# Advances in methods to support store location and design decisions

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Chapter 3

# Store Location Evaluation Based on Geographical Consumer Information[1]

## 3.1 Introduction

The old adage regarding the three most important things in retailing—"location, location, location" (Jones and Simmons 1987)—still holds, because store location remains a crucial driver of store performance in modern retail environments (Levy and Weitz 2004; McGoldrick 1990; Pan and Zinkhan 2006). From a consumer perspective, travel distance to the store strongly affects the store's attractiveness, and from a retailer perspective, store location decisions involve massive and almost irreversible capital investments that, given the behavior of consumers, largely determine the trade area of the store (Achabal, Gorr, and Mahajan 1982; Ailawadi and Keller 2004; Briesch, Chintagunta, and Fox 2009; Craig, Ghosh, and McLafferty 1984). Therefore, successful retailers routinely evaluate the performance of their current stores and predict the sales impact of potential location changes or new store openings (Gauri, Pauler, and Trivedi 2009; Ghosh and McLafferty 1982; Ghosh and Craig 1983; Kumar and Karande 2000).

These observations have given rise to several quantitative approaches to decision making about store locations, such as gravity and regression models (Buckner 1998; Craig, Ghosh, and McLafferty 1984). Two recent developments

[1] This chapter is based on a working paper with the same title co-authored by Tammo H.A. Bijmolt and J. Paul Elhorst, which is currently under publication review.

offer additional opportunities for store location evaluation. First, the widespread adoption of customer loyalty cards has resulted in detailed data about customer purchase behavior (Leenheer and Bijmolt 2008). Second, developments in spatial econometrics provide a means to account for spatial autocorrelation among the error terms of neighboring observations and thereby increase the efficiency of parameter estimates (e.g., Bradlow et al. 2005; Bronnenberg and Mahajan 2001; Bronnenberg 2005). We exploit these developments by proposing and testing a new model for store location evaluation. By combining data about store, competitor, and consumer characteristics, we build a model that can be used to (1) assess the impact of various drivers on store sales, (2) evaluate the expected performance of stores, and (3) predict sales impacts of future changes in competition, changing demographics within markets, location changes, and new store openings.

Expenditures by loyalty program members generally exceed those of nonmembers (Drèze and Hoch 1998; Van Heerde and Bijmolt 2005). Therefore, to understand the mechanisms that drive store sales, we adopt a decomposition framework to investigate how loyalty program members and nonmembers contribute to sales (Farris, Parry, and Ailawadi 1992; Van Heerde and Bijmolt 2005). We further decompose sales to loyalty program members within a particular zip code and specify the penetration rate of the loyalty program, the number of visits, and the average expenditures per visit. This decomposition framework and knowledge of the location or residence of loyalty program members offer a means to relate these variables to store, competitor, and consumer characteristics and thus obtain more detailed insights in drivers of store sales (Van Heerde, Leeflang, and Wittink 2004). Moreover, the collection of zip code-level data is relatively unobtrusive for customers. Thus, the proposed methods are not only managerially useful but also appropriate for the modern retail environment, in which many consumers believe their privacy is at stake. We use the number of competitors as one of the explanatory variables of the different sales components, as well as a variable that needs to be explained. Competition may have a notable effect on sales, and simultaneously, potential sales can attract competitors.

The error terms in model equations that aim to explain store sales variables are likely to be spatially correlated when they include data at the zip code level, because zip codes in close proximity often share unobserved characteristics, such as climate, resources, sociodemographic factors, and economic circumstances. Therefore, unobserved explanatory variables pertaining to consumer lifestyles, attitudes, preferences, and choices within zip codes close to one another cannot be considered completely independent (Steenburgh, Ainslie, and Engebretson 2003; Ter Hofstede, Wedel, and Steenkamp 2002; Yang and Allenby 2003). Thus, failing to account for spatial error autocorrelation when it exists causes inefficiency (Anselin 1988). Models that take spatial dependence into account, among observations in general and the error term in particular, recently have received attention in marketing literature from, for example, Bronnenberg and Sismeiro (2002) and Yang and Allenby (2003). Building on this stream of research, we use random effects models extended with spatial error autocorrelation to account for spatial dependencies in sales components across zip codes.

The remainder of this chapter is organized as follows: First, we provide an overview of existing store location evaluation models that serves as a starting point for further model development. Second, we present the decomposition framework for modeling store sales and introduce spatial-error random-effects models that we use to explain different store sales variables. Third, with data from 28 stores of a Dutch retail clothing chain, we test our framework in an empirical setting. Fourth, we discuss the results, demonstrate how to evaluate the performance of stores and how to predict (potential) sales of new store locations, provide managerial implications of the environmental changes in some explanatory variables, and suggest directions for further research.

## 3.2 Previous Literature

Various analytical tools attempt to evaluate store location decisions (Buckner 1998; Craig, Ghosh, and McLafferty 1984; Levy and Weitz 2004), mostly by considering the amount of sales each location can generate in a certain period, given the current spatial distribution of demand and competition (Ghosh and McLafferty 1982). However, changes in the retail environment may have significant impacts on store sales. These changes might include shifts in the spatial distribution of demand caused by population or income dynamics (Ghosh and Craig 1983), as well as altered activities by competing firms (Ghosh and McLafferty 1982; Singh, Hansen, and Blattberg 2006). Store location evaluation models therefore should accommodate the effects of such changes.

Huff's gravity model and its extensions (Gautschi 1981; Huff 1964; Stanley and Sewall 1976) provides one of the earliest applications of spatial models in marketing. Such models predict the geographical extent of store trade areas on the basis of a negative relation between store patronage and distance to consumers. Thus, they can explain the proportion of visits from a certain area to the store but not any changes in consumers' expenditures. To predict sales, the probability that a consumer will visit the store from a particular location is multiplied by an estimate of the (average) expenditures at that location and by population size or, alternatively, by (average) expenditures per household and number of households. As another important limitation, these models do not include consumer characteristics; they assume store patronage depends only on store size and distance to the store. Some authors include factors other than distance and store size that may affect consumers' store choice, such as retail center characteristics (e.g., Gautschi 1981; Stanley and Sewall 1976), but in general, the number of variables describing the store environment remains limited.

