Identifying Spatial Segments in International Markets

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Abstract

The identification of geographic target markets is critical to the success of companies that are expanding internationally. Country borders have traditionally been used to delineate such target markets, resulting in accessible segments and cost efficient entry strategies. However, at present such ''countries-as-segments'' strategies may no longer be valid. In response to the accelerating trend toward global market convergence and within-country fragmentation of consumer needs, cross-national consumer segmentation is increasingly used, in which consumers in different countries are grouped based on the similarities in their needs, ignoring the country borders.

In this paper, we propose new methodology that helps to improve the identification of spatial segments by using information on the location of consumers. Our methodology identifies spatial segments based on consumer needs and at the same time uses spatial information at the subcountry level. We suggest that segments of consumers are likely to demonstrate spatial patterns and develop a hierarchical Bayes approach specifying several types of spatial dependence. Rather than assigning consumers to segments, we identify spatial segments consisting of predefined regions. We develop four models specifying different types of spatial dependence. Two models characterize situations of *spatial independence* and *countries-as-segments*, which represent existing approaches to international segmentation. The other two models accommodate *spatial association* within and *spatial contiguity* of segments and are new to the segmentation literature. The models account for within-segment heterogeneity in multiattribute-based segmentation, covering numerous applications in response-based market segmentation. We show that the models can be estimated using Gibbs sampling, where for the spatial contiguity model, a rejection sampling procedure is proposed.

We conduct an analysis of synthetic data to assess the performance of the most restrictive spatial segmentation model in situations where spatial patterns do or do not underlie the data-generating process. Data for which the true properties are known were analyzed with models of spatial contiguity and spatial independence of segments. The results indicate that a substantial improvement in parameter recovery may be realized if a spatial pattern underlies the data-generating process, but that the spatial-independence model may provide a better alternative when this is not the case.

We empirically illustrate our approach in the setting of international retailing, using survey data collected among consumers in seven countries of the European Union. A store image measurement instrument was used. This instrument is based on the multiattribute model of store image formation, with overall evaluations of stores as a dependent variable and image perceptions as predictor variables. The segmentation basis consists of (latent) importances of store image attributes, i.e., product quality, service quality, assortment, pricing, store atmosphere, and location. We argue that store image attribute importances are likely to display spatial variation and expect spatial concentration of segments, or even contiguity, to occur.

We apply and compare the four spatial segmentation models to the store image data. The countries-as-segments model receives lowest support from the data, less than that of the spatially independence model, which is in line with the current notion that consumer preferences cut across national borders. However, the spatially contiguity model and spatial-association model demonstrate the best fit. Although the differences between the various models are not very large, we find support, consistent across the two fit indices, for the spatial models.

Substantive results are presented for the spatial contiguity model. We identified five spatial segments that cut across borders. The segments give rise to different retail positioning strategies, and their importance estimates and location demonstrate face validity.

(*International Market Segmentation; MCMC Estimation; Spatial Information*)

0732-2399/02/2102/0160/$05.00
1526-548X electronic ISSN

1. Introduction

The globalization of the marketplace is arguably the most important challenge facing companies today (Yip 1995). Faced with saturation in home markets and lured by growth opportunities, managers are extending their business internationally. Once a company commits itself to international expansion, management is confronted with the task of identifying spatial segments to target. The key to success is to understand the attitudes and behavior of consumers in these segments, and to tailor strategies to their needs (Douglas and Craig 1992). Identifying the right spatial segments for entry or expansion is critical because the nature and location of those segments affects the effectiveness of companies' marketing efforts. In this paper, we propose new methodology that helps improving the identification of spatial segments by using information on the location of consumers.

A commonly used approach to defining spatial segments has been to use the existing national or political borders, resulting in the use of countries as potential target segments (Jeannet and Hennessey 1998). The rationale for this approach is that countries constitute distinct spatially connected areas in which consumers traditionally share language, culture, and often lifestyle and behavior (Hassan and Katsanis 1994). Researchers such as Sethi (1971), Helsen et al. (1993), and Kale (1995) therefore have used "country segmentation" approaches in which countries are grouped based on socioeconomic, cultural, and other national characteristics. This approach, however, ignores within-country heterogeneity among consumers and communalities among consumers in different countries. Recently, trends toward globalization have reduced the homogeneity of behavior of consumers within countries and increased the commonalities among consumers across countries.

Some researchers have therefore proposed to use "cross-national segmentation." Here, country borders are ignored and consumers in different countries are grouped into cross-national segments, based on their similarities in needs (Kamakura et al. 1993, Ter Hofstede et al. 1999, Yavas et al. 1992). The methods in question, however, have ignored that some spatial clustering of consumer behavior persists. Regions near to one another often share climate, resources, history, and sociodemographic and economic makeup (Hawkins et al. 1981). Therefore, consumer culture, lifestyle, values, attitudes, benefits, and consumption tend to be spatially associated as well. Empirical support for such local similarities in cultural, attitudinal, and behavioral patterns can be found in several studies (e.g., Askegaard and Madsen 1998, Ronen and Shenkar 1985, Vandermerwe and L'Huillier 1989, Parker and Tavassoli 2000).

We propose a segmentation methodology that exploits spatial similarities in consumers' needs and incorporates specifications of the spatial configuration of segments. The problem we face is a segmentation of regions, where it is likely that homogeneity of cultural, geodemographic, and lifestyle variables within regions that are near to one another causes regions in segments to be spatially associated or even spatially contiguous. We develop a general model, which identifies a number of unobserved geographic segments, each representing a potential spatial target market. Because consumer behavior within those segments may not be perfectly homogeneous, we allow for variation of that behavior within segments. In specifying and estimating the model, we take a hierarchical Bayes approach that allows us to incorporate different behavior-based beliefs on the spatial configuration of segments (from weak to strong): cross-national spatial independence, spatial associated, spatial contiguity, and country-based segments. We specify priors of spatial dependence that "smooth" the posterior probabilities of segment membership and potentially improve the identification of spatial segments. Our approach enables us to investigate to what extent spatial dependence improves the performance of segmentation models in describing consumers' behavior.

The remainder of this paper is organized as follows. The model formulations are discussed in §2. In §3 we discuss procedures for model estimation and selection. In §4 we apply the methodology to international retailing. We use a representative sample of 2,000 consumers and 120 regions in seven E.U. countries to empirically study spatial segments that are based on store image. Four models are estimated, each capturing different types of spatial dependence, ranging from no information on the spatial configuration of segments to complete information as in the ''countries-as-segments'' segmentation approach. The results are illustrated for the model that is best supported by the data, namely, the spatial contiguity model. Conclusions are drawn and suggestions for further research are provided in the final section.

2. Model Development

2.1. General Model Specification

In formulating the model, we consider the case of a multiattribute model, in which evaluations of marketing stimuli are affected by attributes of those stimuli. The approach accommodates most (unobserved) product-specific segmentation bases including benefits, perceptions, and attribute importances. Thus, it covers numerous applications in response-based market segmentation, including metric conjoint, the formation of attitudes and store image, trade show performance evaluation, and customer satisfaction. Without loss of generality and in line with the empirical application in §4, we focus on store image formation in the model description below.

In the model we distinguish measurement entities at three hierarchical levels. At the highest level, segments are identified that are not observed a priori. At the second level, these segments consist of predefined geographic regions. Consumers within regions present the lowest level of the hierarchy. We focus on the identification of spatial segments of regions, rather than segments of subjects. Let

$t = 1, \ldots, T$ unobserved spatial segments,

$r = 1, \ldots, R$ predefined regions,

$i = 1, \ldots, I_r$ subjects in region r,

$k = 1, \ldots, K$ attributes,

$l = 1, \ldots, L$ marketing stimuli.

