

Applications of Business Analytics in Marketing: Joint Modeling of Correlated Multivariate Outcomes

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DEDICATION

With gratitude, I dedicate this dissertation to my husband, Kangbok Lee, to my son, Junewon Lee, to my parents, Manwoo Han and Gilsook Na, to my brothers Insuk Han and Jisuk Han, and to my other relatives and friends who have provided support and encouragement throughout my years in the PhD program.

ABSTRACT

In this dissertation I develop a general regression methodology for mixed multivariate outcomes. This methodology extends the generalized linear mixed model paradigm (glmm) to allow for correlated multivariate normal random effects across regression equations for differing outcomes. This methodology, referred to as joint modeling, is particularly useful in business and marketing applications where multiple outcomes of varying data type must be analyzed simultaneously with regression.

I apply joint models to binary and continuous measures of customer loyalty in a large multinational survey of car owners. Survey respondents' word-of-mouth and desire to switch brands were used as proxies for attitudinal loyalty and behavioral loyalty and were modeled as a function of product-related attributes, service-related attributes, marketing activities, and overall satisfaction of both their current car and alternatives together. My findings provide insights into customer loyalty in the context of both experience based loyalty and image based loyalty as well as cross-cultural consumer behavior and confirm the mediating role of satisfaction. Furthermore, I find that brand evaluation based on experience with the current brand, and alternative brand evaluations based on image both significantly affect customers' overall satisfaction levels with varying degrees of impact. The study also identifies a significant moderating effect of culture between product-related attribute performance, service-related attributes performance, marketing activities, and satisfaction. The association between functional attribute performance and satisfaction is found to be stronger in collectivistic cultures than more individualistic cultures.

A second study focuses on gaining a better understanding of the interplay between price promotion and consumption of both hedonic and utilitarian retail grocery items. A joint model relating three key outcomes, loyalty, cross-buy, and trip revenue was fit with price promotion, consumption type, and consumer demographic characteristics as explanatory variables. The findings indicate that in-store deal use is associated with significant store loyalty, variety-seeking behavior, and trip revenue for both hedonic and utilitarian goods. More interestingly, we find that coupon use for utilitarian goods is negatively associated with store-loyalty, cross-buy (variety-seeking), and trip revenue.

TABLE OF CONTENTS

CHAPTER I Introduction to Joint modeling approaches	1
1.1 Separate models	3
1.2 The factorization model	5
1.3 The latent model	11
1.4 The joint model	14
1.5 Summary	18
References	21
Appendix	23
CHAPTER II A multi-country study of customer loyalty in the automobile industry	26
Abstract	27
1. Introduction	29
2. Theoretical background	33
3. Empirical methodology	47
4. Concluding remarks	58
References	61
Appendix	66
CHAPTER III Coupon and deal dynamics in utilitarian and hedonic purchases	71
Abstract	72
1. Introduction	75
2. Literature review and research framework	75
3. Empirical methodology	78
4. Concluding remarks	89
References	91
Appendix	93
CHAPTER IV Conclusion	98
References	102
VITA	103

LIST OF TABLES

Table 1.1: Summary of joint modeling approaches.....	23
Table 2.1: Variable operationalization.....	67
Table 2.2: The main effect model.....	68
Table 2.3: The moderating effect model.....	69
Table 3.1: Variable operationalization and descriptive statistics.....	94
Table 3.2: Statistical cluster description.....	96
Table 3.3: The joint model.....	97

LIST OF FIGURES

Figure 2.1. Conceptual model.....	70
Figure 2.2. Conceptual model with moderator.	71
Figure 3.1. Conceptual model.....	98

CHAPTER I

INTRODUCTION TO JOINT MODELING APPROACHES

Many modeling problems in several fields, including social science, economics, finance, biology, and (public) healthcare, involve modeling data with mixed types of dependent variables including continuous variables, count variables, ordered-response or ordinal variables, and unordered-response or nominal variables (Bhat 2015; De Leon and Chough 2013). In fields such as healthcare and clinical biology, various approaches have been used in applications in order to analyze these mixed types of outcome variables (Bhat 2015). For example, time-to-event and longitudinal measurements are a particularly common example of correlated mixed types of outcomes in epidemiology and biostatistics (Rizopoulos 2012). In the study of business, multivariate outcomes are also very natural, and it is important to consider correlation between the outcomes. For instance, in the marketing field, ANOVA or SEM have been used to assess customer loyalty based on discrete outcome variables, including categorical, binary, count, and continuous indicators of the satisfaction. Over the past two decades, statistical/analytical models for analyzing problems that combine a mixture of discrete outcome variables (i.e., categorical, binary, count) and continuously have been developed (Leon and Chough 2012; Daniels and Normand 2006). Unlike standard correlated linear data to which traditional multivariate linear regression can be applied, the presence of mixed-type outcomes (i.e., continuous with discrete outcomes) presents unique challenges to analysts and creates difficulties, since it is hard to formalize a convenient multivariate joint distribution for the association between two outcomes.

Due to these analytic difficulties, in the marketing field, most research has continued to concentrate on a single outcome variable or to analyze data separately, although the nature of the relationships includes correlations between multiple response variables (Schweidel and Knox 2013; Leon and Chough 2012; Fader et al. 2005; Gueorguieva and Agresti 2001). In contrast, many well-established marketing models have been used inappropriately to analyze customer data in such situations. Since there is a high possibility of a loss of accuracy and efficiency in modeling when ignoring or misspecifying a potential correlation between outcome variables (Teixeira-Pinto and Harezlak 2009), it would be useful to identify models that allow for a potential correlation between mixed types of outcome variables. For this purpose, it is important to find an appropriate approach to analyze mixed types of outcome variables simultaneously that overcomes the existing challenges of traditional approaches. One alternative approach proposed in this study that is rapidly gaining popularity is the joint modeling approach allowing additional information to be used and create more coherent and powerful analyses. Unlike traditional approaches, the joint modeling approach can resolve omitted variable problem and capture the heteroscedasticity of a dataset when clustered data set is used. By applying a joint model, some recent studies (references) have begun to employ a more appropriate approach to handling situations requiring simultaneous analysis of mixed types of outcome variables.

This dissertation presents a joint modeling approach with marketing applications. The rest of the dissertation is organized as follows. Chapter 1 reviews and explains four joint modeling approaches for the case of mixed discrete and continuous outcomes: 1) separate independent models for each outcome 2) factorization models, 3) latent models,

and 4) our proposed joint model. I also provide a model description traditionally used in the case of continuous and binary mixture outcomes, the advantages/disadvantages, graphical representations, and mathematical notation of each approach are briefly discussed in Table 1 at the end of Chapter 1. In Chapter 2, I present the marketing application of a joint model with two mixed types of outcomes (discrete and continuous) using multi-country survey data. In chapter 3, joint modeling approach including three outcome variables of longitudinal data is presented. Chapter 4 summarizes the results and provides conclusions and directions for future research in this area.

1.1 Separate models

The first and simplest approach used in the presence of correlated mixed types of outcomes is to ignore the potential association between the outcomes and to model each outcome separately (Bhat 2015; Teixeira-Pinto and Harezlak 2013, 2009; De Leon and Zhu 2008). However, this approach has several analytical disadvantages. When the potential dependence is ignored, the estimated covariate effects in the model can be biased and inefficient, because the model fails to capture the additional information included in the correlation between outcomes (Bhat 2015; Leon and Chough 2013). Also, the estimation of an endogenous outcome is inconsistent when the model includes exogenous variable effects (Bhat 2015; Mokhtarian and Cao 2008; Bhat and Guo 2007). In addition, and more importantly, researchers have limited chances to answer intrinsically multivariate questions such as the effect of a covariate on a multidimensional outcome (De Leon and Chough 2013; 2008).

In order to analyze mixed discrete and continuous outcomes, separate models carry out separate regression analyses for each outcome. I describe this framework using notation in this section. Let Y_{Cij} and Y_{Dij} denote a continuous and discrete pair of outcomes for the i^{th} individual ($i = 1, \dots, n$) in the j^{th} group ($j = 1, \dots, M$). In addition, each subject has an $r_C \times 1$ covariate vector X_{Cij} associated with the continuous outcome vector $Y_{Cij} = (Y_{Cij1}, \dots, Y_{Cijn})^T$ and has another $r_D \times 1$ covariate vector X_{Dij} that may be associated with the discrete outcome vector $Y_{Dij} = (Y_{Dij1}, \dots, Y_{DijM})^T$. In this setting, we adopt a normal linear regression model for the continuous variable, Y_{Cij} and a probit regression model for the discrete outcome Y_{Dij} , as

$$Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij} \quad (1.1)$$

and

$$\text{probit}(\mu_{Dij}) = X_{Dij}^T \beta_D + \varepsilon_{Dij} \quad (1.2)$$

where $\mu_{Dij} = E(Y_{Dij})$, $\beta_C = (\beta_{C1}, \dots, \beta_{Cr_C})^T$, $\beta_D = (\beta_{D1}, \dots, \beta_{Dr_D})^T$, and $\varepsilon_{Cij} \sim N(0, \sigma_C^2)$. One of the advantages of the separate model is that coefficients can be interpreted very easily. The interpretation of regression coefficients in both models is performed the same way as the interpretation of the coefficients in a univariate generalized linear regression model. In many health care research, a logistic regression model is more commonly used for discrete (such as binary) outcomes, however, it appears often in other areas of applied statistics, and economics. Because of the existence of closed-form solution for a probit link, I use a probit model instead of a logistic regression in this study. However,

a probit model and a logistic regression model lead to very similar results (Demidenkon 2004)¹.

In this approach, then, I simply assume that both response variables are statistically independent, or, in terms of the error structure,

$$\begin{pmatrix} \varepsilon_{Cij} \\ \varepsilon_{Dij} \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & 0 \\ 0 & \sigma_B^2 \end{pmatrix} \right), \quad (1.3)$$

where ε_{Cij} and ε_{Dij} are independent for all i and j . The assumption of independence between the two outcomes will be relaxed through the joint regression approaches.

As I mentioned earlier, using this method, the discrete and continuous outcome variables can be analyzed separately, but “it involves some element of subjectivity, with possible loss of information, and does not appear very satisfactory in general (Bhat 2015).” Therefore, I will present progressively more suitable and effective approaches to analyzing mixed types of multivariate outcomes in the next several sections.

1.2 The factorization model

The most commonly used methods for jointly constructing models for mixed discrete and continuous outcome variables involve either simply connecting two error terms of the outcome variables, creating a new latent variable to connect the outcomes

¹ The estimates of the logistic regression model can be calculated to be approximately 1.6 times the estimates of the probit model. Therefore, $\exp(1.6\beta_D)$ is a close approximation to the odds ratio in the logistic regression model.

together, or factorizing the joint distribution (Daniels and Gaskins 2010). The first two approaches using latent variables are sometimes called indirect methods, and the last approach is termed the direct method. In social science, the first two approaches are also famous as structural equation modeling (SEM).

SEM is a construct-based model, one of the most popular and multivariate analysis techniques used in both the marketing and psychology literature to model relationships between unobserved constructs and manifest variables and to control for measurement error (Ansari et al. 2000). SEM is a very general, very powerful multivariate analysis technique that includes versions of a number of other analysis methods as special cases. It consists of “error terms” and substantive variables (Hoshino and Bentler 2013; Gates et al. 2011; Spirtes et al. 2004; Jöreskog 1977), and it contains information both about the joint probability distribution over the substantive variables and about the causal relationship among them. Also, the joint distribution of the error terms, together with a set of structural equations, determines the joint distribution of the substantive variables.

However, this approach has several limitations in analyzing mixed discrete and continuous outcome variables. First of all, SEM estimates the parameters of interest, rather than requiring them to be derived from the model variance/covariance matrix (Sayers et al. 2014). Current SEM software can analyze the means with the covariance matrix, so the estimation of means and the intercepts of constructs can be estimated. Second, fundamentally, SEM is only applicable for continuous variables. In particular, traditional SEM software such as LISREL, MPLUS, and EQS does not have the capability of analyzing nominal variables (Temme et al 2008). Using the SEM framework, the model

including the discrete outcome variable can be reformulated to the terms of the measurement and structural models (Heron et al. 2014). However, the model will produce a significant biases based on the analysis and subsequent inferences if one of the outcome variables is a discrete variable (Hsieh and Eye 2010; Curran et al. 2007). Also, an adequate sample size is required, and the data should satisfy specific distributional assumptions, which, for example, binary responses do not meet, in order to apply SEM. As I mentioned, the SEM model can have difficulty in achieving convergence and accurate estimation (Curran et al. 2007; Vermunt 2007; Nachtigall et al. 2003), so it is required to find more appropriate approach for analyzing mixed types of correlated outcomes in considering all of these issues.

The ideal steps to jointly analyze discrete and continuous variables, is to specify the joint distribution of the mixed outcome variables first, then fit the model using the joint distribution, and finally, make inferences using the parameter estimations (Leon and Chough 2013). A model in which mixed types of outcome variables are analyzed using the joint distribution by treating all variables as continuous through the numerical scoring scheme is called a factorization model. This method suggests formulating the joint distribution by using the product form of the conditional distribution of a continuous outcome variable (or discrete outcome variable) multiplied by the marginal distribution of a discrete outcome variable (or continuous variable). In other words, the factorization model can be expressed as the marginal distribution of a continuous variable (or discrete variable) given by a discrete variable (or continuous variable).

Fitzmaurice and Laird (1995) proposed the factorization model for analyzing correlated continuous and binary outcomes based on the factorization of the joint distribution of the outcomes in two ways, $f(Y_{Dij}, Y_{Cij}) = f(Y_{Dij})(Y_{Cij}|Y_{Dij})$. Like the SEM approach, in the factorization model, correlation between the error terms of the two outcomes is included. The joint distribution is then factorized into the marginal distribution of the binary outcome and the conditional distribution of the continuous variable, given the binary/ordinal outcome. The expected values of the outcomes are related to the covariates X_{Cij} and X_{Dij} . Using a probit model for the binary outcome Y_{Dij} and a linear regression model for the continuous variable Y_{Cij} , conditional on Y_{Dij} , I have

$$probit(\mu_{Bij}) = X_{Dij}^T \beta_D \quad (1.4.1)$$

and

$$Y_{Cij} = X_{Cij}^T \beta_C + \tau(Y_{Dij} - \mu_{Dij}) + \varepsilon_{Cij} \quad (1.4.2)$$

where ε_{Cij} is assumed to follow a $N(0, \sigma_C^2)$, and τ is the correlation between the variables.

A convenient property of the factorization approach is that the model parameters maintain a marginal interpretation in both regression equations, identical to the separate models (1.1) and (1.2). Although the factorization model and separate models use very similar distributional assumptions for the continuous outcome variable, the two approaches are different (Teixeira-Pinto and Harezlak 2013). Unlike the usual normality assumption for a continuous variable in the regression model (1.1), the factorization model assumes the conditional normal distribution. In other words, a continuous outcome variable Y_{Cij} is

assumed to be normally distributed, conditional on Y_{Dij} and the covariates, implying that marginalizing over Y_{Dij} yields a mixture of two normal distributions for the marginal distribution of Y_{Ci} . Fitzmaurice and Laird's (1995) approach is to factorize the joint distribution using a product form as the marginal distribution of a binary outcome variable multiplied by the conditional distribution of a continuous outcome variable, conditional on the binary outcome variable, and then to assume a multivariate normal distribution with mean, depending on the binary outcome variable (Leon and Chough 2013; Daniels and Gaskins 2011; Fitzmaurice and Laird 1997; Little and Schluchter 1985).

Catalano and Ryan (1992) proposed an alternative model, called the reverse factorization model. This model creates a latent continuous variable Y_{Di}^* for the binary (dichotomization) outcome variable Y_{Dij} :

$$Y_{Bij} = \begin{cases} 1, & \text{if } Y_{Di}^* \geq 0 \\ 0, & \text{if } Y_{Di}^* \leq 0 \end{cases} \quad (1.5)$$

Then the underlying variable Y_{Di}^* is assumed, conditional on the covariates X_{Dij} , to follow $N(0, (\sigma_b^*)^2)$. Using the continuous outcome variable and reformulated continuous latent outcome variable underlying the binary outcome variable, as in the following bivariate regression models,

$$Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij} \quad (1.6.1)$$

and

$$Y_{Di}^* = X_{Dij}^T \rho_D^* + \varepsilon_{Dij}^* \quad (1.6.2)$$

with

$$\begin{pmatrix} \varepsilon_{Cij} \\ \varepsilon_{Dij}^* \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} (\sigma_b^*)^2 & \tau^* \sigma_C \sigma_D \\ \tau^* \sigma_C \sigma_D & \sigma_C^2 \end{pmatrix} \right), \quad (1.7)$$

the joint bivariate normal distribution can be written as the product form of the marginal distribution of the continuous outcome variable Y_{Cij} multiplied by the conditional distribution of the latent variable (given the continuous outcome variable) underlying binary outcome variable $Y_{Di}^* | Y_{Cij} = y_{Cij}$.