Regression models enable analysts to identify several factors associated with different levels of sales from stores at different sites. However, existing studies typically do not account for the spatial heterogeneity of the store's trade area, even though retailers in most Western countries serve trade areas with a rather heterogeneous population (Campo and Gijsbrechts 2004). That is, previous studies use aggregate measures of consumer demographics for the entire trade area to predict sales at a particular store location. As such, these models ignore how consumers, competitors, and demographics are distributed throughout the trade area. Recent studies reveal that the geographic location can be an important variable for predicting consumer behavior (e.g., Bronnenberg and Mahajan 2001; Bronnenberg and Sismeiro 2002; Steenburgh, Ainslie, and Engebretson 2003; Yang and Allenby 2003). Bronnenberg and Mahajan (2001), for example, find that 66–95% of the variation in market shares for two homogenous product categories are due to spatial rather than temporal variation. In particular, growing literature on spatial models in marketing (for overviews, see Bradlow et al. 2005; Bronnenberg 2005) reveals how spatial covariation in sales can be exploited to gain better insights into the effectiveness of marketing activities across markets. In other words, despite reasons to believe that these spatial effects can be substantial, most of these effects heretofore have been ignored in store location literature (Duan and Mela 2009).

Similar to Bronnenberg and Mahajan (2001), we adopt a sales model with a spatial autocorrelation component. However, our model differs from theirs in that we decompose sales into various components. Most studies consider only a few components of store sales (e.g., Bawa and Ghosh 1999; Inman, Shankar, and Ferraro 2004) or sales in general (Kumar and Karande 2000) and offer no insights in the underlying mechanisms causing changes in store sales components. Pan and Zinkhan (2006), however, show that various regressors can have different effects across sales components, which suggests that decomposing sales (effects) into constituent parts may offer richer insights than a model of total store sales only. As another difference, Bronnenberg and Mahajan's (2001) model only captures spatial heterogeneity in (secondary) demand arising from unobserved and observed differences in retailer behavior across markets. In contrast, our model accommodates the sales effects of observed spatial differences for a broad range of variables, such as store, competitor, and consumer characteristics, while also accounting for unobserved sources of spatial heterogeneity in store sales.

Another stream of research that we consider belongs to empirical economics literature (Chintagunta et al. 2006). Some examples from this stream include recent studies by Chan and colleagues (2007), Duan and Mela (2009), and Thomadsen (2007), who determine equilibrium prices or sales conditional on outlet location and capacity. These studies show that location competition affects sales, whether positively or negatively, while the reverse can be true as well; that is, (potential) sales may attract competitors. To separate these alternative explanations, we employ the number of competitors as a variable to explain sales components, and also include an equation to explain the number of competitors in a particular location.

## 3.3 Model for Store Location Evaluation

1. Determine perimeters of store trade areas and allocate zip codes to each store.

2. Estimate the store location evaluation model:
   - Decompose total sales into different components;
   - Identify potential drivers of store sales;
   - Assess the impact of drivers of store sales;
   - Explain number of competitors.

3. Use the model for:
   - Explaining sales (components) for previous periods;
   - Predicting sales (components) for current and future periods;
   - Evaluating effects of changes in drivers of store performance;
   - Predicting sales (components) for new store locations.

**Figure 3.1: The store location evaluation process.**

In Figure 3.1, we propose a three-stage decision model for evaluating current and future store performance. The first stage involves defining the trade area on the basis of detailed customer information derived from loyalty cards. Using this definition, we can select zip codes that belong to the stores' trade areas. The second stage requires analyzing store sales using regression-type models that relate data on store sales to data on store and competitor characteristics, as well as consumer characteristics observed at the zip code level within the trade area. Finally, in the third stage, the estimated coefficients of these relations serve to (1) assess the impact of various drivers of store sales, (2) evaluate the overall performance of stores, and (3) predict sales impacts of future changes in competition and demographics within markets and of location changes and new store openings. We discuss these three stages of the decision process in the following subsections.

### *3.3.1 Trade Area Definition*

The first stage of the store location evaluation process (Figure 3.1) involves defining the trade area. Knowledge about the store's trade area is essential, because it allows retailers to identify and serve the consumers who are most likely to purchase at that particular store. The various approaches for trade area delineation (O'Kelly and Miller 1989) generally fall into two broad research streams: studies based on the Reilly model and its extensions (e.g., Huff 1964) and those based on the Applebaum (1966) procedure. These model types differ in the kind of questions they address. Whereas the Reilly model attempts to determine the percentage of consumers in a given area who patronize a particular store, the Applebaum procedure tries to find the fraction of a store's customers from a given area. Because these approaches are highly related, some studies integrate them (O'Kelly and Miller 1989).

Although these approaches establish the spatial distribution of consumers, they typically fail to allow for heterogeneity across space (e.g., Donthu and Rust 1989; Gonzalez-Benito, Munoz-Gallego, and Kopalle 2005; González-Benito and González-Benito 2005). That is, they assume trade areas are homogeneous, such that neighborhoods have similar characteristics and spending patterns. However, in most Western countries, such areas typically consist of a mosaic of small zip codes with specific sociodemographic and lifestyle characteristics (Campo and Gijsbrechts 2004). Therefore, researchers must consider differences in consumer characteristics across the trade area. Information about (changes in) the demographic and competitive characteristics of the store's trade area can help predict how local market potential may evolve over time and indicate whether a store currently is over- or underperforming (Montgomery 1997; Putler, Kalyanam, and Hodges 1996).

Because customers who sign up for loyalty programs must provide the retailer with their addresses and because the system registers their subsequent purchases, we can use this combined information to define the trade area of a store. To this end, we first split sales into those to loyalty program members whose addresses are known and those to nonmembers whose addresses are not known (Van Heerde and Bijmolt 2005), such that

$$S_{it} = SL_{it} + SN_{it}, \qquad (3.1)$$

where $i$ refers to the store ($i = 1,\ldots,I$, where $I$ is the total number of stores), $t$ represents a given time period ($t = 1,\ldots,T$, where $T$ is the number of time periods), $S_{it}$ is total sales of store $i$ at time $t$, $SL_{it}$ is sales to loyalty program members of store $i$ at time $t$, and $SN_{it}$ is sales to nonmembers of store $i$ at time $t$.