Consumers are nested within regions, and regions are nested within segments. Although not critical to the actual formulation of our model, in defining the regions, there is a trade-off between the size of the regions vis-à-vis the sample size. If the number of regions becomes too large (and the regions become smaller), given a fixed sample size, the reliability of the region-specific parameters deteriorates and the precision of the model estimates suffers. If one would have access to very large samples, one could use very small regions.

According to a multiattribute model we assume that the overall evaluation y_{ril} of a particular marketing stimulus l (e.g., a store) by subject i in region r can be expressed as a weighted sum of perceptions of that object's attributes (e.g., a store's image attributes) x_{rikl}, with weights β_{rk}, leading to a linear equation at the lowest level of the model:

$$y_{ril} = \sum_{k=1}^{K} x_{rikl}\beta_{rk} + \epsilon_{ril}, \tag{1}$$

where β_{rk} denotes the importance weight of attribute k in region r. Note that in this formulation the importance weights vary across regions. The disturbances have independent normal distributions with zero mean and variance ω^2:

$$\epsilon_{ril} \sim N(0, \omega^2). \tag{2}$$

To accommodate variation of the β_{rk} across and within segments, we build a hierarchical structure on top of Equation (1). At the regional level of the model, we introduce unobserved segment indicators, $\xi_r \in \{1, \ldots, T\}$, indicating to which spatial segment a region belongs (cf. Robert 1996). Conditional on these segment memberships, $\beta_r = (\beta_{rk})$ follows a normal distribution within segments:

$$[\beta_r \mid \xi_r = t, \bar{\beta}_t, \Sigma] \sim N(\bar{\beta}_t, \Sigma). \tag{3}$$

In this formulation β_r has a segment-specific mean vector $\bar{\beta}_t$ and variance-covariance matrix Σ. The $\bar{\beta}_t$ reflect the mean segment-specific importance of the attributes. The diagonal elements of Σ (σ_{kk}) account for within-segment heterogeneity, i.e., the differences in β_{rk} among regions that exist within segments. The off-diagonal elements of Σ ($\sigma_{kk'}$), capture the covariance between β_{rk} and $\beta_{rk'}$.

2.2. Specification of Four Spatial-Segmentation Models

Equations (1) through (3) define a general model that allows for differences in the importance weights β_r across regions through a normal distribution within segments. Building on Equations (1) through (3) we suggest several spatial specifications of the segment memberships ξ_r. These specifications represent different types of spatial dependence, which are based on different substantive conceptualizations of the spatial similarities in consumer behavior.

Spatial-Independence Model. The spatial-independence model assumes that underlying factors in consumer behavior driving spatial dependence among regions have only a minor influence at best. For example, it has been argued that world cities such as Paris, New York, and Tokyo might have more in common with one another than with neighboring regions, contributing to the rise of a global elite segment that does not show any spatial dependence structure (Hassan and Katsanis 1994). When the segments are not expected to be spatially associated or spatially contiguous, a finite mixture model arises, defined at the regional level, where the segment indicators are assumed to have multinomial distributions with prior parameters:

$$p[\xi_r = t] = \pi_{t0}, \tag{4}$$

with π_{t0} the prior segment membership probability ($\pi_{t0} > 0$ and $\Sigma_t\, \pi_{t0} = 1$). This specification characterizes complete spatial independence of segment memberships, but allows for cross-national segments to be identified. We will refer to this specification as the *spatial-independence model.*

Spatial-Association Model. Consumer behavior theorists have argued that regions might not display spatial independence in consumer behavior because of their similarity in physical landscape (climate, topography, natural resources) and psychological landscape (historical, religious, cultural, sociodemographic, and economic factors) (Gentry et al. 1988, Hawkins et al. 1981, Kahle 1986, Parker and Tavassoli 2000). The primary route through which similarity in the physical landscape affects similarity in consumer behavior is through similarity in usage situations consumers face. The psychological landscape affects consumer behavior primarily through similarity in predominate value and lifestyle systems. Empirical support for regional variations in consumer lifestyle, values, attitudes, and consumption behavior is provided by, e.g., Gentry et al. (1988), Hawkins et al. (1981), Kahle (1986), and Parker and Tavassoli (2000). Empirical support for spatial association in socioeconomic, cultural, attitudinal, and behavioral patterns can also be found in international segmentation research (Askegaard 1993, Kale 1995, Ronen and Kraut 1977, Sirota and Greenwood 1971, Steenkamp 2001, Ter Hofstede et al. 1997).

We accommodate the conceptual notion of spatial association in formal model terms by formulating spatial dependency relations among neighboring regions. Let $\Xi = (\xi_l, \ldots, \xi_R)$ a vector of segment memberships defining a particular partition of the R regions into T geographic segments. We define ''spatial association'' of segments to be the condition in which the membership of a certain region in a segment increases the probability that its neighboring regions fall in the same segment and denote this as the *spatial-association model.* This implies that segment memberships depend on the memberships of surrounding regions.

From a statistical point of view, a motivation for specifying spatial dependence of segment memberships is that the posterior membership probabilities in the ''standard'' mixture model may suffer from a weak posterior update if they are based on limited information, i.e., there are few observations in a specific region, which reduces their stability. We therefore propose to ''borrow'' information from segment memberships from neighboring regions. To that end we propose ''spatial'' formulations that effectively spatially ''smooth'' the posterior probabilities of membership to render them more stable. We base ourselves on work in statistical image analysis (Besag 1974; Ripley 1987, p. 115; Johnson 1994) that has used spatial prior densities based on neighborhood systems of pixels for image restoration. Contrary to the joint distribution of the intensity of pixels across the entire image, the specification of the conditional density for a pixel given its neighbors has proven to yield tractable solutions that lend themselves to the application of the Gibbs sampler (Geman and Geman 1984). We will introduce dependence among regions by specifying spatial relations among segment memberships of regions. This will "smooth" the posterior probabilities of segment membership and potentially improve the identification of spatial segments.

Formally, let $\Xi_{/r} = \{\xi_1, \ldots, \xi_{r-1}, \xi_{r+1}, \ldots, \xi_R\}$, a vector containing all segment memberships in Ξ excluding ξ_r. Furthermore, let $C_r(\Xi_{/r}) \equiv \{t \mid \exists r' : \xi_{r'} = t,\ r' \text{ adjacent to } r\}$, the set of segments neighboring region r and $I(\cdot)$ the indicator function. We condition each region's prior segment membership probability on the segment memberships of the other regions. The ξ_r are thus assumed to have prior multinomial distributions, conditional on $\Xi_{/r}$, with

$$p(\xi_r = t \mid \Xi_{/r}) = \frac{\pi_{t0} I(t \in C_r(\Xi_{/r}))}{\pi_{t0} + \sum_{t' \neq t} \pi_{t'0} I(t' \in C_r(\Xi_{/r}))}. \quad (5)$$

This formulation smoothes the region membership probabilities by borrowing information from neighboring regions, but it does not reflect spatial contiguity of segments. Thus, although being spatially dependent, one particular segment may still be scattered across the area under study.[1]

Spatial-Contiguity Model. Our third model builds upon the notion that in many cases segments in consumer markets not only exhibit spatial association but also, in fact, spatial contiguity. The forces underlying spatial concentration are generally stronger at shorter distances, i.e., between spatially contiguous regions. Social influences typically operate at relatively short distances. Peter et al. (1999) pointed out that *spatially contiguous* segments cross national boundaries resulting from a variety of unifying factors such as common history, dialects, eating habits, cultural rites, and even climate. Empirical evidence on spatial contiguity of segments is provided by a number of studies (Askegaard and Madsen 1998, Ronen and Shenkar 1985, Vandermerwe and L'Huillier 1989). Moreover, all studies providing support for spatial concentration exhibit a substantial degree of (cross-border) spatial contiguity.

