

# Geographic Patterns in Customer Service and Satisfaction: An Empirical Investigation

When firms' customers are located in geographically dispersed areas, it can be difficult to manage service quality because its relative importance is likely to vary spatially. This article shows how addressing such spatial aspects of satisfaction data can improve management's ability to implement programs aimed at enhancing service quality. Specifically, managers can identify areas of high service responsiveness, that is, areas in which overall satisfaction is low but customers are highly responsive to improvements in service quality. The authors estimate the spatial patterns using geographically weighted regression, a technique that accounts for spatial dependence in the variables. They apply this methodology to a large national sample of automobile customers served by a network of dealerships across the United States. The authors also investigate the extent to which factors related to the physical and psychological landscape explain the importance that people in different regions place on dealership service and vehicle quality.

**C**ustomer satisfaction is essential to the long-term success of a firm (Rust, Zahorik, and Keiningham 1995; Rust, Zeithaml, and Lemon 2000). However, especially at firms that provide services using a regionally dispersed network of outlets (e.g., automotive dealerships, bank branches), managers face several challenges in implementing a customer satisfaction strategy. For such geographically dispersed outlets, overall satisfaction and the importance placed on service quality will vary from region to region. The firm's ability to provide superior service may also vary geographically. As such, incorporation of the regional differences in customer satisfaction decisions is important.

This article illustrates an approach that enables a firm to identify regional patterns in satisfaction data using geographically weighted regression (GWR), a spatial-econometrics technique that has been used primarily outside of the marketing literature. We apply this approach to a data set of 164,085 customers who represent 21,636 five-digit zip codes across the United States. We identify locations where overall satisfaction is relatively low but where customers are highly responsive to improvements in service quality. Such identification can provide guidance in the implementation of a service strategy on a national basis.

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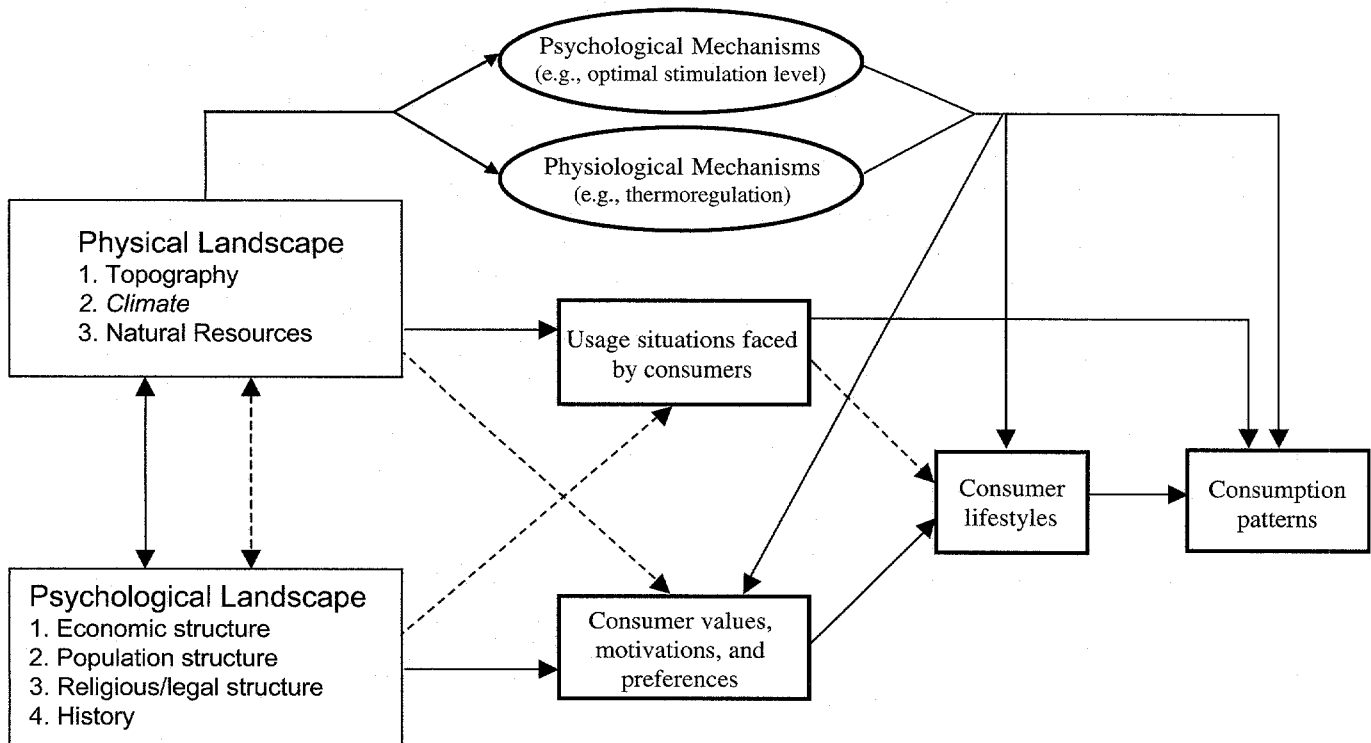
## Regional Differences in Consumption

Within marketing, the movement to understand regional differences in consumer consumption began in the 1970s. Responding to the fear that increasing mass production and mass communication would eliminate any regional differences among U.S. consumers, Wells and Reynolds (1979, p. 347) state:

The homogenization hypothesis is not based upon conclusive evidence.... Even the arguments that support homogenization can be seen to work both ways. Consider the common-influences argument: There is ample evidence that the mass media do not have mass effects; rather, they have differing effects according to the predispositions of the audiences.... Perhaps we should expect a reinforcement of existing values and beliefs among regions, instead of a convergence.

These regional differences were documented in many descriptive studies (Gillin 1955; Glenn and Simmons 1967; Nicosia and Mayer 1976). In 1981, Hawkins, Roupe, and Coney proposed a framework for understanding regional differences in consumption. As is shown in Figure 1, they posit two sets of causative factors. Factors associated with the physical landscape directly influence the usage situations that consumers face, which in turn influence consumption patterns through homeostatic influences (Parker 1995; Parker and Tavassoli 2000). As the ovals in Figure 1 show, Parker (1995) suggests that climate affects consumer behavior through mediating mechanisms that are both physiological (e.g., homeostatic regulation in the hypothalamus) and psychological (e.g., optimal-stimulation level based on the different senses). This is consistent with research in biology and medicine (Anderson, Deuser, and DeNeve 1995; Hill 1992; London and Teague 1985; Spont, Depue, and Kraus 1991). For example, differences in the degree of sunlight can affect the chemical balance in the brain, thus

**FIGURE 1**  
**A Framework for Understanding Geographic Influences on Consumer Behavior**



Notes: Model components shown in rectangular boxes are adapted from the work of Hawkins, Roupe, and Coney (1981). Model components shown in italics and ovals are based on the work of Parker and Tavassoli (2000).

affecting customers' mood states and, in turn, customer satisfaction (Peterson and Wilson 1992). Factors associated with the psychological landscape can affect consumer values, motivations, and preferences, which in turn determine consumer lifestyles and consumption patterns. In marketing, factors associated with the psychological landscape have received more attention (e.g., Grewal et al. 1999; Ingene 1984).

To implement the framework in Figure 1, the regional patterns must be empirically ascertained and the intervening mediators examined. Both steps require data that represent large geographic regions. This study focuses on the first step: determining the spatial variation in overall customer satisfaction and its response to service provided by the firm.

### Empirical Research

Wells and Reynolds (1979) compare consumers from the eastern, southern, midwestern, southwestern, and western regions of the United States. Hawkins, Roupe, and Coney (1981) compare coffee preparation and drinking habits in the same regions. Similarly, Gentry and colleagues (1988) compare students from Wisconsin, Washington, Oklahoma, and Massachusetts to draw conclusions about regional variation. All these studies find significant geographic variation in consumer values, attitudes, and consumption. However, they all compare regions that were defined a priori.

