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"Investigating Spatial Dependence and Spatial Variations in the customer Satisfaction- Customer Loyalty Relationship: The implications for Retailers"_학술논문

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Investigating Spatial Dependence and Spatial Variations in the Customer Satisfaction-Customer Loyalty Relationship
: The Implications for Retailers

Young Han Bae*, Seung Hun Yu**, Moon Young Kang***

For recent decades, a plethora of research in marketing literature has explored the relationship between customer (or market) metrics and firm financial performance. These studies have found that customer metrics have a positively significant impact on firm profitability. The literature has identified that among customer metrics, customer loyalty is one of the most important drivers for firm profitability, and customer satisfaction is a key antecedent to customer loyalty. However, the literature is challenged by the finding that customer satisfaction does not always equate to customer loyalty. This challenge may be due to researchers' failure to identify the spatial dependence and spatial variation in customer satisfaction-loyalty data. Research on the customer satisfaction-loyalty relationship, in general, employs classical global empirical models that do not account for spatial dependence across customers' satisfaction-loyalty behavior or spatial variation in customers' behavior across different geographic spaces and product categories. Therefore, the parameter estimates of customer satisfaction obtained from these models could be biased and inconsistent, which leads to inconsistent empirical results. To remedy this problem, we employ global and multi-level spatial regression models to examine the customer satisfaction-customer loyalty relationship across different product categories, given that these spatial models can effectively handle spatial dependence and spatial variation. The empirical results indicate that customer satisfaction is a very significant antecedent to customer loyalty, and its impact is positive after controlling for spatial dependence. However, the strength of this positive customer satisfaction-loyalty association varies over geographic space and, more importantly, product category. These results provide significant academic and managerial implications for retailers.

Keywords: Customer satisfaction, Customer loyalty, Customer satisfaction-loyalty relationship, Spatial dependence, Spatial variation, Retailers' strategy

I. Introduction

Recent decades have witnessed a dramatic globalization of business due to increasing trade policy liberalization, stability in monetary transactions, regional economic integration, and the convergence of customer preferences (Katsikeas, Samiee, and Theodosiou 2006). As international

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competition increases, it is important for firms to develop and implement successful retailing strategies in order to ensure satisfactory performance outcomes (Casey and Hamilton 2014). As competition in the world market has intensified, increasing numbers of firms are seeking opportunities in huge foreign markets, such as United States, to achieve their objectives. Consistent with this stream, the marketing literature has employed empirical models to explore relationships between customer metrics and firm profitability in the U.S. market. The literature finds that customer loyalty is one of the most important metrics, insofar as there is a positive relationship between customer loyalty and firm profitability (e.g., Anderson, Fornell, and Mazvancheryl 2004; Ittner and Larcker 1996); moreover, customer loyalty is one of the most important drivers of firm profitability among various customer metrics (e.g., Gupta, Lehmann, and Stuart 2004; Reinartz, Thomas, and Kumar 2005). In addition, the literature has explored the issue of which customer metrics are a key driver of customer loyalty. Utilizing classical empirical models, a variety of research finds that customer satisfaction is a key driver of customer loyalty, and satisfying customers results in increased loyalty (e.g., Anderson 1996; Fornell 1992). However, marketing practitioners and academics are facing the challenge that customer satisfaction does not always convert to customer loyalty (e.g., Deming 1986; Jones and Sasser 1995; Seiders et al. 2005).

Recent research in the spatial modeling literature has provided a solution to explaining this challenge in several perspectives. On one hand, the inconsistent findings in the customer satisfaction-loyalty relationship may originate from the failure to identify spatial dependence in customer satisfaction-loyalty data where spatial dependence may exist, given that consumers' behavior tends to be influenced by one another under a social network or neighborhood framework. In a social network, a consumer's decision can be influenced by the decision of other consumers, which is referred to as interdependent or group decision-making (e.g., Yang and Allenby 2003) or neighborhood effect (e.g., Jank and Kannan 2005). Therefore, spatial dependence could exist in the satisfaction-loyalty relationship: a global spatial regression model effectively deals with spatial dependence by utilizing geo-information on the satisfaction-loyalty relationship and helps us draw a general consistent finding in the customer satisfaction-loyalty relationship by accounting for spatial dependence.

On the other hand, the inconsistent results may be due to the fact that there exist spatial variations across different geographic spaces and product categories (or industries) in the satisfaction-loyalty data. Accordingly, the satisfaction-loyalty relationship can vary over geographic space and product category. Mittal, Kamakura, and Govind (2004) observed different geographical patterns in customer satisfaction in his research using a large national sample of automobile customers served by a network of dealerships across the United States; from these observations, the researchers concluded that the impact of customer satisfaction on loyalty may be stronger in some regions than in others. This shows that there seems to be spatial variation in the satisfaction-loyalty linkage over space. Marketing researchers (Fornell et al. 1996; Seiders et al. 2005) argue that the satisfaction-loyalty relationship can vary with observable customer demographics, unobservable lifestyles over geographic space, and unobservable competitive sets over industry. Likewise, both practitioners and academics have found that loyalty behavior and the satisfaction-loyalty association are likely to be affected by the characteristics of customers (Mittal and Kamakura 2001) and competitive information (Oliver 1999; Seiders et. al. 2005). Unfortunately, in many cases, certain parts of the competitive sets and customer-specific information over space and product category are not clearly observed. However, failure to identify the issues of spatial dependence and spatial variation by employing a classical empirical model is likely to result in imprecise and biased estimation in the customer satisfaction-loyalty relationship. Therefore, inconsistent findings may have been generated in the literature. Thus, a multi-level spatial regression model can solve the problem of spatial variations over geographic space and product category, as well as spatial dependence. Since multi-level spatial regression models generate space-level and industry (or category)-level coefficient estimates of customer satisfaction, these models help us explore spatial variation in the strength of the satisfaction-loyalty association across different spaces and product categories in the U.S. market. Furthermore, these models account for spatial dependence that exists due to consumers' interdependent decision-making.

Our study contributes to the marketing literature by extending the previous research on the satisfaction- loyalty relationship. Based on global and multi-level spatial regression models, we account for spatial dependence and spatial variation over space and product category created by unobserved consumer lifestyles and competitive sets varying over space. This effort helps us draw a general and consistent finding of the customer satisfaction-loyalty relationship in the U.S. market. From a methodological perspective, the spatial models employed in this study include several important refinements relative to existing work in the literature. The most notable modification is the use of a multi-level spatial model that generates space-level and product category-level coefficient estimates of customer satisfaction, while adjusting for spatial dependence in customers' behavior across the United States. In our research, we utilize spatial information as a proxy for unobservable variables in investigating the possible spatial variation of the satisfaction-loyalty relationship, which has not been attempted by research in the customer satisfaction-loyalty association arena.