The spatial-contiguity model is more stringent than the spatial-association model, which assumes only segments of adjacent regions to be dependent. Let Ω be the set of admissible values of Ξ, defining the collection of spatially contiguous solutions. Then, the prior probability of a region belonging to a segment, conditionally on segments being contiguous is defined as

$$p(\xi_r = t \mid \Xi_{/r}) = \begin{cases} \dfrac{\pi_{t0} I(t \in C_r(\Xi_{/r}))}{\pi_{t0} + \sum_{t' \neq t} \pi_{t'0} I(t' \in C_r(\Xi_{/r}))} & : \Xi \in \Omega \\ 0 : & \text{otherwise.} \end{cases} \quad (6)$$

Again, π_{t0} is the relative size of segment t, and the ξ_r have multinomial distributions, given $\Xi_{/r}$, with probabilities depending on the sizes of the segments to which neighboring regions belong. This specification imposes a zero prior probability on noncontiguous solutions and is thus stronger than that provided in Equation (5). It imposes spatial dependence on regions but at the same time imposes contiguity, so that a segment cannot occur as collections of disjoint regions.

Because we impose prior contiguity, the posterior probability on noncontiguous partitions is zero as well. However, the pattern of the marginal posterior probabilities of segment membership ($p(\xi_i = t \mid \text{data})$), may not display strict contiguity. Contiguity may not be preserved because we compute the marginal posterior probability of membership by marginalizing across a large number of draws in the Gibbs sampler. Model (6), however, enforces a stronger local spatial smoothing than Model (5). We therefore denote this formulation as the *spatial-contiguity model.*

[1]Alternatively, one could directly impose a spatial covariance on the importances. Such an approach, however, is conceptually not very appealing because the interpretation of a spatial within-segment covariance of the region-specific betas is not entirely clear, and the full conditional posterior distribution of the segment indicators would involve the evaluation of the inverse of the full correlation matrix of size ($R \times R$), which would be very large in most applications (including ours). In addition, both theoretical and empirical results support the segments themselves to show spatial dependence.

Countries-as-Segments Model. The final case we consider is the *countries-as-segments* model. It is the most stringent model because it assumes spatially contiguous segments of a particular shape, viz., as defined by the national boundaries. Conceptually, the countries-as-segments approach assumes that between-segment spatial variation in consumer behavior can be captured effectively by country boundaries. For example, the concept of national culture is based on this notion and forms the basis of much research in international marketing (Steenkamp 2001). The underlying assumption is that country-level legal, cultural, and economic influences are so strong and specific to the country in question that they give rise to unique country segments. Although this might have been a reasonable behavioral model some decades ago, the growing regional unification and globalization renders it less realistic today. Nevertheless, this model still underlies the multidomestic marketing strategy of many multinational companies (Jeannet and Hennessey 1998).

To accommodate the notion of countries-as-segments, we introduce the set $L_t \equiv \{r \mid r \text{ in country } t\}$ and define the prior segment membership probability as

$$p(\xi_r = t) = I(r \in L_t). \tag{7}$$

Using this formulation, our model reduces to a random coefficient regression with parameter heterogeneity specified within countries. The appropriateness of the spatial specifications (4) through (7) depends on the level and type of spatial structure of the segmentation basis and can be investigated empirically.

3. Model Estimation, Identification, and Selection

3.1. Estimation

We use MCMC methods to estimate the different spatial segmentation models, with the objective to derive the posterior distribution of the parameters, given the data. We develop a Gibbs sampling scheme (Casella and George 1992, Gelfand and Smith 1990, Grenander 1983) that approximates the desired posterior distribution of the parameters, by sampling each parameter from its full conditional distribution. The prior distributions of the parameters are taken from conjugate families: $\omega^{-2} \sim \text{Gamma}(\alpha_0, \delta_0)$, $\bar{\beta}_t \sim N(\bar{\beta}_0, V_0)$, and $\Sigma^{-1} \sim \text{Wishart}(t_0, \Sigma_0)$. Here α_0, δ_0, $\bar{\beta}_0$, V_0, t_0, and Σ_0 are fixed hyper-parameters that are specified in the application below as to minimize the influence of prior information on the posterior distributions of the parameters (cf. Gilks et al. 1995).

Except for the segment membership indicators, the full-conditional posterior distributions of the parameters all take a standard form and are given as follows:

$$\beta_r \sim N_K((\omega^{-2}X_r'X_r + \Sigma^{-1})^{-1}(\Sigma^{-1}\bar{\beta}_{\xi_r} + \omega^{-2}X_r'y_r), \quad (\omega^{-2}X_r'X_r + \Sigma^{-1})^{-1}), \tag{8}$$

with y_r an $L{\cdot}I_r$ vector and X_r an $L{\cdot}I_r \times K$ matrix, both with appropriate vectorizations so that the rows in y_r and X_r correspond.

$$\bar{\beta}_t \sim N\left((V_0^{-1} + N_t\Sigma^{-1})\left(V_0^{-1}\bar{\beta}_0 + \Sigma^{-1}\sum_{r:\xi_r=t}\beta_r\right), \quad (V_0^{-1} + N_t\Sigma^{-1})^{-1}\right), \tag{9}$$

with $N_t = \Sigma_r\, I(\xi_r = t)$ the number of regions in segment t.

$$\Sigma^{-1} \sim \text{Wishart}\left(t_0 + R, \quad \left(\Sigma_0^{-1} + \sum_{r=1}^{R}(\beta_r - \bar{\beta}_{\xi_r})'(\beta_r - \bar{\beta}_{\xi_r})\right)^{-1}\right), \tag{10}$$

$$\omega^{-2} \sim \text{Gamma}\left(\alpha_0 + \sum_{r=1}^{R} I_r/2, \quad \delta_0 + \sum_{ril}\left(y_{ril} - \sum_k x_{rikl}\beta_{rk}\right)^2 \Big/ 2\right), \tag{11}$$

The full-conditional posterior distributions of the segment memberships, however, take a nonstandard form. Values of Ξ are sampled from their full-conditional distributions:

$$p(\xi_r = t \mid \Xi_{/r}, \beta_r, \Sigma) = \frac{p(\xi_r = t \mid \Xi_{/r}) p(\beta_r \mid \bar{\beta}_t, \Sigma)}{\sum_{t'} p(\xi_r = t' \mid \Xi_{/r}) p(\beta_r \mid \bar{\beta}_{t'}, \Sigma)}, \tag{12}$$

where the probability $p(\xi_r = t \mid \Xi_{/r})$ can be specified according to Equations (4), (5), (6), and (7) and $p(\beta_r \mid \bar{\beta}_t, \Sigma)$ according to Equation (3). Except for the spatial contiguity specifications in Equation (6), values from the full conditional distribution can be obtained by sampling values from the multinomial distribution. In the case of the spatial-independence model, the full conditional in Equation (12) reduces to that of a standard mixture. For the countries-as-segments model the posterior reduces to Equation (7). In case of the spatial-association model, the multinomial probability in (12) depends on segment indicators of neighboring regions. When Equation (6) is substituted into Equation (12), we need to ensure that the distribution of Ξ is confined to Ω. Therefore we use a rejection method that operates as follows. The probability distribution of partitions Ξ is constrained by the feasible set of admissible partitions Ω for which a closed form expression does not exist in general. Let Ω^* be the set consisting of all possible partitions and $\Omega \subset \Omega^*$ the set of admissible contiguous partitions. Let the $(R \times R)$-matrix $G = [g_{rr'}]$ represent the geographic adjacency pattern of the regions:

$$g_{rr'} = \begin{cases} 1: \text{if region } r \text{ and region } r' \text{ are adjacent} \\ 0: \text{otherwise.} \end{cases} \tag{13}$$