In contrast, recent works define regions on the basis of patterns embedded in the data themselves. Ter Hofstede, Steenkamp, and Wedel (1999) analyze data from 11 European countries and find that segmentation in terms of consumer perceptions and attitudes does not overlap with the political boundaries of the countries. In a more recent article, Ter Hofstede, Wedel, and Steenkamp (2002) develop a market segmentation model in which segment-membership probabilities for a focal region depend on the segment memberships of its immediately adjacent neighbors, thus enabling market segments to be spatially contiguous. They apply this flexible segmentation model to a pan-European study of consumers who provided store-image ratings, and they find evidence of spatial dependence in segment membership. Helsen, Jedidi, and DeSarbo (1993) show that countries classified as similar on the basis of macroeconomic variables may or may not exhibit similar patterns with respect to diffusion of consumer durable goods. Hoch and colleagues (1995) and Bronnenberg and Mahajan (2001) incorporate heterogeneous geodemographic data and find that the location of consumers strongly affects their responses to prices and promotions. However, these studies do not address issues related to customer satisfaction. As such, it is not clear how regional differences should be addressed in an examination of customer satisfaction and its antecedents.

## Regional Patterns in Customer Satisfaction: Issues and Implications

In examinations of customer satisfaction data, differences have typically been incorporated at the customer level, though customer characteristics tend to explain less than 10% of the variation in overall satisfaction (Bolton 1998; Bryant and Cha 1996; Danaher 1998; Mittal and Kamakura 2001). The previous section suggests that it might be useful to examine differences across regions as well, especially because some relevant consumer characteristics may show systematic regional patterns. For example, among automobile drivers, the relative emphasis placed on services may vary regionally not only because of the psychological landscape (e.g., different customer characteristics) but also because of the physical landscape (e.g., different climate and geography). In other words, we expect that regional differences exist, but in any large country such as the United States, the pattern of regional variability in overall satisfaction or the importance of service quality is not likely to map onto political boundaries or zones such as states or counties. In such cases, what options are available to the firm for developing a service strategy?

An option is for the firm simply to ignore geographical patterns and to treat each service unit (e.g., bank branch, dealership) as a separate entity. Such a strategy, though conceptually appealing, may be practically infeasible. First, it may not convey a unified brand image to a customer who patronizes different locations. Differences in policies and procedures at the units can also confuse and irritate customers. Second, such a strategy may be costly. The firm may need to collect data for each individual service unit separately. Although this can be done for the larger dealerships, obtaining a large sample from all the smaller service units not only may be costly but also may irritate customers who believe that they are oversurveyed and intruded on (Nunes and Kambil 2001). Third, this strategy may preclude a firm from benchmarking the service units against one another. Another option is for the firm to ignore regional differences and to treat all service units exactly the same. This strategy would fail to capitalize on geographic differences in the customer base. Instead of this supply (firm) focus, we argue for differentiated strategies based on regional patterns in consumers' responsiveness to changes in satisfaction drivers.

Such a strategy requires a firm to identify empirically the appropriate "region" in which customers' overall satisfaction is similarly responsive to improvements in service. A reasonable strategy is to analyze smaller areas, such as the five-digit zip code, in which customers are more likely to be similar. The smaller regions can be aggregated to produce meaningful regional zones in which consumers place a similar level of importance on service and have similar levels of overall satisfaction. Identification of such regional zones in which overall satisfaction is highly responsive to service improvement can be difficult. The firm may not know a priori the regional factors that drive such variability. Even if such factors are known, they may be too numerous to model in a convenient framework, and/or data on many

of the factors may simply be unavailable. An empirical approach that can detect geographical patterns in the data without relying on explicit variables may be more useful. Several techniques can be used to accomplish this objective. For customer satisfaction data, GWR is particularly appropriate because of its versatility in addressing geographically sparse data (i.e., when data may not be available for all the regions being analyzed). Typically, managers collect satisfaction surveys from customers who patronize different outlets (e.g., dealerships, bank branches). Although such a strategy provides coverage of the entire service area, it does not provide data from each location (e.g., five-digit zip code). The GWR technique is useful because it statistically "borrows" data for neighboring regions during estimation. Next, we briefly discuss GWR and show its application in a customer satisfaction context. Because the contribution of this article is not methodological, we do not address the debate about the various available approaches. For this discussion, we refer the reader to the comprehensive review provided by LeSage (1999).

### GWR and Customer Satisfaction

Brunsdon, Fotheringham, and Charlton (1996, 1998) developed GWR in the field of spatial econometrics. Although it has not been applied in the marketing literature, GWR has been used in agriculture and environmental analysis (Nelson and Leclerc 2001), real estate (Fotheringham, Charlton, and Brunsdon 1999), education (Fotheringham, Charlton, and Brunsdon 2001), and political science (Calvo and Escolar 2002).

Brunsdon, Fotheringham, and Charlton (1996, p. 285) describe how GWR is conceptually similar to kernel regression (Rust 1988). In each, the dependent variable ( $y$ ) is modeled as a function of the predictors ( $x$ ) by weighted regression, and weights for an observation are determined by the proximity of the focal observation and the neighboring observation. The key difference is that in kernel regression, the weighting is done on the "attribute space" of the independent variables, whereas in GWR, it is done in the two-dimensional geographic space, thereby avoiding the well-known "curse of dimensionality" that affects kernel-density estimation methods. Another important distinction is that in kernel regression, the dependent variable is related to predictors through a single, highly flexible, nonparametric relationship that applies to all observations or locations. In contrast, GWR estimates a linear relationship between predictors and the dependent variable, and parameters vary across locations.

The objective of GWR is to estimate a linear model that relates the dependent variable to its determinants after taking into account spatial correlation among observations in neighboring locations. This is accomplished by allowing for spatial nonstationarity in the regression coefficients for each location. A "location" is the geographic unit of analysis for which data may be aggregated. For example, in the United States, the five-digit zip code is a location, which enables estimation of a regression coefficient for each location (i.e., five-digit zip code) after accounting for the spatial correlation with neighboring zip codes. The location is defined on

the basis of factors such as data availability, similarity of customers within the location, cost effectiveness, and implementation considerations.

## Model Description

Consider the traditional linear regression model pooled across all locations:  $Y = X\beta + \varepsilon$ . The objective of GWR is to use all the data available (on the dependent variable  $Y$  and predictors  $X$ , including a column for the intercept) across all locations to obtain location-level estimates of the regression coefficients. Rather than pool all the available data, as in aggregate estimation, or shrink the regional estimates toward a population mean, as in random-coefficient models, GWR assumes that the regression coefficients vary across locations.

The GWR technique takes advantage of spatial dependence in the data. Spatial dependence implies that data available in locations near the focal location are more informative about the relationship between the independent and the dependent variables in the focal location. When calculating estimates for a focal location, GWR gives more weight to data from closer locations than to data from more distant locations. It is assumed that the relative weight of the contributing locations decays at an empirically determined rate as their distance from the focal location increases. Statistically, spatial dependence is operationalized by a weighting scheme in a generalized least squares (GLS) model, such that locations closer to the focal one have a greater weight in determining the regression equation for the focal location. The weighting matrix contains weights ( $w_j$ ) for all locations that are used in computation of the regression equation for the focal location. Using this geographic weighting matrix, we can obtain the weighted least squares estimates for any location  $j$  as follows:

$$(1) \quad \hat{\beta}_j = (X'W_jX)^{-1}X'W_jy.$$

This is a traditional regression estimated with GLS, where  $W_j$  is a  $(n \times n)$  diagonal matrix that contains  $\{w_{jj'}\}$ , ( $j' = 1, \dots, J$ ) in the diagonal, defined by an exponential distance-based decay function,

$$(2) \quad w_{jj'} = \exp(-d_{jj'}^2/\theta),$$

where  $\theta$  is the distance decay parameter, and  $d_{jj'}$  is the Euclidean distance between locations  $j$  and  $j'$ .

Implementation of the exponential distance-based decay function requires estimation of the optimal bandwidth ( $\theta$ ) before the weighted least squares estimates can be obtained. The bandwidth parameter determines the relevance of each neighboring observation for the estimation of the regional-level parameters  $\beta$ . When the bandwidth is sufficiently large, the GWR model reverts to a standard regression pooled across all regions. We determine the most appropriate value of the bandwidth using the least squares cross-validation procedure that Cleveland (1979) suggests. Cross-validation basically relies on the following scoring function to determine the optimal value for  $\theta$ :

$$(3) \quad \sum_{j=1}^n [y_j - \hat{y}_{\neq j}(\theta)]^2,$$

where  $\hat{y}_{\neq j}$  represents the fitted value of  $y$  with the observations from the focal location  $j$  omitted from the calibration process. The value of  $\theta$  that minimizes this score function is used as the bandwidth for calculating the weighting matrix. Details about the estimation of GWR with cross-validated GLS are found in the work of Brunson, Fotheringham, and Charlton (1998).