Trade areas typically consist of two or three zones (Applebaum 1966; Levy and Weitz 2004), depending on the amount of sales generated in each area. A store's primary trade area is the zone from which it gets most of its sales—usually about 65% of total sales. The secondary zone generates the next 20% of total sales, whereas the tertiary zone captures sales from non-regular visitors (i.e., the remaining 15–20%). Because we model the purchase behavior of loyalty card holders who should be regular visitors (Allaway, Berkowitz, and D'Souza 2003; Van Heerde and Bijmolt 2005), we focus on the primary and secondary zones and consider zip codes belonging to those two zones part of the store's trade area. The number of zip codes in the trade area depends on sales, so trade area boundaries should be considered endogenous (Greene 2003). Furthermore, trade areas might be subject to spatial variation. Differences in product assortments, competition, and consumer shopping habits (Huff and Rust 1984) can create variations in trade area boundaries across stores and over time. We therefore specify a model for trade area delineation, in which we model trade area sizes as a function of store and competitor characteristics.

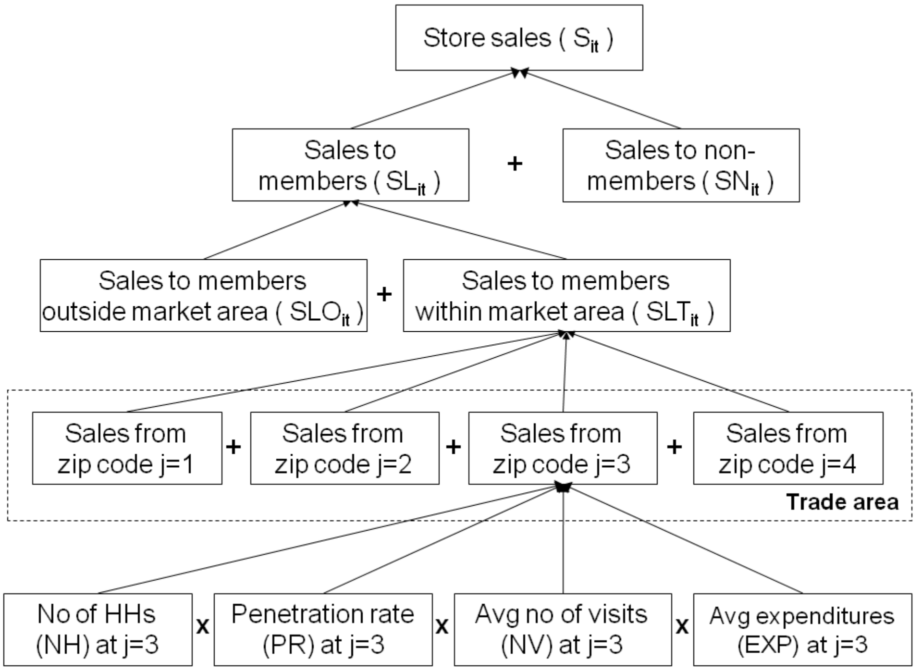


**Figure 3.2: Decomposition framework for store sales.**

Even though members may be responsible for a large proportion of total sales (Singh, Hansen, and Blattberg 2006; Van Heerde and Bijmolt 2005), their spatial distribution does not necessarily coincide with the store's trade area. That is, the primary and secondary zones contain many loyalty program members but not all of them. Therefore, we further decompose sales to members into those sales to members living inside the store's trade area and those to members living outside the trade area, such that

$$SL_{it} = SLO_{it} + SLT_{it}, \tag{3.2}$$

where $SLO_{it}$ is sales to members living outside the trade area of store $i$ at time $t$ and $SLT_{it}$ is sales to members living within the trade area of store $i$ at time $t$. We illustrate both decompositions in Figure 3.2.

### *3.3.2 Components of Store Sales*

The second stage of the store location evaluation process (Figure 3.1) pertains to assessing the impact of store, competitor, and consumer characteristics. The viability of a store depends largely on its capability to satisfy the needs of consumers who live within the trade area. Successful retailers have information about the sociodemographic profiles of consumers who live in the trade areas of their stores and develop strategies to influence responses to the store's marketing activities (Campo et al. 2000; Campo and Gijsbrechts 2004; Hoch et al. 1995; Montgomery 1997; Mulhern 1997). Therefore, store location evaluation models should determine the impact of (changes in) trade area demographics on components of store sales and capture these effects over both space and time.

To obtain detailed insights into the drivers of store sales, we decompose sales into different components and allow the explanatory variables to possess different parameters across these components. From the customer database, we can obtain measures of the membership rate, visit frequency, and average amount spent per visit for each zip code. Thus, sales to loyalty program members living in the trade area of store $i$ at time $t$ can be modeled as follows (see also Figure 3.2):

$$SLT_{it} = \sum_{j=1}^{J_{it}} SL_{ijt} \equiv \sum_{j=1}^{J_{it}} NH_{jt} \times PR_{jt} \times NV_{ijt} \times EXP_{ijt}, \tag{3.3}$$

where $j$ refers to zip codes ($j = 1,\dots,J_{it}$, where $J_{it}$ is the number of zip codes belonging to the trade area of store $i$ at time $t$), $SL_{ijt}$ is sales to members of store $i$ living in zip code $j$ at time $t$, $NH_{jt}$ is the number of households living in zip code $j$ at time $t$, $PR_{jt}$ is the penetration rate of the loyalty card in zip code $j$ at time $t$, $NV_{ijt}$ is the average number of visits to store $i$ at time $t$ among members living in zip code $j$, and $EXP_{ijt}$ is the average expenditures per visit of members from zip code $j$ at store $i$ during time $t$.

In summary, we decompose sales into six variables: $SN_{it}$, $SLO_{it}$, $NH_{jt}$, $PR_{jt}$, $NV_{ijt}$, and $EXP_{ijt}$. The number of households living in a particular zip code, $NH_{jt}$, may be treated as an exogenous variable, but we model the other five sales components as functions of store, competitor, and consumer characteristics. In addition, we model the trade area perimeter ($TAP_{it}$) and the number of competitors ($NC_{it}$).

### *3.3.3 Drivers of Store Sales*

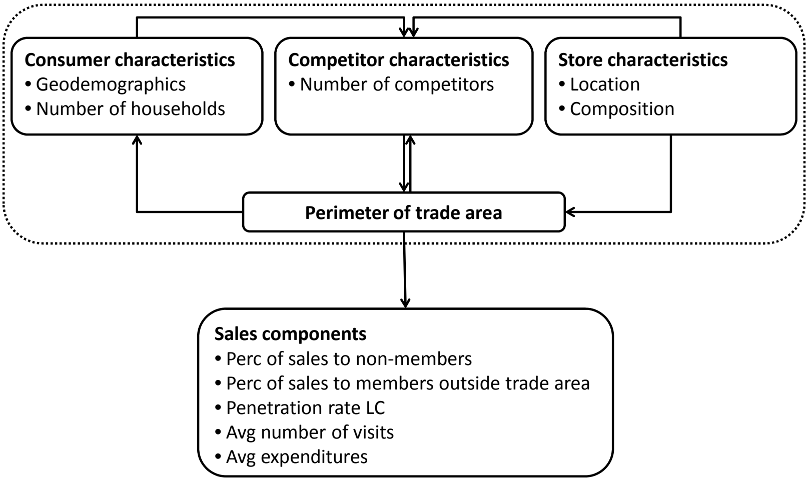


**Figure 3.3: Conceptual model of potential drivers of store sales.**

Following extant literature, we employ both store and trade area (i.e., consumer and competitor) characteristics to explain store sales components, as illustrated in Figure 3.3.