Ⅱ. Literature Review

In this section, we review and integrate a variety of relevant research on the customer orientation approach in the marketing literature and relevant applications of spatial models in the marketing and geography literature.

2.1 Customer Orientation Approach

For several decades, marketing researchers have been interested in marketing metrics. However, among marketing metrics, customer metrics (i.e., metrics related to customers) and linkages between these customer metrics and firm profitability have recently become more and more important in the customer orientation approach in the marketing literature.

Responding to this stream, a variety of research has examined the linkages between customer metrics (e.g., customer satisfaction, customer loyalty, or the customer satisfaction-loyalty link) and firm finance performance (e.g., profitability, stock price, Tobin's q, return on assets, return on investment, or cash flows).

Customers are viewed as being loyal "if they continue to buy the same product over some period of time" (Gupta and Zeithaml 2006). This customer loyalty significantly impacts retention because loyalty measures consumers' intentions to repurchase a product or service (Oliver 1999), and retention is the most important customer metric for firm financial performance. Also, firms have become more and more reliant on loyal customers' repeat purchasing behavior because acquiring new customers is much more expensive than retaining existing ones (Pfeifer 2005). Further, customer loyalty is one of the most important drivers of firm profitability among various customer metrics (Gupta, Lehmann, and Stuart 2004; Reinartz, Thomas, and Kumar 2005). Therefore, customer loyalty is one of the most important metrics in the customer-centric approach. Then, the question of which customer metric is a key driver of customer loyalty naturally arises. Regarding this question, marketing practitioners and academics have continued to view customer satisfaction as the key driver of customer loyalty (e.g., Anderson 1996; Fornell 1992; Fornell et al. 1996). Responding to the customer satisfaction-loyalty relationship, several studies demonstrate that satisfying customers results in increased loyalty (Anderson 1996; Fornell 1992; Fornell et al. 1996), indicating that customer satisfaction positively influences customer loyalty. Therefore, customer satisfaction is a key antecedent to customer loyalty and firm profitability.

However, customer satisfaction does not always convert to customer loyalty. For instance, Deming (1986) showed that it is not enough to have customers who are merely satisfied. Reichheld (1996) showed that high satisfaction scores are not always linked to high purchase intentions. Also, several studies fail to fully explain why some satisfied customers do not become loyal, and why some dissatisfied customers become loyal (Bendapudi and Berry 1997; Ganesh, Arnold, and Reynolds 2000; Keaveney 1995). Further, other studies (e.g., Mittal and Kamakura 2001; Mittal, Kamakura, and Govind 2004; Seiders et al. 2005) show that high satisfaction does not always translate into high loyalty. Most importantly, Kamakura et al. (2002) and Reichheld (1996) indicate that marketing managers need to make efforts in both achieving superior customer satisfaction and translating superior satisfaction into loyalty, since customer satisfaction alone is not an unconditional guarantee of customers' actual repeated purchasing behavior. Therefore, more and more evidence shows that "merely satisfying customers that have the freedom to make choices is not enough to keep them loyal" (Jones and Sasser 1995). Responding to this stream, Reichheld (1996) initiated the term "the satisfaction trap" to describe the challenge in which firms cannot transform customer satisfaction into repeat purchases, such as customer loyalty. Likewise, marketing practitioners and academics have faced the challenge that customer satisfaction does not always convert to customer loyalty, since customer satisfaction is a starting point in the linkage of customer satisfaction-customer loyalty-firm profitability, and satisfaction-loyalty is the central link in the satisfaction-loyalty-firm profitability linkage.

2.2 Spatial Models in the Marketing and Geography Literature

Empirical marketing models have been employed to investigate the effects of firm marketing actions on actual customer decisions. However, traditional empirical models assume conditional independence when information across individuals is pooled to construct the likelihood function for these models (Bradlow et al. 2005). That is, these models do not take into account spatial or temporal correlations across individuals. Since spatial models can successfully incorporate and model this spatial dependence, they have been employed in the marketing literature for the past decade. Spatial models that appeal to marketing academics can be categorized into one of two general types (Bradlow et al. 2005). Type 1 models (Bradlow et al. 2005) predict an outcome (or dependent variable) of an entity of interest (e.g., the consumer's choice behavior, the consumer's loyalty behavior, the firm's marketplace performance measure such as sales or market share, and the firm's financial measure), conditional on a set of covariates, the corresponding coefficient parameter vector and a set of spatial relationships (i.e., the locations of each entity on some type of map). In contrast, type 2 models predict spatial locations at which specific outcomes occurred, conditional on a set of covariates, the corresponding coefficient parameter vector and an outcome (Bradlow et al. 2005). Most spatial models in the marketing literature fall into the type 1 models, since marketing academics and practitioners are interested in the effects of covariates (e.g., marketing actions) on the outcomes of entities.

OLS (Ordinary Least Squares)-based spatial regression models, such as Polynomial surface Trend Regression (PTR) and Nearest Neighbor Regression (NNR), have been extensively adopted in the geography literature. OLS-based spatial regression models, including PTR and NNR, are simply OLS models with additional variables incorporating spatial information. However, each of these models represents spatial dependence differently. The difference between the estimation techniques for spatial data revolves around the assumption of whether the relations between observations are best described as continuous or discrete (Anselin 1988). PTR assumes that the spatial structure is continuous over space (Lambert, Lowenberg-Deboer, and Bongiovanni 2004), while NNR assumes that spatial correlation is a discrete relationship between specific points or polygons. More specifically, PTR additionally includes polynomial trend terms such as map coordinates (including longitude and latitude), their squared terms, and their interaction terms in the OLS formulation in Equation (1):

$$y = X\beta + \varepsilon, \quad \varepsilon \sim N(0,1). \tag{1}$$

The NNR model additionally includes the weighted Nearest Neighbor (NN) variable based on the dependent variable, i.e., weighted average dependent variable values at neighboring locations, in the OLS formulation in Equation (1).

The general form of the spatial autoregressive models used in the marketing and geography literature above is as follows:

$$y = X\beta + \rho Wy + \varepsilon, \quad \varepsilon \sim N(0, \Sigma), \qquad (2)$$

where β is a set of coefficients that is a function of the map coordinates, W is a spatial weight (or spatial lag) matrix, ρ is a scalar spatial parameter, and $\sum$ is a variance-covariance matrix.

