$. To deal with identification issue, we restrict

V' to equal to its correlation matrix. The repurchase model is specified similarly.

Benchmark: Mittal and Kamakura (2001) Model

For the benchmark, we choose Mittal and Kamakura (2001) model, which represents an extant approach in estimating the effects of customer characteristics on repurchase behavior and repurchase threshold. That is,

$$(7) \quad \Pr\{Y_i=1\}=\Pr\{\theta_0 X_i + \sum_{k=1}^K \theta_k z_{ik} X_i - \gamma_0 - \sum_{k=1}^K \gamma_k z_{ik} + \varepsilon_i > 0\},$$

where $\theta_0, \theta_1, \dots, \theta_k, \gamma_0, \gamma_1, \dots, \gamma_k$ are model parameters, K is the number of customer characteristics, z_{ik} represents the k^{th} characteristics of customer i , and ε_i is the error term following normal distribution. The first two components of the left part in the inequality equation represent the adjusted satisfaction, while the third and fourth components represent the repurchase threshold. We use the above specification to estimate separately the recommendation and repurchase threshold.

4. MODEL ESTIMATION

Identification Issue

The proposed model is difficult to estimate because the likelihood function can not be identified by conventional methods with just one observation per respondent. For example, the error terms, ε_i and η_i , in the first level and second level of our model can not be distinguished with MLE methods. However, this identification problem can be circumvented by applying the hierarchical Bayesian method with MCMC approach, which makes draws from a sequence of conditional distributions. Especially, in estimating individual level parameters, HB random effects models do not require that individual level covariate matrices be of full rank (Lenk et al. 1996). When the number of observations per subject is less than the number of parameters per subject, the traditional methods such as MLE would have the problem of near-singular Hessian because they depend on asymptotic assumption. The details of HB method with MCMC algorithms are given in the Appendix.

Simulation

This section presents a simulation study to investigate the recovery of model parameters and to conduct model comparisons. With pre-fixed parameter values, the simulated data are generated according to equation (1) – (3). We gradually increase the sample size n (50, 100, 500, 1000, 1500) to create five sets of data. For each set of data, we compare the LML criterion for three HB models: (1) joint heterogeneity response model (proposed model), (2) bivariate response model (competing model I), and (3) separate response model (competing model II). The number of iterations is 3000 for all five sets of data with the three models. The comparison results, as shown in Table 2, suggest that the joint heterogeneity model significantly outperforms the other two competing models in terms of log marginal likelihood (LML).

Table 2

MODEL COMPARISON (LML)

Models	Sample Size				
	50	100	500	1000	1500
1. Joint heterogeneity model	-1.468	-2.288	-8.390	-19.712	-34.842
2. Bivariate response model	-8.066	-18.636	-112.942	-266.482	-439.983
3. Separate response model	-11.947	-27.034	-173.040	-368.300	-604.657

Next we examine whether the parameters can be accurately identified and recovered with our proposed model. The true parameters in D matrix are randomly fixed as $d_{12} = -0.2$, $d_{13} = -0.4$, $d_{14} = 0.1$, $d_{23} = 0.3$, $d_{24} = 0.2$, and $d_{34} = 0.2$. And those true parameters in Δ matrix are

$$\text{randomly fixed as } \Delta = \begin{bmatrix} -0.33 & -0.17 & 0.50 \\ 0.25 & 0.50 & -0.25 \\ 0.50 & 0.25 & -0.25 \\ 0.17 & 0.50 & 0.33 \end{bmatrix}.$$

We use diffuse and uninformative prior specifications. The chain for the MCMC is run

for a total of 10,000 observations. To reduce serial correlation between parameter draws, we keep every other draw. The first half of the draws is discarded as adaptive burn-in period. The subsequent 2500 draws are kept for inference using summary statistics such as posterior means. The recovery results of parameters are reported in Table 3.

Table 3
RECOVERY OF PARAMETERS

Parameter	True value	Estimated value				
		Mean	SD	Median	Minimum	Maximum
Δ						
δ_{11}	-0.33	-0.34	0.005	-0.337	-0.351	-0.325
δ_{12}	-0.17	-0.15	0.006	-0.145	-0.160	-0.130
δ_{13}	0.50	0.52	0.007	0.518	0.504	0.535
δ_{21}	0.25	0.24	0.010	0.243	0.214	0.271
δ_{22}	0.50	0.53	0.009	0.535	0.509	0.557
δ_{23}	-0.25	-0.22	0.008	-0.221	-0.244	-0.206
δ_{31}	0.50	0.49	0.005	0.492	0.479	0.508
δ_{32}	0.25	0.24	0.007	0.238	0.216	0.253
δ_{33}	-0.25	-0.27	0.007	-0.269	-0.292	-0.252
δ_{41}	0.17	0.14	0.009	0.145	0.118	0.168
δ_{42}	0.50	0.50	0.008	0.503	0.482	0.525
δ_{43}	0.33	0.35	0.007	0.352	0.334	0.371
D						
d_{12}	-0.2	-0.32	0.162	-0.348	-0.690	0.080
d_{13}	-0.4	-0.58	0.167	-0.624	-0.857	-0.198
d_{14}	0.1	0.21	0.146	0.213	-0.215	0.474
d_{23}	0.3	0.21	0.148	0.256	-0.237	0.619
d_{24}	0.2	-0.07	0.229	-0.060	-0.607	0.332
d_{34}	0.2	0.26	0.152	0.152	-0.145	0.617

5. EMPIRICAL APPLICATION

Data and Variable Description

The data is taken from a satisfaction survey conducted in China by an international automotive firm. A total of 1433 customers from the firm's customer base were randomly sampled and surveyed about their satisfaction with respect to vehicle manufacture. As for

loyalty intentions, the respondents were first asked whether they would like to recommend their vehicles, followed by repurchase intentions. Variables measured in this survey were taken from three sections: (1) overall satisfaction with the vehicle manufacture, (2) recommendation and repurchase intentions, and (3) customer characteristics.