The GWR model, as Brunson, Fotheringham, and Charlton (1998) propose, considers the case with only one observation per location. However, in our analysis, we observe multiple responses in each zip code. Rather than aggregate the data in each zip code, we estimate our model at the respondent level. This individual-level estimation can be problematic because it emphasizes each location according to the number of observations in it. Although this would be acceptable in the case of simple random or proportionate stratified sampling, it is likely to bias the estimates otherwise. Therefore, we retain the concept of equal weighting for each location, as in the traditional GWR model, by weighting each observation with the inverse of the sample size in its location. The altered GWR model can be represented as follows:

$$(4) \quad \hat{\beta}_j = (X'W_jfX)^{-1}X'W_jfy,$$

where  $f$  is a  $(n \times n)$  diagonal matrix that contains the inverse of the sample size in the location  $j$  to which the individual observation  $i$  belongs, and the diagonal matrix  $W_j$  now contains the distance-based weights between each individual observation and the focal one ( $i$ ). Note that the regression coefficients  $\beta_j$  are still defined at the location level; the estimates are the same for all observations in the same location. This happens because all observations in the same focal location carry a unit weight, which results in the pooling of all observations from the same location.

Although empirical comparisons between GWR and other approaches are found in the literature (e.g., Brunson et al. 1999; LeSage 2001; Wolfinger and Tobias 1998), it is important to compare GWR with three predominant methods: spatial adaptive filtering (Foster and Gorr 1986), random-coefficients regression (Aitkin 1996), and multilevel modeling (Goldstein 1987). Spatial adaptive filtering incorporates spatial relationships in an ad hoc manner through exponential smoothing and produces nontestable parameter estimates, which limits its usefulness. In the other two approaches, the parameter estimates of the regression model are assumed to be randomly distributed over the population of locations with either a finite (Wedel and Kamakura 2000) or a continuous mixture distribution (Aitkin 1996). Random-coefficients regression also requires repeated measures in each sampling unit for reliable estimates at the individual level, which are rarely available in geographic data. For example, in the application we describe, most locations have only a single observation. Multilevel modeling assumes that there is a hierarchical data structure with individual observations nested under

another level, such as regions. However, both random-coefficients regression and multilevel modeling are silent about the nature of the spatial dependence in the data, a key factor in the determination of which locations should be treated similarly to constitute a region. Jones and Eldridge (1991) attempt a geographic variation of multilevel modeling, but they predefine a hierarchy of spatial units, which may not be appropriate for satisfaction data.

Rust and Donthu's (1995) two-step approach to capture geographically related misspecification errors in discrete-choice models is also closely related. In our situation, their approach would require us to estimate an aggregate regression model in the first stage and analyze the regression residuals in a second stage, using a cubic spline to relate the residuals to their geographic coordinates. The geographically related misspecification error captured by this approach would then be indistinguishable from the GWR intercept for each sampling unit. The GWR model we use herein allows for different geographic patterns for not only the intercept but also each response coefficient.

Ter Hofstede, Wedel, and Steenkamp (2002) take an entirely different approach. Rather than allow for a continuous spatial variation in the regression coefficients, they identify relatively homogeneous segments of regions under different assumptions about the spatial dependence among the segments. In its most strict form, their model requires spatial contiguity among segment members. In a less restrictive form, they assume only that the probability that a region belongs to a segment depends on the membership of its neighbor to the same segment. Rather than assume that there is spatial dependence among segments of regions, we account for spatial dependence in the original regions themselves.

### When Should GWR Be Used?

The GWR technique should be used when there is spatial autocorrelation in the variables. High positive autocorrelation implies that values from neighboring areas are similar to one another, whereas high negative autocorrelation implies that values from neighboring regions are dissimilar to one another. The magnitude and direction of spatial autocorrelation for a variable can be quantified by means of two statistics: Moran's *I* and Geary's *C* (Cliff and Ord 1973, 1981). The computational details for each statistic are shown in the Appendix. As is shown in the Appendix, values of Moran's *I* that are greater than  $-1/(N - 1)$  indicate positive autocorrelation, and vice versa. For Geary's *C*, values less than 1 indicate positive autocorrelation, and values greater than 1 indicate negative spatial autocorrelation. For both statistics, tests of statistical significance can be conducted to detect spatial autocorrelation. Based on these statistical significance tests, a decision to proceed with GWR can be made.

### Research Setting and Data Description

We conducted the study for a domestic automotive manufacturer that sells and services its vehicles nationally in the

United States through a dealership network. Although the manufacturer itself is responsible for the vehicle, it realizes the importance of dealership service as a key driver of overall satisfaction with the vehicle. Dealership service is particularly important during the later stages of vehicle ownership because it plays a significant role in the purchase decision of the next vehicle. Recognizing this, the company conducts a satisfaction survey with customers who have owned their vehicle for 33 months and who have had their vehicle serviced at an authorized dealership in the past 6 months. Thus, all respondents have a relatively high level of experience with the product (vehicle) and at least one service encounter at a dealership. Note that customers who took their vehicle in only for warranty- or recall-related service are excluded from the survey.

### Data

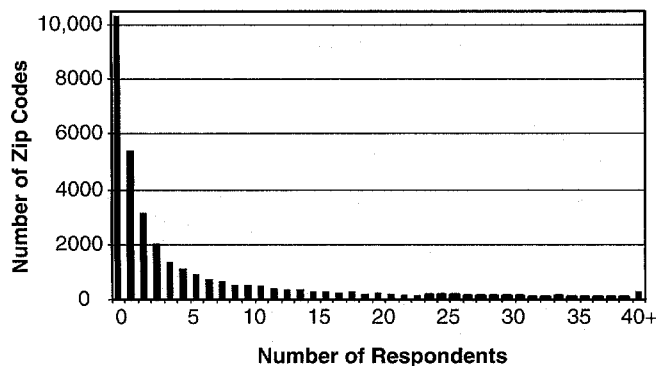
We used data from 164,085 customers who filled out the satisfaction survey. From this data set, we created a holdout sample by randomly selecting 32,000 customers from zip codes that contained at least 5 customers. Therefore, the reported analysis is based on 132,085 respondents, who represent a total of 21,636 five-digit zip codes in the United States. The sample is described in Table 1.

Of the 31,956 five-digit zip codes in the United States, we have data for only 21,636, or 67.7%. In other words, 32.3% of the zip codes have no data. Figure 2 displays the

**TABLE 1**  
Sample Description

Sample Characteristics	Percentage
<b>Sex</b>	
Male	64.2
Female	35.8
<b>Education Level</b>	
High school or less	26.3
Some college	27.3
College graduate	46.5
<b>Marital Status</b>	
Married	76.0
Single	19.5
Other	4.5
<b>Age</b>	
Younger than 30 years	9.4
30–59 years	68.1
60 years or older	22.5
<b>Overall Satisfaction Rating</b>	
1	.9
2	.5
3	.9
4	2.1
5	2.8
6	8.7
7	9.4
8	25.4
9	18.5
10	30.7

**FIGURE 2**  
**Frequency of Respondents by Zip Code**



Notes: Number of respondents = 164,085; respondents used in analysis = 132,085; total zip codes = 31,956; and zip codes with no observations = 10,320.

number of respondents from each zip code for whom data is available. In summary, a large proportion (32.3%) of zip codes are without data; among the remaining zip codes, more than half have five or fewer data points. A zip code-level analysis will systematically exclude approximately one-third of the zip codes. Among the remaining zip codes, zip code-level estimates may be unreliable for those that have five or fewer data points. More important, such an analysis will fail to incorporate the advantages of spatial autocorrelation in the estimation process. This is why the benefits of GWR make it the technique of choice for this problem: GWR statistically borrows observations from neighboring locations when estimating the coefficients for a focal location. This feature of GWR is useful because in most cases the focal location has few observations. In such cases, we obtain better estimates because observations from neighboring zip codes provide additional information. Borrowing from neighboring zip codes also helps identify regions that have similar coefficients, leading to a systematic view of the spatial patterns in the data.

