Geographic Patterns in Customer Service and Satisfaction: 
An Empirical Investigation

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When firms have customers located in geographically dispersed areas, it can be difficult to manage service quality as its relative importance is likely to vary spatially. This paper 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 having high service responsiveness: areas where overall satisfaction is low, but customers are highly responsive to improvements in service quality. The spatial patterns are estimated using Geographically Weighted Regression (GWR), a technique that accounts for spatial dependence in the variables. We apply this methodology to a national sample of 164,085 automobile customers served by a network of dealerships across the United States. We 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.
Customer satisfaction is essential to the long-term success of a firm (Rust, Zahorik and Keiningham 1995; Rust, Zeithaml and Lemon 2000). However, managers—especially at firms that provide services using a regionally dispersed network of outlets—face several challenges in implementing a customer-satisfaction strategy when services are a core element of the consumption experience (Mittal, Kumar and Tsiros 1999). Examples include automotive dealerships or bank branches. For such geographically dispersed outlets, not only will overall satisfaction vary from region to region, but also will the importance placed on service quality. The firm’s ability to provide superior service may also vary geographically. As such, incorporating the regional differences in customer satisfaction decisions is important.

This paper 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 primarily used outside of the marketing literature. We apply this approach to a dataset of 164,085 customers representing 21,636 five-digit zip codes across the United States. We identify locations where overall satisfaction is relatively low, but highly responsive to improvements in service quality. This can provide guidance in implementing a service strategy on a national basis.

**Regional Differences in Consumption**

Within marketing, the movement to understand regional differences in consumer consumption started 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: 347) argued:
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 (1981) proposed a framework to understand regional differences in consumption. As 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. These, in turn, influence consumption patterns through homeostatic influences outlined by Parker (Parker 1995; Parker and Tavassoli 2000). As shown by the ovals in Figure 1, Parker suggests that climate affects consumer behavior via mediating mechanisms that are both physiological (e.g., homeostatic regulation via 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, DeNeve 1995; Hill 1992; London and Teague 1985; Spoont, Depue, and Kraus 1991). For instance, differences in the degree of sunlight can affect the chemical balance in the brain affecting customer's mood states, which in turn can affect 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, Levy, Mehrotra and Sharma 1999; Ingene 1984).

-- Figure 1 about here --
To implement the framework in Figure 1, one must first empirically ascertain the regional patterns followed by the second step of examining the intervening mediators. Both these require data representing large geographic regions. This study focuses on the first step: determining the spatial variation in customer satisfaction and its response to dealership service.

**Empirical Research**

Wells and Reynolds (1979) compared consumers from East, South, Midwest, Southwest and West of the United States. Hawkins et al (1981) compared coffee preparation and drinking habits in the East, Midwest, South and West region of the US. Similarly, Gentry et al (1988) compared 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 compared regions that were defined *a priori*.

In contrast, recent works define regions based on patterns embedded in the data itself. Ter Hofstede, Steenkamp and Wedel (1999) analyze data from 11 European countries and find that the segmentation in terms of consumer perceptions and attitudes do 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 allowing the 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 find evidence of spatial dependence in segment membership. Helsen, Jedidi and DeSarbo (1993) show that countries classified as similar based on macro-economic variables may or may not exhibit similar patterns with respect to diffusion of consumer durable goods. Hoch et al (1995) and Bronnenberg and
Mahajan (2001) incorporate heterogeneous geo-demographic 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 unclear how regional differences should be addressed when examining customer satisfaction and its antecedents.

**Regional Patterns in Customer Satisfaction: Issues and Implications**

When examining 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 it might be useful to examine differences across regions as well, especially since some relevant consumer characteristics may show systematic regional patterns. For instance, 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 due to the physical landscape (e.g., different climate and geography). In other words, not only do we expect regional differences to 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 unlikely to map on to political boundaries or zones such as states or counties. In such cases, what options are available to the firm to develop a service strategy?

One option is to simply ignore geographical patterns and treat each service unit (e.g., bank branch or 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 patronizing different locations. Differences in policies and procedures at these units can also confuse and irritate consumers. Second, it may be costly. The firm may have to separately collect
data for each individual service-unit. While this can be done for the larger dealerships, obtaining a large sample from all of the smaller service-units may not only be costly, but may irritate customers who can feel over-surveyed and intruded upon (Nunes and Kambil 2001). Third, it may preclude a firm from benchmarking the service units against each other. In the second option, the extreme opposite, the firm can ignore regional differences and 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 empirically identify the appropriate “region” where customers’ overall satisfaction is similarly responsive to improvements in service. A reasonable strategy is to analyze smaller regions such as the 5-digit zip code where customers are more likely to be similar. These smaller regions can be aggregated to produce meaningful regional zones where consumers place a similar level of importance on service and have similar levels of overall satisfaction. Identification of such regional zones, where 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 were to be known, they may be too numerous to model in a convenient framework 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, Geographically Weighted Regression (GWR) is particularly appropriate because of its versatility in addressing geographically sparse data, i.e., when data may not be available for all of the regions being analyzed. Typically, managers collect satisfaction surveys from customers patronizing different outlets (e.g., dealerships, bank
branches). While such a strategy provides coverage of the entire service area, it does not provide data from each location (e.g., 5-digit zip code). GWR is useful as it statistically “borrows” data for neighboring regions during estimation. Next we briefly discuss GWR and show its application in a customer satisfaction context. We caution that the contribution of this paper is not methodological, and we do not address the debate about the various available approaches. For this discussion, we refer the reader to the comprehensive review provided by Le Sage (1999).