Many studies document possible relationships between consumer demographics and various components of store sales (e.g., Kumar and Karande

2000; Pan and Zinkhan 2006; Reinartz and Kumar 1999), but no consensus exists about how consumer demographic variables may relate to store sales. Reinartz and Kumar (1999) find that the number of households living in the store's trade area has the largest impact on store performance, followed by store attractiveness and socioeconomic status. The theory of time allocation between different activities, as used by Hoch and colleagues (1995) and Kumar and Karande (2000), suggests that store performance relies, among other things, on household income and size. Because high-income households have higher opportunity costs for their time, they tend to visit stores less frequently but spend more per visit. Pan and Zinkhan (2006) indicate that consumer demographics have the greatest impact on visit frequency, whereas product and market-relevant factors have more influence on store choice. Specifically, gender represents an important predictor of visit frequency, whereas store characteristics (e.g., service quality, store atmosphere) and product attributes (e.g., product selection, quality) determine store choice.

With respect to competitor characteristics, Singh and colleagues (2006) find that the entrance of a large competitor has a significant effect on the number of visits of loyalty program members to an incumbent store, though the residence location of customers appears to moderate this effect. Moreover customer locations, as Allaway and colleagues (2003) show, influence a customer's likelihood of adopting a new loyalty program, according to distance from the store. The number of nearby adopters at a particular location also influences the decision to join a new program. Thomadsen (2007) shows that locations with a large number of people matching the firm's target customer profile typically attract a large number of competitors as well. Finally, Seim (2006) finds that undifferentiated firms avoid direct competition by locating their stores far from those of competitors.

The results of these studies imply that the impact of environmental changes vary across different components of store performance. Therefore, we next model the components of store sales ($SN_{it}$, $SLO_{it}$, $PR_{jt}$, $NV_{ijt}$, and $EXP_{ijt}$), as well as the trade area perimeter ($TAP_{it}$) and the number of competitors ($NC_{it}$), as a function of store and trade area characteristics and allow the coefficients of explanatory variables to differ across the components. We first present model specifications of variables explained at the zip code level and then at the store level.

### *3.3.4 Specification of Zip Code-Level Models*

To explain the average number of visits, $NV_{ijt}$, and the average expenditures per visit, $EXP_{ijt}$, we use a hierarchical random effects model, because we have data at two levels. Zip codes, which we call level 1 units, group within the trade areas of stores, which are the level 2 units. Consequently, each store has its own intercept, which is the sum of a general mean ($\gamma^{NV}$) for all stores and a normally distributed error term with zero mean, $E\left(\nu_i^{NV}\right) = 0$, and constant variance, $Var\left(\nu_i^{NV}\right) = \phi_{NV}^2$. The set of explanatory variables includes variables observed at the store level ($X$) and zip code level ($Z$). The $X$ variables are indexed by $i$ (store), $t$ (time), and $k$ ($k = 1, \ldots, K$) to denote their index within the total number of explanatory variables. The $Z$ variables are indexed by $j$ (zip code) too, while k is replaced by $n$ ($n = 1, \ldots, N$). We take the natural logarithm ($ln$) of both store performance variables, because they are bounded by zero and skewed to the right. The model for $NV_{ijt}$ therefore can be written as:

$$
\begin{aligned}
ln\left(NV_{ijt}\right) &= \gamma_i^{NV} + \sum_{k=1}^{K} \alpha_k^{NV} X_{itk} + \sum_{n=1}^{N} \beta_n^{NV} Z_{ijtn} + \varepsilon_{ijt}^{NV}, \\
\gamma_i^{NV} &= \gamma^{NV} + \nu_i^{NV}.
\end{aligned} \tag{3.4}
$$

If we substitute $EXP_{ijt}$ for $NV_{ijt}$, we obtain the model for the average expenditures per visit.

As we noted in the Introduction section, customers from different zip codes who live in close proximity may share the same unobservable characteristics. To deal with such spatial dependence, we must extend the model. We turn to a well-known model in spatial econometrics literature that corrects for spatial dependence with a first-order spatial autoregressive process that generates the error terms

$$\varepsilon_{it}^{NV} = \lambda^{NV} W_{it} \varepsilon_{it}^{NV} + \xi_{it}^{NV}, \tag{3.5}$$

where $\varepsilon_{it}^{NV}$ and $\xi_{it}^{NV}$ are written in vector form for each cross-section of zip codes ($j = 1, \ldots, J_{it}$) in the trade area of store $i$ at time $t$, such that $E\left(\xi_{ijt}^{NV}\right) = 0$ and $Var\left(\xi_{ijt}^{NV}\right) = \sigma_{NV}^2 I_{J_{it}}$ (Anselin 1988). In addition, $W_{it}$ is a $\left(J_{it} \times J_{it}\right)$ non-negative matrix with zeros on the diagonal that describes the spatial arrangement of the zip codes within the trade area of store $i$ at time $t$. Specifically, each zip code $j$ appears as both a row and a column in $W_{it}$, and the weights $w_{jj'}$ indicate the relation between zip codes $j$ and $j'$. The weights are based on first-order contiguity, meaning that they are set to 1 when zip codes share a common border and 0 otherwise, and row standardized, such that $w_{jj'}^s = w_{jj'} / \sum_{j'} w_{jj'}$ if $j$ and $j'$ are direct neighbors and 0 otherwise. The spatial econometrics literature points out that empirical findings might depend on the operationalization of the spatial weights matrix (Anselin 2002; Leenders 2002; Pace and LeSage 2004). We use first-order contiguity weights matrices, because Stakhovych and Bijmolt (2009) show that these models perform better than those that employ other weights matrix specifications. Finally, $\lambda^{NV}$ is the spatial autocorrelation coefficient, assumed to be fixed. We provide an explanation of how to estimate the parameters of this model in the first part of Appendix A.