Furthermore, let $G_t(\Xi)$ be a submatrix of G, consisting of the columns and rows of G that correspond to the regions belonging to segment t. The submatrix $G_t(\Xi)$ represents a Markov transition matrix for the regions belonging to segment t. In this Markov chain the "states" correspond to regions and "transitions" to spatial connection of regions. Segment t is spatially contiguous if and only if each state (region) of the chain can be reached from another state (region) in a finite number of single-step transitions. In Markov chain theory, for a fixed value of j, the matrix $G_t(\Xi)^j$ has a special interpretation: its entries provide information about the *j-step transitions* between states (Winston 1987). An entry $(G_t(\Xi)^j)_{rr'}$ indicates the number of paths from region r to region r' that run through the regions in segment t in j steps. Hence, region r and r' are connected if and only if there is a $j > 0$ such that $(G_t(\Xi)^j)_{rr'} > 0$. Therefore, segment t is spatially contiguous if and only if $\Sigma_{r=1}^{N_t-1} G_t(\Xi)^r > 0$.[2] This allows us to define the feasible set of partitions as

$$\Omega = \left\{ \Xi \,\middle|\, \sum_{j=1}^{N_t-1} (G_t(\Xi))^j > 0, \ \forall\ t = 1, \ldots, T \right\}. \tag{14}$$

All models can be estimated through Gibbs sampling by generating draws from the full conditional distributions in Equations (8) through (12). We use a rejection algorithm to draw the segment-indicators in Equation (12) when the contiguity specification is used for the segment indicators, which works as follows. After sampling ξ_r, the restrictions on the segments are examined. If the segment memberships are admissible, the sampled value of ξ_r is retained; otherwise new values of ξ_r are sampled until the restriction is satisfied. Note that this approach also allows us to incorporate more extensive restrictions on the segment memberships if desirable.

The convergence of the Gibbs sampler to posterior distributions has been well established in the literature (e.g., Robert and Casella 1999). However, for any of the spatial dependency formulations the segment indicators can be exchanged between segments, which may adversely affect the performance of the Gibbs sampler. This is likely to occur if segments are largely overlapping, the number of segment-specific parameters is small, and a limited number of repeated observations is available. In these cases a simultaneous exchange of all segment indicators (ξ_r) and segment-specific parameters ($\bar{\beta}_t$) could occur because the full-conditional posterior probabilities of segment membership do not discriminate well among segments. Therefore, careful examination of the Gibbs draws is required to see whether such label switches occur.

[2]Note that the shortest path that runs between two regions in a segment will involve at most $N_t - 1$ transitions, in which case it runs through all other regions in that segment.

We analyze synthetic datasets to investigate the performance of our estimation methods. The results of those analyses are reported in the appendix and indicate that spatial specifications affect model performance. If the formulation in Equation (6) is used in situations where no spatial patterns underlie the data-generating process, parameter recovery may decline. On the other hand, a substantial improvement in parameter recovery may be realized when a spatial pattern underlies the data-generating process. In that case we found a substantial increase in the recovery of segments; the correct assignment of regions to segments increased from 62% for the spatial independence prior to 83% for the spatial prior. This means that serious advantages of spatial segmentation models are likely to be realized when a spatial pattern of segments is expected. If this is not the case, the spatial-independence model may provide a better alternative.

3.2. Identification and Selection

Because our model is a mixture type of regression model, its identification requires attention. This holds even for the case of MCMC estimation because sampling algorithms may not converge if models with uninformative priors are not identified. Our model is based on DeSarbo and Cron's (1988) mixture model of which identification was provided by Hennig (2000), supplementing the proof for standard normal mixtures by Titterington et al. (1985). Hennig's results apply to our model since the exceptions delineated in that paper (a single observation per subject combined with limited support points for the independent variables) do not apply to our model. Our spatial specifications (5) and (6) expand on DeSarbo and Cron's model but will not affect identifiability because if a full model is identified, so is the one with restrictions on the parameter space.

Empirical evidence of the identification of our model comes from the sequence of draws from the posterior distributions. In our empirical application, the iteration plots of the parameters demonstrated stationary samples after burn in. Also, the rejection rate of the segment memberships in the spatial contiguity model was modest. The overall rejection rate was 44.6% (ratio of number of accepted and rejected draws), and rejection occurred in less than 10% of the iterations. The rejection step increased the overall estimation time by less than 4%.

The model is defined conditionally on the number of segments (T) in the market. Therefore, we estimate the model for a range of possible values of T and choose the appropriate value using log-Bayes factors (cf. Kass and Raftery 1995). We assign similar prior probabilities to each of the values of T, so that the log-Bayes factor equals the difference of the log-marginal densities (LMD). We estimate the LMD as the log of the harmonic mean of the likelihood values across iterations q of the Gibbs sampler (cf. Allenby et al. 1998, Kass and Raftery 1995):

$$LMD = \ln\left(\frac{1}{Q}\sum_{q} p(y_{ri} \mid \beta^{q}_{ri}, \sigma^{q}_{y})^{-1}\right)^{-1}. \tag{15}$$

To determine the optimal number of segments, we will compute the Bayes factor for T segments versus $(T + 1)$-segments and choose the solution with maximum value of the Bayes factor.

4. Application to Store Image Segmentation

We apply the spatial models to an international store image segmentation study on meat outlets in Europe. In retailing, international expansion has become a dominant strategy to attain growth (Gielens and Dekimpe 2001). Examples of retailers expanding their chains to foreign markets are Ikea, Royal Ahold, Toys 'R Us, Carrefour, and Wal-Mart. Such companies open new outlets in new geographic areas where they communicate their distinct positioning messages. To become successful abroad, the first step is to identify spatial segments where customer demand meets the retailer's positioning strategy. Such areas usually involve parts of several countries.

In retailing, a relevant and distinctive positioning is frequently realized through the development of a particular store image (Samli 1989). Store image has been found to be related to such key indicators of retail success as store patronage, store loyalty, and the share of the household budget spent in the store (Hildebrandt 1988). Different groups of consumers, however, might value the various store image attributes differently. Hence, store image has often served as a basis for segmenting retail customers (see Steenkamp and Wedel 1991 for a review). In this study, we use store image as basis for identifying spatial segments involving food retailing in Europe. With about $750 billion in sales a year, the food retailing industry is among the largest industries in the European Union (E.U.). The Top Ten retailers are already present in virtually all E.U. countries and continue to expand internationally.

Store image attribute importances are likely to display spatial variation. They are the conceptual equivalent of product benefits in store image research (Mazursky and Jacoby 1986, Steenkamp and Wedel 1991) and, as mentioned above, there is evidence that benefit importances differ across geographic areas (Askegaard and Madsen 1998, Kamakura et al. 1993) because of geographic variation in physical and psychological landscape (Hawkins et al. 1981). If anything, behavior of consumers towards retail outlets is typically more local than their behavior toward products, and hence, if product benefit importances differ across regions, this applies even moreso to store image attribute importances. Moreover, consistent with theorizing by Vinson et al. (1977), Erdem et al. (1999) recently showed that the importance of various store image attributes is affected by consumer value importances, documented by previous research to display regional differences (Kahle 1986, Gentry et al. 1988). Thus, we expect spatial association, or even contiguity of segments to occur.