## Variables

We used data from three key variables that we measured using a ten-point scale (1 = “extremely dissatisfied,” 10 = “extremely satisfied”). Each customer  $i$  answered the following questions on the ten-point scale: “On the basis of your experience this far, how would you rate your satisfaction with overall vehicle ownership experience (OVERALLSAT $_i$ ), vehicle quality (PRODQUAL $_i$ ), and dealership service (DLRSRV $_i$ )?”

Customers also indicated the five-digit zip code of their current residence. Although we could have aggregated zip codes up to a larger unit of analysis (e.g., county), we considered this inappropriate because it would imply homogeneity within relatively diverse areas. A finer unit of analysis such as the census block was not feasible because we defined the location of each respondent only by zip code. Thus, we performed a zip code-level analysis. We obtained the latitude and longitude coordinates for the centroid of

each five-digit zip code. From the centroids, we computed the Euclidean distance between each zip code in the data set. We used this distance in the estimation of the GWR model.

Next, we estimated the spatial autocorrelation in the variables. In the absence of spatial autocorrelation, a pooled regression across all the areas should suffice. The measures of spatial autocorrelation (Geary’s  $C$  and Moran’s  $I$ ) across all 21,636 zip codes for all three variables are shown in Table 2. Moran’s  $I$  is greater than  $-1/(N - 1)$  ( $p < .05$ ), and Geary’s  $C$  is less than 1 ( $p < .05$ ). This indicates positive spatial autocorrelations for all three variables; values of observations from areas closer to one another tend to be positively correlated.

## Results

Using GWR, we estimated the following relationship in which satisfaction with the ownership experience is a function of vehicle quality and dealership service:

$$(5) \quad \text{OVERALLSAT}_i = \beta_{0j} + \beta_{1j} \text{PRODQUAL}_i + \beta_{2j} \text{DLRSRV}_i + e_i,$$

where  $e_i$  are i.i.d. normal disturbances. Note that we estimated the three parameters for each location  $j$  and observed disturbances at the individual  $i$ .

Using this model, the automotive firm can identify areas in which it should improve dealership service. For these areas, it can ascertain specific subdrivers of dealership service (Rust, Zeithaml, and Lemon 2000). The GWR model estimates separate coefficients for each five-digit zip code. A listing of coefficients for each location would be neither meaningful nor easy to communicate. Therefore, we depict the results in Figures 3 and 4 by plotting the regression coefficient for each location. In Figures 3 and 4, darker (lighter) color indicates a larger (smaller) regression coefficient (i.e., higher or lower importance) for dealership service and product quality.

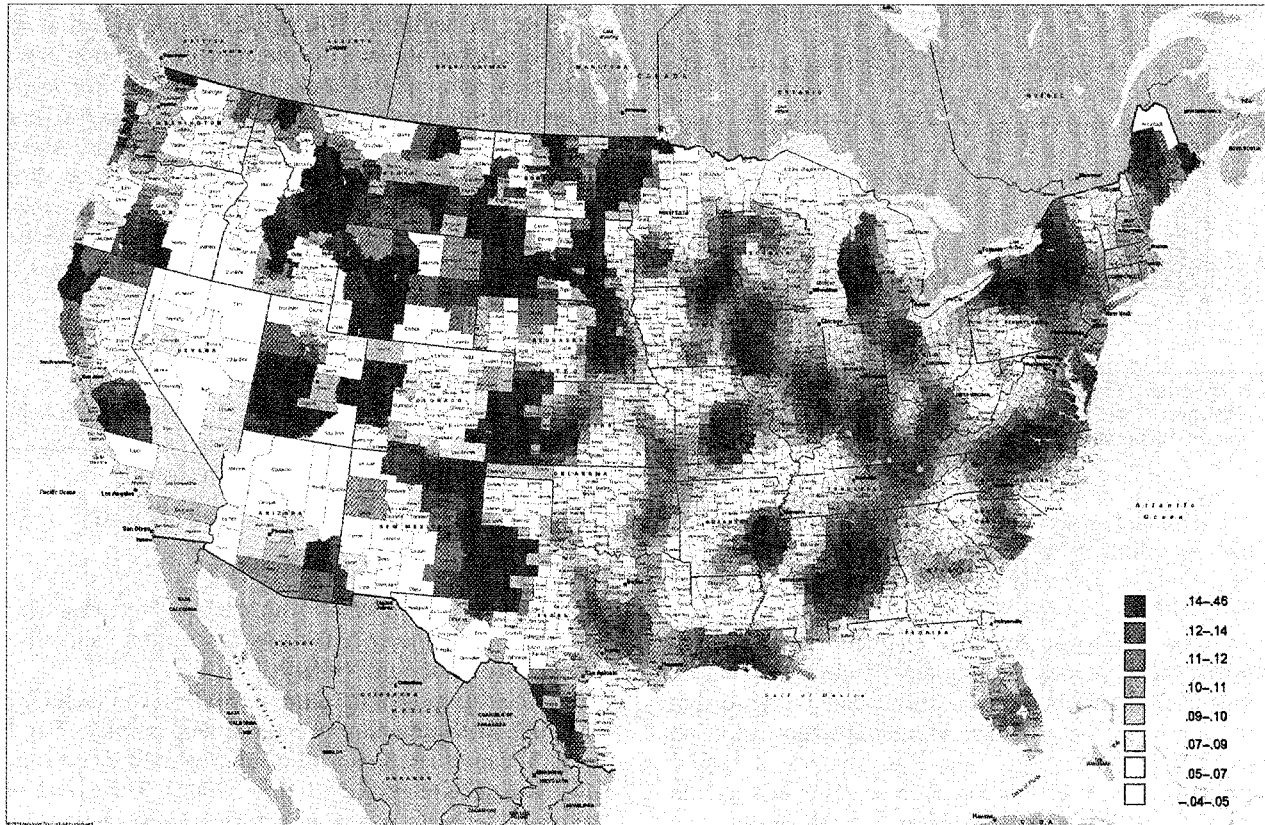
### Regional Patterns in the Importance of Dealership Service

The regression coefficients for dealership service are depicted in Figure 3. Consider Colorado: In the southeastern part of Colorado, the importance of service quality is high (indicated by the dark color), whereas in the southwestern part of the state, it is lower (indicated by the lighter color). From central to northern Colorado, we find the lowest importance of service, indicated by the white shading. Furthermore, in the northeastern part of Colorado, the importance of service satisfaction is uniformly low, as it is in the adjacent state of Nebraska.

**TABLE 2**  
**Spatial Autocorrelation in Variables**

	Moran's I	Geary's C
Overall satisfaction	-.008	.69
Dealership service	-.007	.76
Vehicle quality	-.007	.77

**FIGURE 3**  
**Coefficients for Importance of Dealership Services**



In general, dealership service is more important in the easternmost or westernmost parts of the country, especially in parts of southern Oregon and northern California. Other regions in which service is important include northeastern New Mexico into Colorado and Kansas. In the Midwest, Kentucky, Indiana, and Illinois also share areas in which dealership service has high or medium importance. We were surprised that there is a large area in the western United States—including Nevada, Arizona, Oregon, and Idaho—in which dealership service is less important. In addition, the various major metropolitan areas are located in regions with different levels of importance. Indianapolis; Columbus, Ohio; and Philadelphia have high to medium importance of dealership service, whereas Jacksonville, Fla.; San Francisco; and San Jose, Calif., have medium to low importance.

#### ***Regional Patterns in the Importance of Vehicle Quality***

Results for the importance of vehicle quality are shown in Figure 4. As we expected, they are essentially the inverse of the results for dealership service. Consider Texas: In northeastern Texas, we find that the importance of vehicle quality is relatively high in determining overall satisfaction. This part of Texas shares the pattern of high importance of vehicle quality with the neighboring states of Louisiana and Arkansas. However, between Dallas and Austin, the relative

importance of vehicle quality is medium to low, as it is in northwestern Texas. In contrast, the importance of vehicle quality is high in southern Texas. The pattern of importance of vehicle quality also varies for different metropolitan markets. Whereas Philadelphia, New York, and Washington, D.C., are in areas of low importance, Memphis and San Francisco are in areas of high importance.