**Geographically Weighted Regression (GWR) and Customer Satisfaction**

Geographically Weighted Regression (GWR) was developed in the field of spatial econometrics by Brunsdon, Fotheringham and Charlton (1996, 1998). While it has not been applied within 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, Brunsdon and Charlton, 2002), and political science (Calvo and Escolar 2002).

Brunsdon, Fotheringham, and Charlton (1996: 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, with weights for an observation 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, non-parametric relationship that applies to all observations or
locations. In contrast, GWR estimates a linear relationship between predictors and dependent variable, with parameters that vary across locations.

The objective of GWR is to estimate a linear model relating the dependent variable to its determinants but after taking into account spatial correlation among observations in neighboring locations. This is accomplished by allowing for spatial non-stationarity in the regression coefficients for each location. A location is the geographic unit of analysis for which data may be aggregated. For instance, within the U.S., the 5-digit zip code is a location, enabling one to estimate a regression coefficient for each location (i.e., 5-digit zip code) but after accounting for the spatial correlation with neighboring zip codes. The location is defined based on 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 geographically-weighted regression 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 pooling all the available data as is typically done in aggregate estimation, or shrinking the regional estimates towards a population mean as normally done in random-coefficient models, geographically-weighted regression assumes the regression coefficients to vary across locations.
GWR takes advantage of spatial dependence in the data. Spatial dependence implies that data available in locations near the focal location should be more informative about the relationship between the independent and dependent variable variables in the focal location. When calculating the estimates for a focal location, GWR gives more weight to data from locations that are closer than to data from more distant locations. The relative weight of the contributing locations is assumed to decay—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 model (GLS), such that locations closer to the focal one have a larger weight in determining the regression equation for the focal location. The weighting matrix contains weights \( w_j \) for all locations that are to be used in computing the regression equation for the focal location. Using this geographic weighting matrix, the weighted least-squares estimates for any location \( j \) are obtained as follows.

\[
\hat{\beta}_j = (X'W_j X)^{-1} X'W_j y
\]

This is a traditional regression estimated via generalized least squares, where \( W_j \) is a \((nxn)\) diagonal matrix containing \( \{w_{jj'}\}, (j'=1,\ldots,J) \) in the diagonal, defined by an exponential distance-based decay function,

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

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 the 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 $j$. We determine the most appropriate value of the bandwidth using the least-squares cross-validation procedure suggested by Cleveland (1979). Cross-validation basically relies on a scoring function taking the form shown in (3) to determine the optimal value for $\theta$.

$$\sum_{j=1}^{n} (y_{j} - \hat{y}_{\neq j}(\theta))^2$$

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 via cross-validated GLS can be found in Brunsdon, Fotheringham and Chalrton (1998).

The GWR model, as proposed by Brunsdon et al. (1998) considers the case with only one observation per location. However, in our analysis, we observe multiple responses within each ZIP code. Rather than aggregating the data within each zip code, we estimate our model at the respondent level. This individual-level estimation can be problematic as it will place emphasis on 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:

$$\hat{\beta}_j = (X^tW_tX)^{-1}X^tW_tfy$$
where $f$ is a $N \times N$ diagonal matrix containing the inverse of the sample size in the location $j$ to which the individual observation $i$ belongs, and the diagonal matrix $W_i$ 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, as the estimates are the same for all individual survey respondents in the same location. This happens because all individual survey respondents in the same focal location will carry an equal weight, resulting into the pooling of all observations from the same location.

While empirical comparisons between GWR and other approaches can be found in the literature (e.g., Brunsdon, Aitkin, Fotheringham and Charlton 1999; Le Sage 1999; Wolfinger and Tobias, 1998), it is important to contrast it with three predominant methods: spatial adaptive filtering (Foster and Gorr 1986), random-coefficients regression (Aitkin 1996), and multi-level modeling (Goldstein 1987). Spatial adaptive filtering incorporates spatial relationships in an ad hoc manner via exponential smoothing, and produces non-testable parameter estimates. This 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 either with a finite (Wedel and Kamakura 2000) or continuous mixture distribution (Aitkin 1996). Random-coefficients regression also requires repeated measures within each sampling unit for reliable estimates at the individual level, something rarely available in geographic data. For example, in the application we describe most locations have only a single observation. Multi-level modeling assumes a hierarchical data structure with individual observations nested under another level, such as regions. However, both random-coefficients regression and multi-level modeling are silent about the nature of the spatial dependence in the data, a key factor in determining which locations should be treated similarly to comprise a region. Jones and Eldridge (1991) attempts a
geographic variation of multi-level modeling, but in that study a pre-defined hierarchy of spatial units had to be defined: something that 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 the estimation of an aggregate regression model in the first stage and an analysis of the regression residuals in a second stage, using a cubic spline to relate these residuals to their geographic coordinates. The geographically-related misspecification error captured by their approach would then be indistinguishable from the GWR intercept for each sampling unit. The GWR model we use here allows for different geographic patterns not only for the intercept, but also for each of the response coefficients.