The satisfaction variable was measured on a ten-point scale. The numeric scale corresponds to semantic scale (1 and 2 = “very dissatisfied”; 3 and 4 = “somewhat dissatisfied”; 5 and 6 = “neither satisfied nor dissatisfied”; 7 and 8 = “somewhat satisfied”; 9 and 10 = “very satisfied”). Recommendation and repurchase intentions were measured by a dummy variable (0 = “unlikely,” and 1 = “likely”). Customer characteristic variables include ownership duration (equal to or less than one year, or more than one year), car model (P or S), type of previous car (middle or higher, low, or none), ownership (company or privately owned), area of residence, gender, age, education, and occupation. Among these variables, age and satisfaction rating are treated as continuous variables, while the rest are coded as dummy variables. The comparison of descriptive statistics with the firm’s customers who did not participate in the survey indicates that the sample is representative of the customer base.

Table 4

CROSS TABULATION FOR RECOMMENDATION AND REPURCHASE INTENTIONS

		Repurchase		Total
		0	1	
Recommendation	0	576	29	605
	1	428	400	828
Total		1004	429	1433

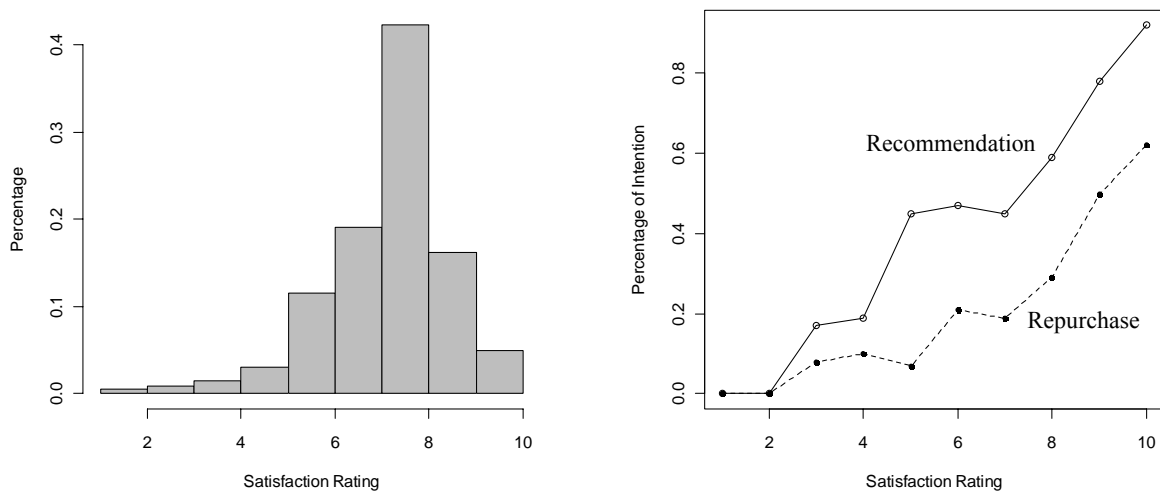
Phi for the two dichotomous variables is 0.469 which is significant at 0.01 level.

The cross tabulation results for recommendation and repurchase intentions are shown in Table 4. Similar to a Pearsonian correlation, the correlation coefficient, Phi, for the two

dichotomous variables, is 0.469 which is significant at the 0.01 level. Figure 1 shows some descriptive statistics for satisfaction ratings. The left of Figure 1 gives the distribution of satisfaction ratings. The average satisfaction rating is 7.611 with a standard deviation of 1.349. Compared with data from other satisfaction surveys conducted by the same automotive firm, this distribution is well-balanced. We also examine the probabilities of recommendation and repurchase intentions across groups with different satisfaction ratings (the right of Figure 1). The results show that on average the probabilities of recommendation and repurchase intentions increase with an increment in satisfaction ratings. In addition, the probability of recommendation intention is always greater than that of repurchase intention within each satisfaction level. These descriptive results are intuitive and indicate that the rationality of this empirical data is acceptable.

Figure 1

DESCRIPTIVE STATISTICS FOR SATISFACTION RATINGS



Model Specification and Comparison

The empirical estimation is developed based on the *bayesm* (Rossi and McCulloch 2008), MASS (Venables and Ripley 2002), *vtnorm* (Genz, Bretz, and Hothorn 2008), and *msm*

(Jackson 2008) packages with the R programming language (R Development Core Team 2008). We use diffuse and uninformative specifications for the priors. The MCMC is run for a total of 20,000 draws. We obtain 4,000 draws by keeping every fifth draw to reduce serial correlation between draws. The first 1,500 draws are discarded as part of the burn-in period and the subsequent 2,500 draws are kept for estimation inference.