4.1. Data

The data collected for this study were part of a large survey on consumer behavior with respect to meat, sponsored by the European Commission. Mail questionnaires were sent out to members of a script panel in seven countries of the European Union. Store image measures were obtained based on Steenkamp and Wedel (1991), where for each respondent data were obtained for stores of varying types, including meat departments in supermarkets, convenience stores, and butcher shops. The store image attributes included in the survey are product quality, service quality, assortment, pricing, store atmosphere, and distance. These attributes have become widely accepted as being relevant to store image (Mazursky and Jacoby 1986, Steenkamp and Wedel 1991). Perceptions on image attributes and overall evaluations of primary meat outlets were measured on 7-point bipolar scales (see Table 1). Scores on the two items measuring overall store evaluations were averaged (correlation between the two items is 0.89). This measurement instrument is based on the multitattribute model of store image formation, with overall evaluations of stores as a dependent variable and image perceptions and distance as predictor variables in Equation (1). Hence, the β_{rk} reflect the derived importances of the image attributes and distance.

Table 1 Items for Perceptions on Image Attributes, Distance, and Overall Store Image

Attribute perceptions	
Of very low quality	Of very high quality
Very bad service	Very good service
Very pleasant atmosphere	Very unpleasant ambiance
Very little variety in meat	Very much variety in meat
Very expensive	Very cheap
Very far away	Very close by
Overall store evaluations	
Very negative	Very positive
Very bad	Very good

Before the data were collected, extensive cross-national pretests were conducted. First, the store image instrument was tested for wording, interpretability, and layout, and appropriate adjustments were made. In a second stage, the questionnaires were refined in pretests conducted in France, The Netherlands, and Spain ($N = 99$). The fieldwork was carried out by a pan-European marketing research agency. Back-translation procedures were used to ensure that the content of the statements was similar across languages. The total sample comprises 1,966 consumers in 120 pre-specified regions from 7 E.U. countries (see Table 2). These regions are defined according to the E.U. *Nomenclature des Unities Territoriales Statistique* classification at level 2 (NUTS2), which includes spatially contiguous regions within the E.U., i.e., the ''*regierungsbezirke*'' in Germany, the ''provinces'' in the

Table 2 Sample Characteristics

Country	Sample Size	
	Subjects	Regions
Belgium	285	9
France	298	21
Germany	320	40
Italy	234	18
Portugal	255	5
Spain	265	15
Netherlands	309	12
Total	1966	120

Netherlands and Belgium, the ''*régions*'' in France, the ''*comunidades autonomas*'' in Spain, the ''*comissaoes de coordenaçao regional*'' and ''*regioes autonomas*'' in Portugal, and the ''*regioni*'' in Italy (cf. Eurostat 1987).[3] The NUTS2 classification was developed in a study for the European Commission and is particularly suitable for our application. It is accommodated in GIS software packages and Eurostat, the central bureau of statistics for the E.U., publishes statistics for each of the NUTS regions, which we will use later for additional profiling of the segments.

4.2. Model Selection, Comparisons, and Segment Profiling

We applied each of the four geographic segmentation models to the data. In addition, we constrained the segments to consist of at least five regions ($N_t \geq 5$), which ensures that segments are sufficiently large to avoid trapping states of the Gibbs sampler. Note that in some regions the degrees of freedom are too small to perform a regression of store image on its attributes, which renders a two-stage procedure infeasible. The models we propose, however, borrow information from other regions to identify region parameters. While the spatial independence model weights the information from the complete sample equally, the spatial contiguity and association models use the spatial information in the data by borrowing information from neighboring regions. In estimating the models, random starting values that comply with the restrictions on the segment memberships are generated, and the parameters are iteratively sampled from the full conditional distributions.[4] We run the Gibbs sampler for 15,000 iterations and discard the first 3,000 samples after inspecting the cumulative percentiles of the samples of the posterior distributions to see whether the MCMC chains have converged. The remaining 12,000 samples are used to compute kernel density estimates of the posterior marginal distributions (Silverman 1992). We inspected the samples for possible switches of the segment labels, but they did not occur. Although we did not experience any difficulties in our empirical application, the rejection-based step in the Gibbs sampler can get stuck if the full conditional probability of segment membership of a particular region is very close to 1, and the allocation of that region leads to an inadmissible partition. The problem is less likely to occur when the number of segments is small, as compared to the number of regions, because the rejection step is only needed for regions that are currently at the segment boundaries. When there are many regions and segments, however, the rejection step may become inefficient. In any case, we recommend monitoring its efficiency.

We estimated the models for several numbers of segments ($T = 2$ through $T = 7$). The log-Bayes factors were minimal for $T = 5$; hence, we describe the results of those solutions. We compare the performance of the four spatial segmentation models using Equations (1) through (3) in combination with either Equation (4), (5), (6), or (7), corresponding to the spatial-independence, spatial-association, spatial-contiguity, and the countries-as-segments models, respectively. Note that our sample contained seven countries. To arrive at five segments, we grouped The Netherlands and Belgium into one segment and Spain and Portugal into another segment. The Netherlands and Belgium have long been united in the ''Low Countries'' (''Nether-lands'') and are more re-

[3]In addition to the NUTS2 level, NUTS1 and NUTS3 classifications are available. However, for our application, the NUTS1 regions were too large, not allowing for sufficient precision in the location of the segments to be derived. The NUTS3 regions were too small, as compared to the sample size.

[4]For the priors not to influence the posterior estimates, we use diffuse, weakly informative prior distributions and specify $\bar{\beta}_0 = 0$, $V_0 = 0.01 \cdot I_K$, $t_0 = 8$, $\Sigma_0 = 100 I_K$, $\pi_{0t} = 1/T$, and $\alpha_0 = \delta_0 = 0.01$.

cently contained in the same free-trade area called The Benelux. Spain and Portugal form the Iberian Peninsula, which has demonstrated parallel economic and political developments throughout the ages (Davies 1996). Note that the fact that the log-Bayes factors indicate five segments already argues against the ''pure'' countries-as-segments model.

To compare these models, we use the mean-squared error of predictions (MSE) of the dependent variable and log-marginal density (LMD). The mean-squared errors are country segmentation: MSE = 0.767; spatial independence: MSE = 0.752; spatial contiguity: MSE = 0.747; spatial association: MSE = 0.746. Thus the data support the spatial-association and spatial-contiguity models. The differences among the models are modest but are comparable to what has been reported among Bayesian models (Allenby and Ginter 1995).

The LMD is defined in Equation (14) and is frequently used in comparing Bayesian models. The model with highest LMD is most supported by the data. The LMD is lowest for the countries-as-segments model (LMD = −112.77). This result is in line with the notion that consumer preferences tend to cut across national borders. The LMD is highest for the spatial-contiguity model (LMD = −112.49). The LMD of the spatial association model (LMD = −112.51) is also higher than that of the spatial-independence model (LMD = −112.60). Note that although the differences are modest, there is still support for the spatial models because the LMD takes both fit and parsimony into account and favors the more constrained spatial models. It is generally acknowledged that support for a constrained model is obtained when fit indices incorporating a penalty against overfitting do not worsen when the constraints are imposed. In sum, although the differences between the various models are not large, we find support, consistent across the two fit indices, for the spatial models. In other applications, differences may be more pronounced. Given these findings we present the results of the spatial-contiguity model.

To further add to the understanding of the geographic segments in terms of their differential accessibility, we relate them to secondary information on regional geodemographics and logistic accessibility, obtained from Eurostat (Eurostat 1997). Additional data were available from the international store image survey itself, including measures of media consumption and consumer attitudes, involving measures for environmental consciousness (Grunert and Juhl 1995), consumer ethnocentrism (Shimp and Sharma 1987), and optimum stimulation level (Steenkamp and Baumgartner 1995). We construct segment profiles that accommodate the uncertainty of the geographic location of the segments and provide the posterior distribution of the segment profiles across all iterations, from which the median and 5th, 25th, 75th, and 95th percentiles were computed.