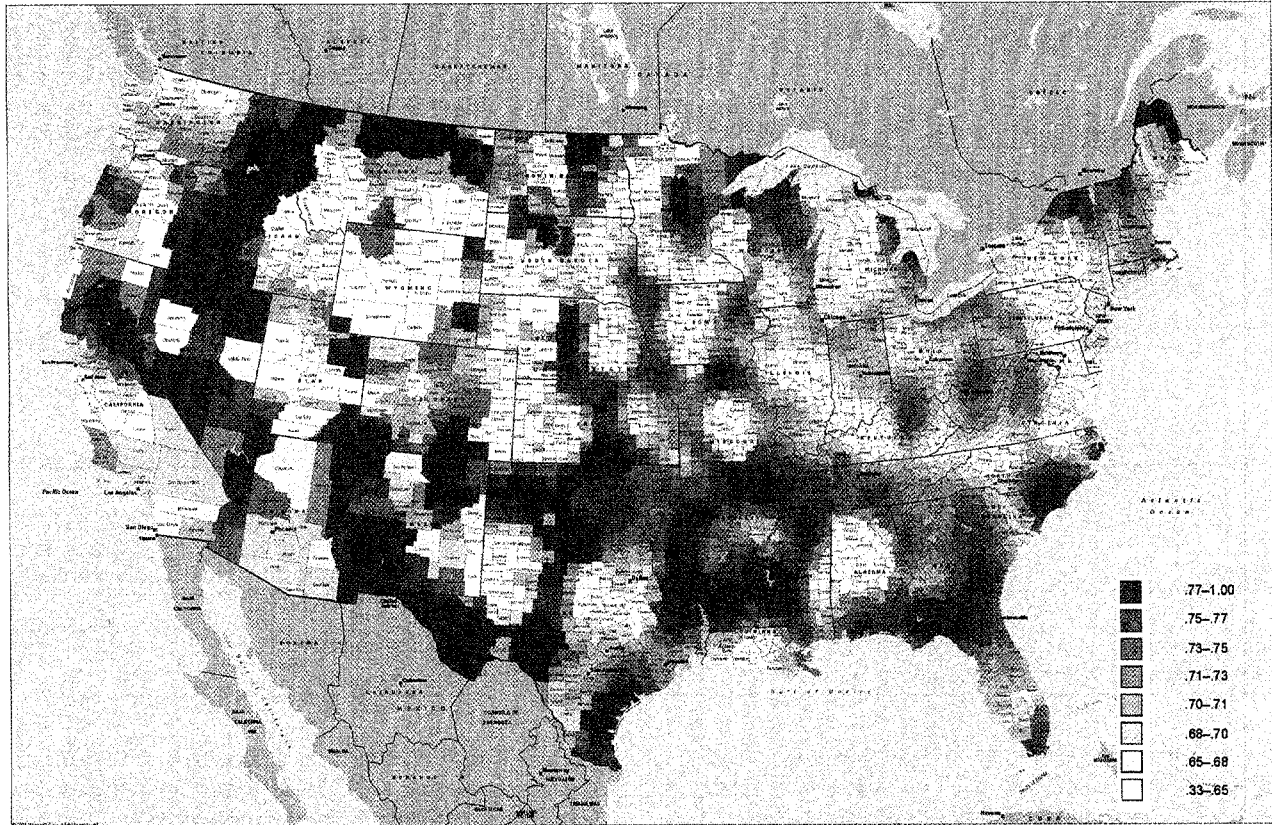
### **Model Performance**

We evaluate model performance using two criteria: (1) the model's ability to predict overall satisfaction and (2) stability of the parameter estimates for the key drivers.

#### ***Predicting Overall Satisfaction***

To evaluate predictive performance, we used the holdout sample created using 20% of the observations. To create the holdout sample, we selected zip codes that had more than five observations so that we could obtain standard regression estimates for each holdout zip code and so that at least two observations would be available for predictive tests. Note that the minimum of three observations for estimation is a requirement imposed by the benchmark models; GWR can compute the parameter estimates even in a zip code area that has no data, on the basis of data in neighboring areas. From the short-listed zip codes that contained five or more observations, we randomly drew 32,000 observations; a few

**FIGURE 4**  
**Coefficients for Importance of Vehicle Quality**



zip codes had multiple observations in the holdout sample. The final holdout sample of 32,000 observations represents 13,846 zip codes.

Table 3 compares the GWR with simple regression using two measures of predictive performance. The first is the range of predicted satisfaction scores (from the 95% confidence interval) for each location, averaged across all locations in the holdout sample. We performed this using the prediction methodology that Nester (1996) and Brunson, Fotheringham, and Charlton (1998) suggest. This measure indicates the model's ability to predict the satisfaction scores on a zip code-level basis, and it indicates the uncertainty associated with the predictions. The second measure is the percentage of observations in the holdout sample for which the actual satisfaction score fell within the 95% confidence interval predicted by the model. This measure provides an empirical verification of the 95% confidence intervals across customers by showing the percentage of times the confidence interval included the actual satisfaction score in a holdout sample.

We examine the results at the zip code level. Model 1 uses GWR estimation at the five-digit zip code level. Model 2 is a zip code-level model without GWR that we estimated by running separate regressions within each zip code. Model 2 uses at least three observations within a zip code and compares predicted satisfaction scores with actual ones for the remaining observations in the zip code. The fourth

column of Table 3 shows that the 95% confidence interval around the mean estimate of the predicted values is lower with the GWR model than with the model without GWR (.28 versus 1.07). Thus, the predictions we obtained with GWR carry a lower degree of uncertainty than do the predictions we obtained under the assumption that all regions are independent. The rightmost column of Table 3 shows that when GWR is used (Model 1), 87.05% of the observations in the holdout sample have a satisfaction score that falls within the 95% confidence interval of the predicted value. Without GWR (Model 2), only 40.42% of the values of overall satisfaction in the holdout sample fall within the 95% confidence interval of the predicted value. Therefore, the interval predictions that the GWR model produces are more likely to include the actual value even though the intervals are narrower, which reflects lower uncertainties about the predictions. The confidence intervals based on independent regressions were not only broader, reflecting higher estimation error, but also less accurate in predicting satisfaction in a holdout sample.

For comparison, we also estimated models at the county level (Model 3) and the state level (Model 4). As is shown in Table 3, the actual satisfaction score falls within the predicted 95% confidence interval for 72.56% of the predictions made with the county-level estimation and 83.58% with the state-level model. At first glance, the results appear to be comparable to those we obtained with zip code-level

**TABLE 3**  
**Model Validation Using a 20% Holdout Sample (Predictive Ability)**

Model	Level of Analysis	Estimation Method	Range of Predicted Value Averaged Across All Areas <sup>a</sup>	Percentage of Observations in a 20% Holdout Sample Falling Within $\pm 1.96(\sigma/\sqrt{n})$ of Predicted Value
1	Zip code (13,846)	GWR	.28	87.05
2	Zip code (13,846)	No GWR	1.07	40.42
3	County (n = 3102)	No GWR	2.39	72.56
4	State (n = 50)	No GWR	3.87	83.58
5	Random sample of zip codes (n = 17,228)	GWR	.62	71.41

<sup>a</sup>95% confidence interval around the mean estimate.

**TABLE 4**  
**Mean and Standard Deviation of Split-Half Correlations (Parameter Stability)**

Parameter	Correlation Between the Two Samples			
	Overall	Zip Codes with Observations	Data Missing in One Sample	Data Missing in Both Samples
Intercept	.61 (.02)	.66 (.04)	.41 (.04)	.41 (.08)
Dealership service	.62 (.04)	.68 (.06)	.41 (.05)	.41 (.07)
Product quality	.58 (.06)	.70 (.08)	.41 (.06)	.46 (.11)

estimation. However, note that the average range of predicted values for each area is much broader for the county-level model (2.39), and even more so for the state-level model (3.87), than for the zip code-level estimates. This means that it is more likely that the actual satisfaction score falls within the broader confidence interval. Because there is more uncertainty in the predictions at the county and state levels, the confidence intervals are much greater, which makes it easier for the interval to contain the actual satisfaction score. Thus, for managers who want to ensure accurate prediction of overall satisfaction for each zip code under consideration, the zip code-level model with GWR performs the best.