We consider four candidates for model comparison: (1) joint heterogeneity response model, (2) bivariate response model, (3) separate response model, and (4) Mittal and Kamakura (2001) model. Table 5 shows that the joint heterogeneity response model provides the best in-sample fit in terms of LML, AIC, and BIC criterion.

Table 5
MODEL COMPARISON (IN SAMPLE)

Model	LML	AIC	BIC
1. Joint heterogeneity response	-146.719	441.438	831.235
2. Bivariate response	-266.731	683.463	1078.527
3. Separate response	-324.215	788.331	1157.158
4. Mittal and Kamakura (2001)	N/A	1813.720	1982.281

Table 6
MODEL COMPARISON (OUT SAMPLE)

Model	Hit Rate		
	Recommendation	Repurchase	Average
1. Joint heterogeneity response	.60	.72	.66
2. Bivariate response	.59	.71	.65
3. Separate response	.58	.70	.64
4. Mittal and Kamakura (2001)	.60	.55	.58

Furthermore, in order to examine the external validity and the predictability of the models, we randomly select half of the data for model calibration and use the rest for model validation. The out-of-sample prediction is measured by hit rate, as shown in Table 6. For

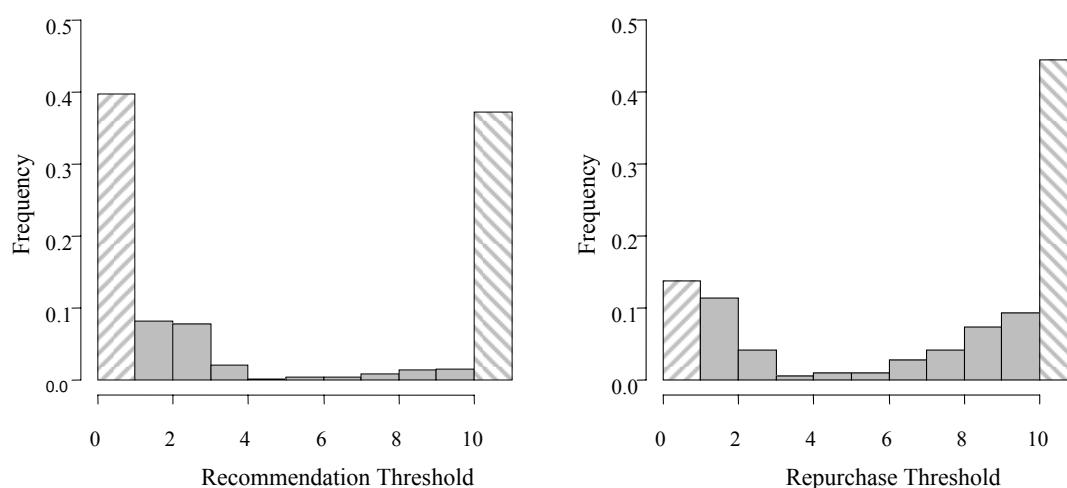
recommendation prediction, our proposed model and Mittal and Kamakura (2001) model are slightly better than the other two. For the repurchase intention, the first three HB response models predict much more accurately than the Mittal and Kamakura (2001) model.

How are Thresholds Distributed Heterogeneously across Customers?

Using the joint heterogeneity response model, we estimate each individual's recommendation and repurchase thresholds. The polarized posterior distributions of the two thresholds are depicted visually in Figure 2. The shaded bars represent those threshold values outside the satisfaction rating range between 1 and 10. The recommendation thresholds for 39.6% of total customers are lower than one, suggesting they have recommendation intentions regardless of their stated satisfaction levels. However, there are only 13.7% of the total customers whose repurchase thresholds are lower than one.

Figure 2

POSTERIOR DISTRIBUTION OF THRESHOLDS



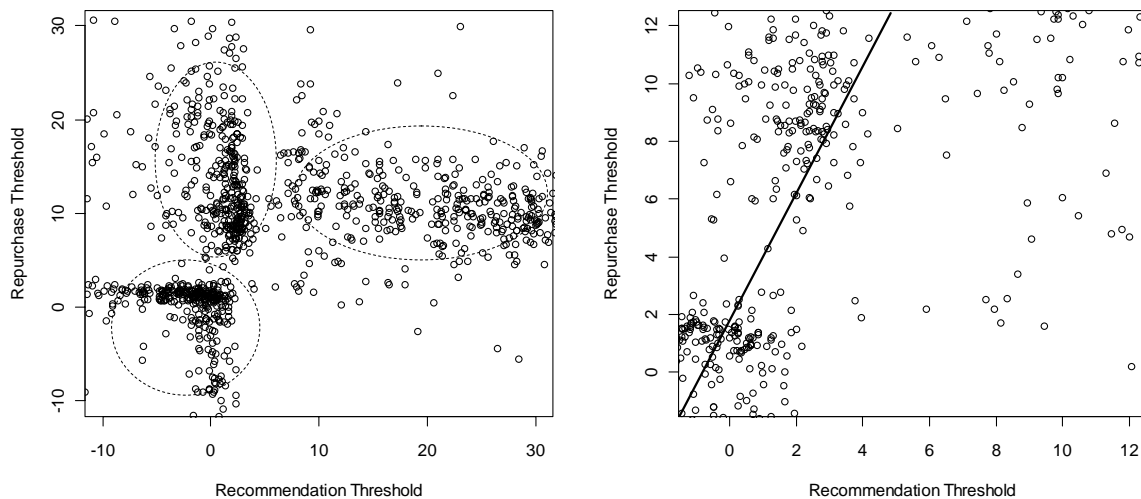
Interestingly, there are also a large proportion of customers with thresholds higher than 10, implying they are not likely to recommend or repurchase no matter how high their stated