However, this model form (1.8) needs to be reparametrized because of the difficulty of estimation (since not all parameters in the model are estimable). Then, the finalized model takes the following form:

$$\text{probit}(\mu_{Dij}) = X_{Dij}^T \beta_D + \tau(Y_{Cij} - \mu_{Cij}) \quad (1.8.1)$$

and

$$Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij} \quad (1.8.2)$$

with

$$\begin{pmatrix} \varepsilon_{Cij} \\ \varepsilon_{Dij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & \tau \sigma_C \sigma_D \\ \tau \sigma_C \sigma_D & 1 \end{pmatrix} \right), \quad (1.9)$$

where X_{Cij} and X_{Dij} are covariates to be associated with Y_{Cij} and Y_{Dij} , and τ is the correlation between variables.

As shown in Equation 1.10, the variance for the error in the binary outcome equation is, without loss of generality, always equal to 1. This follows from the fact that a probit model is a threshold model so that only β/σ is identifiable (Renard et al. 2004). In

addition, it is difficult to compare the covariate effects with their marginal effects directly. It is also impossible to apply the factorization (or reversed factorization) model with SEM for analyzing multi-level data, because most applications for those models assume that all individuals are homogeneous, which may be unrealistic (Ansari, Jedidi, and Jagpal 2000), as individuals are likely to be heterogeneous in their perceptions and evaluations of unobserved constructs. Analyzing data using a factorization model or SEM that ignores heterogeneity present in the data can result in biased estimates based and wrong standard errors, resulting in misleading inferences and incorrect conclusions (Ansari, Jedidi, and Jagpal 2000; Jedidi 1997; Muthen 1989). For that reason, it is beneficial to apply a more appropriate model. The models that follow next overcome these disadvantages and offer a more appropriate approach by using random effects.

1.3 The latent model

The third modeling approach for analyzing mixed discrete and continuous outcome variables is to introduce latent variables to induce a joint distribution for the all the outcome variables. The latent model approach based on the concept of latent variables has been widely used in the social sciences (Catalano and Ryan 1992; Hamerie 1990; Heckman 1978). Sammel et al. (1997) presented a latent variable joint model for mixed binary and continuous outcomes (Teixeira-Pinto and Normand 2009; Teixeira-Pinto and Harezlak 2004). Conditional on the latent variable, the different types of outcome variables are assumed to be independent and are modeled as functions of fixed covariates and of a subject-specific latent variable (Teixeira-Pinto and Harezlak 2011, 2004; Sammel et al.

1997). Therefore, the effects of covariates are modeled both through the latent variable and directly.

Using this approach, both outcome variables are functions of a common unobserved latent variable, and conditional on this latent variable, both outcome variables follow an independent regression model, one variable with normal errors and the other a probit. A conditioning argument then allows a factorization of the joint distribution into two components that can be modeled separately. A major advantage of this approach is that it leads to a set of intuitively appealing covariates in the conditional models. Therefore, the coefficients of the second model are directly related to the variance and correlation terms from the underlying latent variable.

Let U_{ij} denote the latent variable. If the U_{ij} were directly observable for an individual, the linear regression model would be applicable. Since we do not observe U_{ij} , we write the conditional models as

$$probit\{E(Y_{Dij}|U_{ij})\} = \beta_{D1ij} + \beta_{D2ij}U_{ij} \quad (1.10.1)$$

and

$$Y_{Cij} = \beta_{C1ij} + \beta_{C2ij}U_{ij} + \varepsilon_{Cij} \quad (1.10.2)$$

where $\varepsilon_{Cij} \sim N(0, \sigma_C^2)$ and, β_{D2ij} and β_{C2ij} indicate the strength of the relationship between the observed outcomes and the latent variable.

Another approach based on latent variables is proposed by Dunson (2000). A major difference between Dunson's approach and Sammel et al.'s (1997) approach is in the

association between the responses and the covariates. Unlike Sammel et al.'s approach, in Dunson's approach, the covariates are not included in the latent model and are separately introduced. The conditional model for Dunson's approach is written as

$$\text{probit}\{E(Y_{Dij}|U_{ij})\} = X_{Dij}^T \beta_D + \lambda_D U_{ij} \quad (1.11.1)$$

and

$$Y_{Cij} = X_{Cij}^T \beta_C + \lambda_C U_{ij} + \varepsilon_{Cij} \quad (1.11.2)$$

where $U_{ij} \sim N(0, \sigma_U^2)$ and $\varepsilon_{Cij} \sim N(0, \sigma_C^2)$ are subject-specific latent variables. In this approach, both outcome variables share one latent variable, inducing their correlation with the assumption that the two outcomes are independent, given the latent variable.

In the case of continuous and binary outcomes, Teixeira-Pinto and Normand (2009) extend Lin et al.'s (2000) scaled multivariate mixed model by accounting for the potential correlation between two outcomes, Y_{Dij} and Y_{Cij} . In this model, Y_{Cij} is assumed to be normally distributed, given the covariates X_{Cij} . And an underlying variable Y_{Di}^* is also assumed to follow a normal distribution, given the covariates X_{Cij} , by using the same construction of the reverse factorization model. Then, the conditional regression equations can be written as

$$Y_{Di}^* = X_{Dij} \beta_D^* + U_{ij} + \varepsilon_{Dij}^* \quad (1.12.1)$$

and

$$Y_{Ci} = X_{Cij}^T \beta_C^* + U_{ij} + \varepsilon_{Cij}^* \quad (1.12.2)$$

with $\varepsilon_{Dij}^* \sim N(0,1)$, $\varepsilon_{Cij}^* \sim N(0,1)$, and $U_{ij} \sim N(0, \sigma_U^2)$. The variance of both error terms is fixed at 1 by assumption. (This assumption will be relaxed with the next model.)

Unlike the approaches (e.g., factorization model) mentioned above, the latent modeling approach employs a shared random effect through the latent variable in order to link the outcome variables or to structure the covariance matrix to include potential correlations between the outcome variables (Gardiner 2013). Therefore, the latent model includes a random intercept that allows the specification and estimation of heterogeneity in the mean. Moe and Schweidel (2014; 2012) found that the random effect can control the heterogeneity arising from differences in independent variables across different groups. In addition, omitted variable bias, which potentially causes problems in the factorization model, can be resolved by using the latent model.

Although the latent model can overcome several limitations of the previous approaches and is more appropriate for modeling multiple outcomes, including continuous and binary (or discrete) outcome variables, by reducing modeling bias in estimation, it still tends to lead to modeling bias, unreliable model inference, and overfitting problems (Zhou et al. 2014; Leek and Storey 2008). For these reasons, I will propose a more appropriate modeling approach for multiple outcomes in the next section.

1.4 The joint model

The simultaneous analysis of correlated mixed discrete and continuous outcome variables faces to a number of analytical challenges (Schweidel and Knox 2013; Hsieh and Von Eye 2010). First of all, bias is created when the model compensates for the missing

factors by overestimating or underestimating the effect of one of the other factors. Second, increasing the sample size does not guarantee that the estimates converge to the true value of the parameter being estimated, since the estimators are inconsistent. In addition, computational is a major difficulty; there are no common built-in functions for modeling correlated multivariate outcome variables of mixed types in major packages. Several modeling approaches are typically used to handle this situation. However, the traditional modeling approaches, presented above, still suffer from modeling bias, unreliable model inference, or loss of information when the different forms of outcome variables are highly correlated with each other. More importantly, the traditional models are also unable to address the heteroskedasticity of subjects in groups for multi-level and longitudinal repeated-measured data (Gardiner et al. 2008; Gueorguieva and Agresti 2001). For instance, if interest lies primarily on the individual customer's purchase behavior within the same group (e.g., a cultural group), then a detailed consideration of the dependence structure might be necessary for robust inferences. In order to accommodate the limitations and resolve the existing analytical problems, I propose a more reliable model by employing separate random effect terms, not shared random effects, for each outcome variable; we refer to this approach as a joint model.

In the joint model, each outcome variable has its own random intercept, and the potential correlation is linked through those random intercepts. So, using the random intercepts, a correlation between outcome variables is induced through an unobserved heterogeneity (Gardiner et al. 2008). Since the joint model assumes each equation has its own random intercept (or random effect), this model eliminates one strong assumption, the

shared variance of the latent variable across models. (For this reason, the latent model is a special case of the joint model.) I also assume that the random effects that parameterize the covariate process are normally distributed and that an individual's random effects are constant over time. The estimates of the parameters are also obtained by maximizing the joint likelihood for correlated multivariate outcomes, either the same types of outcome variables or mixed types of outcome variables such as binary and continuous outcomes.

One advantage of this approach is that the joint model optimally uses the available information from multivariate outcome variables occurring simultaneously in large, complex datasets such as those with clustered and longitudinal data (Bhat 2014; Hsieh and Von Eye 2010; Catalano and Rayn 1997). I therefore can expect more precise and accurate estimates of the strength of the relationship between the covariates (of independent variables) and the correlated multivariate outcome variables. By using this joint model, it is possible both to control for omitted variables as well as to capture the heteroskedasticity of individuals in the groups. Therefore, critical analytic issues can be resolved, since unbiased statistical inferences are more likely to be obtained via a joint model (Tsiatis, Deguttola, and Wulfsohn 1995; Wulfsohn and Tsiatis 1997). As mentioned above, progress in this area is hindered by the computational difficulty, since there is no packaged software available yet. To overcome the computational difficulty, I used SAS procedures, PROC GLIMMIX, to create custom models that allow correlated multivariate outcome variables of both similar and dissimilar types.

The formulation of a joint model is based on the random effects approach.

Binary outcome Y_{Dij} and continuous variable Y_{Cij} are modeled jointly by including

individual-specific random intercepts ξ_{Cij} and ξ_{Dij} , respectively. Conditional upon the random effects, two outcomes are assumed to be independent. Hence, the correlation between Y_{Dij} and Y_{Cij} is captured by letting ξ_{Cij} and ξ_{Dij} be in association (Molenberghs and Verbeke, 2005).

For example, in Chapter 2 I use a linear regression model for the continuous variable Y_{Cij} and a logit model for the binary variable Y_{Dij} are used for joint modeling. In addition, individual random effect terms ξ_{Cij} and ξ_{Dij} are included in each model. Then we have

$$Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij} + \xi_{Cij} \quad (1.13.1)$$

and

$$P(Y_{Dij} = 1 | X_{Dij} = x_{ij}) = \frac{\exp(x_{Dij}^T \beta_D)}{(1 + \exp(x_{Dij}^T \beta_D))} + \varepsilon_{Dij} + \xi_{Dij} \quad (1.13.2)$$

where $\varepsilon_{Cij} \sim N(0, \sigma_C^2)$ and $\varepsilon_{Dij} \sim N(0, \sigma_D^2)$. Then, the bivariate joint random components can be expressed as follow;

$$\begin{pmatrix} \xi_{Cij} \\ \xi_{Dij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & \tau \sigma_C \sigma_D \\ \tau \sigma_C \sigma_D & \sigma_D^2 \end{pmatrix} \right). \quad (1.14)$$

Using the joint model, the strong variance constraint is relaxed, and the heteroskedastic aspect of the data can be captured making it a more appropriate model in controlling for endogeneity in simultaneous models.

1.5 Summary

In this chapter, I reviewed two traditional joint modeling approaches (i.e., correlated multivariate mixed types of outcome variables) and one univariate (separate) model for mixed types of outcome variables in the case of correlated binary and continuous outcome variables. The separate modeling approach is the simplest and easiest way to analyze data in this situation. However, by ignoring the potential association between outcome variables, this approach results in problems, such as biased and inconsistent estimation. Although this approach is simple enough and may work in some cases, it is conceptually unsatisfactory and inefficient in many applications. Therefore, it is necessary to employ a more appropriate model.

There are two alternative models that include a potential association between mixed types of outcome variables together, either directly or indirectly. Factorization models (Fitzmaurice and Laird 1997, 1995) and reverse factorization models (Catalano and Ryan 1992) directly specify the joint distribution as the product of a conditional distribution of one outcome and a marginal distribution of the other. These approaches assume the conditional normality of the continuous outcome variable, but there is no closed-form distribution of the discrete outcome variable. Both the factorization model and the reverse-factorization model provide direct ways to specify the joint distribution of the mixed outcome variables when they have different forms, but the results in these models are not comparable, since the different factorizations used lead to different interpretations. Nor can these approaches capture the heteroskedastic aspect of the data, meaning that it is hard to apply them to clustered data and longitudinal data.

An indirect approach, called a latent model, specifies the joint distribution of the mixed types of outcome variables indirectly by introducing shared or correlated random effects to link associations between outcome variables (Leon and Withanage 2013). This approach enables one to account for different levels of data, so the latent model can be extended to clustered data and longitudinal data. However, several analytical issues remain. For example, the correlations in the latent model lie within artificially narrow ranges, since the potential association is linked through a shared random effect. Also, computational difficulty may arise for high-dimensional data (De Leon and Carrière Chough 2010; McCulloch 2008).

From an analytic perspective, applying a rigorous model is a very important issue; however, there are many analytical challenges to achieving this in the case of correlated multivariate outcome variables. If the dataset has clustered structure or dependence structure (such as clustered data, longitudinal data, or other big data), it is more difficult to handle this situation. Although many traditional methods have been discussed for combining correlated outcome variables in a more general testing context, their methods do not apply directly to clustered data and longitudinal data, because of the complexity of the models and the computational difficulties. Therefore, I consider a correlated multivariate outcome joint model using generated multiple random effects. In this model, the potential correlations between outcomes are captured through the simultaneous linkage of their own random effects, so the omitted bias problem can be resolved, and the existing heteroskedasticity of the data also can be captured. Therefore, this approach is general enough to include traditional models and to give a more general formulation to extend to

complex structured data (e.g., clustered and longitudinal data). The summary of the traditional approaches and the proposed approach are presented in Table 1.

Based on the literature of modeling approaches for treating correlated multivariate outcome variables, the joint model I propose in this study is the most efficient and rigorous model, minimizing modeling assumptions and resolving analytic problems. In Chapter 2 we explore the joint modeling approach to a marketing study of a multinational auto survey. Chapter 3 applies the method to a longitudinal study of coupon impact in scanner data. Chapter 4 provides results, conclusions, limitations, and future research in this area.

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Appendix

Table 1. 1 Summary of joint modeling approaches.

	Separate Model	Factorization Model (reduced form solution for Structural Equations Modeling)	Latent model	Joint model
Model description	Estimating separate model by ignoring the potential association between the outcomes.	Adding correlated error term of two outcomes. Factorize the joint distribution using a marginal distribution of the of the continuous outcomes and the conditional distribution of the latent variable of the binary/ordinal outcomes.	Adding common and correlated random error term in the model. Special case of Joint model.	Adding random intercept in each model.
Pros	Simple and easy to interpret the regression parameters	• Suitable for a cross-sectional data. • Ability of a marginal interpretation in two equations. • Can compare the marginal effects of the equations. • Allow a different variance for each level of the binary outcome.	• Resolving omitted variable problem. • Capture heterogeneity of multilevel data. • This approach uses the available information optimally because we use information about all dependent variables simultaneously.	• Resolving omitted variable problem. • Capture heterogeneity of multilevel data. • This approach uses the available information optimally because we use information about all dependent variables simultaneously.
Cons	• Inefficient in estimating covariate effects for each outcome. • Limit to answer intrinsic multivariate questions. • Inconsistent estimation when unobserved endogenous outcome presented.	• Difficulty to estimate all parameters in the model. • Cannot be directly extended to a model including nominal outcome which has more than three alternatives.	• Treat the mixed outcomes symmetrically rather than imposing any form of hierarchy.	• Complexity of the model. • Running time for the data analysis.

Table 1.1 Summary of joint modeling approaches (Cont.)

	Separate Model	Factorization Model (reduced form solution for Structural Equations Modeling)	Latent model	Joint model
Cons	Produce biased estimates for missing data.	- Strong assumption that is required; probit model always assumes standard normal distribution with $\sigma=1$. - Cannot explain of differences between individuals and between groups. - Cannot capture heterogeneity.		
Mathematic Notation	i) Continuous Outcome $Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij}$ ii) Binary Outcome $probit(\mu_{Dij}) = X_{Dij}^T \beta_D + \varepsilon_{Dij}$ with $\begin{pmatrix} \varepsilon_{Cij} \\ \varepsilon_{Dij} \end{pmatrix} \sim N \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & 0 \\ 0 & \sigma_D^2 \end{pmatrix} \right)$	i) Continuous Outcome $Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij}$ ii) Binary Outcome $probit(\mu_{Dij}) = X_{Dij}^T \beta_D + \tau(Y_{Cij} - \mu_{Cij})$ with $\begin{pmatrix} \varepsilon_{Cij} \\ \varepsilon_{Dij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & \tau\sigma_C\sigma_D \\ \tau\sigma_C\sigma_D & 1 \end{pmatrix} \right)$	i) Continuous Outcome $Y_{Ci} = X_{Cij}^T \beta_C^* + U_{ij} + \varepsilon_{Cij}^*$ ii) Binary Outcome $Y_{Di}^* = X_{Dij}^T \beta_D^* + U_{ij} + \varepsilon_{Dij}^*$	i) Continuous Outcome $Y_{Cij} = X_{Cij}^T \beta_C + \varepsilon_{Cij} + \xi_{Cij}$ ii) Binary Outcome $P(Y_{Bij} = 1 X_{Bij} = x_{ij}) = \frac{\exp(X_{Dij}^T \beta_D)}{(1 + \exp(X_{Dij}^T \beta_D))} + \varepsilon_{Dij} + \xi_{Dij}$ with $\begin{pmatrix} \xi_{Cij} \\ \xi_{Bij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_C^2 & \tau\sigma_C\sigma_D \\ \tau\sigma_C\sigma_D & \sigma_D^2 \end{pmatrix} \right)$

Table 1.1 Summary of joint modeling approaches (Cont.)