An entirely different approach is taken by TerHoefstede, Wedel and Steenkamp (2002). Rather than allowing for a continuous spatial variation in the regression coefficients, Hoefstede et al identify relatively homogeneous segments of regions under different assumptions regarding the spatial dependence among these segments. In its most strict form, their model requires spatial contiguity among members of a segment. In a less restrictive form, they only assume that the probability that a region belongs to a segment depends on the membership of its neighbor to the same segment. Instead of assuming spatial dependence among segments of regions, our approach accounts for spatial dependence in the original regions themselves.

When Should GWR Be Used?

GWR should be used when there is spatial autocorrelation in the variables. High positive autocorrelation implies that values from neighboring areas are similar to each other while high
negative autocorrelation implies that values from neighboring regions are dissimilar to each other. The magnitude and direction of spatial autocorrelation for a variable can be quantified using 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 shown in the appendix, values of Moran’s I that are larger than -1/(N-1) indicate positive autocorrelation and vice versa. With Geary’s C, values smaller than 1 indicate positive autocorrelation, while values larger than 1 indicate negative spatial autocorrelation. For both, one can conduct tests of statistical significance to detect spatial autocorrelation. Based on these statistical significance tests, a decision to proceed with GWR may be made.

Research Setting and Data Description

The study was conducted for a domestic automotive manufacturer that sells and services its vehicles nationally within the U.S. via a dealership network. While 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 as 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 got their vehicle serviced at an authorized dealership in the last six months. Thus, all respondents have a relatively high level of experience with the product (vehicle) and at least one service encounter at one of the dealerships of this manufacturer. Note that, excluded from the survey are customers who only took their vehicle in for warranty or recall related service.

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

Of the 31,956 5-digit zip codes in the U.S., we have data for only 21,636 or 67.7% of the zip codes. In other words, 32.3% of the zip codes have no data. Figure 2 displays the number of respondents from each zip code for whom data is available. In summary, a large proportion (32.3%) of zip codes is without data and among the remaining zip codes over half have 5 or fewer data points. A zip-code-by-zip-code analysis will systematically exclude about one third of the zip codes. Among the remaining zip codes, zip-code-level estimates may be unreliable for those having 5 or fewer data points. More importantly, such an analysis will fail to incorporate the advantages of spatial autocorrelation in the estimation process. It is here that 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 very useful as in most cases the focal location has few observations. In such cases, we get better estimates because observations from neighboring zip codes provide additional information. Borrowing from neighboring zip codes also helps identify regions having similar coefficients leading to a systematic view of the spatial patterns in the data.

--Table 1 and Figure 2 around here--

Variables

We used data from three key variables measured using a 10-point scale (1=extremely dissatisfied, 10=extremely satisfied). Using the 10-point scale, each customer i answered the
following questions: Based on 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$_i$).

Each customer also indicated the 5-digit zip code of the area of their current residence. While they could be aggregated up to a larger unit of analysis such as the county, it was considered inappropriate because it would imply homogeneity within relatively diverse areas. A finer unit of analysis such as the census block was not feasible because the location of each respondent was defined only by zip code. Thus, an analysis at the zip code level was done. We obtained the latitude and longitude co-ordinates for the centroid of each 5-digit zip code. From these centroids, we computed the Euclidean distance among each of the zip codes in the dataset. This distance was used in the estimation of the GWR model.

---Table 2 about here---

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 larger than $-1/(N-1)$ ($p<.05$), while Geary’s C is smaller than 1 ($p<.05$). This indicates positive spatial autocorrelations for all three variables—values of observations from areas closer to each other tend to be positively correlated.

Results

We estimated the following relationship using GWR where satisfaction with the ownership experience is a function of vehicle quality and dealership service:

$$\text{OVERALLSAT}_i = \beta_0j + \beta_1j \text{PRODQUAL}_i + \beta_2j \text{DLRSRV}_i + e_i,$$
where $e_i$ are i.i.d. normal disturbances. Notice that the three parameters are estimated for each location $j$, while the variables and disturbances are observed at the individual $i$.

Using this model the automotive firm can identify areas where dealership service should be improved. For these areas specific sub-drivers of dealership service can be ascertained (Rust, Zeithaml, and Lemon 2000). The GWR model estimates separate coefficients for each 5-digit zip code. A listing of coefficients for each location would neither be meaningful nor easy to communicate. Therefore, we visually depict the results in Figures 3 and 4 by plotting the regression coefficient for each location. In these figures, 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 visually depicted in Figure 3. Consider Colorado. In the southeast part of Colorado the importance of service quality is high (indicated by the dark color) whereas in the southwest part of this state it is lower (indicated by the lighter color). In the central part of Colorado, all the way to the northern part, we find the lowest importance of service, indicated by the white shading. Further, in the northeast part of Colorado the importance of service satisfaction is uniformly low, similar to the adjacent states of Nebraska.