satisfaction levels are. This indicates that for a large proportion of customers, their loyal intentions are independent of their satisfaction. This result supports the argument from some other studies that satisfaction cannot predict recommendation or repurchase intentions for some customers (Lin, Wang, and Hsieh 2003; Yi and La 2004).

The scatter plots for thresholds are shown in Figure 3. Excluding extreme values, the left shows the scatter for thresholds ranging from -10 to 30. We observe three segments: (1) low recommendation and low repurchase thresholds, (2) high recommendation and high repurchase thresholds, and (3) low recommendation but high repurchase thresholds. The right one zooms in the left scatter and shows the thresholds ranging from -1 to 12, suggesting on average the repurchase thresholds are higher than recommendation thresholds in this range.

Figure 3

SCATTER PLOTS OF THRESHOLDS



How do Customer Characteristics Affect Recommendation and Repurchase Thresholds?

The regression coefficients, Δ , of the second level model in equation (3), capture the threshold differences explained by customer characteristics. Table 7 gives the posterior mean

of these coefficients for the proposed model. Several coefficients are statistically significant.

Table 7

POSTERIOR MEANS OF REGRESSION COEFFICIENTS ON THRESHOLDS

Variable	Recommendation threshold		Repurchase threshold	
	Coefficients (Δ_1) for r_1	Coefficients (Δ_2) for β_1	Coefficients (Δ_3) for r_2	Coefficients (Δ_4) for β_2
Intercept	1.209[0.877]	0.434* [0.106]	1.391* [0.251]	-1.665* [0.670]
Ownership Duration				
More than one year	-0.658[0.493]	-0.412* [0.138]	-1.063[0.761]	-0.458[0.418]
Car Model				
S	0.614[0.807]	-0.104[0.167]	0.480[0.304]	-0.055[0.292]
Type of Previous Car				
Low-end	-2.110[1.528]	-0.320[0.245]	1.201[0.743]	0.151[0.487]
None	0.412[0.786]	0.218[0.130]	-3.913* [1.062]	-0.476[0.332]
Ownership				
Company owned	-5.316* [1.616]	-0.567[0.321]	2.095[1.375]	0.154[0.724]
Area of Residence				
South	2.425* [0.618]	0.043[0.156]	-1.568* [0.411]	-0.722[0.395]
West	-1.197[0.864]	-0.295[0.168]	-0.625[0.534]	0.186[0.454]
North	-1.446[0.993]	0.046[0.200]	0.657[0.535]	0.611[0.404]
Gender				
Female	1.556* [0.411]	-0.001[0.143]	-1.662* [0.529]	-0.575[0.371]
Age	-0.123[0.063]	-0.004[0.012]	0.136* [0.032]	0.049* [0.022]
Education				
College or higher	1.029[0.837]	0.225[0.145]	-0.334[0.592]	-0.322[0.298]
Occupation				
Self-employer	-1.834[0.968]	-0.035[0.231]	-2.360* [0.605]	0.252[0.626]
Technician	-2.326* [0.889]	-0.068[0.207]	-0.780[0.582]	0.484[0.626]
Personnel	-0.145[1.172]	-0.196[0.284]	-4.597* [0.976]	-0.734[0.838]
Other	1.852[2.262]	0.407[0.359]	-3.700* [0.996]	0.073[0.822]

The number inside [] is the posterior standard deviation. *Significant at 0.05 level.

As for ownership duration, the coefficient for β_1 (-0.412, s.d.=0.138) are significant, while that for r_1 are insignificant. This indicates that, compared to customers who have bought the car for more than one year, the recent buyers have lower recommendation threshold. Recall that a lower threshold implies a higher level of tolerance, and a higher likelihood to make recommendations. Therefore, the word of mouth effects are more likely to

come from those new buyers. This also implies that there may exist the time-varying endowment effects among car buyers.

The type of ownership shows significant impact on recommendation thresholds. The coefficient of company-ownership for r_1 (-5.316, s.d.=1.616) are significant, while that for β_1 are insignificant. This suggests that the respondents tend to have lower recommendation thresholds if the car is company-owned than private-owned. The customers are usually more tolerant if the car does not belong to them. Meanwhile, the type of ownership shows insignificant effects on repurchase thresholds. This is probably due to the fact that most respondents are more cautious and prudent for repurchase decisions. In addition, respondents who drive the company car may only consider repurchasing for themselves when asked about their repurchase intentions.

Gender effects on repurchase thresholds have been reported by previous studies (Mittal and Kamakura, 2001). Our significant coefficient for gender on r_2 (-1.662, s.d.=0.529) and insignificant coefficient on β_2 indicates that women are more likely to repurchase than men. However, the coefficients on r_1 and β_1 show that, for the same level of reported satisfaction, men are more likely to make recommendations than women.