The Simultaneously AutoRegressive (SAR) and Conditional AutoRegressive (CAR) models have different specifications on the variance-covariance matrix in Equation (2). The Error Simultaneously AutoRegressive (ESAR) model is of the following form:

$$y = X\beta + \rho W_{\varepsilon} + \varepsilon, \quad \varepsilon \sim N(0, \Sigma). \qquad (3)$$

Since both spatial autoregressive models (e.g., SAR, ESAR, and CAR) and OLS-based spatial regression model (e.g., NNR), assume that the spatial structure is discrete, the geography literature reports that the fitted results from NNR are very similar to those from the spatial autoregressive models (Lambert, Lowenberg-Deboer, and Bongiovanni 2004).

Ⅲ. Empirical Framework

3.1 Data and Explanatory Data Analysis

Responding to our empirical framework, which accounts for unobservable variables in the customer satisfaction-loyalty data, such as spatial dependence (i.e., the neighborhood effect) in customers' behavior over space and spatial variation over space and category, using spatial models, we collected two datasets, including the American Customer Satisfaction Index (ACSI) and postal code datasets.

First of all, we collected the American Customer Satisfaction Index (ACSI) dataset. Since the ACSI dataset is a dataset surveying customers across all regions in the United States, the ACSI used in this study is reported at the national level for all states in the United States.[1)]

The ACSI dataset contains surveyed information on customer satisfaction, customer loyalty, and various customer demographics, such as age, gender, education, income, race, and geographic location (e.g., the postal code of a location). Fornell et al. (1996) presents the descriptions of these variables. The customer loyalty and satisfaction variables are continuous, whose scale ranges from 0 to 100 (Fornell et al. 1996). Age is a continuous variable, ranging from 18 to 84. Income is an ordinal categorical variable. A value of 1 indicates less than high school; 2 indicates a high school graduate; 3 represents some college or an associate's degree; 4 indicates a college graduate; and finally, 5 represents a post-graduate education. The gender variable is a binary variable representing male or female. The income and race variables are nominal categorical variables. In addition, the ACSI dataset includes information on these variables across 18 industries such as food processing, beverages (beer), beverages (soft drinks), tobacco-cigarettes, apparel, athletic shoes, personal care products, gas stations, personal computers, household appliances, consumer electronics, automobiles, parcel delivery (express), the US postal service, airlines (passenger), utilities (electric service), utilities (gas), and hotels.

1) http://www.theacsi.org/

Since ACSI, however, does not contain information on map coordinates (such as longitude and latitude) of the locations surveyed, we collected the postal code dataset.2) This dataset contains information on the city and state, as well as the corresponding longitude and latitude.

Spatial information (e.g., map coordinates of the locations in the ACSI data) had to be incorporated into the ACSI dataset in order to reflect differences in the unobserved variables (e.g., customer lifestyles and competitive sets varying over space) and to compute a polynomial trend coordinates for PTR, a weighted NN variable for NNR, and a spatial weight matrix for SAR, ESAR, and CAR. Also, the nominal categorical variables had to be converted into binary variables for regression analysis. For these purposes, we conducted several data management procedures. First of all, in the ACSI dataset, we created binary indictor variables to represent an individual respondent's demographic information on gender, education, and race. Specifically, we created a gender binary indicator (male equal to one). We also created four educational dummies for high school (high school graduate equal to one), some college (some college graduate equal to one), college (college graduate equal to one), and post-graduation (masters or PhD program graduate equal to one). These education dummies represent all of the educational statuses in the dataset, such as the four above-mentioned educational statuses and an "other" category, which includes respondents with less than high school. Therefore, the "other" category is the basis for these educational dummies. We next created four race dummies for white (white respondent equal to one), black (black respondent equal to one), Native American (Native American respondent equal to one), and Asian (Asian respondent equal to one). These racial dummies represent all of the races in the dataset, such as the four above-mentioned races and an "other" category, which includes other races. Therefore, the "other" category is the basis for these racial dummies. Then, we merged the two datasets, such as the ACSI and postal code datasets. Since only one observation should exist within each postal code to compute a spatial weight matrix that is used for Moran I's tests of spatial autocorrelation (or dependence) of satisfaction-loyalty behavior in a spatial autoregressive model, we next aggregated all of the variables by 9,411 distinct postal codes in the merged dataset. In the aggregation, we computed the average of the variables, except for the categorical variables (in this case, we computed the proportion for these categorical variables) when multiple observations exist within a postal code area, as suggested in the geography literature. Finally, we conducted spatial clustering for multi-level spatial modeling over space in the United States (i.e., 48 states, except Hawaii and Alaska, due to their outlier characteristics in the clustering analysis). Based on a plot of within- group sums of squares, with respect to the number of clusters using the spatial k-means method of clustering, we identified twelve clusters across the continental United States. Also, the weighted NN variable was computed for use in global and ML NNR models (this variable was computed within each cluster and each product category for use

2) http://www.boutell.com/zipcodes/

in ML NNR models across space and product category).

After all of the data management jobs, we obtained the final data. The final data contain 9,411 observations on twelve covariates, two coordinates (u (longitude) and v (latitude)) of the locations of data points, the weighted NN variable, and cluster (12 spatial clusters) and product categories (18 product categories) variables showing which cluster and category to which a point belongs. The list and description of these variables in the final data are provided in Table 1.

The descriptive statistics for the 13 covariates, two coordinates, and postal code are provided in Table 2. We have also examined the correlation matrix of the final data. Small correlations between the covariates indicate that there is no multicollinearity concern; hence, there is no need for a variable reduction technique, such as factor analysis.

<Table 1> List and Description of the Variables

Variable			Notation	Description
Response Variable		Loyalty	y	The average customer loyalty surveyed within each zip code, continuous measure scaled from 0 to 100
Covariates	Main covariate	Customer Satisfaction	x_1	The average customer satisfaction surveyed within each zip code, continuous measure scaled from 0 to 100
		Age	x_2	The average age of customers surveyed within each zip code
		Male	x_3	% of male of customers surveyed within each zip code
	Education: Base is less than high school	High school	x_4	% of surveyed customers having graduated from high school within each zip code
		Some college	x_5	% of surveyed customers having attended some college within each zip code
		College	x_6	% of surveyed customers having graduated from college within each zip code
		Post graduation	x_7	% of surveyed customers having received a masters or Ph.D. degree within each zip code
		Income	x_8	The average income of customers surveyed within each zip code
	Race: Base is other race	White	x_9	% of white customers surveyed within each zip code
		Black	x_{10}	% of black customers surveyed within each zip code
		Native American	x_{11}	% of native American customers surveyed within each zip code
		Asian	x_{12}	% of Asian customers surveyed within each zip code
Information on spatial locations of observations		Zip code		Zip code
		u coordinate	Z	Longitude coordinate for each zip code
		v coordinate		Latitude coordinate for each zip code
Necessary for ML modeling across clusters		Cluster		Index of 12 spatial clusters
Necessary for ML modeling across industries		Category		Index of 18 categories
Necessary for NN regression		Weighted loyalty	w	Weighted NN variable