--Figures 3 and 4 here--

In general, dealership service is more important in the extreme east or west, especially in parts of south Oregon and north California. Other regions where service is very important include northeastern part of New Mexico all the way into Colorado and Kansas. In the Midwest, Kentucky, Indiana and Illinois also share areas where dealership service has high or medium
importance. Strikingly, there is a large area in the western part of the USA—Nevada, Arizona, Oregon and Idaho—where dealership service is less important. Also, the various major metropolitan areas are located in regions with varying levels of importance. Indianapolis, Columbus and Philadelphia have high to medium importance of dealership service whereas Jacksonville, San Francisco and San Jose 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 expected, they are essentially the inverse of those for dealership service. Consider Texas. In the northeast part of the state we find the importance of vehicle quality to be relatively high in determining overall satisfaction. This pattern of high importance of vehicle quality is shared with neighboring states of Louisiana and Arkansas. However, between Dallas and Austin, the relative importance of vehicle quality is medium to low. This is similar to northwest Texas. In contrast, the importance is high in south Texas. The pattern of importance of vehicle quality also varies for different metropolitan markets. While Philadelphia, New York, and Washington D.C. are located in areas of low importance, Memphis and San Francisco are located in areas of high importance.

Model Performance

We evaluate model performance using two criteria: (a) the model’s ability to predict overall satisfaction, and (b) stability of the parameter estimates for the key drivers.

Predicting Overall Satisfaction: To evaluate predictive performance, we used the holdout sample that was created using 20% of the observations. To create the holdout sample we first selected zip codes having more than five observations so that standard regression estimates could be obtained for each of these hold-out zip codes and at least two observations would be available for
predictive tests. Note that the minimum of 3 observations for estimation is requirement imposed by the benchmark models; GWR can impute the parameter estimates in a zip code area even when there are no data in that area, based on the data in neighboring areas. From the short listed zip-codes containing 5 or more observations, we randomly drew 32,000 observations, with a few zip-codes having multiple observations in the holdout sample. The final holdout sample of 32,000 observations represents 13,846 zip codes.

Table 3A 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. This is done using the prediction methodology suggested by Nester (1996), and by Brunsdon, Fotheringham, and Charlton (1998). This measure indicates the model’s ability to predict the satisfaction scores on a zip code by zip code basis and it indicates the uncertainty associated with these predictions. The second measure is the percent 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 percent of times when the confidence interval included the actual satisfaction score in a holdout sample.

First, we look at the results at the zip code level. Model 1 uses GWR estimation at the 5-digit zip code level. Model 2 is a zip code level model, but without GWR, estimated by running separate regressions within each zip code. This model uses at least three observations within that zip code and compares predicted satisfaction scores with the actual ones for the remaining observations in that zip code. Column D of Table 3 shows that the 95% confidence interval around the mean
estimate of the predicted values is smaller with the GWR model than the model without GWR (.28 versus 1.07). Thus the predictions obtained with GWR carry a lower degree of uncertainty than those obtained under the assumption that all regions are independent. Column E 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 produced by the GWR model are more likely to include the actual value even though these intervals are narrower, reflecting lower uncertainties about the predictions. The confidence intervals based on independent regressions not only were broader reflecting higher estimation error, but less accurate in predicting satisfaction in a hold-out sample.

For comparison, we also estimated a model at the county level (Model 3) and the state level (Model 4). As 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% for the state level model. At first glance, these results appear to be comparable to those obtained with zip-code level estimation. However, one should 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 makes it more likely that the actual satisfaction score would fall within the broader confidence interval. Because there is more uncertainty in the predictions at the county and state levels, the confidence intervals are much larger making it is 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 did a holdout test with another set of observations. In this case, we randomly drew 32,000 observations from the dataset without limiting ourselves to those zip-codes that had five or more observations. This sample of 32,000 data points represented 17,228 zip-codes. The remaining 80% of the data was used to estimate a GWR model. The set of parameters obtained from this model were used to predict the observations from the holdout sample. The results from this analysis are shown in Row 5 of Table 3. Note that, the results from this prediction are not comparable to the estimates from OLS because for many of the zip-codes involved, we had very few observations left to be able to estimate an OLS model. The range of predicted values is now larger than when we included only zip-codes with five or more observations (0.62 vs. 0.28). This is so because we have many zip-codes for which we have no observations in the focal region, and thus predictions had to be imputed from neighboring locations through the GWR model. In addition, the number of observations falling within $+1.96(\sigma/\sqrt{n})$ was 71.41% compared to 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, it was randomly assigned to one of the split samples, and designated as missing in the other. Then we applied GWR on the two halves, imputing the coefficients for those 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: (a) zip codes where the data was available in both samples, (b) zip codes where the data was missing in one of the samples, and (c) zip codes where the data was missing in both samples (i.e., parameter estimates were imputed in both halves). We replicate the
split-half test 10 times and report the mean and standard deviation for the correlations across the 10 replications. These 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. The results of the analysis are shown in Table 3B. When data was available in both the split halves, the correlation was greater than 0.65. We see this as strong evidence of parameter stability since these correlations were computed between two estimates and across a very large (31,956) sample size. When the parameter estimate is imputed for one of the random samples (i.e., no data was available for the particular zip code) the correlation goes down to around 0.40. This attenuation in the split-half correlations is expected since these correlations now involve one parameter estimate and one imputed value. A surprising result was that the split-half correlations were not further attenuated when both samples had imputed values (last column of Table 3B).