The impacts of a few other factors on the two thresholds are also observed. For example, with the same level of reported satisfaction, older customers have higher repurchase thresholds (the coefficient on r_2 is 0.136 with s.d. of 0.032, and that on β_2 is 0.049, with s.d. of 0.022.) than younger customers. This result is different from Mittal and Kamakura (2001) probably due to two reasons. First, age is a continuous variable in our data, but a dichotomous variable in their data. Second, unlike developed countries where Mittal and

Kamakura (2001) collected their data, there are few drivers over the age of 60 in China. This implies that, for this automotive firm, the older customers show lower levels of intrinsic retainability than the younger. However, age displays no significant effects on the recommendation thresholds. Likewise, the effects on thresholds from some other customer characteristics such as occupation, area of residence, and type of previous car are observed.

The unobserved customer characteristics may also affect the thresholds through their joint effects on r and β . Table 8 shows the posterior estimation results of the correlation matrix D . For example, the correlation coefficient d_{24} captures the positive correlation of unobserved characteristics on the two satisfaction coefficient β_1 and β_2 . Similarly, d_{12} captures the negative correlation on coefficient r_1 and β_1 .

Table 8

POSTERIOR MEANS OF D MATRIX

	Mean	SD		Mean	SD
d_{12}	-0.681*	0.095	d_{34}	0.151	0.578
d_{23}	0.046	0.415	d_{14}	-0.858*	0.117
d_{24}	0.690*	0.084	d_{13}	-0.185	0.537

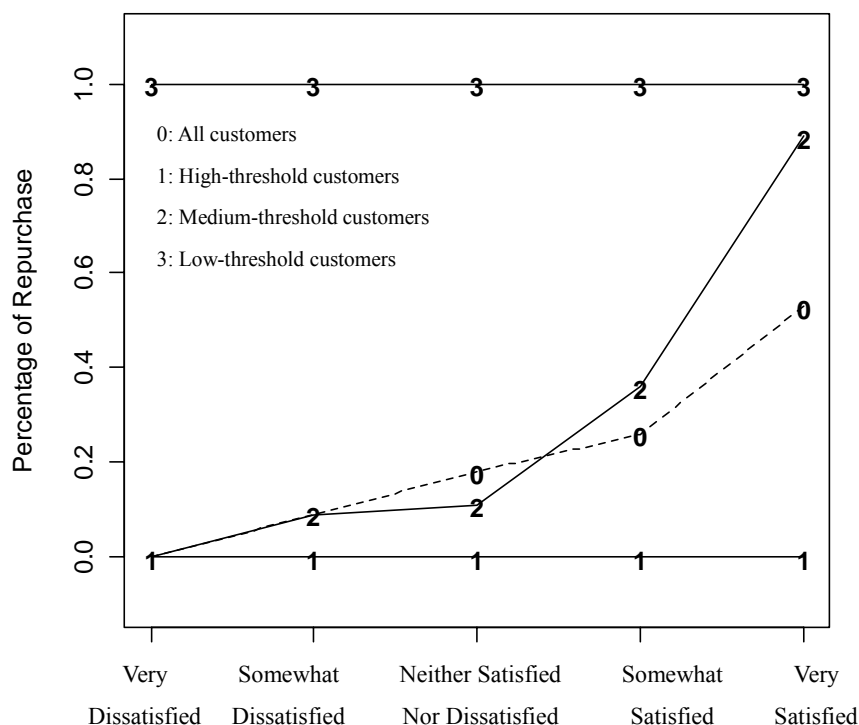
*Significant at 0.05 level.

Does Satisfaction-Intention Linkage Vary with Different Levels of Thresholds?

The above results have shown the heterogeneity of recommendation and repurchase thresholds across customers. A large proportion of customers has repurchase thresholds higher than 10, implying their irresponsiveness to satisfaction changes. For customers with high thresholds, how are satisfaction and intention linked? Does satisfaction-intention linkage vary with customers who have different levels of thresholds? To answer these questions, we next examine the satisfaction-intention linkages for different customer segments based on thresholds.

Figure 4

SATISFACTION-REPURCHASE RELATIONSHIP BY SEGMENT



Based on our estimated individual-level repurchase thresholds, customers are segmented into three groups with high (greater than 10), medium (between 1 and 10), and low (smaller than 1) thresholds. The relationship between satisfaction level (in semantic scale) and repurchase intention for different segments is illustrated in Figure 4. Line 0 depicts the satisfaction-intention linkage for all customers. This shows that with an increase in satisfaction level, average customers become more likely to repurchase. It is commonly assumed that customer repurchase intentions are always sensitive to satisfaction. However, Line 1 denotes that the repurchase intentions of high-threshold customers are indifferent to satisfaction improvement. Failure to consider segment specific differences may lead firms to overestimate the impact of satisfaction improvement for high-threshold customers (44.5% of all customers).

Line 2 represents the satisfaction-intention curve for customers with medium repurchase thresholds. For this segment (41.8% of the total), customer repurchase intentions are sensitive to satisfaction levels. As satisfaction improves from “neither satisfied nor dissatisfied” to “very satisfied”, the percentage of customers with repurchase intention increases dramatically, suggesting a completely different pattern from that obtained for all customers. Without considering segment specific differences, firms may underestimate the impact of changes in satisfaction level from middle level to “very satisfied”. This result implies that, in order to improve retention effectively, firms should focus on the “neither satisfied nor dissatisfied” customers with medium threshold.