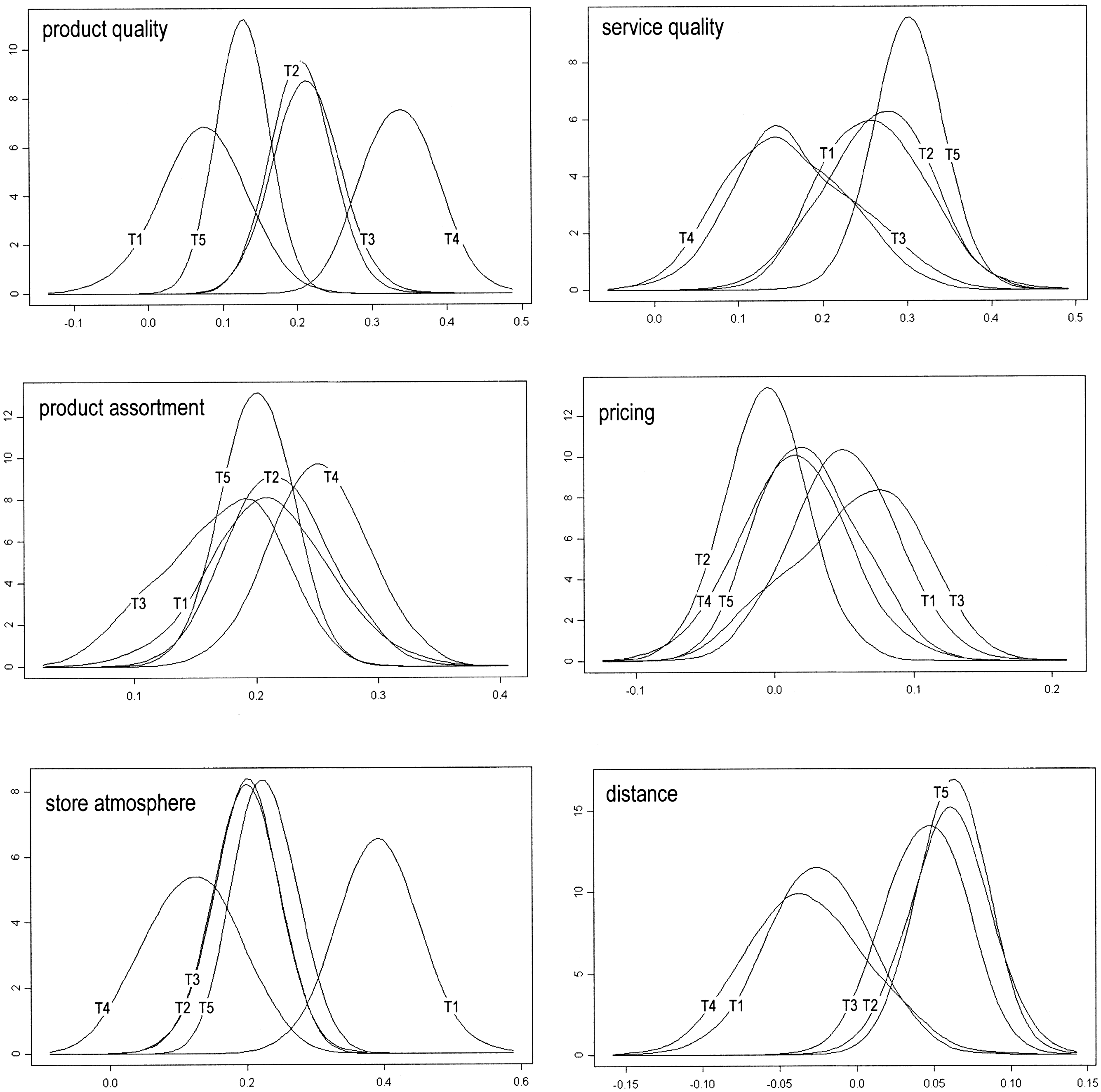
4.3. Results

In Figure 1 we report kernel density plots of the posterior marginal distributions of the $\bar{\beta}_{tk}$.[5] For 25 of the 35 parameters, the 90% credible intervals are completely contained in the positive domain and the sign of these parameters are as expected. While the posterior distributions of the price parameters are spatially concentrated around zero, four of them have median values exceeding zero. The relatively low importance of price is consistent with previous studies that found weaker price effects in Europe, as compared to those of other continents (e.g., Tellis 1988). We graphically present the locations of the geographic segments in Figure 2. The shading intensity assigned to a particular region is higher for increasing posterior probability of that region belonging to a segment, i.e., $P(\xi_r = t \mid \text{data})$. As can be seen from the figures, the segments have fuzzy boundaries. The percentiles of the posterior distributions of the segment profiles are depicted in box plots in Figure 3.

With posterior distributions of the attribute importances well in the positive domain, segment *T1* exhibits large effects for service quality, store atmosphere, and assortment (see Figure 1). The posterior distributions of the coefficients for price, product quality, and distance are concentrated around zero, which means that store positioning on those attri-

[5]Because all 95% credible intervals of the off-diagonal elements of Σ covered the zero value, we report the results where these covariances are restricted to zero.

Figure 1 Kernel Estimates of Posterior Distributions of Image Importance (Spatial-Contiguity Model)



butes is not very effective in gaining appeal from consumers in this segment. A retailer deciding to target this geographic segment may position its chain on store atmosphere. Figure 2 indicates that segment *T1* is located in a single country, Italy, with high segment membership probabilities for the regions on the east coast. The northern part of Italy does not belong to this segment, which is consistent with the large cultural, economic, and political differences that exist between the north and the south of Italy. This segment

Figure 2 Spatial Location of the Geographic Segments (Spatial-Contiguity Model)