---Tables 3A and 3B around here---

Regional Patterns in Dealership Service: Strategic Implementation

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

We selected the sub-par 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 cut off used to define sub-par satisfaction regions is a subjective
issue to be decided with managerial consultation. For the sub-par satisfaction regions we plotted the importance of dealership service (Figure 6). In figure 6, regions having a darker shade are those where service improvement should be implemented first: these are regions where such improvement has a relatively large impact on overall satisfaction, and where overall satisfaction is relatively low. Obviously, other factors such as market size and competition must also be taken into consideration in deciding where to invest in improving dealership service.

---Figures 5 and 6 about here---

As a next step, performance on various attributes that drive dealership service should be measured. A key driver analysis could identify specific sub-drivers of dealership service, and importance-performance charts could help the firm isolate those drivers that need improvement (Rust, Zahorik and Keiningham 1995). The firm may also gather information on its customer base in those regions (e.g., extreme southwest and south part of Kansas) for further insights. That is, why is dealership service so important in those 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. This is described next.

Factors Determining Regional Variability in the Importance of Product and Service

Our goal is to empirically determine the extent to which different factors related to the physical and the psychological landscape affect the importance of the drivers of overall satisfaction. The national coverage of our dataset provides a unique opportunity to investigate this issue. To get measures of some of these factors, we appended variables from the U.S. Census and from the Weather Bureau for each zip code. We included only those variables for which data on at least 95% of the zip codes was available. These variables were merged with the survey measures and GWR results at the zip code level. Table 4 shows the variables used in the final models.
Two models are shown in Table 4 with dependent variables being 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 more driven by supply-side factors (for which we do not have data) than customer characteristics. The importance coefficients, on the other hand, measure how customers respond to these supply-side factors (product quality and dealership service) and are more intrinsic to the consumer. They are therefore more likely to be affected by the physical and psychological landscape.

The regression coefficients in Table 4 have been standardized to make them directly comparable. We also tested the predictors for multicollinearity using the Variance Inflation Factor (VIF). The VIF was lower than 6, except for a couple of predictors which were excluded from our analyses.

---Table 4 about here---

Consistent with previous studies we find that the importance of the automobile and dealership service varies based on customer characteristics (e.g., Bolton 1998; Bryant and Cha 1996; Mittal and Kamakura 2001). In this regard several interesting patterns are evident. For instance, as Per Capita Income increases the importance placed on the automobile (β=.023) as well as the dealership services increases (β=.071). However, as the proportion of males in a region increases, the importance of dealership service declines (β= -.031) but the importance of the automobile increases (β=.016). This result is fully consistent with Mittal and Kamakura (2001) who found that males place a lower importance on service than females. Regarding age, younger buyers (less than 25 years of age) place more importance on the automobile (β=.117) than on dealership service (β= -.025). In contrast, those older than 60 years place higher importance on
both the automobile ($\beta=0.062$) and the dealership service ($\beta=0.090$). Similar results can be seen for education. In an area, as the proportion of those with less than 9th grade education increases so does the importance of the automobile ($\beta=0.085$) and the dealership service ($\beta=0.026$). However, among those having a graduate degree the importance of the automobile seems lower ($\beta=-0.046$) but the importance of service seems higher ($\beta=0.073$). Perhaps increased education and income make consumers more sensitive to service though simply older consumers attach higher importance to both the automobile as well as the dealership service. Driving habits and driving conditions also seem to influence the importance placed on the automobile and the dealership service. As expected, as the proportion of carpooling consumers increases, the importance of automobile increases ($\beta=0.077$) but the importance of dealership service decreases ($\beta=-0.124$). The importance of automobile as well as dealership service decreases ($\beta=-0.041$ and -0.031) as the proportion of those using public transportation in an area increases. Perhaps in these areas, alternative means of transportation assume higher importance.