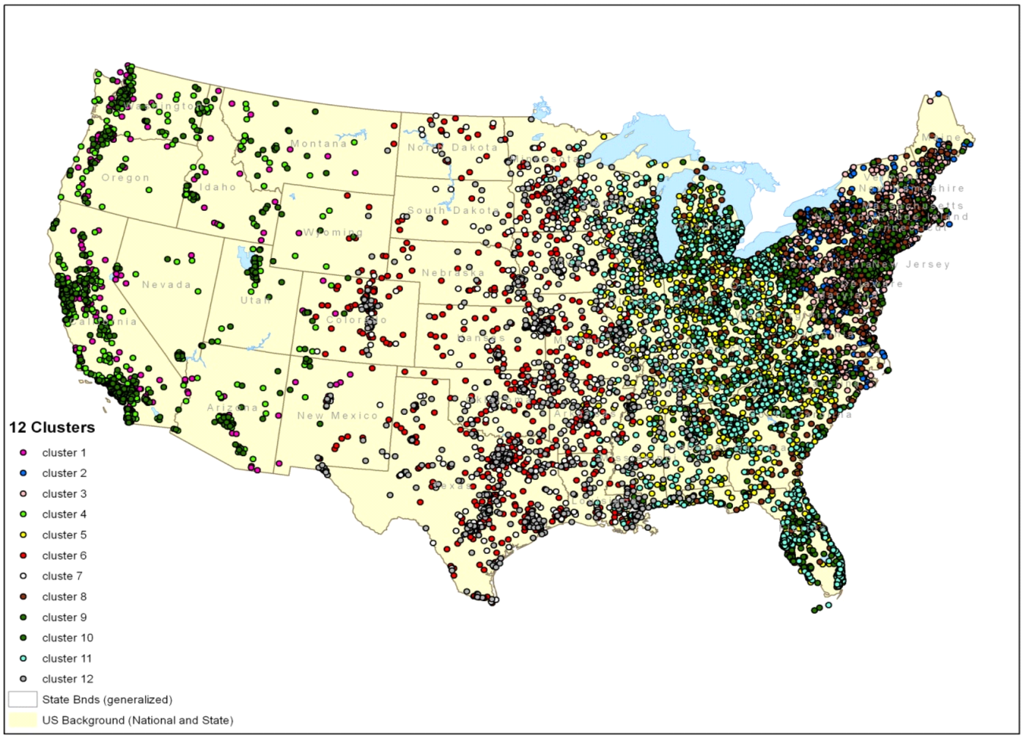
<Table 2> Descriptive Statistics of the Variables

	Min	Max	Mean	Standard Deviation
Loyalty	0	100	72.94	22.17
Customer satisfaction	0	100	77.76	16.01
Age	18	84	48.26	13.28
Male	0	1	0.40	0.42
High school	0	1	0.23	0.37
Some college	0	1	0.31	0.40
College	0	1	0.24	0.36
Post graduation	0	1	0.17	0.33
Income	1	7	4.17	1.75
White	0	1	0.86	0.31
Black	0	1	0.07	0.23
Native American	0	1	0.01	0.10
Asian	0	1	0.01	0.09
Zip code	1,002	99,400	47,000	28,133.84
u coordinate	-124.40	-67.39	-89.60	14.22
v coordinate	24.57	48.96	38.15	4.90

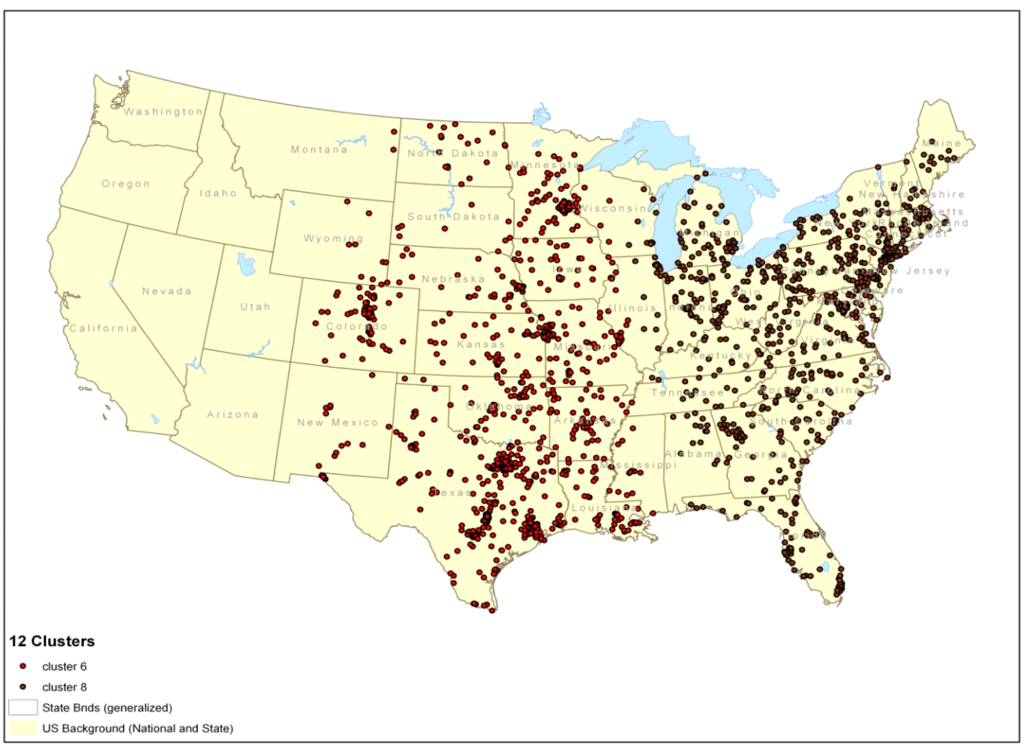
In Explanatory Data Analysis (EDA), it is important to examine the spatial dependence or autocorrelation structure in the variables of interest, such as the response variable (i.e., customer loyalty) and the main covariate (i.e., customer satisfaction) before employing the spatial regression models because the main objective of this study is to obtain precise coefficient estimates of customer satisfaction by adjusting for spatial dependence (neighborhood effect) in customers' behavior over space and spatial variation across space due to different consumers' lifestyles and industries' competitive sets across space in the United States in the customer satisfaction-loyalty data. If spatial autocorrelation and variation do not exist in the data, there is no need to employ a spatial regression model in examining the effects of satisfaction on loyalty. In this case, it suffices to employ a classical empirical model that does not account for these unobservable factors.