	Separate Model	Factorization Model (reduced form solution for Structural Equations Modeling)	Latent model	Joint model
Graphical Represent s				

CHAPTER II
A MULTI-COUNTRY STUDY OF CUSTOMER LOYALTY
IN THE AUTOMOBILE INDUSTRY

Abstract

Although the literature on marketing has recognized that customer loyalty is affected by significant antecedents such as satisfaction, marketing activities, and attribute performance, the antecedents of customer loyalty have mostly been studied separately. As customer loyalty has been infrequently examined with simultaneous consideration for its attitudinal (Words of Mouth, WOM) and behavioral (brand switching) dimensions, this study aims to explore the relationships between the two dimensions of loyalty (WOM and brand switching) and their antecedents, including satisfaction as a mediator, in a simultaneous model. I assess how and why current brands' experience-based evaluations and alternative brands' image-based evaluations affect customer loyalty through customers' overall satisfaction in the integrated framework. I also explore whether culture moderates these relationships. The integrated research framework is tested using cross-sectional survey data collected by an automobile manufacturer in eight countries (n=7,624).

To account for a potential correlation between the two dimensions of loyalty (attitudinal loyalty and behavioral loyalty), a joint modeling approach is employed. The results show a positive relationship between satisfaction and attitudinal loyalty (WOM) and a negative relationship between satisfaction and behavioral loyalty (brand switching). Functional attributes, emotional attributes, and dealership service experiences for the current car have direct positive effects on attitudinal loyalty. Perceived image of emotional attributes of alternative cars has a positive effect on behavioral loyalty. On the other hand, behavioral loyalty is directly and negatively affected by after-purchase service and

marketing activities. In addition, the in-group collectivistic culture has a negatively impact on the relationships of the two dimensions of customer loyalty with their antecedents.

1. Introduction

Shaping customer loyalty, a customer's decision on whether to retain their current brand or to switch brands, is critical to a company's or brand's long-term survival, performance, and bottom-line returns in the automobile industry (Sambandam and Load 1995). Customer loyalty has been the dominant paradigm in explaining how customers formulate their future purchase intentions. Particular emphasis has been placed on experience-based product attribute evaluation and customer satisfaction. However, many researchers have defined brand loyalty only from the behavioral perspective despite extensive research considering the impact of an attitude-behavior relationship on loyalty (Dandyopadhyay and Martell 2007; Rundle-Thiele and Bennett 2001; Baldinger and Robinson 1996; Dick and Basu 1994).

Customer loyalty to car brands has been traditionally conceptualized as a function of customer satisfaction based on actual experience with a product or service and its marketing activities. Despite a considerable amount of research drawing and testing conceptual links, examining performance information, and investigating the impact of satisfaction with chosen or not chosen brands on customer loyalty (Voss, Godfrey, and Seiders 2010; Jones and Sasser 1995; Oliver 1980, 1997), surprisingly little work has been done to assess the effects of experience-based product attribute performance and of current and potential customers' satisfaction on customer loyalty. Automobile consumption, in comparison with other product categories, is characterized by high complexity (Sambandam and Load 1995). Thus, product/image information of forgone alternatives

may also have an important role in shaping loyalty to a car brand, along with product knowledge and satisfaction with the current car brand.

These relationships have particularly puzzled global brands that do business in numerous countries with highly varied cultures. Therefore, although several empirical studies have investigated the effects of current purchase evaluation, including experience-based product attribute performance and satisfaction, on post-purchase behavioral intentions, more work on the impact of cultural diversity is required.

The current research fills gaps in previous research and integrates two different paths of brand evaluations—direct (from the current car experience) and indirect (from the image of alternative car brands)—by considering a two-dimensional concept of loyalty (attitude-behavior relationship). Using cross-national data on the automobile industry, this study also investigates whether the national culture could influence the relationship between brand evaluation and customer loyalty. Specifically, this study seeks to answer the following questions about the associations among product evaluation (based on both experience-based attribute and image-based attribute performances and satisfaction with the current brand), loyalty (as measured in two different dimensions) and cultural factor:

1. To what extent are brand/product attributes and satisfaction associated with post-purchase behavioral intention, particularly a direct experience path and an indirect (image) path, in the context of the automobile industry?

2. To what extent do cultural differences influence the relationship between brand evaluation and post-purchase behavioral intention?

Although much research has studied the effect of direct experience and indirect experience (image) on individual post-purchase intentions, little is known about both experiences together. I propose that the inconclusiveness of previous research may partly stem from a “black-box” approach, which has been applied in empirical studies in both areas (Bodet 2008; Homburg and Giering 2001; Hollowell 1996). In addition, As Inman, Dyer, and Jia (1997) suggested, research is needed to consider the indirect experience (image) of forgone alternatives together with the direct experience of the chosen brand. Whether and how both experiences shape post-purchase behavioral intention is also an important question that this study seeks to address. Therefore, I formally integrate the concepts of experience (both indirect and direct) and post-purchase behavioral intentions toward chosen and forgone alternatives, which have been discussed separately for many years, into a single model based on a multi-attribute preference structure.

To answer the research questions, I apply a joint modeling approach. The conceptual model proposed in this paper includes two different types of correlated dependent variables: attitudinal loyalty, a continuous variable, and behavioral loyalty, a binary variable. In addition, the international customer survey used in this study is cross-cultural, a form of multi-level (or clustered) data. Traditional statistical approaches are difficult to apply in cases of mixed types of outputs, particularly when considering the dependence relationship between two outcomes. The models must also explain individual

similarities and differences among several cultural groups. Many traditional approaches ignore the potential dependence of outcomes or attempt to control the correlation in some limited way. However, those approaches require very strong and potentially unrealistic assumptions and suffer from hard-to-resolve statistical problems such as omitted variables and biased estimation. These methods are also less capable of dealing with differences in individuals when the data are clustered. To account for potentially correlated outcomes of varying types in multi-level data, a more appropriate model is needed. Therefore, a joint model approach is introduced in this study as an appropriate method to analyze multi-level data.

Recognizing that drivers of brand evaluation affect attitudinal loyalty and behavioral loyalty differently, this study contributes to the literature by considering factors that deal with customers' current car experience along with their perceived image of alternative products. This study also contributes to analytical methods by applying a joint model to address potential associations between different types of outcomes in the framework. Therefore, this study suggests more relevant and rigorous methods for analyzing multi-level data including mixed types of outcome variables. The study also suggests new directions for future research and provides implications for managers involved in marketing.

The rest of the study is organized as follows: In Section 2, I provide the theoretical background for the study. In Section 3, I discuss the conceptual framework and describe the methodology employed to analyze the data. In particular, I describe the survey data obtained from a large global automotive company. In Section 4, I present the findings and

the implications for practitioners dealing with brand marketing. I conclude with a discussion on the scope of future research on loyalty and international marketing and the limitations of the present study.

2. Theoretical Background

Figure 1 diagrams a conceptual framework for this study based on our literature review. In this model, the effects of product/service attributes and satisfaction are related to two measured dimensions of customer loyalty in the form of a favorable attitude (attitudinal loyalty) and repeat purchase (behavioral loyalty). This is accomplished by focusing on the different aspects of direct experience from a survey respondent's current car and indirect experience based on the image of alternative car brands in the automotive market. Also, national culture will be investigated as a potential moderator among the linkages between brand/product evaluation and post-purchase behavioral intention.

2.1 Customer loyalty

Customer loyalty has been continuously considered to be an important concept in marketing. For example, marketing researchers revealed that customer loyalty is the most important driver of long-term corporate financial performance (Frank et al. 2013; Reichheld and Sasser 1990). Oliver (1997,p 392) defines loyalty as “a deeply held commitment to rebuy or repatronize a preferred product or service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts that have the potential to cause switching

behavior”. Numerous studies over last three decades assumed that repeat purchasing can be used as a proxy for the loyalty of a customer towards the brand of interest. However, more recent studies suggested that two key dimensions operationalize brand loyalty, behavioral loyalty and attitudinal loyalty, and other researchers found that the significant link between two dimensions of the customer loyalty (Bandyopadhyay and Martell 2007; Evanschitzky and Wunderlich 2006; Uncles et al. 2003; Oliver 1999, 1997; Dick and Basu 1994; Jacoby and Chestnut 1978). Despite the many attempts to consider customer loyalty as a key dependent variable, relatively little empirical research has been conducted on testing the two loyalty dimensions together.

2.1.1 Behavioral loyalty

As noted above, in the most of earlier studies of brand loyalty (Sharp et al. 2002; Ehrenberg 2000; Ehrenberg et al. 1990; Kahn et al. 1986; Jacoby and Chestnut 1978; Jacoby and Kyner 1973), brand loyalty was defined as a repeated purchase of a specific brand over time by a customer. Many researchers assumed that repeated purchasing behavior can capture the customer loyalty toward the brand of interest. For instance, behavioral loyalty is viewed as retention of the brand in industrial and service marketing (East et al. 2005; Reinartz and Kumar 2000). For the analytical test, customers’ belief toward brand, affect, and repurchase intention used as proxy variables for behavioral loyalty (Jacoby and Chestnut 1978).

In addition to using repeat purchases as an operational definition, some researchers have operationally defined loyalty with metrics such as intention to repurchase, or intention

to switch brands (Yi and La 2004; Dekimpe, Steenkamp, Mellens, and Vanden 1997). Intention to switch is therefore another important reflection of customer loyalty and is rigorously defined as the customers' self-reported likelihood of using a brand again in the future (Fornell 1992). For example, Olsen (2002) found that brand switching is positively associated with indirect experience about alternative brands (or image) through advertisement and marketing activities (Deighton, Henderson, and Neslin (1994). Thus, brand switching is included as the first dependent variable in this research.

However, the behavioral loyalty approach ignores existence of situational factors, intrinsic factors, or socio-cultural factors, which can explain loyalty beyond the repeated purchasing of brand (Oliver 1999; Day 1969). Therefore, several recent works suggested to (1) distinguish between repeat purchasing behavior and brand loyalty and (2) extend behavioral brand loyalty measures to the multidimensional phenomenon including attitudinal aspects of loyalty.

2.1.2 Attitudinal loyalty

Attitudinal loyalty relates to a favorable attitude toward a specific brand or product (Evanschitzky and Wunderlich 2007). Several researchers postulate that attitudinal brand loyalty could fill the gap between the traditional definition of “spurious loyalty” as defined only from the behavioral perspective and “true/intentional loyalty” (Bakdinger and Robinson 1996; Day 1969). The need for the inclusion of an “attitudinal” perspective along with behavioral perspective to define customer loyalty has been expressed by many researchers. For example, Dick and Basu (1994) mentioned that the definition of loyalty

only including a behavioral view is insufficient towards how and why brand loyalty is developed and modified, and they were precise in suggesting that a favorable attitude was required to define loyalty with repeat purchase behavior. Later, they tested a brand loyalty construct that encompassed both customer repurchasing behavior and attitude. Also, Chaudhuri and Holdrook (2001) modeled two aspects of loyalty, repurchase loyalty and attitudinal loyalty, as linking variables in the sequence of effects from brand trust and relative outcomes. In a more recent paper, East et al. (2005) empirically examined how customer loyalty is operationalized by a favorable attitude and repeat purchases.

The favorable attitude can be expressed by customers in forms of word-of-mouth (WOM), since WOM is expression of perceived vital information about a brand to help building loyalty (Maxham 2001). In other words, loyal customers with a good attitude toward a brand share their brand experience with other people, and the positive experience makes them to recommend the brand to others (Alba and Marmorstein 1987; Hasher and Zacks 1984). Therefore, intention of brand recommendation is considered as a second dependent variable in this study. WOM may highly correlated with another dimension of loyalty, brand switching (behavioral loyalty), it is necessary to integrate these two types of loyalty very carefully. We will discuss this further in Section 3.

2.2 Antecedents of customer loyalty

Customer loyalty with two aspects, behavioral loyalty (i.e., brand switching) and attitudinal loyalty (i.e., intention of recommendation) are directly influenced by customer satisfaction, and they are both directly and indirectly affected by perceptions of quality

about product- and service-related attributes and marketing activities (Hellier et al. 2000). In the following sections I briefly review the antecedents of customer loyalty.

2.2.1 Satisfaction

Traditionally, customer satisfaction is studied as a key driver of brand loyalty in situations marked by the existence of many alternatives (Oliver 2009; Brunner, Stocklin, and Opwis 2008; Cronin et al 2000; Jones and Sasser 1995). There are many definitions of satisfaction in the marketing literature. Satisfied customers highly recommend the brand more and retain their current brand, whereas dissatisfied customers less recommend the brand to others and intent to switch brand (Johnson et al. 2001). In this study, satisfaction can be defined as “the degree of overall pleasure or contentment felt by the customer, resulting from the ability of the product (or brand) to fulfill the customer’s desires, expectations and needs in relation to the product (Hellier et al. 2003)”. Prior studies used satisfaction as an important antecedent of customer loyalty both theoretically and empirically in the marketing literature, and researchers have tested the effects of satisfaction on the customer loyalty (Brunner, Stocklin and Opwis 2007; Cooil et al. 2007; Bolton, Leron, and Bramlett 2006; Mittal and Kamakura 2001). In addition, numerous studies find a positive impact of satisfaction on repurchase behavior, repurchase intention, brand switching, and customer retention (Brunner, Stocklin and Opwis 2007; Yi and La 2004; Cronin et al. 2000; Bonton 1998; Anderson and Sullivan 1993). For example, according to Yi and La (2004), both cumulative and episodic customer satisfaction affects behavioral loyalty. This agrees with earlier researchers who found that all three types of

satisfaction (transactional, cumulative, and episodic) influence future expectations and repurchase intentions (Boulding et al. 1993). Sambandam and Load (1995) found a significant direct effect of satisfaction in models of switching behavior, i.e. a highly satisfied customer may remain less likely to switch to a different make than a less satisfied customer. Furthermore, most research that has examined the satisfaction-customer loyalty link empirically has concluded that satisfaction's impact on intentions of repurchase and brand switching is significant (Oliver 1997; Anderson and Sullivan 1993; Mazursky and Geva 1989)

Despite theoretical and empirical supports for satisfaction as an important factor of customer loyalty, recent studies argue that satisfaction alone may explain little variance in future purchase intention under certain circumstances (Kumar, Pozza, and Ganesh 2013; Voss, Godfrey, and Seiders 2010; Agustin and Singh 2005; Seiders et al. 2005; Verhoef 2003), therefore it is required to consider additional factors in order to explain customer loyalty.

2.2.2 Attribute-level performances

Another key determinant of customer loyalty is attribute-level performance. Attribute-level performance is defined as “the ingredients necessary for performing the product or service function sought by consumers” (Keller 1998, p.93). As quality indicators, product and service attribute performance are very important factors to shape customer loyalty (Mittal et al. 2001; Mittal and Katrichis 2000; Mazur 1998; Griffin and Hauser 1993).

According to this research stream, satisfaction deriving from attribute-level performances captures a significant amount of variations of overall satisfaction (Mittal et al. 1999; Gardial et al. 1994; Griffin and Hauser 1993; Oliver 1993; Bolton and Drew 1991). According to the Alba and Marmorstein (1987), positive attribute experiences towards a brand influence customer loyalty through high level of satisfaction. Prior research highlighted that customer loyalty, brand switching behavior and intentions to recommend, are explained by satisfaction level (Crosby and Stephens 1987) and perceptions of quality about brand attributes in terms of the product itself (Rust and Zahorik 1993) and service (Ganesh et al. 2000; Kelly et al. 1993). For example, experience-based product/service knowledge at the attribute level provides a significant amount of variation in post-purchase intention (Mittal, Katrichis, and Kumar 2001; Mittal, Kumar, and Tsiros 1999; Sambandam and Load 1995; Oliver 1993). An attribute-level evaluation based on performance of the product itself and service typically captures a significant effect on repurchase intention and brand switching (Mittal, Kumar, and Tsiros 1999). According to the Sambandam and Lord (1995), experience-based product attribute performance implies “a well-developed and potentially readily accessible memory structure”, and it is positively associated with behavior at the stage of post-purchase intention. In addition, Gardial et al. (1994) found that consumers use product/service attributes rather than the overall product more than twice as frequently when evaluating the current choice and describing consumption outcomes post purchase. Gustafsson and Johnson (2004) also found that product and service attributes are essential parts to explain both customers’ satisfaction and loyalty.