Factors comprising 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 non-significant ($p>0.05$). The mean amount of snow not only increases the importance placed on the vehicle ($\beta=0.171$) but also the service ($\beta=0.091$). The variance in the amount of snowfall has a different effect, increasing (as expected) the importance of the vehicle ($\beta=0.156$) but decreasing the importance of dealership service ($\beta=-0.067$). Regarding rainfall, the mean amount of rainfall only affects the importance placed on service but the variance in rain has no impact. The mean maximum temperature increases the importance placed on the vehicle ($\beta=0.056$) but decreases the importance placed on the dealership service ($\beta=0.039$). Higher variance in weather conditions—
rain, snow and maximum temperature—has no or positive affect on the importance of the vehicle, but it almost always decreases the importance placed on the service element. In other words, consumers seem to be more concerned about the vehicle than the dealer service in areas with highly varied climate. However, areas where the mean amount of snow and rain is generally high deserve special attention as 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 statistically significant, customer demographics 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 these variables in a model \textit{a priori}. In other words, a strategy for explicitly including these variables in a model predicting overall satisfaction is unlikely to be very useful, and potentially biasing, if the model does not account for heterogeneity across regions beyond these observable characteristics\textsuperscript{1}. These results also indicate the need for improving our understanding of marketing phenomenon vis a vis 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 should be addressed in future research.

\textsuperscript{1} One might argue that the two-stage approach used here, while producing unbiased estimates, might be less efficient statistically. However, given the large sample sizes involved, efficiency should not be a reason for concern.
Based on GWR, our results (for one 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. While the specific pattern of regional variation is likely to differ based on the category investigated, the presence of systematic spatial variability should be incorporated in future 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 due to the fact that specific mediating mechanisms were not explicitly incorporated into the response model.

- The regional differences in the importance of key drivers as well as the overall satisfaction patterns enable a firm to identify regions where service improvements should be made. The firm can prioritize regions to make investments in improving dealership service.

Two decades ago, Wells and Reynolds (1979) 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 on to 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 of a picture as the one produced using 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, generating such an exhaustive set of predictors and obtaining information on them could prove cost prohibitive. Further, information at the desired level of granularity may simply
not be available leading to higher number 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 the mediating factors in the analysis. When we attempted to directly relate regional characteristics—physical as well as psychological—to the importance placed on service and product the explained variance was low despite the large number of regional characteristics included in the analysis. We believe this happened because specific mediators such as usage situations, and consumer motivations and values (See Figure 1) were not incorporated in the analysis. Incorporating 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 and 2001; Peterson and Wilson 1992) or industry characteristics (Anderson, Fornell and Rust 1997). Some recent 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 where ratings are obtained is also important. To our knowledge previous satisfaction studies—even those using nationally representative samples of customers—have not incorporated spatial variability in the analysis (e.g., Anderson, Fornell, and Rust 1997; Mittal and Kamakura 2001). Yet, as our results show the location of the consumer is a systematic factor accounting for variation in satisfaction data. Combined with other sources of systematic
variation—the industry, consumer, time, and place we should be better able to understand satisfaction ratings. The challenge is to develop theory and analytic models that can simultaneously examine all of these sources of variation—additively and interactively—to explain customer satisfaction. For instance, how do geographic patterns in satisfaction data change over time and what role does changing demographic patterns have to play in the observed patterns? Large-scale data (spanning a wide geographic region) with a longitudinal design will be needed to answer these questions.

This research can help in designing satisfaction measurement programs after accounting for regional differences. First, even in the comprehensive and large database that we used, data were missing from nearly one third of the zip codes because the sampling methodology was not designed to get the type of data that may address regional issues. Sampling strategies that can provide geographic coverage within limited resources are sorely needed. Second, firms should carefully consider the geographic unit of analysis. Though we used the 5-digit zip code as the unit of analysis, it also made the data collection task more daunting. A larger unit of analysis such as the county level could reduce the data collection burden, but may result in loss of data resolution. Striking a balance between these two is an important issue that a firm should decide. Of course, the level at which the results are implemented by the firm will be 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 linking the geographic conditions to customer behaviors.

Though small, the statistically significant impact of weather conditions on the importance of product quality and dealership service deserves more attention. Though Peterson and Wilson
(1992) mention it, 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 may influence consumer judgments. Our results imply that these mechanisms are not as straightforward as once thought. For instance, variance in weather conditions was found to impact the importance placed on service and product. In this respect, the homeostatic approach advocated by Parker and his colleagues seems to accounts for the pattern observed in the data. Such research will be especially important for categories where consumption patterns are season-dependent.

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

The limitations of our data also deserve attention. We focus only on the automotive industry. As such, our results are specific to the automotive industry, though the insights developed should be universally applicable 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 will, no doubt, surface new and interesting
challenges—theoretical, empirical, and managerial that should provide the impetus for future research in this area.
APPENDIX

Moran’s I

Moran’s I is calculated using the following formula:

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

$w(i,j)$ is the weight that is given to region $i$ for 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 values or low values are spatially clustered. Values of I below $-1/(N-1)$ indicate negative spatial autocorrelation (values from neighboring regions are dissimilar) whereas values larger than $-1/(N-1)$ indicate positive spatial autocorrelation (values from neighboring regions are similar).

Geary’s C

Geary’s C is obtained using the formula:

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

The theoretical expected value for Geary’s c is 1. A value less than 1 indicates positive spatial autocorrelation, while a value larger than 1 indicates negative spatial autocorrelation.