The magnitude and direction of spatial autocorrelation for a variable can be quantified by means of Moran's I statistics. More specifically, tests of both global and local Moran's I statistics are included in the spatial autocorrelation analysis (Anselin, Syabri, and Kho 2006). When we test the spatial autocorrelation of a variable using the Moran test, if the p-value of the Moran test statistic is less than 0.05, we reject the null hypothesis of no spatial autocorrelation, and hence, the spatial autocorrelation is statistically significant at the 5 % level.

To explore global spatial dependence in loyalty and satisfaction, we conducted Moran I's tests on these variables in the final dataset. Based on the Moran test statistics and associated p-values on these variables, the spatial autocorrelation in the loyalty and satisfaction variables is statistically significant



<Figure 1.a> Distribution of the Location of Loyalty Events over 48 States in the U.S. by Cluster



<Figure 1.b> Distribution of the Location of Loyalty Events for Clusters 6 and 8

because the associated p-value for the Moran test statistics are less than 0.05, regardless the style of the five different spatial weight matrices. As such, global spatial dependence exists across all spaces for loyalty and satisfaction.

We also conducted Moran tests for the loyalty and satisfaction variables across 12 spatial clusters and 18 industries to explore "the kind of" local spatial dependence of these variables across geographic space (i.e., clusters) and product category. The results indicate that local spatial dependence or spatial variation exists over space and product category for these variables.

In addition to these tools, it is effective to analyze data in a graphical way. We mapped the 9,411 point events of loyalty in the final dataset onto the continental United States map in Figure 1.a to examine the distribution of the location of all point events across all spaces and industries in our data. Figure 1.a indicates that the ACSI surveyed a large number of customers in highly populated regions, while it surveyed a small number of customers in less populated regions. We can also explore how the point events vary by cluster.

The results from the EDA indicate that there exist spatial dependence (detected by the global Moran tests) and spatial variation over space and product category (detected by the local Moran tests across clusters and industries). This suggests that it is reasonable to employ spatial regression models to adjust for such unobservable factors as global spatial dependence on the loyalty and satisfaction variables and spatial variation in these variables over space and product category.

3.2 Empirical Model

As the EDA indicates, there exists spatial dependence in customer behavior over space and spatial variation over space and category due to different consumers' lifestyles and industries' competitive sets across space in the customer satisfaction-loyalty data. Failure to account for these unobservable factors that are prevalent in our customer satisfaction-loyalty data could lead to a biased estimation in the customer satisfaction-loyalty regression model; thus, inconsistent findings in the relationship could be generated. Therefore, we intend to account for these unobservable spatial factors in order to obtain the precise coefficient estimate of customer satisfaction in the customer satisfaction-loyalty regression.

To adjust for these factors, we employ both global and Multi-Level (ML) spatial regression models, since global spatial models that utilize geo-demographical information can effectively adjust for the problem of spatial dependence over space, and ML spatial models can effectively account for spatial variation over space and product category. More specifically, to explore the global relationship between customer satisfaction and loyalty across continental space in the U.S., we fit global OLS-based spatial regression models, such as PTR and NNR, and global spatial autoregressive regression models, such as SAR, ESAR, and CAR. Spatial variation over space and category is ignored in these global spatial models, but these models help us examine the global relationship between two important customer metrics.

In addition, we fit two kinds of ML OLS-based spatial regression models, such as ML PTR and ML NNR, across clusters and industries to our data to generate cluster-level and product category-level coefficient estimates of customer satisfaction, which help us adjust for spatial variation over space and category in the United States.

The ML PTR and NL NNR models across the clusters are a mixed-effects model in which the coefficients of intercept, satisfaction, and polynomial trend terms (for ML PTR) or weighted NN variable based on loyalty (for MN PTR) are at the cluster level; hence, they vary across the twelve clusters, but the coefficients of other covariates are fixed. Also, the ML PTR and NNR models across the industries are a mixed-effects model, in which the coefficients of intercept, satisfaction, and polynomial trend terms (for ML PTR) or weighted NN variable based on loyalty (for MN PTR) are at the product category level; hence, they vary across the 18 industries, but the coefficients of other covariates are fixed. More specifically, we fit ML PTR and ML NNR across twelve spatial clusters. These cluster-level spatial models effectively adjust for spatial variation over space, which exists due to different unobserved customer lifestyles across geographic space, while accounting for spatial dependence in customer satisfaction-loyalty behavior over space. We fit ML PTR and ML NNR across 18 industries. These category-level spatial models effectively take into account spatial variation over industries that exist due to different unobserved competitive sets across industries, while adjusting for spatial dependence. As such, the global and ML spatial regression models employed in this study help us obtain the precise coefficient estimate(s) of customer satisfaction by adjusting for the unobservable spatial factors; accordingly, a general and consistent finding in the satisfaction-loyalty linkage can be obtained.

The ML PTR and NNR models allow the coefficients of intercept, satisfaction, and polynomial trend terms or weighted NN variable to vary across clusters and industries, while fixing the coefficients of other covariates such as observed demographics, including age, gender, education, and race. We do so because we are mainly interested in spatial and industrial heterogeneity in the main covariate, satisfaction, and spatial terms, either the polynomial trend or weighted NN variable.

3.3 Empirical Results

We display the information on the coefficient estimates of the covariates from the employed spatial regression models in Tables 3 through 6. The coefficient estimates of the covariates from the global PTR and NNR models and those from the global spatial autoregressive models are presented in Table 3. The fixed-effects coefficient estimates of the covariates from ML PTR and NNR across the twelve clusters (i.e., over space) are provided in Table 4. The fixed-effects coefficient estimates of the covariates from ML PTR and NNR across the 18 industries are provided in Table 5. The random effects coefficient estimates of customer satisfaction and weighted NN variable across the clusters from ML NNR over the cluster are presented in Table 6.a. The random effects coefficient estimates of customer satisfaction and weighted NN variable across the industries from ML NNR over product category are shown in Table 6.b.