Next we specify a model for the penetration rate of the loyalty program, $PR_{jt}$, which is defined as the ratio between the number of loyalty card holders and the number of households in a particular zip code. Even though loyalty cards may be issued at different stores, a loyalty card adopted by a customer is valid for all outlets of the chain. We cannot allocate loyalty program members in a zip code to a particular store, so we lack the hierarchical structure in the data that we attain for visit frequency and average expenditures. We therefore model the penetration rate at the chain level rather than the store level and explain loyalty card penetration for the whole region in which the chain operates, not only the zip codes belonging to the stores' trade areas. The model also includes a random intercept at the zip code level rather than at the store level. We measure the store-specific explanatory variables so that they refer to the nearest store. By applying a logit transformation to the loyalty card penetration rate, we ensure that this performance variable follows a normal distribution by approximation. In summary, the model for the penetration rate can be written as follows:

$$\begin{aligned} logit(PR_{jt}) &= \gamma_j^{PR} + \sum_{k=1}^{K} \alpha_k^{PR} X_{jtk} + \sum_{n=1}^{N} \beta_n^{PR} Z_{jtn} + \varepsilon_{jt}^{PR}, \\ \gamma_j^{PR} &= \gamma^{PR} + \nu_j^{PR}, \end{aligned} \tag{3.6}$$

where $E\left(\nu_j^{PR}\right) = 0$ and $Var\left(\nu_j^{PR}\right) = \sigma_\nu^2$. If the observations are stacked in a vector for each cross-section of zip codes at time $t$ $\left(j = 1,\ldots,J\right)$, we take spatial error autocorrelation into account with:

$$\varepsilon_t^{PR} = \lambda^{PR} W \varepsilon_t^{PR} + \xi_t^{PR}, \tag{3.7}$$

where $E\left(\xi_t^{PR}\right) = 0$, $Var\left(\xi_t^{PR}\right) = \sigma_{PR}^2 I_J$, $W$ is a row-standardized first-order contiguity weight matrix of size $\left(J \times J\right)$ that describes the spatial arrangement of zip codes, and $J$ is the total number of zip codes within the country. We explain how to estimate the parameters of this model in the second part of Appendix A.

Finally, it is likely that a zip code that has high unobserved variables for one sales component also has them for another. As a result, the disturbance terms for the sales components will not be independent. The seemingly unrelated regressions (SUR) model allows for correlation among the error terms of a set of model equations. However, if all equations have the same explanatory variables, as is the case for the model equations estimated at zip code level, then estimating each equation separately yields identical results as estimating all equations simultaneously (Greene 2003).

### *3.3.5 Specification of Store-Level Models*

The percentage of sales to nonmembers $\left(SN_{it} / S_{it}\right)$, the percentage of sales to members living outside the store's trade area $\left(SLO_{it} / SL_{it}\right)$, the trade area perimeter ($TAP_{it}$), and the number of competitors ($NC_{it}$) can be explained using an ordinary random effects model at the store level. We take the logit of the first two variables and the natural logarithm of the last two variables to ensure that they follow a normal distribution by approximation. The model for the first variable can be written as:

$$
\begin{aligned}
logit\left(\frac{SN_{it}}{S_{it}}\right) &= \gamma_i^{SN} + \sum_{q=1}^{Q} \alpha_q^{SN} X_{itq} + \sum_{n=1}^{N} \beta_n^{SN} \overline{Z}_{itn} + \varepsilon_{it}^{SN}, \\
\gamma_i^{SN} &= \gamma^{SN} + \nu_i^{SN},
\end{aligned}
\tag{3.8}
$$

in which the $\overline{Z}_{itn}$ variables are the averages for each zip code-level variable $Z_{ijtn}$ for all zip codes belonging to the store's trade area in a particular time period. Furthermore, $E\left(\nu_i^{SN}\right) = 0$, $Var\left(\nu_i^{SN}\right) = \eta_{SN}^2$, $E\left(\varepsilon_{it}^{SN}\right) = 0$, and $Var\left(\varepsilon_{it}^{SN}\right) = \sigma_{SN}^2$. If we replace $\left(SN_{it} / S_{it}\right)$ by $\left(SLO_{it} / SL_{it}\right)$ and logit$\left(SN_{it} / S_{it}\right)$ by log($TAP_{it}$) and log($NC_{it}$), we obtain the model for the other variables.

Just as in the previous section, it is likely that a store that has high unobserved variables for one sales component has them for another, as a result of which the disturbance terms for the sales components will not be independent. The SUR model allows for correlation among the error terms of a set of model equations. Because the equations estimated at the store level will have different sets of explanatory variables, estimating each equation separately does not yield identical results as estimating all equations simultaneously. We therefore adopt the estimation procedure spelled out in Magnus (1982). However, generalized least squares (GLS) offers no improvement in efficiency if the variables in one equation are a subset of those in another block of equations (Greene 2003). This warning applies to the model for the number of competitors in a particular area, which shares all variables with the other store model equations.

### *3.3.6 Prediction in Spatial Random Effects Model*

An important element of store location evaluation involves predicting sales, which constitutes the third stage of our store location evaluation process (Figure 3.1). In this section, we discuss the properties of prediction in random effects models with spatial autocorrelation. Baltagi and Li (2004) provide more information on prediction in spatial models based on panel data.

Goldberger (1962) shows that for the error variance–covariance matrix $\Psi$, the best linear unbiased predictor (BLUP) for the $j$th area at a future period $T+C$ is given by:

$$\hat{y}_{j,T+C} = U'_{j,T+C}\hat{\theta}_{GLS} + \psi'\Psi^{-1}\hat{\varepsilon}_{GLS}, \tag{3.9}$$

where $\psi = E\left(\varepsilon_{j,T+C}\varepsilon\right)$ is the covariance between the future disturbance $\varepsilon_{j,T+C}$ and the sample disturbances $\varepsilon$, $U'$ covers the explanatory variables of the model, $\theta_{GLS}$ corresponds to the GLS estimator of $\theta$, and $\hat{\varepsilon}_{GLS}$ denotes the corresponding GLS residual vector.