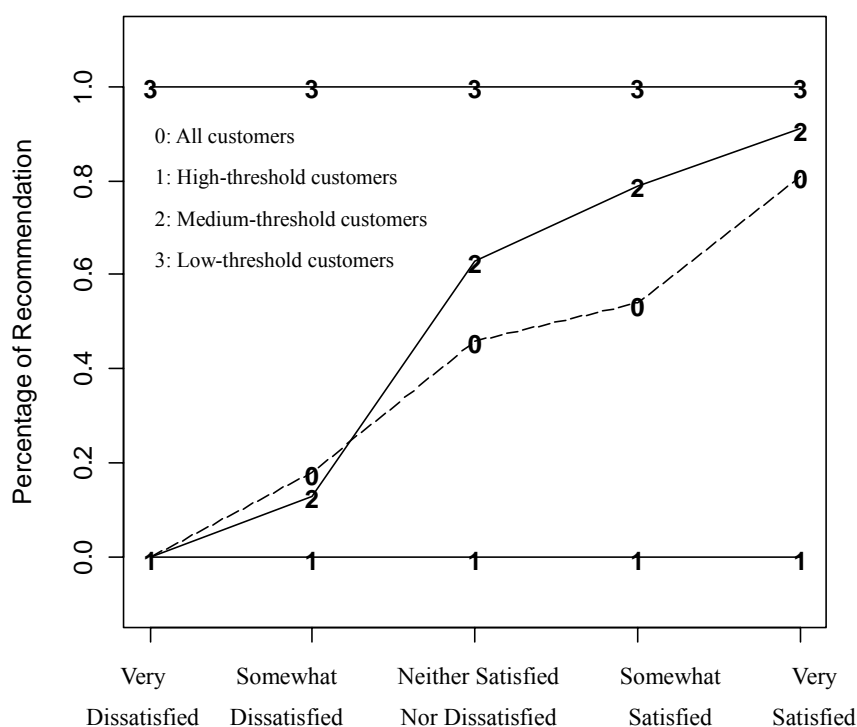
Unlike Line 0 for all customers, Line 3 is a straight line, describing the satisfaction-intention relationship for those customers with low repurchase thresholds. Separating this segment (13.7% of all customers) can help firms to identify their loyal customers whose repurchase intentions do not decline when satisfaction level drops.

Similarly, the relationship between satisfaction and recommendation intention is decomposed into three segments based on recommendation thresholds. Figure 5 shows the differences among different segments of customers. After separating low threshold customers from high threshold customers, Line 2 denotes the satisfaction-intention curve for customers with medium recommendation thresholds. For this segment (23.2% of the total), customer recommendation intentions jump considerably with satisfaction levels changing from “somewhat dissatisfied” to “neither satisfied nor dissatisfied”. Those “somewhat dissatisfied” customers in this segment are more likely to recommend this brand to other people when their satisfactions are only incrementally improved. Without taking into account of this

segment-specific difference, firms may underestimate the seriousness of having customers who are only “somewhat dissatisfied”.

Figure 5

SATISFACTION-RECOMMENDATION RELATIONSHIP BY SEGMENT



7. CONCLUSIONS

This paper develops a joint heterogeneous response model with HB estimation approach to simultaneously calibrate the individual-level recommendation and repurchase thresholds. It is important for firms to identify customers with different levels of intrinsic retainability, using repurchase thresholds as an indicator. Having obtained individual-level recommendation and repurchase thresholds from satisfaction surveys, firms can allocate resources more optimally and design different loyalty programs for different customer segments based on estimated thresholds.

We conduct a simulation study to examine the proposed model in terms of parameter recovery and model comparison. In the empirical part, we apply our model to the satisfaction survey data in automotive industry. The results show that the joint heterogeneity model outperforms the other three alternative models in terms of both in-sample fit and out-sample prediction.

We find that recommendation and repurchase thresholds are heterogeneously distributed across customers. Some customer characteristics show different effects on recommendation and repurchase thresholds. In addition, our results demonstrate that the nature of satisfaction-intention relationships vary across customers with different levels of satisfaction thresholds. Segmentation based on recommendation and repurchase thresholds provides additional insight into how to improve loyalty programs.

Our approach can easily be modified to jointly evaluate other duple responses. For example, loyalty intention and actual behavior can be jointly modeled. Two major response categories (complaining and returning) with dissatisfied products can also be jointly modeled with our approach.

One of the limitations of this study lies in the unavailability of empirical data on actual customer behavior. Thus, conclusions from this paper are drawn on the basis of customers' stated intentions rather than actual loyalty behavior. Due to the intention-behavior discrepancy in satisfaction studies (Mittal and Kamakura 2001; Chandon, Morwitz, and Reinartz 2005), modeling both intention and behavior thresholds is an important extension to this research. In addition, although intention is an emphasis of customer loyalty, firms may ultimately be interested in behavior and not just intentions. It would be valuable to go one

step further to examine the variation of satisfaction-behavior linkage based on behavior thresholds.