However, several studies found the significant relationship between attribute-level performance and customer loyalty, but not the attribute-level performance-satisfaction link (Mittal et al. 1993). For example, based on this attribute-level conceptualization of the antecedents of satisfaction and loyalty, many studies emphasize that attribute-level performance should affect both satisfaction and customer loyalty, but differently (Ostrom and Lacobucci 1995; Oliva et al. 1992). In addition, evaluation about attribute-level performance varies based on the customer's goals or product categories (Mittal et al. 1993). In the automotive industry, customers are more likely use attribute-level information rather than product level when they choose a future car brand (Gustafsson and Johnson 2004; 1997). To test the conflicting findings of these studies, both product-related and service-related attribute level performance are included as independent variables.

2.2.3 Marketing activities

The last key antecedent needed to explain the variations of both satisfaction and customer loyalty are marketing activities. Marketing activities can be defined as all activities designed to engage the customer to develop products and services that they can employ to satisfy their needs (Trusov et al. 2008). Marketing activities including advertising, promotions, and public-relations differentiated brands to competitors' brand (Srivastava et al., 1999; Keller 1993). According to the Chi et al., (2009), brand awareness can be increased through marketing activities. Also, the marketing activities that are characterized by an offer from the companies enhance brand loyalty, perceived satisfaction, and a firm's reputation (Van et al. 2006; Shugan 2005; Delgado-Ballester 2001; Peterson

1995). Dick and Basu (1994) mentioned that a firm's marketing activities have very important role of development, maintenance, or enhancement of customers' loyalty toward both product brand and corporate brand. Like the effects on customer loyalty, studies have consistently found a relationship between marketing activities and customer overall satisfaction (Spreng 1995; Yi 1990). In the brand literature, customer satisfaction and loyalty are considered to be the most important outcomes of all marketing activities in a market oriented firm (Durvasula 2000; Kandampully and Shhartanto 2000). More importantly, marketing activities are directly related toward external customers for creating new customers (Gummesson 1996). Thus, marketing activities of a firm were considered as another factor for determining satisfaction and both customer loyalties, word-of-mouth (attitudinal loyalty) and brand switching (behavioral loyalty).

2.3 Impacts of the current brand and alternative brands

2.3.1 Role of alternative brands

To explain customers' loyalty through their satisfaction level, it is necessary to consider the mixed aspects of alternative brands. The performance information of the attributes of a chosen brand (or owned brand) has an important role on the brand loyalty and satisfaction. In addition, performance information about the product attributes of "forgone alternatives" (i.e., alternative that were considered but not chosen) also has a significant impact on brand loyalty and satisfaction (Inman, Dyer, and Jia 1997). With knowledge about chosen brand (or current/owned brand), performance information from the indirect experience (or perceived image) about forgone alternatives also has a

significant impact on the post-purchase evaluation and, consequently, post-choice attitudes and, and behavioral intention (Inman, Dyer, and Jia 1997; Boulding et al. 1993). The well-known decision making models (i.e., AIDA, hierarchy-of-effects) denote cognition/brand knowledge as the first step in choice situations, where the firm's marketing activities serve to inform prospects about the merits of an offering, convey its superiority in relation to competing products, with the aim of increasing the consideration set size (Mitra and Lynch 1995; Amos 2010). As the consideration set increases, the retention rate decreases correspondingly (Anderson and Mittal 2000). Experimental studies have shown that brands with greater recall tend to enjoy higher choice shares, with the inclusion in customers' consideration set as the accepted causal mediating mechanism (Nedungadi 1990; Hutchinson 2011).

In addition, in complex, highly-involved purchase situations such as auto purchasing, Capraro, Broniarczyk, and Srivastava (2003) find that customers are amenable to receiving information about not only their current (incumbent) brand, but also potential alternatives. In spite of this importance, much of the post-valuation literature focuses only on the selected brand or forgone alternatives individually (Anderson and Sullivan 1993; Bolton and Drew 1991). Very few studies consider both chosen and forgone alternatives in the same model (Inman, Dyer, and Jia 1997; Loomes and Sugden 1986, 1982). This, despite of the fact that several researchers have suggested, that it is necessary to consider both the chosen brand and foregone alternatives for testing post-purchase behavioral[testing what ?] in a single model based on multi-attribute preference structure (Inman, Dyer, and Jia 1997; Loomes and Sugden 1986;1982).

2.3.2 Direct vs. indirect experiences

A customer's consideration set is considered a critical factor in investigating the brand/product evaluation process because a decision to repurchase the same brand, to switch to other brands, or to recommend is likely to consider the availability and attractiveness of alternatives along with evaluation of the current brand (Sambandam and Load 1995). Many researchers explain overall experience as a mixture of direct and indirect experience; the product experience occurs directly if customer has contact with the product (or brand) (Brakus, Schmitt, and Zarantonello 2009; Hoch and Ha 1986) or indirectly if products (or brands) are presented through advertising, or marketing communications (Brakus, Schmitt, and Zarantonello 2009; Kempf and Smith 1998; Hoch and Ha 1986).

In many cases, consumers build their consideration set through product/brand experience and they gain experience with a product (or brand) through many forms of contact. Numerous studies in the consumer and marketing literature have shown that the overall brand/product experience occurs through searching for products, receiving service, and consuming or using the products (Brakus, Schmitt, and Zarantonello 2009; Brakus, Schmitt, and Zhang 2008; Arnould, Price, and Zinkhan 2002). Here the product could refer to either a good or a service. Another form of direct experience occurs when products are consumed and is called consumption experience (Brakus, Schmitt, and Zarantonello 2009).

From direct experience, customers gain information and learn about attributes of products/brands performance. However, customers only depend on indirect experience if experience via direct consumption and usage does not exist. For that reason, indirect

experience can be regarded as the image of brands (or products). Several researchers define that image as a function of accumulated experience provided by information environments such as marketing activities, advertising, and direct marketing (Opwis 2008; Andreassen and Lindestad 1998, Ostrowski et al. 1993). The perceived indirect experience (image) of an unused product (or brand) can obviously play an instrumental role when considering future purchase. For example, Bloemer and Ruyter (1997) concluded that image [has a bigger impact?] than satisfaction on loyalty behavior such as repurchase intention.

Consumers with the greatest experience have more information and can structure choice criteria better, both of which lead to likelihood of repurchase in the future (Chattopadhyay and Laborie 2005; Anderson et al.,1979). In the consumer behavior and marketing literatures, a number of studies have shown that direct experience is generally based on more accurate information regarding products rather than indirect experience, which is called second-hand information. Although direct experience provides more accurate information in the stage of future purchase, perceived image (as indirect path of experience) may also play an instrumental role when considering alternatives. Based on a number of studies, researchers examine the effects of direct experience on different types of post-purchase behavioral intentions such as future purchase intention, brand preferences, and product judgment (Brakus, Schmitt, and Zarantonello 2009; Huffman and Houston 1993; Hoch and Deighton 1989; Hoch and Ha 1986).

As I mentioned before, customer experience about product or brand has also attracted a lot of attention both marketing literature and marketing practice as a factor affecting post-purchase behavioral intention (Brakus, Schmitt, and Zarantonello 2009).

While the link between product/brand experience and post-purchase behavioral intention in post-valuation and marketing literatures focuses on the selected brand, referred to as an owned brand in this study (Anderson and Sullivan 1993; Bolton and Drew 1991), prior studies fail to consider both chosen and forgone alternatives in this relationship (Inman, Dyer, and Lia 1997).

2.4 Culture

Global companies can drive growth in the markets in which they compete by garnering purchases from existing customers and/or attracting new customers (Rust, Zahorik, and Keiningham 1995; Reinartz, Thomas, and Kumar 2005). One possible moderating factor of post-purchase behavioral intention proposed and studied by Fazio and his colleagues, has been the role of national culture in the formation of attitudes (Fazio & Zanna, 1978a, 1978b; Sherman et al., 1982; Regan & Fazio, 1977). In international business studies and marketing scholarship, national culture is an important variable hypothesized to moderate the customer experience and satisfaction-post purchase behavioral intention relationship (Kirkman, Lowe, and Gibson 2006; Bianchi et al. 2000; Schwartz 1994; Clark 1990). Considering the international nature of the data considered in this study, it is natural to examine the moderating effect of culture on the relationship between indirect or direct experience and purchase intentions.

Culture is defined as shared pattern of norms, assumptions, values, and beliefs among the members in the same group (Hofstede 1980). Furthermore, individuals' attitudes, beliefs, and values impact the way that they process and evaluate information

from their environments (Triandis 1989). Therefore, the moderating impact of national culture has been explored in the cross national business literature (Kirkman, Lowe, and Gibson 2006; Bianchi et al. 2000; Schwartz 1994; Clark 1990). Because of the international nature of our data, it is natural to explore the moderating effect of culture on the relationships in particular to explain the paths of post-purchase behavioral intentions (see Figure 2).

Customers' differing cultural background as represented by nationality affects not only the way they evaluate the product experience but also the product (or brand) choice (Lord et al. 2008; Davies and Fitchett 2004). That is, customers personal (e.g. motivation, expectation, and personality) and situational (e.g. experience and evaluation) could be affected by the individual's cultural background (Masgoret and Ward 2006). Considering the potential significance of this effect, many researchers have attempted to investigate the direct influence of national culture on customer motivations, expectations, perceptions, and evaluations of intangible and tangible goods; however, a comprehensive evaluation of the moderating effect is lacking (Kirkman, Lowe, and Gibson 2006; Stahl and Caligiuri 2005; Hofstede 2001; Triandis 1995). Research in international business has also continuously examined the relationship between cultural similarity and customer behavior.

A conceptual framework is displayed in Figure 1 and 2. In this model, the effects of product/service attributes and satisfaction are related to both dimensions/measures of customer loyalty in the form of a word-of-mouth as a favorable attitude (attitudinal loyalty) and repeat purchase (behavioral loyalty). This is accomplished by focusing on the different aspects of direct experience from current car and indirect experience based on the image

of alternative car brands in the automotive market. Also, national culture will be investigated as a potential moderator among the linkages between brand/product evaluation and post-purchase behavioral intention. In addition, Table 1 summarizes the definitions of each concept I reviewed above. I next formalize a statistical model for analysis, then describe the procedure used to collect the data for study in the following sections.

3. Empirical Methodology

In the marketing literature, customer loyalty consists of multiple dimensions- behavioral loyalty and attitudinal loyalty. More recently, many studies collect multiple outcomes to characterize customer loyalty and those multiple outcomes of customer loyalty are highly correlated, but still the common approach used by researchers is to ignore this correlation and analyze each outcome separately.

To achieve accurate results and more realistic implications for managers, it is required to apply a rigorous modeling approach by considering a potential association between two outcome variables, behavioral loyalty and attitudinal loyalty. However, ignoring the correlation between two outcome variables does cause bias and inconsistency in the parameter estimation, especially if these outcome variables are likely explained by common predictors. This is similar to omitted variable bias because the second (or first) outcome variable that is correlated with both first (or second) outcome variable and independent (predictor) variables is omitted from a regression equation. The bias is created when the model compensates for the missing pattern by overestimating or underestimating the effect of one of the other factors. Since the estimators are inconsistent, increasing the

sample size does not guarantee the estimates converge to the true value of the parameter being estimated.

Researchers working in the areas of marketing, applied statistics, and business analytics have developed a number of models that attempt to either capture or explain the effect of the possible antecedents on multi-dimensional loyalty simultaneously (Bodet 2008). Although the joint analysis of outcomes measured in the same scale (commensurate outcomes) can be undertaken with standard statistical methods, outcomes measured in different scales (noncommensurate outcomes), such as mixed binary and continuous outcomes, present more difficult challenges (Teixeira-Pinto et al. 2011).

In this study, interest focuses on the relationship between customer loyalties such as intention of recommendation and brand switching behavior reflecting possible effects of the attribute-level performances and marketing activities based on both experience of current brand and perceived image of alternative brand through customers' overall satisfaction. Since multiple outcomes thought to be associated with the common predictors, a joint modeling framework that represents these relationships is an appropriate one in which these questions may be addressed.

Because the two dependent variables (outcomes) are associated and also likely explained by common predictors and cluster structure, I modeled them simultaneously using a random-effects approach and thereby directly estimating the correlation among outcomes within a country. The conceptual model in the present study accounts for the mixed types of outcome variables; a binary variable, choice of brand, and a second dependent measure, intention to recommend the brand to others (WOM), which is

operationalized as a 10 point Likert-scale and treated as a continuous variable for modeling purposes. I develop joint modeling equations using a normal mixed linear model for the Likert outcome, intention of recommendation, and a discrete choice probit model for the binary variable, brand switching.

3.1 Model specification

To formulate the joint models, we begin with the two dependent variables, the approximately continuous outcome, word-of-mouth (WOM), and the binary indicator of brand switching on a future brand choice. As mentioned in Section 3.1, WOM is modeled as a normal regression model and a discrete choice model is used for the construct of brand switching (BS, binary outcome variable). Let subscript i index the individual survey respondents while j denotes the country of origin. Brand switching (BS) of customer i will be modeled as a function of the information about the current brand (z_{ij1}) and characteristics of the alternatives (z_{ij2}) using a probit model for the binary variable. A customer's word of mouth (WOM) score and the brand switching decision (BS) of customer i in country j depends on the customer's brand evaluation about product-related attribute performance (functional attribute (FA) and emotional attribute (EA)), service-related attribute (dealership service (DS) and after-purchase service (AS)), a firm's marketing activities (MA), and the customer's overall satisfaction (SAT) for both current car brand and alternative car brands. I include the customer's overall satisfaction as mediator in this study by following the literature. I also include national culture as a moderator by estimating culture specific parameters for the individual attributes. This is

accomplished by including an interaction between the GLOBE score for in-group collectivism and each independent attribute listed above. In addition, demographic factors, household size (HS), marriage status (MS), age (AGE), and education level (EL) are included as control variables.

The first step in model construction diagrammed in Figure 1 is to model a customer's overall satisfaction as mediator. In mathematical terms, this is formulated as

$$\begin{aligned}
 SAT_{current,ij} = & \alpha_0 + \alpha_{1C}FA + \alpha_{2C}EA + \alpha_{3C}DS + \alpha_{4C}AS + \alpha_{5C}MA \\
 & + \alpha_{6A}FA + \alpha_{7A}EA + \alpha_{8A}DS + \alpha_{9A}AS + \alpha_{10A}MA \\
 & + \alpha_{11}HS + \alpha_{12}MS + \alpha_{13}AGE + \alpha_{14}EL + \varepsilon_{C,ij}
 \end{aligned} \tag{2.1}$$

Second, a discrete choice model is formulated based on the utility functions. Assume T_{ijk} is the utility of person i in country j from choosing alternative k ($k = 0$ if current vehicle, 1 if one of the alternative models in the choice set). Then the utility of each alternative depends on the attributes' differences between $z_{current,ij}$ and $z_{alternative,ij}$ and the probability can be expressed as

$$T_{current,ij} = \theta z_{current,ij} + \varepsilon_{current,ij} \tag{2.2.1}$$

and

$$T_{alternative,ij} = \theta z_{alternative,ij} + \varepsilon_{alternative,ij} \tag{2.2.1}$$

where $\varepsilon_{current,ij} \perp \varepsilon_{alternative,ij}$.