The inverse of the variance–covariance matrix of the ordinary random effects model, such as in Equation (3.8), is:

$$\Psi_{RE}^{-1}=\frac{\sigma_{SN}^{2}}{T\eta_{SN}^{2}+\sigma_{SN}^{2}}\left(\frac{1}{T}\iota_T\iota_T^{'}\otimes I_I\right)+\left(I_T-\frac{1}{T}\iota_T\iota_T^{'}\right)\otimes I_I, \tag{3.10}$$

where $\iota_T$ is a vector of dimension $T$, and $I_I$ is an identity matrix of dimension $I$. If the observations are stacked in a vector for each cross-section of stores $(i=1,\ldots,I)$, the corresponding BLUP correction term is (Baltagi and Li 2004):

$$\psi^{'}\Psi_{RE}^{-1}\hat{\varepsilon}_{GLS}=\frac{T\eta_{SN}^{2}}{T\eta_{SN}^{2}+\sigma_{SN}^{2}}\frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{t,GLS}. \tag{3.11}$$

In words, we first average the residuals of each store over the sample period and then multiply them by a factor that can take values between 0 and 1. We combine this term with Equation (3.8) and thereby predict the percentage of sales to nonmembers at the store level. An equivalent procedure predicts the percentage of sales to members living outside the store's trade area, the trade area perimeter, and the number of competitors.

For a random effects model with spatial autocorrelation, such as in Equation (3.6), Baltagi and Li (2004) demonstrate that the BLUP correction term for each cross-section of zip codes ( $j=1,\ldots,J$ ) is:

$$\frac{\sigma_{\nu}^{2}}{\sigma_{PR}^{2}}V^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_{t,GLS}, \tag{3.12}$$

where $V=T\dfrac{\sigma_{\nu}^{2}}{\sigma_{PR}^{2}}I_J+\left(\left(I_J-\lambda^{PR}W\right)^{'}\left(I_J-\lambda^{PR}W\right)\right)^{-1}$. In other words, the BLUP correction term to $U_{j,T+C}^{'}\hat{\theta}_{GLS}$ is a weighted average of the GLS residuals for the $J$ zip codes. The weights depend not only on $(1/T)$ but also on the spatial weight matrix $W$ and the spatial autocorrelation coefficient $\lambda^{PR}$. We combine this formula with Equation (3.6) and thereby predict the penetration rate of the loyalty card at the zip code level.

For a hierarchical random effects model with spatial autocorrelation, such as in Equation (3.4), one may use the BLUP correction term of a random effects model in combination with the Kelejian and Prucha (2007) correction for spatially autocorrelated errors. For a cross-section of zip codes ( $j = 1,..., J_{it}$ ) of a particular store i ( $i = 1,\ldots, I$ ) this takes the form

$$\frac{\tilde{T}_i \phi_{NV}^2}{\tilde{T}_i \phi_{NV}^2 + \sigma_{NV}^2} \frac{1}{\tilde{T}_i} \sum_{t=1}^{T} \sum_{j=1}^{J_{it}} \hat{\varepsilon}_{ijt,GLS}^{NV} + \lambda^{NV} \frac{1}{T} \sum_{t=1}^{T} W_{it} \hat{\varepsilon}_{it,GLS}^{NV}, \tag{3.13}$$

where $\tilde{T}_i = \sum_t J_{it}$ .[2]

When taking the exponent of the log number of visits, the log expenditures per visit, the log trade area perimeter, and the log number of competitors, we obtain biased predicted values due to Jensen's Inequality. That is, the error term when $\ln(\hat{y})$ gets transformed into $\hat{y}$ will follow a log-normal instead of a normal distribution, which has a mean greater than 0. Therefore, the detransformed predictor systematically underestimates the true values of $\hat{y}$. A remedy suggested by Miller (1984) takes the following form for the random effects model of the log perimeter of the trade area:

$$\hat{E}(y \mid U) = e^{U' \theta_{GLS} + \text{BLUP correction}} e^{1/2\left(\sigma_{TAP}^2 + \eta_{TAP}^2\right)}, \tag{3.14}$$

A similar procedure applies to *NV*, *EXP*, and *NC*. The antilogit of the predicted values of the penetration rate, percentage of sales to nonmembers, and percentage of sales to members living outside the store's trade area are not biased, because the transformation achieves a mean of 0.

Finally, when new stores open, the BLUP correction terms are set to 0, because the error terms on which they depend cannot be observed. To assess the quality of the prediction, we follow Verbeek (2000) and define the $R^2$ for panel data applications in terms of the squared correlation coefficient between actual and fitted values, instead of using the usual $R^2$ in terms of the sums of squares.

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[2] Alternative forms but without spatial error correlation are discussed in Frees (2004). Kelejian and Prucha (2007) consider predictors based on cross-sectional data. We adopt its space-time counterpart. The advantage is that this correction term does not involve observations at T+C, as a result of which it is feasible.

## 3.4 An Empirical Analysis

We structure this section around potential applications of the proposed store evaluation model. Specifically, after discussing the empirical data in section 3.4.1, we analyse the determinants of the trade area perimeter and the number of competitors of a particular store in section 3.4.2. Next, we examine the impact of store, competitor, and consumer characteristics on store sales in section 3.4.3. Because the second goal of our model is to evaluate the performance of stores, we discuss this point in section 3.4.4. Finally, section 3.4.5 deals with answering "what-if" questions, such as determining the effect on total sales if we were to change the relative sizes of certain departments of the store.

### *3.4.1 Empirical Setting*

We use data from 28 Dutch clothing stores that belong to a single chain to test our conceptual framework and methodological model in an empirical setting. The stores offer a medium-quality assortment and are mostly located in medium-sized towns. The company's loyalty program attempts to strengthen its relationship with customers. Those who participate in the loyalty program obtain a 5% cash reward on every purchase, which is credited to their loyalty card and can be spent two times a year.

The customer database contains personal data in addition to purchase data. We use the addresses of members to overlay several sociodemographic variables for the zip code in which each address appears. In addition, we supplement these data with information from a chain-wide survey of outlet managers that provides, for each store, information about the store itself and the competitive environment.

We use information gathered from store managers to identify (direct) competitors, who can be defined as clothing stores targeting the same customer segment. For the store characteristics, we include store size (in 10,000 $m^2$), the relative size of the various departments (women's, men's, and children's assortments), the number of months the store is open in a particular year, and the year of establishment of that particular outlet (1932 = 0). Unfortunately, the data base does not contain information about marketing variables such as price and quantity, but the lack of these variables is not a severe limitation of the model. First, these variables do not differ to a great extent among the stores, because outlet managers must follow the marketing activities dictated by the head office. Second, we study yearly data, whereas marketing mix variables generally exhibit most of their variance and effects at a much shorter temporal rate. We do account for the effect of assortment composition of the store, which is a key strategic variable for retailers. Finally, to the extent that they are spatially correlated across zip codes, the marketing activities of the chain and its competitors are covered by the spatially autocorrelated disturbance terms.