Note: For our analysis the weighting matrix for the two indices was constructed using the physically adjacent neighbors as regions that influenced the focal region. The immediate physical neighbors were identified using Delauney Traingulation (LeSage, 1999).
Table 1

Sample Description

<table>
<thead>
<tr>
<th>Sample Characteristics</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
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<tr>
<td>Male</td>
<td>64.2</td>
</tr>
<tr>
<td>Female</td>
<td>35.8</td>
</tr>
<tr>
<td><strong>Education Level</strong></td>
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<tr>
<td>High school or less</td>
<td>26.3</td>
</tr>
<tr>
<td>Some College</td>
<td>27.3</td>
</tr>
<tr>
<td>College Graduate</td>
<td>46.5</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>76.0</td>
</tr>
<tr>
<td>Single</td>
<td>19.5</td>
</tr>
<tr>
<td>Other</td>
<td>4.5</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
</tr>
<tr>
<td>Under 30 years</td>
<td>9.4</td>
</tr>
<tr>
<td>30-59 years</td>
<td>68.1</td>
</tr>
<tr>
<td>60 years or older</td>
<td>22.5</td>
</tr>
<tr>
<td><strong>Overall Satisfaction Rating</strong></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.9</td>
</tr>
<tr>
<td>2</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>0.9</td>
</tr>
<tr>
<td>4</td>
<td>2.1</td>
</tr>
<tr>
<td>5</td>
<td>2.8</td>
</tr>
<tr>
<td>6</td>
<td>8.7</td>
</tr>
<tr>
<td>7</td>
<td>9.4</td>
</tr>
<tr>
<td>8</td>
<td>25.4</td>
</tr>
<tr>
<td>9</td>
<td>18.5</td>
</tr>
<tr>
<td>10</td>
<td>30.7</td>
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</table>
### Table 2
Spatial Autocorrelation in Variables

<table>
<thead>
<tr>
<th></th>
<th>Moran’s I</th>
<th>Geary’s c</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Satisfaction</td>
<td>0.008</td>
<td>0.69</td>
</tr>
<tr>
<td>Dealership Service</td>
<td>0.007</td>
<td>0.76</td>
</tr>
<tr>
<td>Vehicle Quality</td>
<td>0.007</td>
<td>0.77</td>
</tr>
<tr>
<td>Model</td>
<td>Level of Analysis</td>
<td>Estimation Method</td>
</tr>
<tr>
<td>-------</td>
<td>------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>1.</td>
<td>Zip Code (13,846)</td>
<td>With GWR</td>
</tr>
<tr>
<td>2.</td>
<td>Zip Code (13,846)</td>
<td>Without GWR</td>
</tr>
<tr>
<td>3.</td>
<td>County (n=3,102)</td>
<td>Without GWR</td>
</tr>
<tr>
<td>4.</td>
<td>State (n=50)</td>
<td>Without GWR</td>
</tr>
<tr>
<td>5.</td>
<td>Random sample of Zip Codes (n=17,228)</td>
<td>With GWR</td>
</tr>
</tbody>
</table>
Table 3B
Mean and Standard Deviation of Split-Half Correlations (Parameter Stability)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Overall</th>
<th>Zip codes with observations</th>
<th>Data missing in one sample</th>
<th>Data missing in both samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.61(0.02)</td>
<td>0.66(0.04)</td>
<td>0.41(0.04)</td>
<td>0.41(0.08)</td>
</tr>
<tr>
<td>Dealership Service</td>
<td>0.62(0.04)</td>
<td>0.68(0.06)</td>
<td>0.41(0.05)</td>
<td>0.41(0.07)</td>
</tr>
<tr>
<td>Product Quality</td>
<td>0.58(0.06)</td>
<td>0.70(0.08)</td>
<td>0.41(0.06)</td>
<td>0.46(0.11)</td>
</tr>
</tbody>
</table>
### Table 4
Determinants of Importance of Automobile Quality and Dealership Service