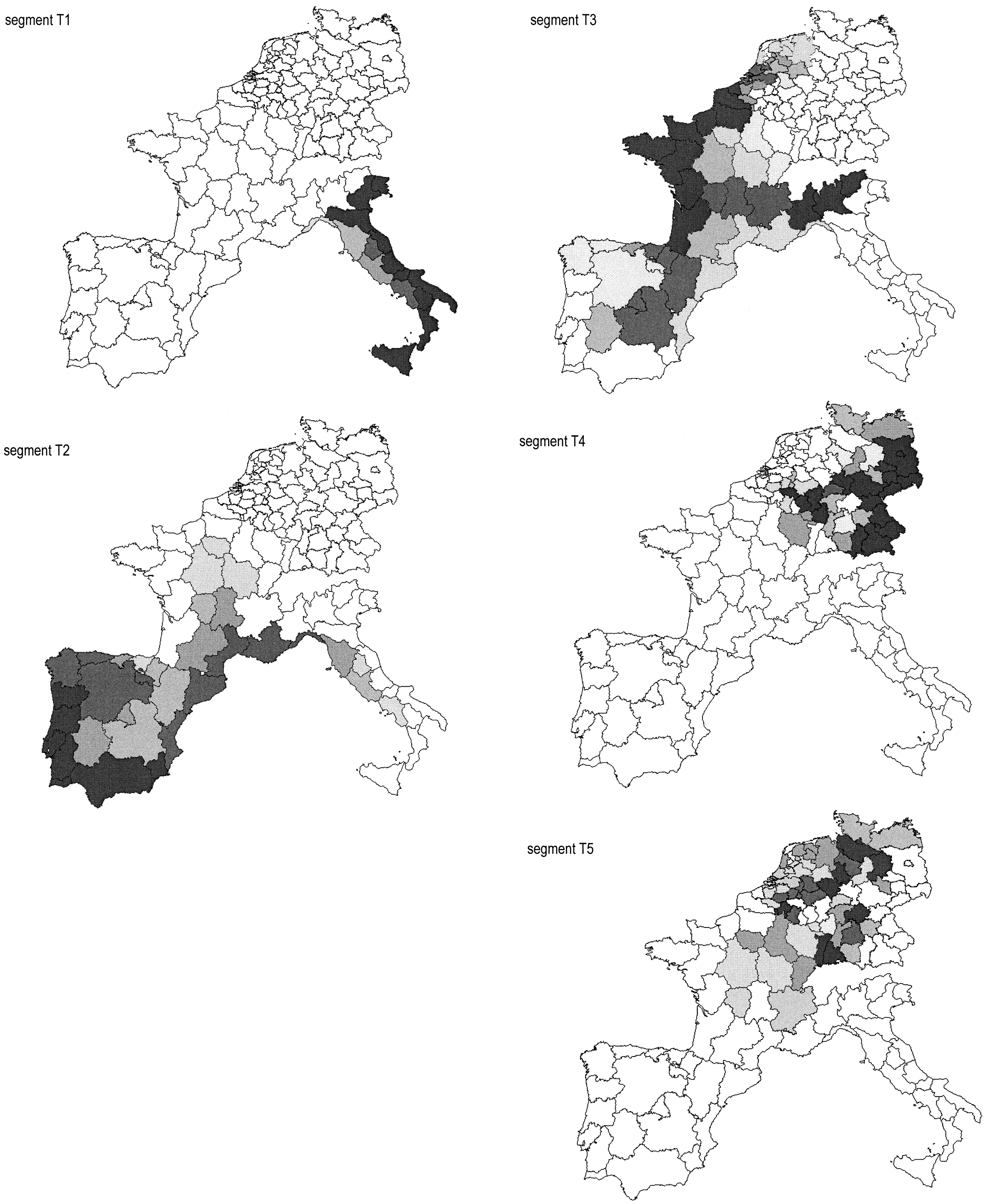
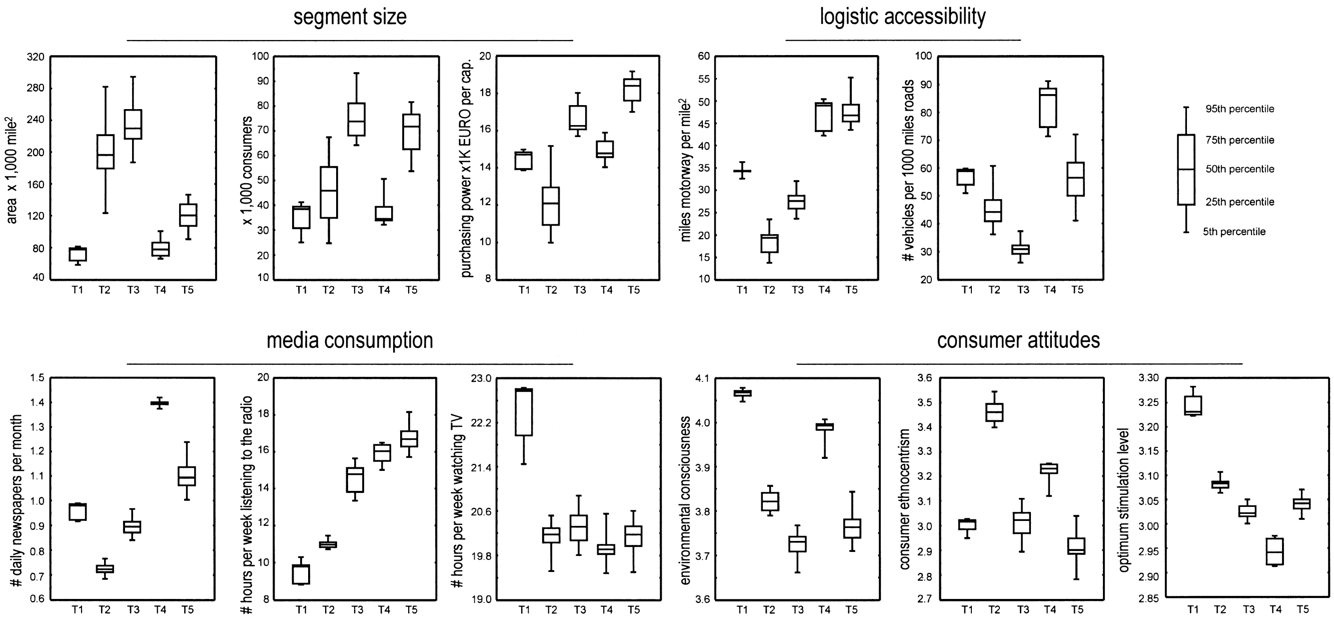


Figure 3 Profiles of the Segments (Spatial-Contiguity Model)



is relatively small in area and population and is characterized by an average pattern of purchasing power and logistic accessibility. This segment has a relatively high exposure to television broadcasts and can therefore be accessed well through television advertising. Consumers in this segment are on average highest on ecological concern and optimum stimulation (Figure 3).

Except for price and distance, the mean image attribute importances in segment *T2* are quite large, as indicated by the medians of their posterior distributions. This segment bases its image for stores on product quality, store atmosphere, assortment, and especially service quality. Segment *T2* encompasses a typical coastal area and transcends national borders (see Figure 2). It includes Portugal, the western parts of Spain and the Mediterranean coastal areas of Spain, and France. Regions in central France, central Spain, and western Italy have moderate segment memberships (well below 0.5). In this segment, strong similarities exist between regions in different countries, whereas the similarities between regions within countries are often weak. This segment provides opportunities for cross-border retail operations, targeting an area that covers parts of different countries. It covers about 200,000 square miles of less developed area and has the lowest population density. It is less attractive in terms of purchasing power (20% below average) and logistic accessibility, and this segment is the most ethnocentric (see Figure 3).

Segment *T3* is not characterized by one single important image attribute (Figure 1). Price and distance have negligible effect on store evaluation and are less important in formulating expansion strategies. The effects of product quality and store atmosphere are much stronger, given that the median values of the corresponding posterior distributions are high. Segment *T3* is mainly located on the west coast of France and stretches out toward central Spain, northern Italy, and The Netherlands. Interesting again is the clear border between northern Italy and the rest of Italy. The northern part of Italy is united with the Lyon area, with which it historically shares strong economic and cultural ties (Davies 1996). As Figure 3 shows, segment *T3* is the largest segment in terms of area and population and is high in purchasing power. The limited traffic density may facilitate the logistic accessibility, but this is mitigated by the relatively low density of motorways. Consumers in segment *T3* are less concerned with the environment and demonstrate an average media consumption pattern.

The most important image attributes in segment *T4* are product quality and assortment (see Figure 1). This segment provides opportunities for upscale hypermarkets, such as Carrefour, that carry a wide assortment of high-quality private labels and national brands (Steenkamp and Dekimpe 1997). Segment *T4* is mainly located in the former German Democratic Republic, with offshoots to Bavaria in the south of Germany and the border regions where Belgium, Germany, and France meet (Liege, Trier, and Lorraine; see Figure 2). Segment *T4* covers a relatively small area, has the smallest number of inhabitants, and has average purchasing power. It is well developed in terms of motorways but suffers from high traffic density. This segment is more exposed to print advertising; its consumers are concerned with the environment; and they are lowest in optimum stimulation level (see Figure 3).

In segment *T5* store image is predominantly based on service quality and, to a lesser extent, on store atmosphere and assortment (Figure 1). The segment covers part of northwest Europe, including The Netherlands, northeast France, southwest and northwest Germany, and parts of Belgium. The geographic configuration of this segment lends itself to geographically staggered rollouts across borders. Segment *T5* is an attractive segment to target with high population density and highest purchasing power. This segment is accessed well through radio advertisements and through logistics because of its high density of motorways and average traffic density. Consumers in this segment score lowest on consumer ethnocentrism, which indicates that they are more open to buying foreign products (Figure 3).