We have data from a period of five years, 2002–2006, of which we use the first four years for estimation and the last year for validation. Withholding the last year for validation enables us to verify whether the results apply to a new time period. In addition, the chain opened two new stores in 2006, so we can assess whether the results apply to new stores as well by comparing their actual sales figures with the model predictions.

To determine the geographical extent of markets, we first sort all zip codes in descending order of travel distance to the stores and then selecting, for each store and each year, the (first) zip codes responsible for 85% of total sales (we also consider 75% and 95% of total sales). For these zip codes, we determine the perimeter of the trade area according to the maximum travel distance to the store. Travel distance to the store is hereby defined as the shortest time distance (in miles) a car can travel from (the centroid of) a four-digit zip code to the store under consideration. Next, we model the perimeter of store trade areas using an ordinary random effects model as a function of store and competitor characteristics based on 102 (24 stores in 2002 + 26 stores × 3 years) observations. Even if a store does not exist yet, we can use the estimated coefficients to predict the (potential) extent of its trade area at a particular point in time by including all zip codes that reside closer to the store than the predicted trade area perimeter. In this way we obtain an endogenously determined trade area perimeter for each store. The number of zip codes belonging to a store's trade area varies across stores: from 44 to 307, with an average of 110 zip codes.[3] We explain the loyalty card penetration for all zip codes in the Netherlands (N = 4008) in four successive years (2002–2005), which is how we obtain 16,032 (4008 zip codes × 4 years) observations. Since the number of zip codes belonging to one of the trade areas is smaller than 4008, the number of observations on the number of visits is 11,140 and the expenditures per visit 9,884. The latter number is lower than the former, because the number of visits in some zip codes equals zero.

The average perimeter of a store's trade area is 15 miles and the high standard deviation in the third column of Table 3.1 indicates substantial variation in trade area sizes. Table 3.1 also shows that, on average, nonmembers account for 27 percent of store sales. The number of competitors is large, ranging from 22 to 78 across stores. We also see that approximately 10% of the households in the zip codes belonging to a store's trade area have a loyalty card, that they, on average, visit the store once every two years, and that the average cardholder spends €66 per visit (Table 3.2).

[3] The trade areas of stores show little overlap. Only about 15 percent of the zip codes in the Netherlands belong to two or more trade areas, with a maximum of four. To test whether the results were affected by trade area overlap, we included a dummy variable that indicates whether a zip code is assigned to one (0) or multiple stores (1) in the models for visit frequency and average expenditures per visit. In neither of these models, this dummy is significant.

**Table 3.1: Descriptive statistics of models estimated at the store level**

| **Variable** | **Mean** | **St.dev** |
|---|---|---|
| *Dependent variables* | | |
| Trade area perimeter (in miles) | 15.86 | 5.54 |
| % Unscanned sales | 0.27 | 0.09 |
| % Outside trade area | 0.15 | 0.06 |
| Number of competitors | 42.30 | 12.64 |
| *Store characteristics* | | |
| Size (in 10,000 $m^2$) | 0.07 | 0.01 |
| % female assortment | 0.44 | 0.05 |
| % children's assortment | 0.20 | 0.05 |
| Proportion of the year the store is open (in months) | 0.99 | 0.07 |
| Year of establishment (/100) | 0.23 | 0.10 |
| Distance to the nearest store (in miles) | 19.55 | 8.85 |
| *Competitor characteristics* | | |
| Number of competitors (/100) | 0.42 | 0.13 |
| *Consumer characteristics* | | |
| Population size (/100,000) | 0.80 | 0.40 |
| % households with children | 0.43 | 0.04 |
| % couples without children | 0.39 | 0.02 |
| % households with high SES | 0.21 | 0.01 |
| % households with above-average SES | 0.08 | 0.02 |
| % households with average SES | 0.32 | 0.03 |
| % households with low SES | 0.42 | 0.04 |
| % of double-income families | 0.14 | 0.02 |
| Average number of low-educated | 0.34 | 0.10 |
| > average number of low-educated | 0.47 | 0.19 |
| Average number of middle-educated | 0.78 | 0.08 |
| > average number of middle-educated | 0.10 | 0.06 |
| Average number of high-educated | 0.31 | 0.08 |
| > average number of high-educated | 0.22 | 0.12 |
| Time trend | 2.53 | 1.11 |
| Number of observations | 102 | |

**Table 3.2: Descriptive statistics of models estimated at the zip code level**

| | Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| | **Loyalty card penetration** | | **Visits** | | **Expenditures** | |
| | **Mean** | **St.dev** | **Mean** | **St.dev** | **Mean** | **St.dev** |
| *Dependent variables* | | | | | | |
| Loyalty card penetration | 0.10 | 0.13 | | | | |
| Visits | | | 0.40 | 0.44 | | |
| Expenditures | | | | | 66.33 | 29.90 |
| *Store characteristics* | | | | | | |
| Size (in 10,000 $m^2$) | 0.08 | 0.01 | 0.07 | 0.01 | 0.07 | 0.01 |
| % female assortment | 0.42 | 0.04 | 0.43 | 0.04 | 0.43 | 0.04 |
| % children's assortment | 0.20 | 0.04 | 0.20 | 0.04 | 0.20 | 0.05 |
| Proportion of the year the store is open (in months) | 0.99 | 0.05 | 1.00 | 0.05 | 1.00 | 0.05 |
| Year of establishment (/100) | 0.55 | 0.09 | 0.21 | 0.09 | 0.21 | 0.09 |
| *Competitor characteristics* | | | | | | |
| Number of competitors (/100) | 0.40 | 0.13 | 0.44 | 0.13 | 0.45 | 0.13 |
| *Consumer characteristics* | | | | | | |
| Distance to the store (in miles) | 21.93 | 6.14 | 11.85 | 6.14 | 11.23 | 5.94 |
| Distance to next-nearest store (in miles) | 31.63 | 18.87 | 25.72 | 18.87 | 26.21 | 19.38 |
| % households with children | 0.43 | 0.12 | 0.43 | 0.12 | 0.43 | 0.11 |
| % couples without children | 0.38 | 0.09 | 0.39 | 0.09 | 0.39 | 0.08 |
| % households with high SES | 0.08 | 0.13 | 0.08 | 0.13 | 0.08 | 0.11 |
| % households with above-average SES | 0.32 | 0.19 | 0.32 | 0.19 | 0.32 | 0.18 |
| % households with average SES | 0.42 | 0.20 | 0.42 | 0.20 | 0.42 | 0.18 |
| % households with low SES | 0.14 | 0.13 | 0.14 | 0.13 | 0.14 | 0.12 |
| % of double-income families | 0.21 | 0.05 | 0.21 | 0.05 | 0.21 | 0.05 |
| Average number of low-educated | 0.32 | NA | 0.34 | NA | 0.34 | NA |
| > average number of low-educated | 0.47 | NA | 0.46 | NA | 0.47 | NA |
| Average number of middle-educated | 0.74 | NA | 0.76 | NA | 0.78 | NA |
| > average number of middle-educated | 0.10 | NA | 0.10 | NA | 0.10 | NA |
| Average number of high-educated | 0.31 | NA | 0.31 | NA | 0.32 | NA |
| > average number of high-educated | 0.24 | NA | 0.24 | NA | 0.22 | NA |
| Time trend | 2.50 | 1.11 | 2.54 | 1.11 | 2.53 | 1.11 |
| Number of observations | 16,032 | | 11,140 | | 9,884 | |