<table>
<thead>
<tr>
<th>FACTORS RELATED TO THE…</th>
<th>Imp. of Automobile</th>
<th>Imp. of Dealer Service</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>…PSYCHOLOGICAL LANDSCAPE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>.023**</td>
<td>.071**</td>
</tr>
<tr>
<td>Gender (% of people who are male)</td>
<td>.016*</td>
<td>-.031**</td>
</tr>
<tr>
<td>% of people who are less than 25 yrs of age</td>
<td>.117*</td>
<td>-.025**</td>
</tr>
<tr>
<td>% of people who are 26-35 yrs of age</td>
<td>.064**</td>
<td>-.010*</td>
</tr>
<tr>
<td>% of people who are 36-45 yrs of age</td>
<td>.042**</td>
<td>.020</td>
</tr>
<tr>
<td>% of people who are 46-60 yrs of age</td>
<td>.053**</td>
<td>.037**</td>
</tr>
<tr>
<td>% of people who are older than 60 years</td>
<td>.062**</td>
<td>.090**</td>
</tr>
<tr>
<td>% of people who did not go to school</td>
<td>.017</td>
<td>-.076**</td>
</tr>
<tr>
<td>% of people who studied till less than 9th grade</td>
<td>.085**</td>
<td>.026**</td>
</tr>
<tr>
<td>% of people who have high school diploma</td>
<td>-.069**</td>
<td>.072**</td>
</tr>
<tr>
<td>% of people who have associate’s degree</td>
<td>-.012</td>
<td>.028**</td>
</tr>
<tr>
<td>% of people who have bachelor’s degree</td>
<td>-.031**</td>
<td>.048**</td>
</tr>
<tr>
<td>% of people who have a graduate degree</td>
<td>-.046**</td>
<td>.073**</td>
</tr>
<tr>
<td>% of population that is Asian</td>
<td>-.039**</td>
<td>-.009</td>
</tr>
<tr>
<td>% of population that is American Indian</td>
<td>-.025*</td>
<td>-.016</td>
</tr>
<tr>
<td>% of population that is African American</td>
<td>-.047**</td>
<td>.052**</td>
</tr>
<tr>
<td>% of population that is Caucasian</td>
<td>-.031</td>
<td>.016</td>
</tr>
<tr>
<td>% working in administration</td>
<td>.008</td>
<td>.017</td>
</tr>
<tr>
<td>% working in managerial jobs</td>
<td>-.008</td>
<td>.049**</td>
</tr>
<tr>
<td>% working as a laborer</td>
<td>-.081**</td>
<td>.028*</td>
</tr>
<tr>
<td>% working in the farming sector</td>
<td>-.051*</td>
<td>.131**</td>
</tr>
<tr>
<td>% working as a technician</td>
<td>.005</td>
<td>-.044**</td>
</tr>
<tr>
<td>% of people who carpool</td>
<td>.077**</td>
<td>-.124**</td>
</tr>
<tr>
<td>% people using public transportation</td>
<td>-.041**</td>
<td>-.031**</td>
</tr>
<tr>
<td>% of people who drive less than 20 minutes to work</td>
<td>-.056**</td>
<td>-.002</td>
</tr>
<tr>
<td>% of people who drive between 20-30 minutes to work</td>
<td>-.009</td>
<td>.011</td>
</tr>
<tr>
<td>% of people who drive between 31-90 minutes to work</td>
<td>.016*</td>
<td>-.080**</td>
</tr>
<tr>
<td>% of people who drive for over 90 minutes to work</td>
<td>-.020**</td>
<td>-.031**</td>
</tr>
<tr>
<td><strong>…PHYSICAL LANDSCAPE</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>.016</td>
<td>-.017</td>
</tr>
<tr>
<td>Mean minimum temperature</td>
<td>.012</td>
<td>.002</td>
</tr>
<tr>
<td>Mean rain</td>
<td>.015</td>
<td>.085**</td>
</tr>
<tr>
<td>Mean snow</td>
<td>1.71**</td>
<td>0.91**</td>
</tr>
<tr>
<td>Mean maximum temperature</td>
<td>.056**</td>
<td>-.039**</td>
</tr>
<tr>
<td>Variance in minimum temperature</td>
<td>.074**</td>
<td>.068**</td>
</tr>
<tr>
<td>Variance in rain</td>
<td>-.016</td>
<td>-.012</td>
</tr>
<tr>
<td>Variance in snow</td>
<td>.156**</td>
<td>-.067**</td>
</tr>
<tr>
<td>Variance in maximum temperature</td>
<td>-.016</td>
<td>-.053**</td>
</tr>
<tr>
<td>N</td>
<td>27,584</td>
<td>27,584</td>
</tr>
<tr>
<td>R²</td>
<td>6.18%</td>
<td>8.71%</td>
</tr>
</tbody>
</table>

* p<.05  ** p<.01
Figure 1

A Framework for Understanding Geographic Influences on Consumer Behavior

Physical Landscape
1. Topography
2. Climate
3. Natural Resources

Psychological Landscape
1. Economic structure
2. Population structure
3. Religious/legal structure
4. History

Use Situations faced By Consumers

Psychological Mechanisms (e.g., optimal stimulation level)

Physiological Mechanisms (e.g., thermoregulation)

Consumer Values, Motivations, & Preferences

Consumer Lifestyles

Consumption Patterns

Sources:
1. Model components shown in rectangular boxes adopted from Hawkins, Roupe, and Coney (1981)
2. Model components shown in italics and ovals are based on Parker and Tavassoli (2000)
Figure 2
Frequency of respondent by Zip Code

Notes:
- Number of respondents: 164,085
- Respondents used in analysis: 132,085
- Total Zip-codes: 31,956
- Zip-codes with no observations: 10,320
Figure 3: Coefficients for Importance of Dealership Service
Figure 4: Coefficients for Importance of Vehicle Quality
Figure 5: Overall Customer Satisfaction
Figure 6: Service Responsiveness for Sub-Par Satisfaction Areas
References


Grewal, Dhruv, Michael Levy, Anuj Mehrotra, and Arun Sharma (1999) “Planning merchandising decisions to account for regional and product assortment differences,” *Journal of Retailing*, 75 (3), 405-