In the third step, the mathematical formulation of the joint model of WOM (continuous variable) with normal regression model and BS (brand switching, binary) with probit choice model using the estimated value of $SAT_{current,ij}$ to capture the mediated indirect effects of antecedents along with the direct are as follows

$$\begin{aligned}
WOM_{ij} = & \beta_{11} + \beta_{1W}FA + \beta_{2W}EA + \beta_{3W}DS + \beta_{4W}AS + \beta_{5W}MA \\
& + \beta_{6W}FA + \beta_{7W}EA + \beta_{8W}DS + \beta_{9W}AS + \beta_{10W}MA \\
& + \beta_{11W}\widehat{SAT}_{current,ij} \\
& + \beta_{12}HS + \beta_{13}MS + \beta_{14}AGE + \beta_{15}EL + \varepsilon_{wom,ij} + \xi_{wom,j} \quad (2.3)
\end{aligned}$$

$$\begin{aligned}
BW_{ij}^* = & \beta_{11} + \beta_{1BW}FA + \beta_{2BW}EA + \beta_{3BW}DS + \beta_{4BW}AS + \beta_{5BW}MA \\
& + \beta_{6BW}\widehat{SAT}_{current,ij} + \varepsilon_{BW,ij} + \xi_{BW,j} \quad (2.4)
\end{aligned}$$

In the joint model, the random effects and the random errors are assumed to follow the multivariate normal distribution,

$$\begin{pmatrix} \xi_{W,ij} \\ \xi_{BW,ij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_W^2 & \tau\sigma_W\sigma_{BW} \\ \tau\sigma_W\sigma_{BW} & \sigma_{BW}^2 \end{pmatrix} \right) \quad (2.5)$$

and

$$\begin{pmatrix} \varepsilon_{W,ij} \\ \varepsilon_{BW,ij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{eW}^2 & \sigma_{eWBW}^2 \\ \sigma_{eWBW}^2 & \sigma_{eBW}^2 \end{pmatrix} \right). \quad (2.6)$$

To allow for moderating effects of culture, the model is extended as follows;

$$\begin{aligned}
SAT_{M,ij} = & \alpha_0 + \alpha_{1CM}FA + \alpha_{2CM}EA + \alpha_{3CM}DS + \alpha_{4CM}AS + \alpha_{5CM}MA \\
& + \alpha_{6AM}FA + \alpha_{7AM}EA + \alpha_{8AM}DS + \alpha_{9AM}AS + \alpha_{10AM}MA \\
& + \alpha_{11M}IGC + \alpha_{12CM}FA \times IGC + \alpha_{13CM}EA \times IGC + \alpha_{14CM}DS \times IGC \\
& + \alpha_{15CM}AS \times IGC + \alpha_{16CM}MA \times IGC + \alpha_{17AM}FA \times IGC + \alpha_{18AM}EA \times IG \\
& + \alpha_{19AM}DS \times IGC + \alpha_{20AM}AS \times IGC + \alpha_{21AM}MA \times IGC \\
& + \alpha_{22M}HS + \alpha_{23M}MS + \alpha_{24M}AGE + \alpha_{25}EL + \varepsilon_{CM,ij} \quad (2.7.1)
\end{aligned}$$

$$\begin{aligned}
WOM_{M,ij} = & \beta_{MW11} + \beta_{1WM}FA + \beta_{2WM}EA + \beta_{3WM}DS + \beta_{4WM}AS + \beta_{5WM}MA \\
& + \beta_{6WM}FA + \beta_{7WM}EA + \beta_{8WM}DS + \beta_{9WM}AS + \beta_{10WM}MA \\
& + \beta_{11WM}IGC + \beta_{12WM}FA \times IGC + \beta_{13WM}EA \times IGC + \beta_{14WM}DS \times IGC \\
& + \beta_{15WM}AS \times IGC + \beta_{16WM}MA \times IGC + \beta_{17WM}FA \times IGC + \beta_{18WM}EA \times IG \\
& + \beta_{19WM}DS \times IGC + \beta_{20WM}AS \times IGC + \beta_{21WM}MA \times IGC \\
& + \beta_{22WM}\widehat{SAT}_{current,ij} \\
& + \beta_{23M}HS + \beta_{24M}MS + \beta_{25M}AGE + \beta_{26M}EL + \varepsilon_{WM,ij} + \xi_{WM,j} \quad (2.7.2)
\end{aligned}$$

$$\begin{aligned}
BW_{M,ij}^* = & \beta_{BWM11} + \beta_{1BWM}FA + \beta_{2BWM}EA + \beta_{3BWM}DS + \beta_{4BWM}AS + \beta_{5BWM}MA \\
& + \beta_{6BWM}IGC + \beta_{7BWM}FA \times IGC + \beta_{8BWM}EA \times IGC + \beta_{9BWM}DS \times IGC \\
& + \beta_{10BWM}AS \times IGC + \beta_{11BWM}MA \times IGC + \varepsilon_{BWM,ij} + \xi_{BWM,j} \quad (2.7.3)
\end{aligned}$$

Like main effect models, the random effects and the random errors are assumed to be follow the same multivariate normal distributions,

$$\begin{pmatrix} \xi_{WM,ij} \\ \xi_{BWM,ij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{WM}^2 & \tau \sigma_{WM} \sigma_{BWM} \\ \tau \sigma_{WM} \sigma_{BWM} & \sigma_{BWM}^2 \end{pmatrix} \right) \quad (2.8.1)$$

and

$$\begin{pmatrix} \varepsilon_{WM,ij} \\ \varepsilon_{BWM,ij} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{eWM}^2 & \sigma_{eWMBWM}^2 \\ \sigma_{eWMBWM}^2 & \sigma_{eBWM}^2 \end{pmatrix} \right). \quad (2.8.2)$$

For the parameter estimation in the joint model I used maximum likelihood techniques (Ascarza and Hardie 2013; Mintz et al. 2013; Teixeira-Pinto et al, 2011; Catalano and Rkyan 1992). To fit the joint model we applied a maximum likelihood approach. Because of the absence of standardized software package, I created a customized fitting procedure using GLIMMIX in SAS 9.4 to estimate the models specified above.

3.2 Data collection

A top global automotive manufacturers provided a survey administered by a professional market research firm in June 2011, which included extensive survey data on 8,231 individuals. Car owners over 19 years of age that had purchased a new car between 2009 through 2011 were canvassed via an online survey. Using a computer-based program written for the survey, participants list top-of-mind car brands and other car brands in their brand consideration set, then score their familiarities with each brand they listed. Based on this process, their current brand and other three alternative brands were selected (randomly chosen from the brands with high familiarity score, i.e. familiarity score >5). During the

survey, participants answer the survey questions for the current brand and three alternatives elicited in the earlier steps. The participants received a nominal monetary incentive for completing the survey.

The data collection yielded 8,231 completed surveys of current auto owners from the sponsoring firm's eight largest markets: China (n=1,841), the U.S. (n=1,643), Korea (n=1,047), Germany (n=756), France (n=755), Spain (n=746), the U.K. (n=742), and Italy (n=701). Observations for respondents whose current car was not their first owned car were eliminated from the data set leading to a final sample size of 7,624. The complete data set included information about 57 car models across 14 brands in the global car market.

3.3 Results

In the main effect model, summarized in Table 2, a customer's WOM and brand switching are modeled by sets of the common factors directly and indirectly through customer satisfaction. The log likelihood value of the model is 8,425.7, and correlation between two dependent variables is -.825, which is very strong association (Note that this makes sense since a customer that intends to switch brands is unlikely to provide high levels of WOM). Table 2 shows the main effects of the key antecedents to explain satisfaction, recommendation intention, and brand switching. A customer's overall satisfaction level toward their current car is positively affected by both current car's product-related attributes such as functional attributes (FA, $\alpha_{1C} = .183, P < 0.01$) and emotional attributes (EA, $\alpha_{2C} = .208, P < 0.01$) and service-related attributes including dealership service (DS, $\alpha_{3C} = .048, P = .065$) and after-purchase service (AS, $\alpha_{4C} = .148, P <$

0.01). Also, a firm's marketing activity has a positive impact on satisfaction level (MA, $\alpha_{5C} = .068, P = .029$). Although household size and education level have negative (HS, $\alpha_{23} = -.046, P = .07$) and positive effects (EL, $\alpha_{26} = .041, P = .03$) on customer satisfaction, marriage status (MS, $\alpha_{24} = -.007, n.s.$) and age (Age, $\alpha_{25} = -.010, n.s.$) do not have a significant impact on satisfaction. A customer's overall satisfaction level toward their current car is evaluated not only by experience about the current car but also their image of the alternatives. Specifically, product-related attributes of alternative products such as functional attributes (FA, $\alpha_{6A} = -.128, P < 0.01$) and emotional attributes (EA, $\alpha_{7A} = -.124, P < 0.01$) along with after-purchase service as service-related attributes (AS, $\alpha_{9A} = .065, P < 0.01$). Also, a firms' marketing activity has positive impact on satisfaction level (MA, $\alpha_{10A} = -.075, P = .04$). However, dealership service does not have significant effect on customer satisfaction (DS, $\alpha_{8C} = .044, n.s.$). Since dealership service is a very experience oriented attribute, evaluation about alternative dealership service for products that a customer does not own cannot provide satisfaction. In this image driven path, demographic characteristics do not show significant impact on satisfaction (HS, $\alpha_{23} = -.022, n.s.$; MS, $\alpha_{24} = .092, n.s.$; Age, $\alpha_{25} = .027, n.s.$; EL, $\alpha_{26} = .027, n.s.$).

In the joint model for brand switching and WOM, dependent variables, functional attributes (FA, $\beta_{1W} = .079, p < .01$), emotional attributes (EA, $\beta_{2W} = .184, 0 < .01$), and dealership service (DS, $\beta_{3W} = .076$) have positive effects on the attitudinal loyalty and word-of-mouth (WOM) through satisfaction level. Also, customers' satisfaction toward their current car has a positive and significant effect on WOM ($\beta_{11W} = 1.011, p < .01$). On the contrary, after-purchase service (AS, $\beta_{4W} = .036, n.s.$), and marketing activities (MA, $\beta_{5W} = .033, n.s.$) have a positive but insignificant effect. In direct

modeling, customer characteristics such as household size ($\beta_{12} = -.020, p < .01$), marriage status ($\beta_{13} = -.080, p < .01$), age ($\beta_{12} = .034, p < .01$), and educational level ($\beta_{12} = .020, p < .01$) have significant effects on WOM. For brand switching (BW), emotional attributes (EA, $\beta_{2BW} = .255, p = .04$) and after-purchase service (AS, $\beta_{4BW} = -.282, p = .02$) have positive effects. Marketing activities offered from alternative car brands have also have a significant effect on brand switching (AS, $\beta_{5BW} = .232, p = .04$). Not surprisingly, in addition, overall satisfaction level based on the current car negatively affects a customer's brand switching intention ($\beta_{6BW} = -.815, p < .01$). These results indicate that customers who have positive image about an alternative's emotional attributes such as trust, respectable, feeling friendly, and feeling comfortable and explore marketing activities provided by alternative car brands are more willing to switch their car brand to an alternative. On the other hand, customers who have good experience with their current car's after-purchase service and a high satisfaction level with their current car are more willing to stay their current brand. In addition, functional attributes and dealership service do not have an impact on brand switching intention.

After examining the main effects, the model is augmented with a cultural effect introduced as a moderator in the model; see Figure 2. Results of the model fit are given Table 3. The log likelihood value of this model is 7450.8, and the correlation between the two dependent variables, $\rho = -.731$, is slightly weaker than in the case without moderators. The relationship between perceived overall satisfaction of a respondent's current car and experience with their current car, in-group collectivism negatively moderates functional attributes ($\beta_{12WM} = .035, p = .02$), emotional attributes ($\beta_{13WM} = -.057, p < .001$),

and after-purchase service ($\beta_{15WM} = -.021, p = 0.02$). However, this cultural dimension does not effect on the relationship between perceived overall satisfaction level of current car and current car's dealership service ($\beta_{14WM} = .003, n.s$) or the firm's marketing activities ($\beta_{16WM} = .007, n.s$). These results show that customers in a collectivistic culture have low overall satisfaction even if they are both functionally and emotionally satisfied with their current car brand. This suggests that group thinking can reshape an individual's satisfaction level. Similar to the satisfaction with their current car experience, satisfaction based on an alternative's image is negatively affected by culture. Among the associations between perceived overall satisfaction of their current car and an alternative car's image , higher levels of in-group collectivism also negatively moderates the effects of functional attributes ($\beta_{12BWM} = .025, p < .001$) , emotional attributes ($\beta_{13BWM} = -.017, p < .001$) , dealership service ($\beta_{14BWM} = -.022, p = 0.068$) , after-purchase service ($\beta_{15BWM} = -.025, p < .001$) and firm's marketing activities ($\beta_{16BWM} = .015, p = 0.058$). This suggests that a more collectivistic culture negatively re-shapes a customer's satisfaction based on the functional attributes, emotional attributes, and marketing activities. Also, functional attributes ($\beta_{2WM} = 3.21, p < .001$) , emotional attributes ($\beta_{3WM} = .107, p = 0.037$) , and dealership service ($\beta_{6WM} = -.091, p = .07$) directly effect WOM. In addition, higher levels of in-group collectivism in a population significantly moderate the effects of emotional attributes related to an alternative car's image ($\beta_{3BWM} = -.255, p = .07$) and perceived after-purchase service quality ($\beta_{4WM} = -.243, p = .06$) on brand switching. A customer's perceived overall satisfaction from their current car creates partial mediation in the relationship between brand switching and

its key drivers ($\beta_{SATBWM} = -.586, p = .029$), which means that both direct and indirect effects of satisfaction are significant. However, satisfaction is not a significant mediator for WOM ($\beta_{SATWM} = .153, n.s.$).

4. Concluding Remarks

In this chapter, I examined two dimensions of customer loyalty—Word-of-Mouth (WOM) as attitudinal loyalty and brand switching as behavioral loyalty—using product-related attributes, service-related attributes, marketing activities, and overall satisfaction with both the current car and the alternatives. The analysis of these factors was based on an international customer survey on automobile preferences and used a random-effect approach to jointly model mixed types of outcome variables.

Many of the findings reported in this study support the findings on the general nature of customer loyalty and overall satisfaction reviewed in Sections 2.1 and 2.2. For example, customers who have high overall satisfaction with their own car are more likely to spread positive WOM to others and willing to retain their current car brand. The findings in the present study provide insights regarding customer loyalty in the context of both experience-based loyalty and image-based loyalty as well as cross-cultural consumer behavior. With regard to the direct versus indirect (via satisfaction) impact of brand evaluation through product-related attributes, service-related attributes, and marketing activities on brand loyalty, the findings of this study confirm the mediating role of satisfaction.

It is important to emphasize the unique and important contributions of this study. Despite customer satisfaction being strongly related to two brand-based sources, direct experience with the purchased car and indirect experience from the perceived image of alternatives, most studies focus on only one source of customer satisfaction. Using a unique set of survey data, this study integrates these independent streams of customer satisfaction literature and tests these two possible sources of customer satisfaction simultaneously in a single model. This study found that brand evaluation based on experience with the current brand and alternative brand evaluations based on the perceived image of other brands can significantly affect customers' overall satisfaction level. In this integrated framework, satisfaction acts as a partial mediator between two different dimensions of loyalty (i.e., behavioral loyalty and attitudinal loyalty) and their key drivers such as functional attributes, emotional attributes, dealership service, after-purchase service, and marketing activities.

Another important finding of this study is the significant moderating effect of culture. High levels of in-group collectivism negatively moderate the relationships between product-related attribute performance, service-related attribute performance, marketing activities, and satisfaction. For example, the association between functional attribute performance and satisfaction is stronger in collectivistic cultures than in more individualistic cultures. This is consistent with previous research findings showing that individuals sharing the same cultural backgrounds, attitudes, beliefs, and emotions tend to have similar behavior (Hong and Lee 2014; Ndubisi et al. 2012; Brewer 1999). A more important finding is that the association between satisfaction and emotional factors,

particularly service-related attribute performance and emotional attribute performance, is stronger in individualistic cultures than in collectivistic cultures. These key findings suggest that marketers in international firms emphasize a brand's emotional features when appealing to customers in an individualistic culture and emphasize the brand's functional attributes when appealing to customers in nations with a more collectivistic culture.

Another major contribution of this research is the use of an appropriate analytic method for mixed types of correlated outcome variables. The joint model proposed in this study performed fairly well and allowed the clustered/multi-level characteristics of the data to be treated properly. Through the joint modeling approach, the potential correlations between outcome variables, WOM, and brand switching provided more realistic and rigorous results.

The present study has several limitations. First, the customer survey used in this study contains data only on customers' intention to switch brands and to spread WOM. In some cases, intentions are not representative of actual behavior (Perkins-Munn et al. 2005; Mittal and Kamakura 2001). Second, this study used cross-sectional data, which means that it examined the conceptualized relationships at one point in time. It is important for future analyses to combine intention data with historical purchase data so that the actual behavioral loyalty (brand switching) and attitudinal loyalty (WOM) can be examined over time. Third, this study used a single cultural dimension, namely collectivism. Although the dimension of collectivism is the most accurate dimension used to explain the effect of culture in the current study, many previous studies have revealed this effect, reducing the novelty of this finding. It is important for future research to examine the moderating effects

of other individual cultural dimensions identified by GLOBE (House et al. 2004) or to combine multiple dimensions for a better understanding of the effects of culture in international marketing.