<Table 3> Coefficient Estimates of the Covariates for the Global Spatial Models

Variable	Null PTR	PTR	Null NNR	NNR	Null SAR	SAR	Null ESAR	ESAR	Null CAR	CAR
Intercept	37.923 (18.292)	6.402 (14.250)	64.217** (2.197)	6.329** (2.374)	72.943** (0.236)	9.180** (1.690)	72.943** (0.236)	9.180** (1.690)	72.941** (0.237)	9.139** (1.690)
Customer satisfaction		0.870** (0.011)		0.870** (0.011)		0.870** (0.011)		0.870** (0.011)		0.870** (0.011)
Age		0.034** (0.014)		0.034** (0.014)		0.034** (0.014)		0.034** (0.014)		0.036** (0.014)
Male		0.448 (0.424)		0.455 (0.424)		0.456 (0.424)		0.456 (0.424)		0.443 (0.424)
High school		-2.767** (1.065)		-2.762** (1.065)		-2.765** (1.064)		-2.765** (1.064)		-2.799** (1.064)
Some college		-4.032** (1.060)		-4.010** (1.060)		-4.038** (1.059)		-4.038** (1.059)		-4.061** (1.059)
College		-4.007** (1.114)		-3.970** (1.114)		-4.010** (1.113)		-4.010** (1.113)		-4.061** (1.113)
Post_grad		-3.079** (1.162)		-3.032** (1.162)		-3.080** (1.162)		-3.080** (1.162)		-3.138** (1.162)
Income		-0.286** (0.117)		-0.282** (0.117)		-0.285** (0.117)		-0.285** (0.117)		-0.273** (0.117)
White		-1.265 (1.004)		-1.301 (0.987)		-1.262 (0.987)		-1.262 (0.987)		-1.285 (0.987)
Black		-1.256 (1.236)		-1.608 (1.218)		-1.604 (1.220)		-1.604 (1.220)		-1.611 (1.220)
Native American		2.212 (1.948)		2.216 (1.942)		2.258 (1.942)		2.258 (1.942)		2.353 (1.942)
Asian		0.952 (2.129)		1.089 (2.124)		1.025 (2.122)		1.025 (2.122)		1.024 (2.122)
u	-0.754** (0.280)	-0.142 (0.217)								
v	-0.064 (0.613)	-0.355 (0.474)								
u^2	-0.005** (0.001)	-0.0002 (0.001)								
v^2	-0.004 (0.009)	0.008 (0.007)								
uv	-0.005 (0.004)	0.002 (0.003)								
Weighted loyalty			0.120** (0.030)	0.040* (0.023)						
ρ					0.034*	0.019**	0.034*	0.019**	0.070**	0.039**
AIC	85,083	80,176	85,020	80,123	85,032	80,125	85,032	80,125	85,032	80,123

Note: * = p<0.10, ** = p<0.05

<Table 4> **Fixed-Effects Coefficient Estimates of the Covariates from the ML Spatial Models over Cluster**

Variable	ML PTR	ML NNR
Intercept	9.734 (15.115)	10.657** (2.355)
Customer satisfaction	0.869** (0.017)	0.868** (0.017)
Age	0.028* (0.016)	0.034** (0.016)
Male	0.458 (0.424)	0.461 (0.424)
High school	-2.765** (1.065)	-2.673** (1.064)
Some college	-4.099** (1.060)	-4.016** (1.059)
College	-4.023** (1.114)	-3.937** (1.114)
Post_grad	-3.105** (1.162)	-3.037** (1.162)
Income	-0.300** (0.119)	-0.307** (0.118)
White	-1.266 (1.004)	-1.113 (0.988)
Black	-1.224 (1.236)	-1.339 (1.221)
Native American	2.262 (1.948)	2.355 (1.942)
Asian	1.049 (2.127)	1.159 (2.123)
u	-0.067 (0.240)	
v	-0.285 (0.478)	
u^2	0.00004 (0.001)	
v^2	0.007 (0.007)	
uv	0.002 (0.003)	
Weighted loyalty		0.019* (0.011)
AIC	80,141	80,119

Note: * = p<0.10, ** = p<0.05

<Table 5> Fixed-Effects Coefficient Estimates of the Covariates from the ML Spatial Models over Category

Variable	ML PTR	ML NNR
Intercept	-2.265 (14.183)	10.758** (4.009)
Customer satisfaction	0.818** (0.038)	0.815** (0.038)
Age	0.037** (0.014)	0.037** (0.014)
Male	0.408 (0.416)	0.394 (0.416)
High school	-2.860** (1.041)	-2.820** (1.040)
Some college	-4.044** (1.037)	-4.034** (1.036)
College	-3.686** (1.090)	-3.662** (1.089)
Post_grad	-2.912** (1.137)	-2.889** (1.137)
Income	0.056 (0.117)	0.049 (0.116)
White	-1.212 (0.981)	-1.021 (0.965)
Black	-1.097 (1.208)	-1.183 (1.191)
Native American	1.237 (1.908)	1.348 (1.902)
Asian	1.766 (2.084)	1.633 (2.079)
u	-0.453 (0.218)	
v	-0.429 (0.468)	
u^2	-0.002 (0.001)	
v^2	0.011 (0.007)	
uv	0.003 (0.003)	
Weighted loyalty		0.031** (0.013)
AIC	79,842	79,761

Note: $^{*} = p<0.10$, $^{**} = p<0.05$

<Table 6.a> Random Effects Coefficient Estimates across 12 Clusters from ML NNR over 48 States

	ML NNR	
	Satisfaction	Weighted Loyalty
Cluster 1	0.896	0.034
Cluster 2	0.835	0.002
Cluster 3	0.885	0.020
Cluster 4	0.862	0.018
Cluster 5	0.894	0.032
Cluster 6	0.804	0.007
Cluster 7	0.860	0.016
Cluster 8	0.907	0.038
Cluster 9	0.823	0.001
Cluster 10	0.884	0.026
Cluster 11	0.885	0.029
Cluster 12	0.884	0.024

<Table 6.b> Random Effects Coefficient Estimates across Industries from ML NNR over Category

	ML NNR	
	Satisfaction	Weighted Loyalty
Food processing	0.762	0.033
Beverages, beer	0.782	0.028
Beverages, soft drinks	0.832	0.030
Tobacco-cigarettes	0.554	0.057
Apparel	0.926	0.012
Athletic shoes	0.938	0.012
Personal care products	0.669	0.039
Gas stations	0.672	0.048
Personal computers	1.014	0.001
Household appliances	0.897	0.016
Consumer electronics	0.971	0.034
Automobiles	0.923	0.040
Parcel delivery-express	0.715	0.032
US postal service	0.571	0.056
Airlines-passenger/scheduled	0.806	0.042
Utilities-electric service	0.828	0.008
Utilities-gas	0.842	0.044
Hotels	0.876	0.035

To account for such unobserved spatial factors as spatial dependence and spatial variation over space and category, we fitted a variety of spatial regression models (global versus ML models and OLS-based spatial versus spatial autoregressive models), and the fitted results vary across the models, which suggests that we need to determine the best model among all of these models and draw a general and consistent finding in the coefficient estimates of the covariates (especially, customer satisfaction) in the best model. The residuals from these models were used to conduct Moran spatial autocorrelation tests, along with Akaike's Information Criterion (AIC), whose value is computed via $-2lnL+2k$, where L denotes the likelihood function of the model, and k denotes the number of parameters to be estimated for model comparison and criteria for model robustness.