Because satisfaction thresholds are latent indicators, research on the mechanism for the formation of thresholds is missing. Although the difference in thresholds based on some customer characteristics has been observed, we do not have a clear understanding of the underlying process. Consequently, it is unknown how to reduce customer thresholds effectively. However, estimating thresholds explicitly is the first step in this research direction. To solve the above research issues, more future studies in different industries and other research fields are needed to extend and advance the research on satisfaction thresholds.

APPENDIX: ESTIMATION ALGORITHMS

The proposed joint heterogeneity response model is estimated by a hierarchical Bayesian method with a two-level structure. As for model calibration, extending the frameworks of Bayesian multivariate probit models (Chib and Greenberg, 1998; Manchanda, Ansari, and Gupta, 1999; Rossi, Allenby and McCulloch, 2005), we employ a hybrid algorithm based on the Gibbs sampler and Metropolis-Hastings algorithm to implement the estimation.

Prior Specification

Following standard practice in Bayesian modeling, the prior distributions of parameters Δ and V are specified as

$$\text{vec}(\Delta) \sim \text{Multivariate Normal} (\text{vec}(\bar{\Delta}), V \otimes A^{-1}), \text{ and}$$

$$V \sim \text{Inverted Wishart} (v_0, V_0),$$

where A^{-1} is a diagonal matrix, and V follows the Inverted Wishart distribution.

Posterior Simulation Algorithm

In the Bayesian paradigm, with the specification of priors, the conditional distributions of parameters and the likelihood of the data given the parameters are considered sequentially.

Our posterior simulation algorithm is implemented by the following Gibbs steps.

First, draw latent variables w_{1i} and w_{2i} given $\beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}$.

Second, draw $\beta_{1i}, r_{1i}, \beta_{2i}$, and r_{2i} given V . In this step, we adopt a random walk Metropolis-Hastings algorithm to draw individual-level parameters $\beta_{1i}, r_{1i}, \beta_{2i}$, and r_{2i} . The algorithm consists of two main iteration steps. At step k , we first sample proposed value B_i by $B_i^{(k-1)} + h$, given h from Normal $(0, s^2V)$, where B_i denotes $\{\beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}\}$ and s is a predefined proportion constant. Then, move to B_i with probability

$$\alpha(B_i^{(k-1)}, B_i) = \min \left\{ \frac{\Pr(B_i) \text{Likelihood}(Y_i | B_i)}{\Pr(B_i^{(k-1)}) \text{Likelihood}(Y_i | B_i^{(k-1)})}, 1 \right\},$$

and stay at $B_i^{(k-1)}$ with probability $1 - \alpha(B_i^{(k-1)}, B_i)$.

Finally, draw Δ and V given $\beta_{1i}, r_{1i}, \beta_{2i}$, and r_{2i} . Draw V from

$$V | \beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}, Z_i \sim \text{Inverted Wishart}(v_0 + n, V_0 + S),$$

where $S = E'E$, $E = B - Z\tilde{\Delta} + (\tilde{\Delta} - \bar{\Delta})'A(\tilde{\Delta} - \bar{\Delta})$, and $\tilde{\Delta} = (Z'Z + A)^{-1}(Z'B + A\bar{\Delta})$. let V

equal to its correlation matrix. Given V , Δ can be drawn from

$$\Delta | \beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}, Z_i, V \sim \text{Normal}(\text{vec}(\bar{\Delta}), V \otimes (Z'Z + A)^{-1}).$$

Estimation Algorithm for Bivariate Response Model

The prior specification of the competing model I is the same as proposed model except that the prior of Σ is assumed to follow an Inverted Wishart(v_0, Λ_0). The posterior simulation of the bivariate response model is also similar to the proposed model except the following two steps. First, draw $\beta_{1i}, r_{1i}, \beta_{2i}$, and r_{2i} given V and Σ . In this step, we move to B_i with probability

$$\alpha(B_i^{(k-1)}, B_i) = \min \left\{ \frac{\Pr(B_i) \text{Likelihood}(Y_i | B_i, \Sigma)}{\Pr(B_i^{(k-1)}) \text{Likelihood}(Y_i | B_i^{(k-1)}, \Sigma)}, 1 \right\},$$

and stay at $B_i^{(k-1)}$ with probability $1 - \alpha(B_i^{(k-1)}, B_i)$.

Second, draw Σ given $\beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}, w_{1i}$ and w_{2i} . Equations (1) and (2) constitute a two-equation Seemingly Unrelated Regression (SUR) model (Zellner 1962), given $\beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}, w_{1i}, w_{2i}$, and X_i . For a SUR model, if Σ is assumed to follow an Inverted Wishart(v_0, Λ_0), then its posterior follows an Inverted Wishart($v_0 + n, S + \Lambda_0$). n is the sample size, and $S = E'E$, where error terms, E , can be computed given $\beta_{1i}, r_{1i}, \beta_{2i}, r_{2i}, w_{1i}, w_{2i}$, and X_i . Then, Σ is drawn by its posterior distribution. For identification purposes, the diagonal elements in

covariance matrix, Σ , need to be restricted to one. Hence the covariance matrix becomes the

same as its correlation matrix, $\Psi = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$.