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Appendix

Table 2.1 Variable operationalization

Categorical variable	Operationalization
Behavioral Loyalty (Brand Switching)	1 if a customer choose alternative car brand for the future purchasing
Marital Status	Dummy=1 if a customer married
Age (18-29)	1 if customers aged between 18 and 29 (reference from Bureau of Labor Statistic/American Time Use Survey)
Age (30-39)	1 if customers aged between 30 and 39 (reference from Bureau of Labor Statistic/American Time Use Survey)
Age (40-49)	1 if customers aged between 40 and 49 (reference from Bureau of Labor Statistic/American Time Use Survey)
Age (50-59)	1 if customers aged between 50 and 59 (reference from Bureau of Labor Statistic/American Time Use Survey)
Educational level (High school graduated)	1 if customers graduated high school (reference from Bureau of Labor Statistic/American Time Use Survey)
Educational level (College/University graduated)	1 if customers graduated College or University (reference from Bureau of Labor Statistic/American Time Use Survey)
Educational level (Graduate school or higher)	1 if customers educated graduate school or higher (reference from Bureau of Labor Statistic/American Time Use Survey)
Quantitative variable	Operationalization
Attitudinal Loyalty (Word-of-Mouth)	Likelihood to recommend products and service to others (10-likert scale)
Satisfaction	Overall satisfaction with customers' current brand (10-likert scale)
Functional Attributes (FA)	Likelihood to agree the statement about functional attributes (multi-items, 10-likert scale)
Emotional Attributes (EA)	Likelihood to agree the statement about emotional attributes (multi-items, 10-likert scale)
Dealership Service (DS)	Likelihood to agree the statement about dealership service (multi-items, 10-likert scale)
After-purchase Service (AS)	Likelihood to agree the statement about after-purchase service (multi-items, 10-likert scale)
Marketing Activities (SA)	Likelihood to agree the statement about marketing activities (multi-items, 10-likert scale)

Table 2.2 The main effect model

Variables	Outcome Variables			
	Mediation 1.1= C.Satisfaction	Mediation 1.2= A.Satisfaction	DV2.1= Words of Mouth	DV2.2= Brand Switching
Equation Number	(1)	(2)	(3)	(4)
Main Effects				
Product-related attribute performance				
Functional Attributes (FA)	.183***(.036)	-.128 *** (.037)	.079*** (.001)	.090 (.035)
Emotional Attributes (EA)	.208***(.033)	-.124*** (.033)	.184*** (.0005)	.255**(.096)
Service-related attribute performance				
Dealership Service (DS)	.048*(.036)	.044 (.036)	.076*** (.001)	-.183 (.108)
After-purchase Service (AS)	.148***(.034)	.065*** (.030)	.036 (.001)	-.282** (.096)
Marketing Activities (MA)	.063**(.033)	-.075**(.034)	-	-
Satisfaction(SAT)	-	-	1.011*** (.023)	-.815***(.035)
Controls				
Household size	-.046*(.025)	-.022(.029)	-.020*** (.020)	-
Marriage status	-.007(0.052)	.092(.060)	-.080*** (.094)	-
Age	-.010(.021)	.027(.024)	.034*** (.019)	-
Education level	.041**(.020)	.027(.024)	.020*** (.011)	-
Constant	-.036(.036)	-.250*** (.041)	8.403*** (.236)	.949***(.035)
Std. Dev random effect				
Common parameter				
ρ_{12}	-.825*** (.162)			
-2log-likelihood	8425.7			

Table 2.3 The moderating effect model

Variables	Outcome Variables			
	Mediation 1.1= C.Satisfaction	Mediation 1.2= A.Satisfaction	DV2.1= Word-of-Mouth	DV2.2= Brand Switching
Equation Number	(1)	(2)	(3)	(4)
Main Effects				
Product-related attribute performance				
Functional Attributes (FA)	-2.796***	1.999***	.310**	.238(n.s.)
Emotional Attributes (EA)	4.012***	.991***	.294*	.474**
Service-related attribute performance				
Dealership Service (DS)	-.134	1.314***	.114*	-.011(n.s.)
After-purchase Service (AS)	-1.087**	1.503***	.058(n.s.)	-.395**
Marketing Activities (MA)	-.349	-.887**	-	-
Satisfaction(SAT)	-	-	.153(n.s.)	-.586**
Moderating Effects				
In-group collectivism(IGC)	-.300**	-.009(n.s.)	-.052(n.s.)	-.009***
FA×IGC	.035***	.025***	3.207***	.028(n.s.)
EA×IGC	-.057***	-.017***	.107**	-.255*
DS×IGC	.003(n.s.)	-.022*	-.091*	.124(n.s.)
AS×IGC	-.021**	-.025***	-.052(n.s.)	-.243*
MA×IGC	.007(n.s.)	.015*	-	-
Controls				
Household size	-.031 (n.s.)	.019(n.s.)	-.052(n.s.)	-
Marriage status	.012 (n.s.)	.053(n.s.)	.044(n.s.)	-
Age	.008 (n.s.)	.020*	.027(n.s.)	-
Education level	.016 (n.s.)	.033(n.s.)	.0503(n.s.)	-
Common parameter				
ρ_{12}	-.731*** (.259)			
-2log-likelihood	7450.8			

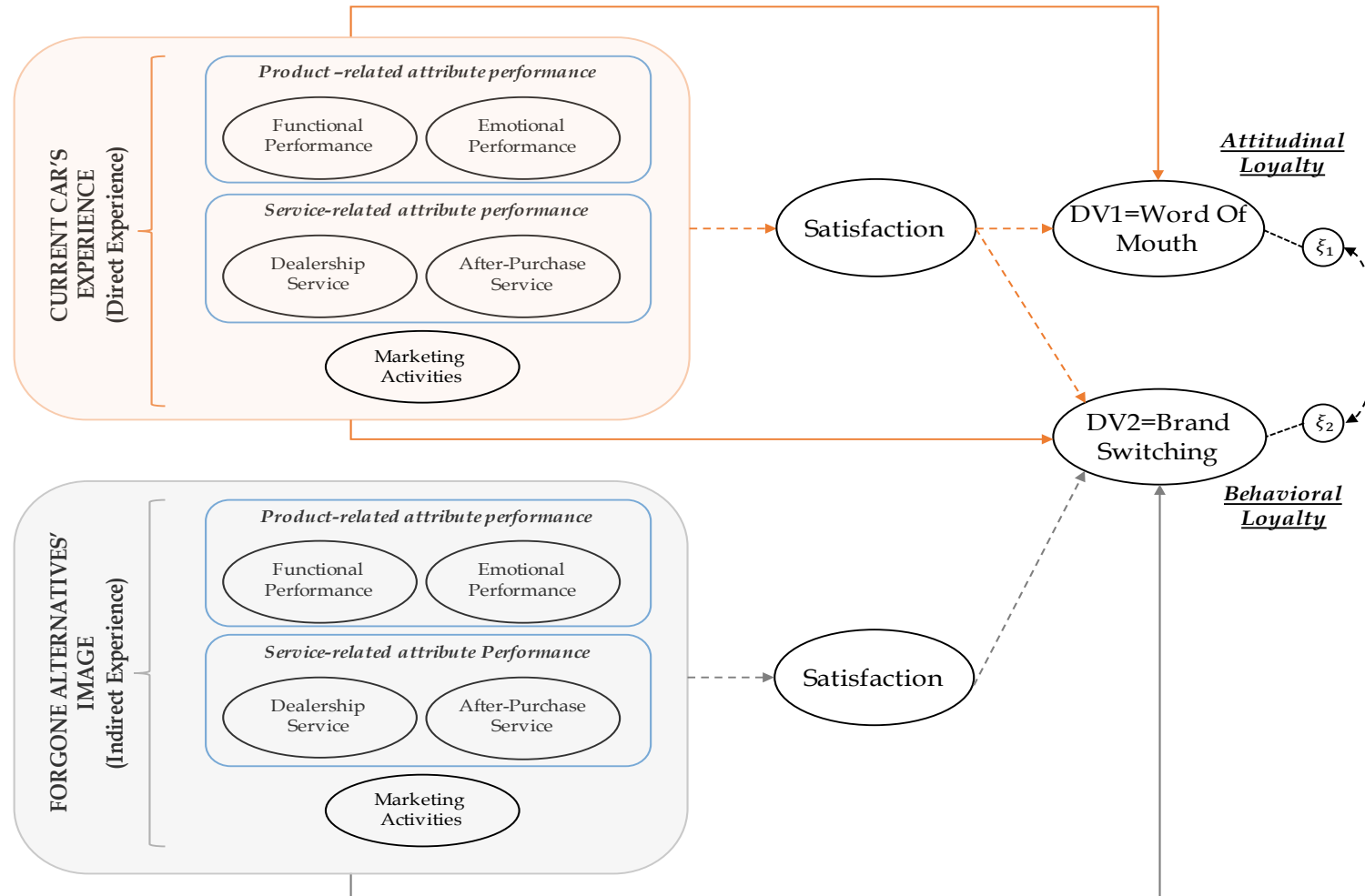


Figure 2.1 Conceptual model

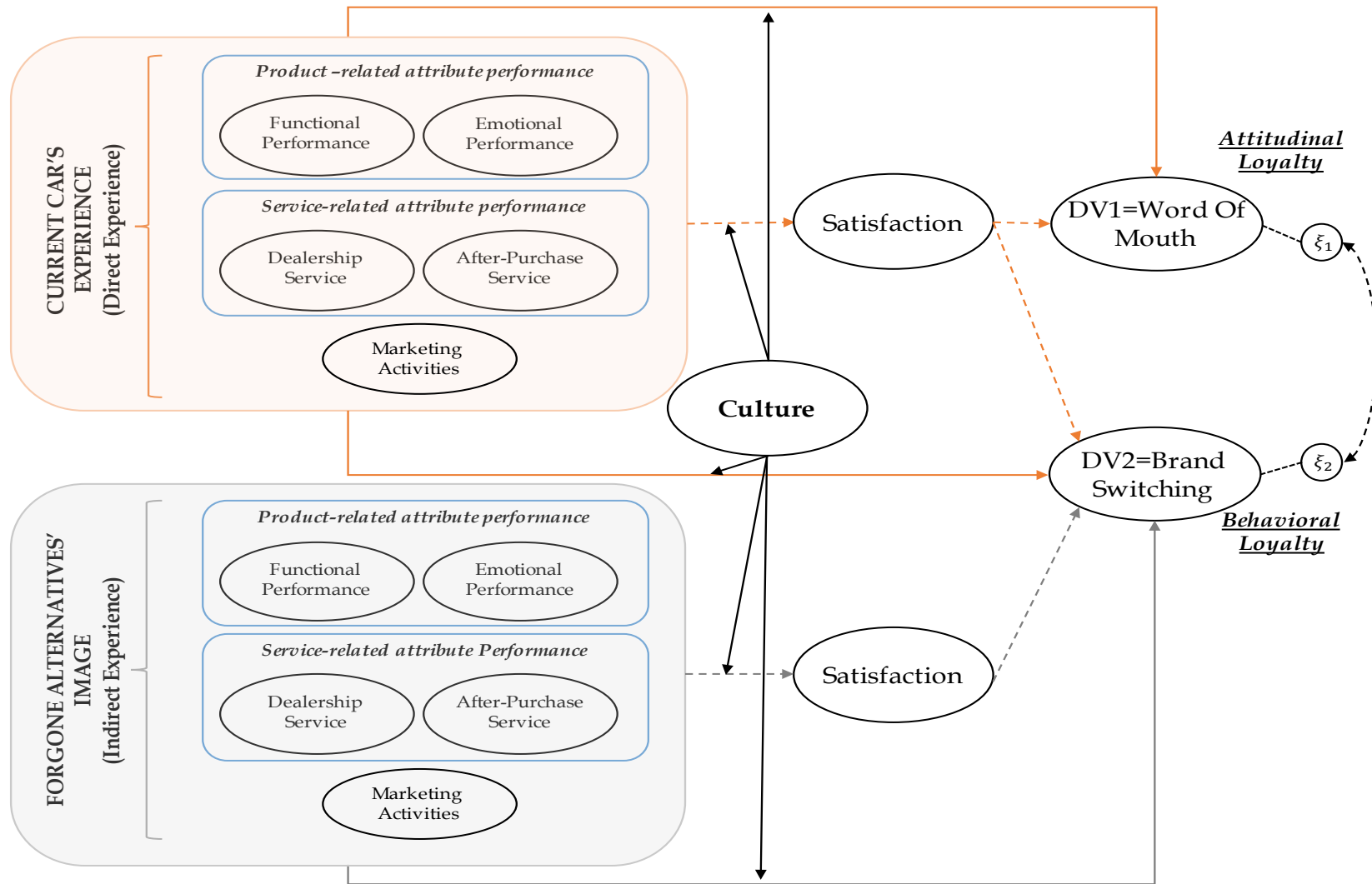


Figure 2.2 Conceptual model with Moderator

CHAPTER III
COUPON AND DEAL DYNAMICS IN
UTILITARIAN AND HEDONIC PURCHASES

Abstract

In the context of price promotions, coupons and in-store deals have continuously achieved some popularity. In addition, how different types of product categories such as hedonic versus utilitarian products influence consumer purchase behavior has been of interest to marketing practitioners and scholars. Although many previous studies have sought to test consumers' coupon proneness and in-store deal proneness by promotion types (Venkatesan and Farris 2012; Colombo et al. 2003; Walters and Jamil 2003) and consumer characteristics (Carretson and Burton 1998; Mittal 1994), few studies have considered the effects of these two types of price promotion proneness across product types. The question arises as to whether such price promotion tools—coupons and in-store deals—affect store loyalty, cross-buying, and trip revenue across different types of products. The outcome variables of store loyalty, cross-buying (variety seeking), and trip revenue, which were previously introduced in research on price promotions, are associated with each other. To account for potential correlations among the three outcome variables, a joint model, which allows the linking of correlations through random effects, is proposed. This model is based on two different promotional tools—coupons and in-store deals—via different types of products, which are supposed to trigger three different responses in consumer characteristics. The results show the presence of distinct segments among consumers across price promotion types and product categories. The results also indicate that coupon and in-store deal proneness affect store loyalty, cross-buying, and trip revenue differently across product categories.

1. Introduction

In the marketing mix, sales promotions including price reduction tools have one of the strongest impacts on customer behavior because price promotions encourage consumers to purchase non-promoted merchandise (Laroche et al. 2003). Accordingly, several studies have focused on consumers' purchase behaviors via different types of price promotions including coupons and in-store deals (Lichtenstein et al. 2007). Like these constructs, behavioral constructs that contrast purchase behavior for hedonic goods versus utilitarian goods have also been continuously highlighted in the marketing and retailing literature (Cavusgil and Kim 2009; Garretson and Burton 1998).

While considerable knowledge has been generated by past research, a deeper understanding of the impact of price promotions across hedonic and utilitarian shopping segments is of significant value to both researchers and practitioners interested in consumer behavior. This study attempts to combine these two behavioral constructs and understand their impact on the overall activity and profitability of customers. This study addresses the need for research in this area by integrating two popular streams of literature and examining the effects of different price promotions (coupons and deals) across product segments (utilitarian and hedonic) using modern multivariate analytical techniques.

A key component of this study is that it takes a novel analytic point of view by jointly modeling several key outcome variables with various factors to explain consumers' shopping behavior. Few marketing studies have tried to combine three correlated outcome variables simultaneously. Therefore, developing and applying a rigorous model is crucial. The present study addresses the following research questions:

1. Do different types of price promotions and different types of consumption of hedonic and utilitarian goods effectively segment consumers' shopping behavior?
2. Do consumers' price-promotion choices differ when considering hedonic versus utilitarian grocery purchases?
3. How can a simultaneous equation modeling approach be used to address these questions while accounting for the dependence between the three response variables?

This study contributes to the literature on retail promotions by addressing each of these questions. In the remaining sections of this study, I briefly review the literature on price promotions and customers' behavior toward product types. Next, I discuss the conceptual framework and describe the methodology employed to analyze the data. I then report the findings and draw implications for practitioners involved in consumer marketing. I conclude with some possible directions for future research.

2. Literature Review and Research Framework

2.1 Coupons and in-store deals

Grocery shopping has been considered a high-frequency functionalistic marketplace activity (Collins et al. 2014; Maher et al. 1997). Consumers are motivated by different forms of price incentives such as good deals and promotions on their grocery shopping trips (Griffith et al. 2009; McAlister et al. 2009). Thus, marketers offer various forms of price promotions to consumers to increase revenue. Price promotion through price reduction is one of the traditional elements of the promotional marketing mix (Slotegraaf and Pauwels 2008; Pauwels et al. 2002; Franses et al. 2001; Blattberg and Neslin 1990). Coupons are another of the most popular price promotion techniques that require consumers to redeem the promotion to provide savings; they are often provided by manufacturers of groceries and packaged goods (Lichtenstein et al. 1995; Shimp 1993; Walters and Jamil 2003). Consumers invest their time and effort to locate, clip, transport, and redeem coupons before and during the shopping trip (Mittal 1994). Consumers who plan purchasing trips are more likely to redeem manufacturer coupons even though they cannot be certain what products are available until after they enter the grocery.

Realistically, between half and two thirds of product purchase decisions are made after entering the grocery (Thomas and Garland 1996). Therefore, some grocery shoppers are exposed to opportunities to make better deals in the store, such as “one-day-only specials,” “everyday low prices,” or “extra product free” promotions. In-store deals are unexpected events (Volle 2001; Sheth 1983) and lead consumers to unplanned purchasing (Walters and Jamil 2003). Several researchers have found that in-store deals induce consumers’ unplanned buying (Inman et al. 1990) as well as switching from the usual

brands they buy to promoted brands. According to Blattberg et al. (1994), “it is acknowledged that store promotions generate additional traffic that leads to the purchase of complementary products at full-margin; nevertheless, it has never been proven.” In-store specials also increase store loyalty (Walters and Rinne 1986) and trip revenue (Laroche et al. 2003).

One of the traditional research streams in marketing focuses on modeling and testing the effects of different price promotions on store loyalty (Volle 2001), variety-seeking behavior, and trip revenue (Venkatesan and Farris 2012; Mittal 1994). In the retailing context, price promotions significantly affect consumers’ perception of price (Walters and Jamil 2003; Folks and Wheat 1995). Several researchers have suggested that different types of price promotions lead to different types of responses from consumers (Laroche et al. 2001; Schneider and Currim 1991). Thus, as one key part of this study, I compare price promotions, coupons, and in-store deals in the model as separate constructs.