Between the global PTR and NNR, the global NNR model fits our customer satisfaction-loyalty data better than the global PTR because the associated AIC for NNR is smaller than that for PTR. Among the spatial autoregressive models, CAR fits our data best, given that the AIC for CAR is the smallest. Between the global NNR and CAR, there is no difference in the goodness of fit of the two models because the AIC values for these two models are identical. In addition, the performance, significance, magnitude, and direction of the coefficient estimates of the covariates are very similar between these two models. For instance, satisfaction, age, educational dummies, and income are statistically significant and satisfaction, age, and gender are positive, while educational dummies and income are negative across these two models. More importantly, the parameter estimate of the weighted NN loyalty variable (W) from NNR, which is analogous to ρ, and that of the spatial weight matrix from CAR, ρ , are statistically significant and positive; moreover, their magnitude is almost identical (0.040 from NNR and 0.039 from CAR). Furthermore, the Moran test statistics on the residuals from the global models indicate that the Moran statistic on the residuals from CAR is the most insignificant (because the associated p-value is the highest), and that from NNR is second most insignificant (because the associated p-value is the second highest). These results suggest that CAR and NNR are likely to fit the data best, and the performance between these models is very similar, which makes it reasonable to fit the ML NNR models across clusters and industries instead of ML spatial autoregressive models involving heavy computations.

Among ML PTR and ML NNR over space, ML NNR over space fits the data better than ML PTR over space, given that the AIC for ML NNR over space is smaller than that for ML PTR over space, and the Moran statistic on the residuals from ML NNR over space is more insignificant than that from ML PTR over space. Among ML PTR and ML NNR over product category, ML NNR over category fits the data better than ML PTR over category, since the AIC for ML NNR is smaller than that for ML PTR, and the Moran statistic on the residuals from ML NNR is more insignificant than that from ML PTR. Therefore, the parameter interpretation and findings reported in the remainder of the paper correspond to Global NNR and ML NNR over space and product category, which are our best fitting models.

Ⅳ. Findings and Managerial Implications

The coefficient estimates of the covariates from the global NNR model indicate that customer satisfaction is statistically very significant and positive, which suggests that customer satisfaction is a very significant and positive antecedent to customer loyalty after adjusting for global spatial dependence in customer behavior across geographic space in the United States. The coefficient estimate is 0.870, which implies that customer satisfaction is likely to increase customer loyalty by 0.870 (87.0%), after controlling for the other independent variables and spatial dependence. Among demographics, age, educational status, and income are statistically significant, while gender and race are statistically insignificant. Age is positively associated with loyalty. Its coefficient estimate is 0.034, which means that loyalty for older customers tends to be 0.034 (3.4%) higher than that for younger customers after controlling for the other independent variables and spatial dependence. However, customers' educational levels have a negative impact on customer loyalty, since their coefficient estimates are -2.767 for the high school dummy, -4.032 for the some college dummy, -4.007 for the college dummy, and -3.079 for the post-graduation dummy. The results indicate that compared to the baseline of these dummy variables (such as the other category representing customers with less than high school), graduates with less than high school tend to have a 2.767 (276.7%) higher rate of loyalty than graduates of a high school, have a 4.032 (403.2%) higher rate of loyalty than graduates with some college, have a 4.007 (400.7%) higher rate of loyalty than graduates of college, and have a 3.079 (307.9%) higher rate of loyalty than graduates of post-graduate school, after controlling for the other independent variables and spatial dependence. In addition, customers' income has a negative impact on customer loyalty, since its coefficient estimate is -0.286. The coefficient estimate means that a customer with a lower income tends to have a 0.286 (28.6%) higher rate of loyalty than a customer with a higher income, after controlling for the other independent variables and spatial dependence.

However, the strength of the positive customer satisfaction-loyalty association (or the sensitivity of customer satisfaction on loyalty) varies over space and product category. First of all, the random effects coefficient estimates of customer satisfaction across the twelve clusters from ML NNR over clusters demonstrate how the strength of the customer satisfaction-loyalty association varies over spatial clusters, as shown in Table 6.a. This association tends to be stronger in some regions than in others and tends to be weaker in some regions than in others. Among clusters, the middle part of the U.S. (cluster 6 shown in Figure 1.b) has the lowest impact of satisfaction on loyalty, whereas the eastern part (cluster 8 shown in Figure 1.b) has the highest impact of customer satisfaction on customer loyalty. Since the random coefficient estimate of customer satisfaction for cluster 6 is 0.804 and that for cluster 8 is 0.907, the positive strength of the satisfaction-loyalty relationship (or the positive impact of satisfaction on loyalty) for the middle part is 0.103 (10.3%) lower than that for the eastern part of the U.S.

On one hand, customers living in the middle part tend to be more conservative than customers living in other parts of the U.S. market (Phillips 2015), given that many of them participate in the agricultural or manufacturing industries. These conservative customers are less likely to be involved in variety-seeking behavior; hence, they are less likely to switch to another brand. This results in a lower effect of customer satisfaction on loyalty. As such, the effects of satisfaction on loyalty are lower for conservative customers living in the middle part of the U.S. On the other hand, customers living in the eastern part are likely to be more liberal than customers living in other parts of the U.S. market (Phillips 2015). These liberal customers are more likely to be involved in variety-seeking behavior, which leads to a higher effect of customer satisfaction on loyalty. Therefore, the effects of satisfaction on loyalty will be higher for these liberal customers living in the eastern part of the U.S.