REFERENCES

- Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, market share and profitability: findings from Sweden. *Journal of Marketing*, 58 (July), 53–66.
- Anderson, E. W., & Mittal, V. (2000). Strengthening the satisfaction-profit chain. *Journal of Service Research*, 3 (2), 107–20.
- Andreassen, T. W. (2001). From disgust to delight: do customers hold a grudge? *Journal of Service Research*, 4 (1), 39–49.
- Brady, M. K., Cronin, J. J., & Brand, R. R. (2002). Performance-only measurement of service quality: a replication and extension. *Journal of Business Research*, 55 (January), 17–31.
- Bryant, B. E., & Cha, J. (1996). Crossing the threshold. *Marketing Research*, 8 (Winter), 4, 20-28.
- Chandon, P., Morwitz, V. G., & Reinartz, W. J. (2005). Do intentions really predict behavior? self-generated validity effects in survey research. *Journal of Marketing*, 69 (April), 1-14.
- Chib, S., & Greenberg, E. (1995). Understanding the metropolis-hastings algorithm. *The American Statistician*, 49 (November), 327–35.
- Garbarino, E., & Johnson, M. S. (1999). The different roles of satisfaction, trust, and commitment in customer relationships. *Journal of Marketing*, 63(April), 70–87.
- Genz, A., Bretz, F., & Hothorn, T. (2008). Mvtnorm: multivariate normal and t distribution. R package version 0.9–0, [available at [http:// www.R-project.org](http://www.R-project.org)].
- Hall, B. L., & Hamilton, B. H. (2004). New information technology systems and a Bayesian hierarchical bivariate probit model for profiling surgeon quality at a large hospital. *The Quarterly Review of Economics and Finance*, 44, 410–29.
- Jackson, C. (2008). MSM: multi-state markov and hidden markov models in Continuous Time. R package version 0.8, [available at [http:// www. R-project. org](http://www.R-project.org)].
- Johnson, M. D., Anderson, E. W., & Fornell, C. (1995). Rational and adaptive performance expectations in a customer satisfaction framework. *Journal of Consumer Research*, 21 (January), 695–707.
- Jones, T. O., & Sasser, W. E. Jr. (1995). Why satisfied customers defect. *Harvard Business Review*, 73 (November/December), 88–99.

- Lenk, P. J., DeSarbo, W. S., Green, P. E., & Young, M. R. (1996). Hierarchical Bayes conjoint analysis: recovery of partworth heterogeneity from reduced experimental designs. *Marketing Science*, 15(2), 173-191.
- Lin, C. T., Wang, S. M., & Hsieh H. Y. (2003). The brand-switching behavior of taipei female consumers when purchasing U-V skincare products. *International Journal of Management*, 20 (4), 443-52.
- Manchanda, P., Ansari, A., & Gupta, S. (1999). The 'shopping basket': a model for multicategory purchase incidence decisions. *Marketing Science*, 18(2), 95-114.
- McCulloch, R. E., Polson, N. G., Rossi, P. E. (2000). A Bayesian analysis of the multinomial probit model with fully identified parameters. *Journal of Econometrics*, 99, 173-193.
- Mittal, V., & Kamakura, W. A. (2001). Satisfaction, repurchase intent, and repurchase behavior: investigating the moderating effect of customer characteristics. *Journal of Marketing Research*, 38 (February), 131-42.
- Mittal, V., & Katrichis, J. M. (2000). Distinctions between new and loyal customers. *Marketing Research*, 12 (Spring), 26-32.
- Ngobo, P. V. (1999). Decreasing returns in customer loyalty: does it really matter to delight the customers?. In *Advances in Consumer Research*, Vol. 26, Eric J. Arnould and Linda M. Scott, eds. Valdosta, GA: Association for Consumer Research, 469-76.
- Olsen, L. L., & Johnson, M. D. (2003). Service equity, satisfaction, and loyalty: from transaction-specific to cumulative evaluations. *Journal of Service Research*, 5(3), 184-95.
- R Development Core Team. (2008). R: a language and environment for statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, [available at <http://www.R-project.org>].
- Ralston, R. W. (1996). Model maps out sure path to growth in marketplace. *Marketing News*, 30 (May), 12.
- Reichheld, F. F. (1996). Learning from customer defections. *Harvard Business Review*, 74 (March-April), 56-69.
- Rossi, P. E., Allenby, G., & McCulloch, R. (2005). *Bayesian Statistics and Marketing*. New York: John Wiley and Sons.
- Rossi, P. E., & McCulloch, R. (2008). Bayesm: bayesian inference for marketing/micro-econometrics. R package version 2.2-1, [available at <http://www.R-project.org>].

Rust, R. T., & Oliver, R. L. (2000). Should we delight the customer? *Journal of the Academy of Marketing Science*, 28 (1), 86–94.

Soderlund, M. (2006). Measuring customer loyalty with multi-item scales: a case for Caution. *International Journal of Service Industry Management*, 17(1), 76–98.

Soderlund, M., & Ohman, N. (2003). Behavioral intentions in satisfaction research Revisited. *Journal of Customer Satisfaction, Dissatisfaction and Complaining Behavior*, 16, 53–66.

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S*. New York: Springer.

Yi, Y., & La, S. (2004). What influences the relationship between customer satisfaction and repurchase intention? Investigating the effects of adjusted expectations and customer loyalty. *Psychology & Marketing*, 21 (May), 351–73.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, 57 (June), 348–68.