2.2 Hedonic vs. Utilitarian

Consumer shopping activities are driven by hedonic and utilitarian product choice (Dhar and Wertenbroch 2000). Both hedonic and utilitarian goods offer different types of shopping benefits to consumers (Okada 2005; Voss 2003). Hedonic goods can be defined as those characterized by “an affective and sensory experience of aesthetic or sensual pleasure, fantasy and fun” (Hirschman and Holbrook 1982). These goods provide more experiential consumption, fun, pleasure, and excitement (Dhar and Wertenbroch 2000). On the other hand, utilitarian goods can be defined as those that are “more cognitively driven,

instrumental, and goal oriented and [accomplish] a functional or practical task” (Strahilevitz and Myers 1998). According to Bazerman et al. (1998), hedonic and utilitarian goods can be differentiated by the want/should distinction or by affective preferences (“wants”) and cognitive or reasoned preferences (“should”). Wertenbroch (1998) defined hedonic goods and utilitarian goods using the term “vices,” which means negative payoffs, and the term “virtues,” which connotes positive payoffs.

The consumption of hedonic and utilitarian goods has been examined in the grocery market context both separately (Okada 2005; O’Curry and Strahilevitz 2001; Dhar and Wertenbroch 2000) and together (Voss et al. 2003; Corwley et al. 2003) using various definitions and classification systems. Those prior studies revealed the relationship between consumer behavior and consumer choice of types of goods (Sheng and Teo 2012; Kwok and Uncles 2005). For example, Sheng and Teo (2012) found that utilitarian and hedonic products affect consumer behavior and repurchase intentions differently.

Although price promotions and the consumption of hedonic and utilitarian goods are well studied as independent phenomena, few, if any, researchers have attempted to study these two concepts together. More importantly, a limited number of researchers have empirically examined the effects of these two constructs. Responding to this lack of previous investigation, the current study attempts to understand the impact of price promotion type on both utilitarian and hedonic consumption, as well as its overall impact on shopping trips.

3. Empirical Methodology

3.1 Data Collection Procedure

To address the research questions and identify the research framework, I used data obtained from the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business.² The longitudinal data included purchasing information from a panel of approximately 40,000–60,000 households from 2004–2011. The data were provided at the “trip level” with all the products purchased in each trip to a retail store. At the product level, there were 40 million–60 million product records in each year. Table 1 shows the number of trips per product category included in the data set.

Panel data has been used in previous studies to explain customer purchasing behavior (Cavusgil and Kim 2010; Briesch et al. 2009; Ailawadi et al. 2008; Hansen and Singh 2008). Many studies have employed grocery scanner panel data to examine the effect of marketing promotions such as coupons and in-store specials (Venkatesan et al. 2012).

To better understand household-level customer purchasing behavior, this study investigates all four combinations of price promotion (coupons and in-store deals) and commodity type (hedonic and utilitarian goods). Although this data set consists of 1,075 product modules, I was interested in only utilitarian and hedonic goods. Therefore, I sorted out the utilitarian and hedonic goods from the larger universe of product modules (the

² Data were collected and provided by the Nielsen Company, LLC. The marketing database was provided by the Kilts Center for Marketing at the University of Chicago Booth School of Business. Information about the data is available at <http://research.chicagobooth.edu/nielsen/>.

product list is presented in Appendix A). As a result, this study used a subset of the purchasing data involving transactions where a coupon or in-store deal was used for utilitarian or hedonic products. After aggregating the data, the data set was composed of 209,000 shopping trips from 810 households.

3.2 Measurement Procedure

For the exploratory and joint modeling analysis, utilitarian coupons, utilitarian in-store deals, hedonic coupons, and hedonic in-store deals were used as key variables to characterize customers' purchasing behavior when a price promotion exists. Each combination variable was measured based on the dollars spent in a week. For example, dollars spent on utilitarian couponed (UC) products were operationalized as the dollar amount spent on utilitarian products purchased with a coupon deal by a household in a week. Like coupons, dollars spent on utilitarian products with an in-store deal promotion (UD) were simply measured by the dollar amount spent on utilitarian products purchased with a deal promotion by a household in a week. The dependent variables of interest in this study include trip revenue (dollar amount spent by a household on the retailer in a week), store loyalty (frequency or number of shopping trips made in a given week),³ and cross-

³ Approximately 2% of the records in the current study include weeks with zero values for visits. These records were log-transformed with the value 1 added to ensure numerical stability.

buying (variety level or number of unique product categories bought by the household per trip); these will be discussed in Section 3.1.

This study also includes several demographic factors such as income, age, and marital status, which are commonly used to characterize customers' shopping behavior. In addition, the proportion of necessary items (number of necessary items purchased in a week divided by the total number of products purchased in a week) and the seasonality of purchasing (dummy variables for the second to fourth quarters, with the first quarter as the base category) are included as control variables. The operationalization of variables and the descriptive statistics are presented in Table 3.1.

3.3 Analysis and Results

I conducted two sets of analyses in an attempt to answer the research questions posed in the present study. First, I performed cluster analysis as an exploratory method to identify groups of customers using the four different promotion/commodity combinations based on the promotion usage and product types. Once the clusters were identified, I conducted a joint modeling analysis to determine how various types of price promotions affect store loyalty, cross-category purchasing, and trip revenue differently.

3.3.1 Exploratory Clustering

As an exploratory cluster analysis was used to characterize customer groups that use coupons and deal in the utilitarian products and hedonic product categories, cluster analysis is an appropriate approach to identify unique features of customer behavior that

differentiate groups (Homburg et al. 2008b) in the form of a general typology. This study identifies distinct customer clusters based on their purchasing behavior toward coupon and in-store deals in utilitarian and hedonic products. By applying the cluster analysis, similarities and differences in customer behavior during repeated exposure to utilitarian product and hedonic products using coupons and in-store deals can be revealed. From a market segmentation point of view, therefore, clustering customers according to their planned (coupon use) or/unplanned (in-store deal use) shopping patterns for utilitarian products and hedonic products may reveal demographic and other characteristics which may better represents these customers.

To pursue such a classification scheme, the choice of variables on which to cluster requires careful consideration and often presents different options. We chose to use a combination of two price promotions and two product types as the clustering variables. These variables include utilitarian purchases using coupons, utilitarian purchases using in-store deals, hedonic purchases with coupons and hedonic purchases with utilitarian. The logic in this choice was that clustering on these variables would allow the emergence of fundamentally different customer profiles that would be associated with three outcomes: store loyalty, cross-buy, and trip revenue.

To begin the cluster analysis, I aggregated data using average of dollar spending in a year, then the standardized clustering variables were computed by subtracting the mean value from the original value and then dividing the subtracted value by its standard deviation. The Ward method used in the following stages is sensitive to outliers and scales of measurement (Milligan and Hirtle 2003). Using standardized variables improves the

performance of the Ward method by minimizing the potential influence of outliers on the clustering solution and reducing the discrepancy caused by measurement scales. In addition, standardizing variables creates common variation in measurement scales across the individual variables (Sharma and Kumar 2006).

The next stage of the cluster analysis entailed identifying potential outliers and eliminating low-frequency clusters. Including non-responses and missing values, about 10% of the observations were identified as potential outliers. The literature supports the removal of these cases, particularly in previous cluster analysis-based studies (e.g., Homburg et al. 2008b; Punj and Stewart 1983). The final sample for the cluster analysis consists of 768 observations. To determine the appropriate number of clusters, we used the PROC CLUSTER solution in SAS to achieve valid clusters from a two-stage hybrid clustering approach. For validation of the number of clusters, we considered three of the most effective tests (Bowen 1990), pseudo F-statistics (Caliński and Harabasz 1974), the pseudo- t^2 index (Duda and Hart 1973) and the cubic clustering criterion (Sarle 1983). The pseudo F-statistics and pseudo $-t^2$ statistics strongly recommended a seven-cluster solution. Using a hierarchical clustering approach, cubic clustering criterion (CCC) is also supportive of a seven-cluster solution. Considering the top-performing criteria that Milligan and Cooper (1985) propose, I found strong support for a seven-cluster solution.

A combination of Ward's method and the K-means method was applied to assign observations into seven clusters (Punj and Stewart 1983). This procedure was used in the current study because, according to previous research (Helsen and Green 1991), using Ward's hierarchical method starting with seed selection generated from the centroids of a

K-means clustering approach is the most powerful clustering procedure. Initially, to assign the observation to the correct cluster, a K-means clustering algorithm was used to minimize the within-cluster sum of squares. Ward's method was then applied to these results to clarify the results.

To check the validity of the clustering solution, we compared the cluster solutions produced by a FASTCLUS (a non-hierarchical technique) with the Ward's method which is a hierarchical technique (Bowen 1990). According to the three criteria, the pseudo F-statistics, pseudo- t^2 , and CCC statistics peaked at four in Ward's method, providing strong evidence to support a seven-cluster solution. The stability of the cluster assignment was tested by the reliability test that Bowen (1990) proposed. We randomly split the data into two subsamples, with each split sample consisting of 384 observations. Then, we applied the same clustering procedure to the independent samples. In both of these samples, a seven-cluster solution was obtained, illustrating stability in our clusters. In the last stage, Waller and Duncan's multiple comparison procedure, or k-ratio t-test, was used to test for differences between the descriptive variables in the study (Waller and Duncan 1969). Specifically, this test was used to show differences between the clusters in the demographic characteristics and outcome variables including store loyalty, cross-buy, and trip revenue. Table 3.2 summarizes the empirical segments resulting from the cluster analysis and we describe them below.

Type I deal seekers (6%). Customers in this cluster display a high level of in-store deal use for both utilitarian and hedonic products, whereas the use of coupons for both utilitarian and hedonic products is low. In terms of size, this segment is the smallest. Based

on a pairwise comparison, customers in this cluster tend to visit the store more often, try diverse products, and generate the largest amount of trip revenue compared with customers in other clusters. A large proportion (60%) of the working population in the data (ages 25–54) is included in this cluster. These customers are in the third income quintile; 39% of the customers in this cluster have at least one child.

Retailer-discount-driven shoppers (9%). This cluster is composed of customers who use more retailer discounts (in-store deals) than manufacturer discounts (coupons). This cluster has the second smallest size (9%) and demonstrates low frequency of shopping trips, cross-buying, and trip revenue. Customers in this group tend to focus their purchases on items viewed as necessary.

Freewheeling hedonic shoppers (16%). This cluster is the second largest cluster (16%). It is composed of customers who enjoy hedonic products. Customers in this cluster tend to use in-store discounts more than coupons. Their shopping patterns depart from the standard pattern. Because of their freewheeling shopping behavior, customers in this group visit a store less often than customers in other clusters, and they create the smallest trip revenue among the clusters.

Hedonic shoppers (9%). Customers in this cluster display a high level of hedonic purchasing behavior using both coupons and in-store deals, while spending little money on coupons and in-store deals for utilitarian products. Baskets for shoppers in this cluster include a large number of necessary items. Most of these customers are married without children. These customers visit stores less often than customers in other clusters, tend to

use coupons and in-store deals, try a limited number of products, and spend relatively small amounts of money.

Lapsed-faith shoppers (37%). Customers in this group do not differentiate the use of coupons and in-store deals between utilitarian and hedonic products. This segment is the largest in terms of size. Customers in this cluster buy a large number of necessary items and are less likely to seek a variety of products. They visit the store less often and spend less money than customers in other clusters do.

Utilitarian shoppers (11%). This cluster includes customers who enjoy promotions (such as coupons and in-store deals) for utilitarian products rather than for hedonic products. They have highly planned purchasing behavior, so they visit the store regularly and spend money moderately in comparison with other clusters. Customers in this group are relatively high-income customers compared with other groups. Most of the customers (85%) in this group are married.

Type II deal seekers (12%). Customers in this cluster use more in-store deals than coupons, but they also use coupons often. The difference between the Type I deal-seeker cluster and the Type II deal-seeker cluster is that the latter is less diverse in terms of products purchased and contains a larger number of poor customers. Therefore, the trip revenue created by this cluster is lower than that of the Type I deal-seeker cluster.

As Table 2 shows, the seven clusters based on customer behavior toward coupons and in-store deals for utilitarian and hedonic products differ significantly in terms of store loyalty (frequency of shopping trips), cross-buying (variety seeking), and trip revenue. This

result requires additional analysis to determine the effects of different customer behaviors based on promotion types and product types on these three different outcomes.

3.3.2 Joint Modeling Analysis

The maximum likelihood (ML) parameter estimates of the joint model are reported in Table 3. There is no standard software package for the proposed model, so a custom program was developed using the GLIMMIX procedure in SAS 9.6 and used to estimate the three marginal models jointly. The log-likelihood value of the model is 154,208. The large log-likelihood value may be related to the large sample size used for the estimation, along with the relatively small number of independent variables (Cavusgil and Kim). Correlations between store loyalty and cross-buying and between store loyalty and trip revenue are estimated at .632 and .616, respectively, which indicate very strong associations. A very strong association was also found between cross-buying and trip revenue ($\rho_{23}=.935$), again indicating the importance of taking the correlation into account in the joint model.

For the first outcome variable, hedonic coupons ($\alpha_{1ij} = .0022, p = .03$), hedonic in-store deals ($\alpha_{2ij} = .012, p < 0.01$), and utilitarian in-store deals ($\alpha_{4ij} = .13, p < 0.01$) show positive effects on store loyalty. That is, the frequency of customer visits to groceries is positively associated with using hedonic coupons, hedonic in-store deals, and utilitarian in-store deals. However, the coefficient for utilitarian coupon use is negative ($\alpha_{3ij} = -.004, p < 0.01$), which means that customers who use utilitarian coupons tend to visit stores less often. This finding is consistent with that of Walters (2003), who noted that such

shoppers also spend less money in the store due to their planned purchasing behavior. In addition, married customers visit stores more often than other customers do ($\alpha_{6ij} = .184, p < 0.01$). Other demographic characteristics such as age, income, and presence of children are not significantly related to store loyalty.

As with the previous outcome, hedonic coupons ($\beta_{1ij} = .005, p < 0.01$), hedonic in-store deals ($\beta_{2ij} = .015, p < 0.01$), and utilitarian in-store deals ($\beta_{4ij} = .022, p < 0.01$) show a positive association with cross-buying, whereas utilitarian coupons are negatively ($\beta_{3ij} = -.006, p < 0.01$) associated with cross-buying. Therefore, customers who use hedonic coupons, hedonic in-store deals, and utilitarian in-store deals tend to purchase a wider variety of products, whereas utilitarian coupon users purchase a narrower range of products. This result can also be explained by the utilitarian shopping behavior, since customers who redeem utilitarian coupons often restrict themselves to following shopping lists and using clipped coupons (Walters 2003). In contrast to the results for store loyalty, having children has a positive effect on cross-buying ($\beta_{5ij} = .195, p < 0.01$), which means that customers with children show more variety-seeking behavior than customers without children. Marital status ($\beta_{6ij} = .324, p < 0.01$) and the number of necessary items in the customer's basket ($\beta_{13ij} = 1.023, p < 0.01$) have significant positive effects on cross-buying with seasonal effects; however, other demographic variables such as age and income have negative and statistically insignificant effects.

The results for trip revenue are consistent with those of the first two outcome variables. Trip revenue significantly increases with hedonic coupon use ($\theta_{1ij} = .004, p < 0.01$), hedonic in-store deal use ($\theta_{2ij} = .018, p < 0.01$), and utilitarian in-store deal use

$(\theta_{4ij} = .024, p < 0.01)$, but utilitarian coupon use is associated with lower trip revenue $(\theta_{3ij} = -.003, p < 0.01)$. Again, these results indicate that customers with planned purchasing behavior who shop using utilitarian coupons tend to avoid unnecessary spending and therefore have slightly decreased trip revenue. Married customers generate higher revenue on average $(\theta_{6ij} = .282, p < 0.01)$, but having children does not have a significant effect on this outcome $(\theta_{5ij} = .117, n.s)$. In contrast to the other outcome variables, trip revenue is negatively associated with older customers (over 65; $\theta_{9ij} = -.162, p = .42$) and positively associated with mid- to high-income customers $(\theta_{12ij} = .144, p = .68)$. Furthermore, the number of necessary items in the shopping basket $(\theta_{14ij} = -.085, p = 0.27)$ and seasons of purchase $(\theta_{15ij} = -.042, p < .01; \theta_{16ij} = -.039, p < 0.01; \theta_{17ij} = -.059, p < 0.01)$ are negatively related to trip revenue. Young age $(\theta_{7ij} = .117, n.s)$, middle age $(\theta_{8ij} = .117, n.s)$, and income, except the third income quintile $(\theta_{10ij} = -.057, n.s; \theta_{11ij} = .103, n.s; \theta_{13ij} = .102, n.s)$, do not have a significant effect on trip revenue.