Finally, we also performed a holdout test with another set of observations. In this case, we randomly drew 32,000 observations from the data set without limiting ourselves to the zip codes that had five or more observations. This sample of 32,000 data points represented 17,228 zip codes. We used the remaining 80% of the data to estimate a GWR model. We used the set of parameters we obtained from this model to predict the observations from the holdout sample. The results from this analysis are shown in the fifth row of Table 3. Note that the results from this prediction are not comparable to the estimates from ordinary least squares because for many of the zip codes involved, we had few observations left to be able to estimate an ordinary least squares model. The range of predicted values is now larger than when we included only zip codes with five or more observations (.62 versus .28). This is because we have many zip codes for which we have no observations in the focal region, and thus we needed to form predictions from neighboring locations through the GWR model. In addition, the

number of observations that fall within  $\pm 1.96(\sigma/\sqrt{n})$  was 71.41%, compared with 87.05% for the previous model. Nevertheless, this predictive performance is still superior to the benchmark models.

#### **Stability of Parameter Estimates**

To evaluate the stability of our estimates of the importance of dealership service and vehicle quality, we randomly split the sample within each zip code into two halves. When only one observation was available for a zip code, we randomly assigned it to one of the split samples, and it was designated as missing in the other sample. We then applied GWR on the two halves, computing the coefficients for the zip codes that had no data. To assess parameter stability, we computed the correlation from the two halves and for the complete data for the following three sets of zip codes: (1) ones for which the data were available in both samples, (2) ones for which the data were missing in one sample, and (3) ones for which the data were missing in both samples (i.e., we computed parameter estimates in both halves). We replicated the split-half test ten times, and we report the mean and standard deviation for the correlations across the ten replications. The split-half correlations, computed across 31,956 zip codes (including those with no data), provide an assessment of parameter stability for our application of the GWR model. When data were available in both split halves, the correlation was greater than .65. We consider this strong evidence of parameter stability because we computed the correlations between two estimates and across a large (31,956) sample size. When we impute the parameter estimate for one random sample (i.e., no data were available for the particular zip code), the correlation decreases to approx-

imately .40. We expected this attenuation in the split-half correlations because the correlations now involve one parameter estimate and one imputed value. A notable result is that the split-half correlations were not further attenuated when both samples had imputed values (rightmost column of Table 4).

### Regional Patterns in Dealership Service: Strategic Implementation

To implement the results, the firm should first identify regions in which overall satisfaction is relatively low. Then, among these regions, it can ascertain the responsiveness of overall satisfaction to dealership-service improvements. Then, the firm can give priority to the regions in which the importance of dealership service is relatively higher.

We selected the subpar satisfaction regions. For this study, we chose regions that were below the median in overall satisfaction. The regional pattern in overall satisfaction is shown in Figure 5. Thus, in these regions, there is relatively more room for customer satisfaction improvements. Note that the criterion and/or cutoff that is used to define subpar satisfaction regions is a subjective issue to be decided with managerial consultation. For the subpar satisfaction regions, we plotted the importance of dealership service (Figure 6). In Figure 6, regions with a darker shade are those in which the firm should implement service improve-

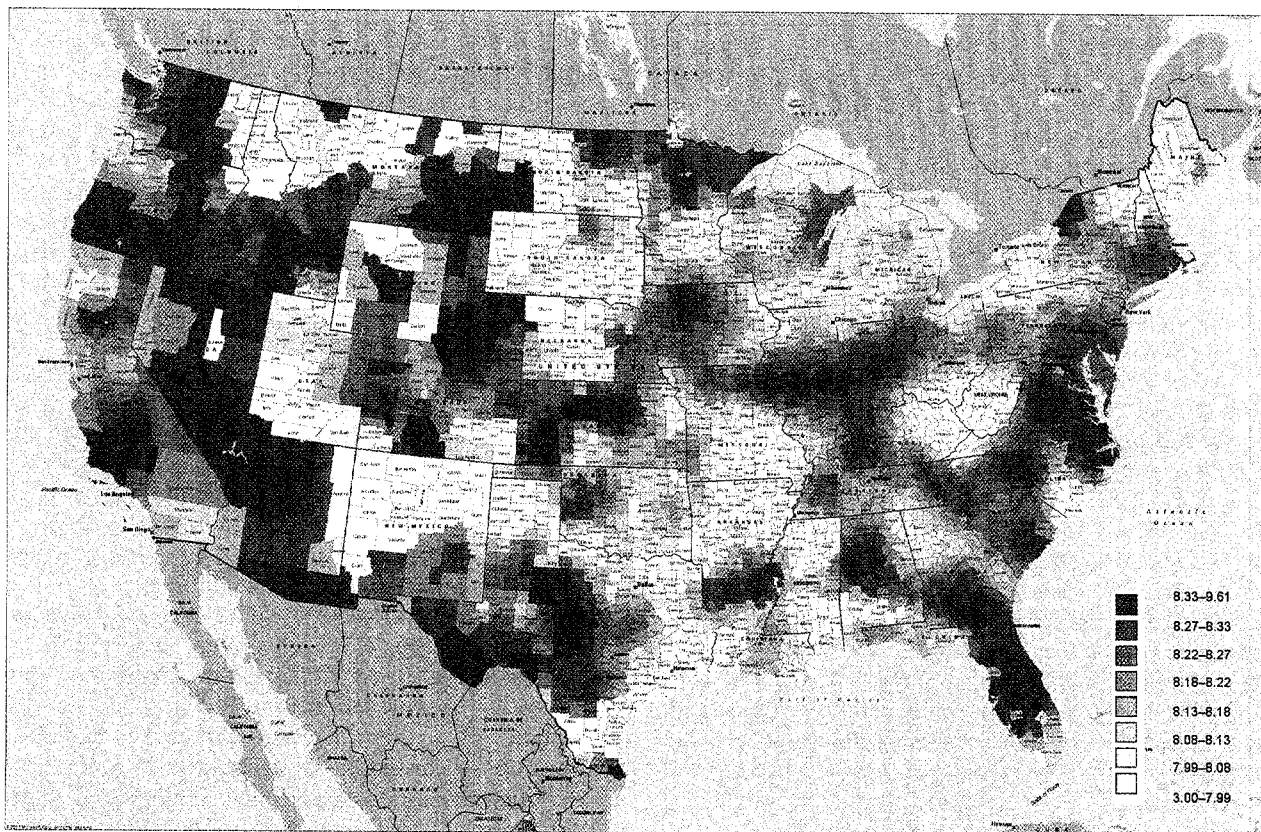
ment first: They are regions in which such improvement has a relatively large impact on overall satisfaction and in which overall satisfaction is relatively low. In deciding where to invest in improving dealership service, the firm must also consider other factors such as market size and competition.

As a next step, performance on various attributes that drive dealership service should be measured. A key driver analysis can identify specific subdrivers of dealership service, and importance-performance charts can help the firm isolate the drivers that need improvement (Rust, Zahorik, and Keiningham 1995). The firm may also gather information on its customer base in such regions (e.g., the Southwest, southern Kansas) for further insights. That is, why is dealership service so important in such regions? Some of this could be related to structural factors and geographic conditions. Although the firm did not have primary data on these factors, we undertook such an exercise using secondary data, which we describe next.