Second, the random effects coefficient estimates of customer satisfaction across the 18 industries from ML NNR over the industries show how the strength of the satisfaction-loyalty link varies across industries, as shown in Table 6.b. The association is likely to be stronger in some industries than in others. Among industries, the tobacco and U.S. postal service industries have a relatively lower impact of satisfaction on loyalty, while the athletic shoe, personal computer, consumer electronics, and automobile industries have a relatively higher impact of satisfaction on loyalty. This heterogeneity in the positive strength of the satisfaction-loyalty association over industries is likely to stem from category characteristics. The positive strength of the satisfaction-loyalty relationship for a category tends to be lower as the category becomes more concentrated (e.g., tobacco and the U.S. postal service industries) because customers tend to be less involved in their repurchase behavior due to a lack of product offerings and differentiations; as a result, the effects of customer satisfaction on customer loyalty will be lower (Anderson 1994; Voss, Godfrey, and Seiders 2010). In contrast, the more competitive a category is (e.g., athletic shoe, personal computer, consumer electronics, and automobile industries), the higher the positive strength will be of the satisfaction-loyalty relationship. This is because customers are more likely to switch to another brand in these highly competitive industries due to an abundance in product offerings and differentiations, which will lead to a higher effect of customer satisfaction on loyalty. Therefore, the effects of satisfaction on loyalty would be higher in this case.

Among heterogeneity in the coefficient estimates of customer satisfaction over space and product category, heterogeneity in the satisfaction coefficients over category is higher than that over space, given that the difference between the highest and lowest coefficient estimates of customer satisfaction for ML NNR over space is 0.103 (10.3%), while that for NL NNR over category is 0.460 (46.0%). This finding indicates that the positive strength of the satisfaction-loyalty relationship varies over product category more than over space.

Likewise, spatial regression analysis in this study helps us more accurately explore the relationship between satisfaction and loyalty, and more importantly, explore heterogeneity in the satisfaction-loyalty link over space and product category in the U.S. market. Therefore, we are able to explain why in some cases, customer satisfaction does not translate into repeat purchase, which helps develop marketing strategy to effectively translate customer satisfaction investment into customer retention or loyalty.

This study provides important managerial implications. From a managerial perspective, the findings of this study underscore the need for managers to consider both spatial and product category variations in order to effectively implement marketing mix for enhanced customer satisfaction in the U.S. market. For instance, Korean multinational car companies such as Hyundai and Kia may need to focus on their investment in marketing mix that leads to an increase in customer satisfaction, since the satisfaction-loyalty link is stronger in the automobile product category than some other more concentrated product categories in the U.S. market. Hence, high investments in customer satisfaction will lead to high customer loyalty, which will, in turn, result in high firm profitability in this product category. Likewise, Samsung Electronics and LG Electronics will experience higher effects of their investment in marketing mix leading to an increase in customer satisfaction on customer loyalty (and hence, firm profitability), since the effects of satisfaction on loyalty are higher in the consumer electronics and personal computer categories than in other product categories. Also, several Korean companies operating in the athletic shoe category will experience the same investment effects in increasing their customer satisfaction in the U.S. market. Furthermore, these Korean companies may need to focus on their investment in the eastern part of the U.S., since the effects of satisfaction on loyalty is higher in this part than in other parts of the U.S. Likewise, the study provides implications on how much investment retailers decide to make in different geographical areas and product categories, depending on different satisfaction-loyalty links across different spaces and categories. This study also provides a theoretical implication. Our study is able to extend the current customer orientation research of retailers by shedding light on the gap in the literature that customer satisfaction does not always convert to customer loyalty.

V. Limitations and Future Research Directions

Although the framework developed using spatial regression models in this paper suggests a general and consistent finding in the customer satisfaction-loyalty relationship in the U.S. market, this study involves several limitations. One important limitation is associated with our customer satisfaction-loyalty data. Since the data are cross-sectional, we fit a spatial model instead of a spatio-temporal model. Although we believe that the temporal structure in the data may be very slow or weak, hence, allowing us to ignore the temporal structure, there could be a temporal structure (and hence, spatio-temporal dependence) in the data. If spatial-temporal dependence exists, we need to employ a spatio-temporal model in order to adjust for the spatio-temporal dependence.

Since we identify significant heterogeneity in the coefficient estimates of customer satisfaction across industries in the satisfaction-loyalty regression, the next step is to explain this heterogeneity. This explanation can be made by incorporating category-level covariates, including competition measures such as the Herfindahl-Hirschman Index (a commonly accepted measure of industry concentration), the number of firms, and average sales growth, and the types of categories (goods or services) in the second stage of our ML NNR model. Since NNR is a crude approach for real spatial autoregressive models such as SAR, ESAR, and CAR, we may need to employ an ML spatial autocorrelation model by including product category-level covariates in the second stage, which incorporates spatial dependence and spatial variation and simultaneously explains the heterogeneity in the coefficient estimates of satisfaction across product categories. If this Bayesian ML CAR model is fitted to the data, a more precise coefficient estimate of satisfaction may be obtained, and the heterogeneity in the coefficient estimates may be more effectively explained.

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고객 만족도와 고객 충성도의 관계에서 공간 의존성과 공간 변화성에 대한 연구

- 유통 산업에 대한 시사점 -

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ABSTRACT

최근 마케팅에서 고객 관련 지수와 기업의 재무 성과에 대한 연구가 활발하다. 이러한 연구들은 고객 관련 지수가 기업의 수익성에 긍정적으로 영향을 미친다고 밝혔다. 고객 관련 지수 중에서 특히 고객 충성도가 기업의 수익성에 가장 중요한 요인이고, 고객 만족도가 고객 충성도에 가장 큰 기여를 하는 요인이라고 알려져 있다. 그러나, 최신 연구에서 고객 만족도가 반드시 고객 충성도로 연결 되지는 않는다는 사실이 밝혀졌다. 이 같은 사실은 고객 만족도와 고객 충성도 데이터에서 공간 의존성과 공간 변화성을 고려하지 않았기 때문으로 설명될 수 있다. 고객 만족도와 고객 충성도의 관계에 대한 기존 연구들은 전통적으로 고객의 만족도와 충성도에 대한 공간 의존성과 다양한 지리적 공간과 상품 카테고리에 대한 공간 변화성에 대해 고려하지 않았었다. 따라서 이러한 모델로부터 도출한 모수들은 편향되고 일관성이 없는 문제가 있을 수 있다. 이러한 문제를 해결하고자, 본 연구에서는 공간 의존성과 공간 변화성을 반영한 공간 모형들을 사용하여 다양한 상품 카테고리에 대해서 고객 만족도와 고객 충성도의 관계에 대해 입증하였다. 본 연구를 통해 고객 만족도가 고객 충성도에 긍정적으로 영향을 미치지만, 이러한 긍정적 관계는 지리적 공간에 따라서 변화하고, 특히 상품 카테고리에 따라 변화한다는 사실을 확인했다. 본 연구의 결과는 학문적인 시사점 및 정부와 기업의 유통 정책/전략 수립에 근거를 제시한다.

주제어: 고객 만족도, 고객 충성도, 고객 만족도-충성도 관계, 공간 의존성, 공간 변화성, 유통 정책

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