5. Discussion

Groups of consumers in different countries often have more in common with one another than with other consumers in the same country. This requires firms to market their products in areas spanning national borders, which is facilitated by the methodology proposed in this paper. We propose the inclusion of spatial priors in international segmentation models, using a Bayesian framework. The spatial prior was motivated from behavioral theory. Consumer behavior toward goods and services displays spatial dependence resulting from the similarities in the physical and psychological landscape of neighboring regions. While the physical landscape causes spatial correlation by inducing similarity of the usage situations consumers face in neighboring regions, the psychological landscape does that by affecting similarity of values and lifestyles. We argue that firms may gainfully exploit these similarities across regions by identifying and targeting segments that are spatially contiguous. In particular, retailing and logistic operations may be greatly facilitated if spatial segments are identified that can be more easily accessed. There is substantial evidence that consumer behavior is spatially correlated. Because several studies (cited earlier in this paper) have revealed spatial dependencies in segmentation bases—such as values, lifestyles, attitudes, and behavior—segmentation studies utilizing any one of these bases could potentially benefit from spatial prior information. The issue of whether spatial information leads to a better representation of consumer segments is an empirical one. Models with various forms of spatial dependence may be tested for relative fit to a particular market, as was done in the present paper. Once a spatial association or contiguity prior provides an acceptable fit, the identified segments can be effectively used to support decisions of entry, rollout, and logistics, enhancing the efficiency of international marketing operations. We applied the spatial segmentation models in an international store image segmentation study in the European Union. The methodology is, however, more general and can be adapted to accommodate other situations as well. It can be applied to domestic data or to multidomestic marketing problems, where companies prefer to use a hybrid two-stage approach, segmenting first a priori by country and subsequently within countries.

We note that the definition of the regions used for spatial segmentation may affect the solutions obtained. These regions need to be spatially contiguous. In Europe, the NUTS regions are spatially connected and so are the counties and five-digit zip codes in the

United States. Given a particular sample size, the regions also need to be sufficiently large to warrant a sufficient coverage of the area under study. The choice of the region sizes in applications of our model is an important one, because the precision of the region-specific parameter estimates depends on the number of observations per region. Our approach uses the information in the sample more efficiently based on Bayesian shrinkage, so that smaller regions can be used for a given sample size. In general, we recommend the use of standard documented regions, as we did in our study in the E.U. This offers the important advantage of standardization and replicating studies in spatial segmentation.

The countries included in the empirical study were part of the continent of Europe, sharing a vast cultural history. Other "newer" continents such as the United States may display less clear-cut spatial patterns in preferences. In that case, model tests may favor the spatially concentrated or even the spatially independent models. Future research may shed more light on these issues by applying the models in other settings and using different products and services, other countries, and more elaborate measurement instruments.

Acknowledgments
The authors gratefully acknowledge the insightful comments of Eric Bradlow, Peter Lenk, two anonymous reviewers, the area editor, and the editor.

Appendix
Synthetic Data Analysis

An important issue is how the spatial segmentation models perform when spatial patterns do or do not underlie the data. We conduct an analysis of synthetic data for which the true properties are known and analyze these data with the spatial-contiguity and spatial-independence models. We assess the performance of the model with the strongest spatial-dependence (Equations (1) through (3) and (6)) versus the spatial-independence model given by Equations (1) through (3) and (4).

Two datasets are generated, representing situations of spatial contiguity and spatial independence of segments, respectively. For each dataset, two segments are constructed ($T = 2$) by assigning 50 regions to the first segment ($\xi_r = 1$) and the remaining 50 regions to the second segment ($\xi_r = 2$). When generating the spatially independent data, regions are randomly assigned to segments. For the spatially dependent data, the indicators are generated such that the segments represent spatially connected areas as follows. We define regions on a 10-by-10 grid and partition this grid in two halves, where all regions on one half are assigned to the same segment. Except for the spatial configuration of segments, the datasets share the same properties. The total number of observations is set to 4,200 and the number of regions to 100. We consider five attributes ($K = 5$) and a single measurement per subject on the dependent variable y_{ril} ($L = 1$). Values of $\{x_{rik1}\}$ are drawn from a uniform distribution on the interval $[-0.50, 0.50]$ and the $\bar{\beta}_{tk}$ from $[0, 1]$ ($k = 1, \ldots, 5$). Then, region-specific parameters β_{rk} are drawn independently from normal distributions with means $\bar{\beta}_{\xi_r k}$ and standard deviations $\sqrt{\sigma_{kk}} = 0.75$. Finally, for each subject values of the dependent variable y_{ri1} are sampled from normal distributions with means $\Sigma_{k=1}^{K} x_{rik1}\beta_{rk}$ and residual variance $\omega^2 = 0.20$, which corresponds to approximately 50% of the variance explained by the regressions.

The spatial segmentation models are estimated, using MCMC methods, by sampling values from the conditional distributions in Equations (8) through (12). We sample 15,000 values from the conditional distributions and discard the first 3,000 iterations. Convergence of the chains is inspected, and measures of model performance are calculated across the remaining 12,000 iterations. We compute the percentage of correct predictions of the segment memberships (hit rate) by assigning the regions to the segments with highest segment membership. For the parameters $\bar{\beta}_{tk}$, $\sqrt{\sigma_{kk}}$, and β_{rk}, we compute the root mean-squared error (RMSE) of the median values of the posterior distribution versus the true parameter values, taking the mean over the segments, regions, and/or attributes.

In Table A1 we report the performance measures for the resulting four conditions (denoted as 1, 2, 3, and 4). When the data are spatially contiguous (conditions 1 and 2), the spatial contiguity formulation increases the stability of segment memberships considerably. It results in a better allocation of regions to segments (hit rate of 83% versus 64%) and improves the identification of segment means, within-segment variances, and region-specific parameters; the RMSEs of $\bar{\beta}_{tk}$ and $\sqrt{\sigma_{kk}}$ decrease by 55% and 40%, respectively (from 0.166 to 0.107 and from 0..071 to 0.050) but less for the region-specific parameters β_{rk} (from 0.241 to 0.239).

When no spatial patterns underlie the data-generating mechanism (conditions 3 and 4), imposing spatial contiguity adversely affects model performance, but the effect is moderate (Table A1). The hit rates of the segment indicators decrease from 67% to 62%. Apparently, across iterations of the Gibbs sampler the segments moved over the total area, emphasizing mainly those partitions that approximated the true (not spatially contiguous) partition best, so that most regions are often allocated to the correct segments. Still, the precision of the segment parameters decreases for the spatial contiguity model, i.e., the RMSEs increase by 23% for $\bar{\beta}_{tk}$ and 40% for $\sqrt{\sigma_{kk}}$.

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Table A1 Statistics for Model Comparison in the Analyses of Synthetic Data*

	Design Factors: Assumptions of Spatial Configuration Made		Performance Measures			
			Hit Rate	RMSE		
Condition	Data Generation	Model Estimation	(ξ_r)	$\overline{\beta_{tk}}$	$\sqrt{\sigma_{kk}}$	β_{rk}
1	Spatial Configuration	Spatial Configuration	83%	0.1069	0.0503	0.2393
2	Spatial Configuration	Random Configuration	64%	0.1658	0.0709	0.2405
3	Random Configuration	Random Configuration	67%	0.1692	0.0627	0.2456
4	Random Configuration	Spatial Configuration	62%	0.2092	0.0874	0.2454

*All true parameter values were contained in the 95% Bayesian credible intervals of the posterior medians, a Bayesian analogue of a frequentist confidence interval. Bayesian credible intervals have a natural interpretation: The probability of a parameter belonging to the Bayesian credible interval is equal to 0.95.

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This paper was received July 19, 1999, and was with the authors 19 months for 4 revisions; processed by Greg Allenby.