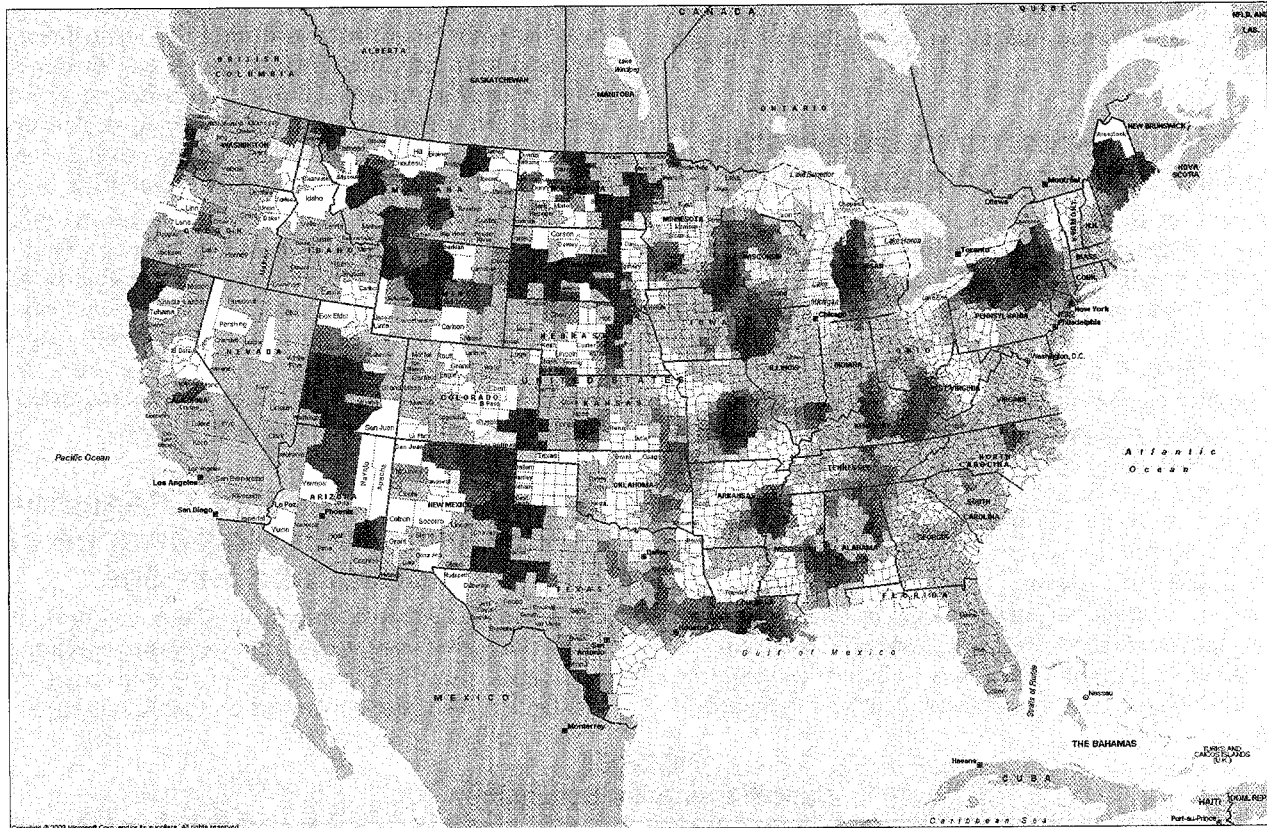
### Factors Determining Regional Variability in the Importance of Product and Service

Our goal is to determine empirically the extent to which different factors related to the physical and psychological landscapes affect the importance of the drivers of overall satisfaction. The national coverage of our data set provides

**FIGURE 5**  
**Overall Customer Satisfaction**



**FIGURE 6**  
**Service Responsiveness for Subpar Satisfaction Areas**



a unique opportunity to investigate this issue. To obtain measures of some of the factors, for each zip code we appended variables from the U.S. Census and the Weather Bureau. We included only variables for which data on at least 95% of the zip codes were available. We merged the variables with the survey measures and GWR results at the zip code level. Table 5 shows the variables we used in the final models.

Table 5 shows two models in which dependent variables are the importance of automobile quality and dealership service (as measured by the regression coefficients obtained from GWR). We did not use overall satisfaction because it has the product quality and dealership service embedded in it and is therefore driven more by supply-side factors (for which we do not have data) than by customer characteristics. In contrast, the importance coefficients measure how customers respond to the supply-side factors (product quality and dealership service) and are more intrinsic to the consumer. Thus, they are more likely to be affected by the physical and psychological landscape.

The regression coefficients in Table 5 have been standardized to make them directly comparable. We also tested the predictors for multicollinearity using the variance inflation factor, which was lower than 6, except for a few predictors that we excluded from the model.

Consistent with previous studies, we find that the importance of the automobile and dealership service varies

on the basis of customer characteristics (e.g., Bolton 1998; Bryant and Cha 1996; Mittal and Kamakura 2001). In this regard, several notable patterns are evident. For example, as per capita income increases, the importance placed on the automobile ( $\beta = .023$ ) and the dealership services ( $\beta = .071$ ) increases. However, as the proportion of men in a region increases, the importance of dealership service declines ( $\beta = -.031$ ), but the importance of the automobile increases ( $\beta = .016$ ). This result is fully consistent with the work of Mittal and Kamakura (2001), who find that men place a lower importance on service than do women. Regarding age, younger buyers (age 25 or younger) place more importance on the automobile ( $\beta = .117$ ) than on dealership service ( $\beta = -.025$ ). In contrast, buyers older than age 60 place higher importance on both the automobile ( $\beta = .062$ ) and the dealership service ( $\beta = .090$ ). We found similar results for education. Within an area, as the proportion of people with less than ninth-grade education increases, so does the importance of the automobile ( $\beta = .085$ ) and the dealership service ( $\beta = .026$ ). However, among people who have a graduate degree, the importance of the automobile seems to be lower ( $\beta = -.046$ ), but the importance of service seems to be higher ( $\beta = .073$ ). Perhaps increased education and income make consumers more sensitive to service, though older consumers also attach higher importance to both the automobile and the dealership service. Driving habits and driving conditions also seem to influence the importance

**TABLE 5**  
**Determinants of Importance of Automobile Quality and Dealership Service**

Independent Variables	Standardized Regression Coefficients	
	Importance of Automobile	Importance of Dealership Service
<b>Psychological Landscape Factors</b>		
Per capita income	.023**	.071**
Sex (percentage of people who are male)	.016*	-.031**
Percentage of people who ...		
are younger than age 25	.117*	-.025**
are ages 26-35	.064**	-.010*
are ages 36-45	.042**	.020
are ages 46-60	.053**	.037*
are older than age 60	.062**	.090**
did not go to school	.017	-.076**
studied until less than ninth grade	.085**	.026**
have a high school diploma	-.069**	.072**
have an associate's degree	-.012	.028**
have a bachelor's degree	-.031**	.048**
have a graduate degree	-.046**	.073**
are Asian	-.039**	-.009
are American Indian	-.025*	-.016
are African American	-.047**	.052**
are Caucasian	-.031	.016
work in administration	.008	.017
work in managerial jobs	-.008	.049**
work as a laborer	-.081**	.028*
work in the farming sector	-.051*	.131**
work as a technician	.005	-.044**
carpool	.077**	-.124**
use public transportation	-.041**	-.031**
drive less than 20 minutes to work	-.056**	-.002
drive 20-30 minutes to work	-.009	.011
drive 31-90 minutes to work	.016*	-.080**
drive for more than 90 minutes to work	-.020**	-.031**
<b>Physical Landscape Factors</b>		
Elevation	.016	-.017
Mean minimum temperature	.012	.002
Mean rain	.015	.085**
Mean snow	.171**	.091**
Mean maximum temperature	.056**	-.039**
Variance in minimum temperature	.074**	.068**
Variance in rain	-.016	-.012
Variance in snow	.156**	-.067**
Variance in maximum temperature	-.016	-.053**
N	27,584	27,584
R <sup>2</sup>	6.18%	8.71%

\* $p < .05$ .  
\*\* $p < .01$ .

placed on the automobile and the dealership service. As we expected, as the proportion of carpooling consumers increases, the importance of the automobile increases ( $\beta = .077$ ), but the importance of dealership service decreases ( $\beta = -.124$ ). The importance of the automobile and dealership service decreases ( $\beta = -.041$  and  $-.031$ , respectively) as the proportion of people who use public transportation in an area increases. Perhaps in such areas alternative means of transportation assume higher importance.

Factors that constitute the physical landscape are also related to the importance placed on vehicle and dealership

service, though the pattern of results is complex. Elevation is statistically not significant ( $p > .05$ ). The mean amount of snow increases the importance placed not only on the vehicle ( $\beta = .171$ ) but also on the service ( $\beta = .091$ ). The variance in the amount of snowfall has a different effect; it increases (as we expected) the importance of the vehicle ( $\beta = .156$ ) but decreases the importance of dealership service ( $\beta = -.067$ ). The mean amount of rainfall affects only the importance placed on service, whereas the variance in rain has no impact. The mean maximum temperature increases the importance placed on the vehicle ( $\beta = .056$ )

but decreases the importance placed on the dealership service ( $\beta = .039$ ). Higher variance in weather conditions (e.g., rain, snow, maximum temperature) has no effect or a positive effect on the importance of the vehicle but almost always decreases the importance placed on the service element. In other words, in areas with highly varied climate, consumers seem to be more concerned about the vehicle than the dealer service. However, areas in which the mean amount of snow and rain is generally high deserve special attention because both service and product elements are important.