4. Concluding Remarks

The present study had two main goals, both focusing on gaining a better understanding of the interplay between price promotions and product categories. The first goal was to segment consumer groups via a combination of price promotions and hedonic versus utilitarian consumption. These two behavioral constructs were applied as clustering variables to characterize the consumer groups. The results of cluster analysis as explanatory analysis show that consumers can be segmented into seven different groups according to the price promotion usage and product categories. Each group has distinct consumer characteristics and different levels of store loyalty, cross-buying behavior, and trip revenue (see Table 2).

The joint model presented and tested here integrated constructs of two price promotion techniques for hedonic versus utilitarian goods with consumer demographic characteristics. The findings indicate that in-store deals significantly increase store loyalty, variety-seeking behavior, and trip revenue for both hedonic and utilitarian goods. A more interesting finding is that coupon use for utilitarian goods is negatively associated with store loyalty, cross-buying (variety seeking), and trip revenue. Perhaps consumers who use coupons more often to buy utilitarian goods are grocery shoppers with extremely planned purchasing behavior. Therefore, their purchases are limited by their shopping list, budget, and coupon availability. They also avoid unexpected purchases and in-store specials. Because of their lack of flexibility and tendency to use coupons, their trip revenue is reduced. Moreover, consumers who redeem coupons for utilitarian goods try a smaller variety of products because they only buy the products on their shopping list, which is already

planned (Laroche et al. 2003). They try to save time on their shopping trip by following the plan; thus, store loyalty is decreased by redeeming coupons (Barat et al. 2013; Kumar 2005).

Although this study contributes to the literature and methodology, it has a number of limitations. First, this study categorized products into hedonic and utilitarian; however, some products are ambiguous. It is also hard to capture hedonic versus utilitarian consumption during purchasing. Therefore, survey data should be collected to classify products according to consumers' perceptions. Second, this study investigated consumer behavior via price promotions across product categories using data from only one year. To increase the generalizability of the findings, future studies should use data over a number of years. Lastly, store loyalty, cross-buying, and trip revenue are all continuous variables. To achieve more benefits from the joint model, different types of outcome variables should be considered.

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Appendix

Table 3.1 Variable operationalization and descriptive statistics

Categorical variable	Operationalization	Proportion (number of households)	S.E.
Poverty	1 if Income under \$24K or income between \$25-35K and 2 adults with kids (reference from U.S Census Bureau/Poverty thresholds definition)	.17	.37
Reference Income	1 if Income between \$25 and \$49K but not \$25-35K and 2 adults with kids as this is considered poverty as noted above (reference from U.S. Census Bureau/ Income quartile)	.26	.39
Third quintile income	1 if Income between \$50K and \$74K (reference from U.S. Census Bureau/ Income quartile 40-60%)	.25	.43
Fourth quintile income	1 if Income between \$75 and 174K (reference from U.S. Census Bureau/ Income quartile 60-80%)	.18	.38
Fifth quintile income	1 if Income above \$175K (reference from U.S. Census Bureau/ Income quartile 80%+)	.14	.35
Households with kids	1 if households with kids	.18	.39
Age (19-24)	1 if household aged between 19 and 24 (reference from Bureau of Labor Statistic/American Time Use Survey)	.002	.38
Age (25-54)	1 if household aged between 25 and 54 (reference from Bureau of Labor Statistic/American Time Use Survey)	.21	.41
Age (55-64)	1 if household aged between 55 and 64 (reference from Bureau of Labor Statistic/American Time Use Survey)	.33	.47
Age (65+)	1 if household aged above 65 (reference from Bureau of Labor Statistic/American Time Use Survey)	.23	.42
Marital status	Dummy=1 if a customer married	.65	.47
Quantitative variable	Operationalization	Mean	S.D.
Dollar spent on hedonic couponed products (HC)	Dollar amount spent on hedonic products with coupons by a household in a week	1.13	4.93
Dollar spent on utilitarian couponed products (UC)	Dollar amount spent on utilitarian products with coupons by a household in a week	1.61	6.52
Dollar spent on hedonic products with deal promotion (HD)	Dollar amount spent on hedonic products with deal promotion by a household in a week	3.73	10.07

Table 3.1 Variable operationalization and descriptive statistics (Cont.)

Quantitative variable	Operationalization	Mean	S.D.
Dollar spent on utilitarian products with deal promotion (UD)	Dollar amount spent on utilitarian products with deal promotion by a household in a week	2.50	7.84
Trip revenue	Dollar amount spent by a household with the retailer in a week	132.67	123.59
Store Loyalty (Frequency)	Number of shopping trips made in a given week	2.38	1.35
Cross-buying (variety level)	Number of unique (different) product categories bought by the household per trip	17.64	4.61
Proportion of necessary items in one's basket	Number of necessary items purchased in a week / total number of products purchased in a week	.21	.14
Q2, Q3, and Q4	Dummy variables for quarters 2 through 4 (the first quarter is the base category)	.25, .25, and .25	.43, .43, and .43

Table 3.2 Statistical cluster descriptions

		Total	1 Deal- seekers (type I)	2 Retailer- discount driven shoppers	3 Freewheeling hedonic shopper	4 Hedonic shopper	5 Lapsed- faith	6 Utilitarian shopper	7 Deal- seekers (type II)
Percentage of observations		786 (100%)	48 (6%)	71 (9%)	122 (16%)	72 (9%)	292 (37%)	87 (11%)	94 (12%)
Hedonic coupons			2.33	-.30	-.58	.65	-.65	-.10	1.37
Hedonic discounts			1.54	1.08	.37	.31	-.98	-.27	.97
Utilitarian coupons			2.09	.107	-.67	-.09	-.74	1.19	.92
Utilitarian discounts			1.80	.96	-.22	-.24	-.93	.88	.86
Frequency		2.32	2.73 ^a	2.34 ^c	2.21 ^c	2.44 ^{bc}	2.16 ^c	2.37 ^c	2.67 ^{ab}
Cross-buy ⁴		2.88	3.44 ^a	2.87 ^{cd}	2.78 ^d	2.86 ^{cd}	2.71 ^d	3.17 ^b	2.99 ^c
Trip Revenue		136.3	223.6 ^a	132 ^c	116.3 ^c	125.8 ^c	117.2 ^c	174.8 ^b	157.2 ^b
Necessary items		.20	.17 ^b	.21 ^a	.21 ^a	.21 ^a	.21 ^a	.20 ^a	.19 ^{ab}
Kids	$\chi^2(6) = 25.67 ***$	.19	.39	.19	.12	.10	.17	.22	.30
Marital Status	$\chi^2(6) = 37.86 ***$	.65	.83	.72	.58	.56	.57	.82	.74
Age		1.00							
Age (25-54)	$\chi^2(6) = 17.37 ***$	.44	.60	.43	.43	.29	.43	.46	.59
Age (55-64)	$\chi^2(6) = 4.95$	.33	.29	.33	.34	.35	.35	.29	.3
Age (65+)	$\chi^2(6) = 10.06$	.22	.10	.23	.23	.34	.21	.24	.17
Income		1.00							
Poverty	$\chi^2(6) = 26.60 ***$	.18	.02	.16	.15	.19	.16	.13	.25
Income (24K-40%)	$\chi^2(6) = 17.49 ***$	.24	.25	.19	.24	.34	.29	.15	.15
Income (3 rd quintile)	$\chi^2(6) = 5.57$	.25	.33	.29	.27	.21	.23	.23	.19
Income (4 th quintile)	$\chi^2(6) = 24.08 ***$	.18	.22	.19	.20	.07	.13	.25	.32
Income (Highest)	$\chi^2(6) = 16.84 ***$	.15	.16	.16	.13	.18	.09	.23	.23

Note: we dropped age<25 since it contains only 2 samples.

⁴ Log-transformed variable

Table 3.3 The joint model

Variables	Outcome Variables		
	DV1.1= Log(Store Loyalty+1)	DV1.2= Log(Cross-buy)	DV1.3= Log(Trip Revenue)
Equation Number	(1)	(2)	(3)
Main Effects			
HC	.0022** (.001)	.005*** (.001)	.004*** (.001)
HD	.012*** (.001)	.015*** (.0005)	.018*** (.0006)
UC	-.004*** (.001)	-.006*** (.001)	-.003** (.001)
UD	.013*** (.001)	.022*** (.001)	.024*** (.001)
Kids	-.0002 (.077)	.195*** (.077)	.117 (.079)
Marital status	.184*** (.063)	.324*** (.063)	.282*** (.066)
Age (reference: 25-54)			
Age (19-24)	-.252 (.547)	-.467 (.547)	-.003 (.567)
Age (55-64)	.054 (.067)	-.042 (.067)	-.057 (.069)
Age (65+)	.124 (.076)	-.081 (.076)	-.162** (.078)
Income			
(reference: 24K-40%)			
Poverty	.008 (.085)	-.029 (.086)	-.057 (.089)
Income (Third quintile)	.024 (.079)	-.026 (.079)	.103 (.082)
Income (Fourth quintile)	-.071 (.087)	-.056 (.087)	.144* (.089)
Income (Highest quintile)	-.093 (.093)	-.087 (.093)	.102 (.096)
Controls			
Necessary items	.029 (.034)	1.023*** (.034)	-.085** (.035)
Q2	-.035*** (.012)	-.034*** (.012)	-.042*** (.013)
Q3	-.031*** (.012)	-.035*** (.012)	-.039*** (.013)
Q4	-.105*** (.011)	-.075*** (.012)	-.059*** (.013)
Constant	-.223*** (.075)	2.412*** (.076)	2.264*** (.045)
Std. Dev random effect	.756*** (.003)	.075*** (.0003)	4.207*** (.079)
Common parameter			
ρ_{12}	.632*** (.023)		
ρ_{13}	.616*** (.024)		
ρ_{23}	.935*** (.005)		
-2log-likelihood	154,208		

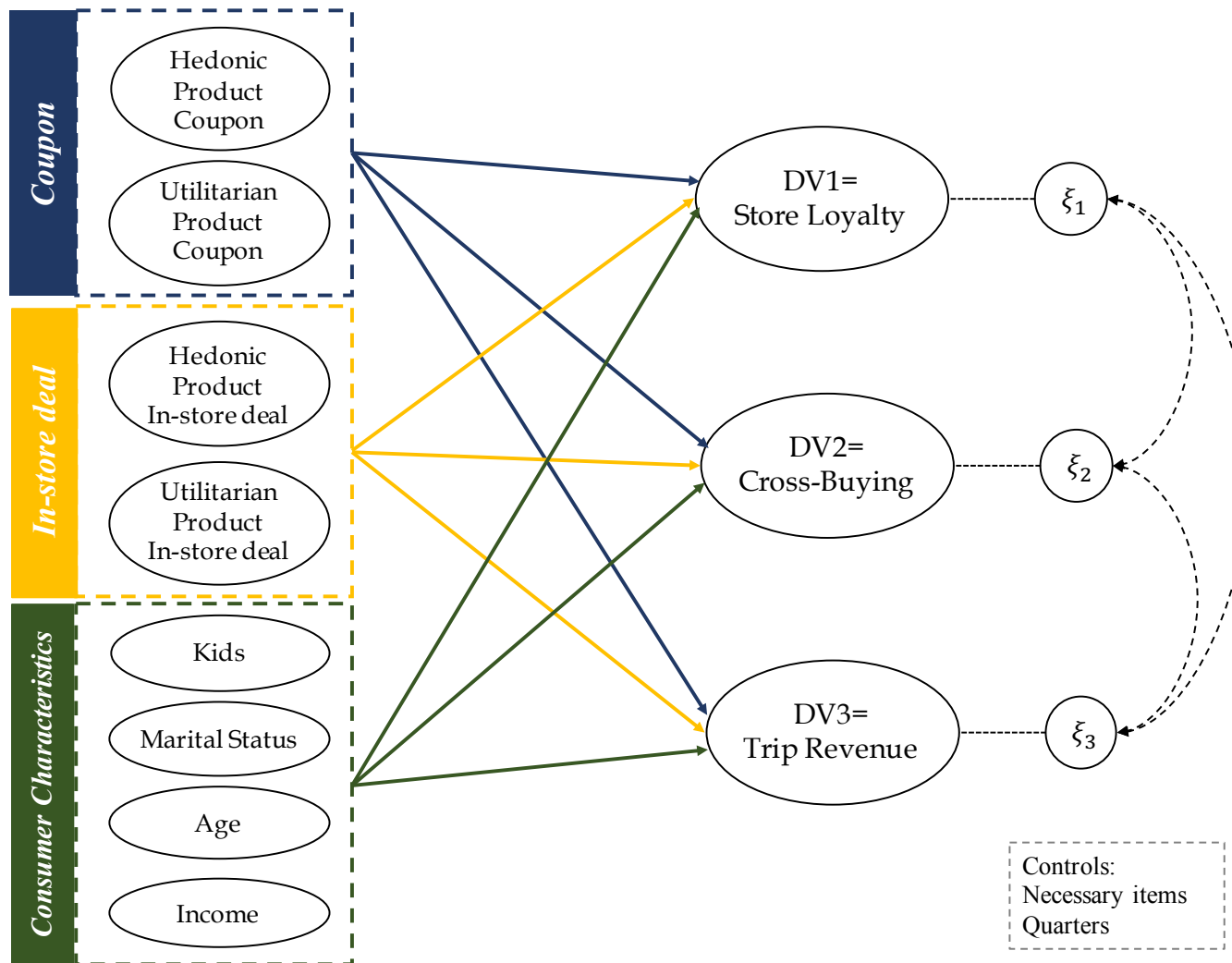


Figure 3.1 Conceptual model

CHAPTER IV

CONCLUSION

In this dissertation, I reviewed three simultaneous modeling approaches and proposed a joint model for analyzing correlated multivariate outcomes. For the joint model, I employed correlated multivariate normal random effects across regression equations for each outcome variable to extend the generalized linear mixed model. The normal random effects relax the assumption of variance, resolve omitted variable problems, and capture the heteroscedasticity of the data set. Therefore, the joint modeling approach is more appropriate, especially for clustered data and longitudinal data.

In the first study, I applied a joint model to analyze mixed types of outcomes (binary and continuous) in data from a large multinational survey. Using the joint model, the relationship between brand evaluation (based on attribute performance, marketing activities, experience with the current car, and the perceived image of alternative cars) and two types of brand loyalty (WOM and brand switching) was examined. In this joint model framework, the mediating role of overall customer satisfaction and the moderating role of culture were also considered. I found that experience-based functional attribute performance (e.g., fuel efficiency and safety) and dealership service were positively related to the overall satisfaction and WOM. Image-based emotional attribute performance (e.g., prestige, image, and friendliness) and marketing activities had a significant effect on brand switching through a high level of overall satisfaction. Customers' overall satisfaction level had a significant mediating effect between the relationships. The findings also showed that culture had a significant moderating effect in the relationships between product-related attribute performance, service-related attribute performance, marketing activities, and satisfaction. Compared with customers from a more individualistic culture, customers in a

culture with a high level of collectivism are more likely to be satisfied when they have positive experiences with functional attribute performance. The findings indicated that both experience-based brand evaluation and image-based brand evaluation have important roles in shaping overall satisfaction and customer loyalty. Furthermore, collectivistic and individualistic cultures weaken or strengthen the links between brand evaluation and overall satisfaction for both experience and image.

In the second study, I focused on the interplay between price promotions and the consumption of both hedonic and utilitarian retail grocery items using longitudinal data. I used joint models to investigate the effects of price promotions for product categories (i.e., hedonic and utilitarian products) on three outcome variables, namely store loyalty (frequency of shopping trips), cross-buying (variety seeking), and trip revenue, and to account for potential correlations among the outcome variables.

In the first step, I applied cluster analysis to classify consumer groups based on their price promotion usage and consumption of both hedonic and utilitarian retail grocery items. The results indicated that consumers can be classified into seven different segments; each consumer segment creates store loyalty, cross-buying, and trip revenue differently. The findings of the cluster analysis supported the validity of the joint modeling analysis by showing that the price promotions and consumption of both hedonic and utilitarian retail grocery items affect the three key outcome variables. I jointly modeled store loyalty, cross-buying, and trip revenue with price promotions and consumption of both hedonic and utilitarian retail grocery items. The findings of the joint modeling analysis indicated that consumers who consume hedonic grocery items using manufacturers' coupons and in-store

deals are more likely to visit the grocery store (high store loyalty), try a variety of products (high cross-buying), and spend more money (high trip revenue). Consumers who consume utilitarian grocery items via in-store deals are more likely to visit the grocery store frequently, try a wider variety of products, and spend more money than others. However, consumers who consume utilitarian grocery items by redeeming manufacturer coupons tend to visit the grocery store less frequently, try a smaller variety of products, and spend less money than other consumers. These results confirm previous research findings that utilitarian coupon users have highly organized and planned shopping behavior, so it is difficult to lead them to make unexpected purchases.

The findings of this study provide a number of managerial implications. First, both coupons and in-store deals are effective price promotions for hedonic grocery items. Therefore, retailers can get benefits such as high trip revenue from the price promotions for hedonic grocery items. Second, different promotional tools should be used for consumers who have highly organized and planned purchasing behavior. For example, 99-ending prices have a strong savings appeal to utilitarian coupon users (Gaston-Breton and Duque 2015).

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VITA

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