In summary, factors associated with the psychological and physical landscape are statistically associated with the importance of dealership service and vehicle quality, though the nature of the association is rather complex. Consistent with previous studies (Bryant and Cha 1996; Mittal and Kamakura 2001), we find that though customer demographics are statistically significant, they have low power ( $R^2 < 9\%$ ) in explaining the importance of satisfaction drivers. Empirically, this provides additional evidence for the robustness of using a GWR methodology that obviates the need for explicit inclusion of the variables in a model a priori. In other words, a strategy for explicit inclusion of the variables in a model that predicts overall satisfaction is unlikely to be useful, and potentially biasing, if the model does not account for heterogeneity across regions beyond these observable characteristics.<sup>1</sup> The results also indicate the need to improve the understanding of marketing phenomena with respect to the framework shown in Figure 1. Specifically, the mediating constructs (usage situations, homeostatic mechanisms, and consumer values) are not explicitly incorporated in our analysis. We believe that it is this lack of mediating mechanisms that may lead to the low observed explanatory power and that should be addressed in further research.

## Discussion

Based on GWR, our results (for a firm in the automotive industry) show the following:

- There is systematic spatial variability in the pattern of overall satisfaction and the importance placed on its key drivers. Although the specific pattern of regional variation is likely to differ on the basis of the category investigated, the presence of systematic spatial variability should be incorporated in further investigations of satisfaction data.
- Explicit inclusion of physical and psychological factors explains less than 9% of the variability in the importance of key drivers. This may be because we did not explicitly incorporate specific mediating mechanisms into the response model.
- The regional differences in the importance of key drivers and the overall satisfaction patterns enable a firm to identify regions in which it should improve service. The firm can prioritize regions to make investments in improving dealership service.

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<sup>1</sup>It can be argued that the two-stage approach we use herein, though it produces unbiased estimates, may be less statistically efficient. However, given the large sample sizes involved, efficiency should not be a reason for concern.

Two decades ago, Wells and Reynolds (1979, p. 347) asked: "If, then, regionalism is persistent, the substantive question is the nature of the regions. How do regions differ in life styles, in consumption-related variables? How are they similar?" Our results demonstrate that the nature of the regions and regional differences is unlikely to map onto political boundaries or other impressionistic characterizations based on regional stereotyping (Wells and Reynolds 1979). Firms should take a data-based view of regional differences to improve their decisions.

For identifying the appropriate regions, our results suggest that a strategy of explicitly including demographic and geographic factors in the model may not provide as good a picture as the one produced with GWR. Even with a large set of predictors, less than 9% of the variance in the importance of the automobile and dealership service could be explained. From a practical standpoint, a firm's generating such an exhaustive set of predictors and obtaining information on them could prove cost prohibitive. Furthermore, information at the desired level of granularity simply may not be available, thus leading to higher numbers of missing observations. By obviating the need for collecting such variables, GWR can be used to address such issues more easily. Other empirical approaches may prove equally useful.

Moving forward, it will be important to identify and incorporate mediating factors in the analysis. When we attempted to directly relate regional characteristics (physical and psychological) to the importance placed on service and product, the explained variance was low despite the large number of regional characteristics we included in the analysis. We believe that this happened because we did not incorporate specific mediators, such as usage situations, and consumer motivations and values (see Figure 1) in the analysis. Incorporation of these mediators should not only increase the explanatory power of the models but also improve theorizing by examining how regional characteristics influence distal outcomes such as consumer judgments.

Many scholars have argued that implementation of an appropriate service strategy must account for customer differences (Bolton and Drew 1994). However, prior work has been limited to accounting differences based only on customer demographics (Mittal and Kamakura 2001; Peterson and Wilson 1992) or industry characteristics (Anderson, Fornell, and Rust 1997). Some studies also show that satisfaction ratings and the importance of key drivers can vary over time (Mittal, Kumar, and Tsiros 1999). We show that in addition to the consumer, industry, and time, the geographic location in which ratings are obtained is important. There is a need to develop theory and analytic models that can simultaneously examine all these sources of variation, additively and interactively, to explain customer satisfaction. For example, how do geographic patterns in satisfaction data change over time, and what role do changing demographic patterns play in the observed patterns? Large-scale data (spanning a wide geographic region) with a longitudinal design are needed to answer such questions.

This research can help in the design of satisfaction measurement programs after accounting for regional differences. First, even in the comprehensive and large database

we used, data were missing from nearly one-third of the zip codes because the sampling methodology was not designed to obtain the type of data that may address regional issues. Sampling strategies that can provide geographic coverage with limited resources are needed. Second, firms should carefully consider the geographic unit of analysis. Although we used the five-digit zip code as the unit of analysis, this made the data collection task more daunting. A larger unit of analysis (e.g., county) could reduce the data collection burden, but it may result in loss of data resolution. Striking a balance is an important issue for firms. The level at which the firm implements the results is a key deciding factor. Finally, qualitative research is needed to delineate why customer satisfaction and its responsiveness to antecedent variables varies regionally. This should help identify the mediators that link geographic conditions to customer behaviors.

Although the statistically significant impact of weather conditions on the importance of product quality and dealer-service is small, it deserves more attention. Peterson and Wilson (1992) mention the relationship, but we are not aware of any large-scale empirical tests of this "taken-for-granted" relationship. It would be especially useful to test competing mediating mechanisms, such as mood and arousal, by which weather conditions might influence consumer judgments, especially for categories with a seasonal component. Our results imply that the mechanisms are not as straightforward as has been believed. For example, we found variance in weather conditions to affect the importance placed on service and product. In this respect, the homeostatic approach that Parker (1995) and Parker and Tavassoli (2000) advocate seems to account for the pattern observed in the data.

Finally, many methodological challenges need to be addressed. Customer satisfaction data have unique characteristics, such as skewed distributions and high multicollinearity, that make applications of standard spatial models problematic. Different methods should be compared in order to develop guidelines about the conditions in which one class of models may be more appropriate than another. Another important area of research concerns the development of spatial models that can accommodate consumer choice and multiequation systems (Bolton and Drew 1994). Many aspects of the GWR could be improved as well. For example, the assumption of a homogeneous decay parameter for model estimation could be relaxed.

The limitations of our data also deserve attention. Although the results are specific to the automotive industry, the insights developed herein should be universally applica-

ble in several other industries, such as pharmaceuticals, home building, and consumer perishables. As consumers become more mobile, it will become even more important to address the spatial aspects of data. This no doubt will surface new and interesting challenges—theoretical, empirical, and managerial ones that should provide the impetus for further research in this area.

## Appendix

### Moran's I

We calculated Moran's I using the following formula:

$$(A1) \quad I = \frac{\sum_{i=1}^N \sum_{j=1}^N w(i,j)(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^N (x_i - \bar{x})^2}, j \neq i,$$

where  $S_0 = \sum_{i=1}^N \sum_{j=1}^N w(i,j)$ , and  $w(i,j)$  is the weight given to region  $i$  for focal region  $j$ . The expected value of Moran's I is  $-1/(N-1)$ . Values of I that exceed  $-1/(N-1)$  indicate positive spatial autocorrelation. In positive spatial autocorrelation, similar values (either high or low) are spatially clustered. Values of I that are less than  $-1/(N-1)$  indicate negative spatial autocorrelation (values from neighboring regions are dissimilar), whereas values greater than  $-1/(N-1)$  indicate positive spatial autocorrelation (values from neighboring regions are similar).

### Geary's C

We obtained Geary's C using the following formula:

$$(A2) \quad c = \frac{\sum_{i=1}^N \sum_{j=1}^N w(i,j)(x_i - x_j)^2}{2S_0 \sum_{i=1}^N (x_i - \bar{x})^2}, j \neq i.$$

The theoretical expected value for Geary's C is 1. A value less than 1 indicates positive spatial autocorrelation, and a value greater than 1 indicates negative spatial autocorrelation.

For our analysis, we constructed the weighting matrix for the two indexes using the physically adjacent neighbors as regions that influenced the focal region. We identified the immediate physical neighbors using Delauney triangulation (LeSage 1998).

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