### *3.4.2 Trade Area Sizes and Competition*

We test for random store effects in the model that explains the size of store trade areas. The resulting test statistic of 16.04 is highly significant under a $\chi^2(1)$ distribution ($p < 0.001$), which allows us to reject the null hypothesis of $\eta^2 = 0$. We therefore conclude that (random) store effects should appear in the model. In the first column of Table 3.3, we provide parameter estimates for this model. We find that many store characteristics do not have a significant impact on trade area boundaries apart from a store's size, which positively affects the extent of its trade area. This finding is consistent with Reilly's law of retail gravitation, which states that consumers are willing to travel farther to visit larger stores (McGoldrick 1990).

As we show in the last column of Table 3.3, the level of competition in a particular area is positively related to the number of people living there. Attractive locations, with large populations and therefore high potential demand, not only attract the focal firm but also appeal to its competitors. However, location attractiveness depends on more than the number of potential customers; the nature of these consumers may be just as important (Duan and Mela 2009). For example, the results in Table 3.3 show a positive relation between the number of middle-educated inhabiting the store trade area and the number of competitors, which suggests that this group matches the chain's target customer profile.

### *3.4.3 Drivers of Store Performance: Estimation Results*

We used Lagrange multiplier (LM) tests for the panel data regression models to test for potential misspecifications of the proposed models. In particular, we employ the LM test derived by Baltagi and colleagues (2003) to check for spatial error correlation and the presence of random effects in the penetration rate model. The resultant test statistic of 8,909 is highly significant under a $\chi^2(2)$ distribution

($p < 0.001$). Therefore, we reject the null hypothesis that $\lambda = \sigma_\nu^2 = 0$. For the hierarchical random effects model with spatial autocorrelation, we derive the LM test statistic numerically and find that $\phi^2$ and $\lambda$ are significantly different from 0 for both the average expenditures and the average number of visits (all p-values < 0.05). We also test for $\eta^2 = 0$ in the ordinary random intercept models for the percentage of sales from outside the trade area (LM = 4.86; $p < 0.05$) and the percentage of sales to nonmembers (LM = 4.88; $p < 0.05$), which indicates that random store effects should appear in both models (Baltagi, Chang, and Li 1992; Breusch and Pagan 1980).

In Table 3.3, we present the parameter estimates for the models estimated at the store level, explaining the trade area perimeter, the percentage of sales from outside the trade area, the percentage of sales to nonmembers, and the number of competitors.

In Table 3.4, we provide the parameter estimates for the models that explain loyalty card penetration rates, members' average number of visits, and members' expenditures per visit. Consistent with Van Heerde and Bijmolt's (2005) results, we find that the explanatory power for the average expenditures model is the lowest. Moreover, the effects of predictor variables differ considerably across criterion variables, which supports our decision to adopt a decomposition framework. For example, the distance to the store negatively affects loyalty card penetration rate and visit frequency, whereas the average expenditures per visit depend positively on travel distance.

*Store Characteristics*

The parameter estimates for the share of space reserved for women's and children's clothes suggest a gender effect for all sales components (Table 3.4). If more of the assortment consists of clothes for women and children, the loyalty card penetration rate increases. This positive relation may be caused by an increase in the number of households adopting the chain's loyalty program, because they expect to derive more economic benefits from the program if the chain offers a larger assortment (Leenheer et al. 2007). The number of visits also increases if the share of space reserved for women's and children's clothes is larger. Evidence that women visit stores more frequently than men emerges from the meta-analysis provided by Pan and Zinkhan (2006). However, if men visit the store, their expenditures are generally higher than those in the women's and children's assortments.

The results in Table 3.3 show that distance to the nearest store has a positive effect on the percentage of sales outside the store's trade area. Cannibalization among different stores thus is present (Kalnins 2004): sales to members living outside the trade area of each store decrease if two stores of the same chain are located close to each other.

*Competitor Characteristics*

The number of competitors has positive effects on the loyalty card penetration rate but no significant impact on visit frequency or expenditures. Consumers living in zip codes close to agglomerations of clothing stores, including stores in this particular chain, are more likely to become members of the loyalty program.

The percentage of sales to nonmembers is positively affected by the number of competitors. Because nonmembers are more likely to live far from the store (Allaway, Berkowitz, and D'Souza 2003; Kivetz and Simonson 2003), this positive relationship may be caused by the effect of retail agglomeration. That is, consumers are willing to drive long distances if they can reduce the risk of product unavailability and search and compare among a large set of stores. The spatial concentration of competitors makes a shopping trip more attractive, because it facilitates visits to multiple shops with different assortments during the same trip (González-Benito and González-Benito 2005).

*Consumer Characteristics*

Loyalty card penetration rates are lower among members living farther from the store (Table 3.4), which is consistent with findings by Allaway et al. (2003) and Kivetz and Simonson (2003). Furthermore, members living closer to the store visit it more frequently than do members living farther away, in line with literature on spatial interaction models, which assumes that the probability of consumers patronizing a store is inversely related to distance to the store (e.g., Huff 1964). Average expenditures appear to increase with distance to the store; that is, members living farther away buy in larger quantities, perhaps because they are more likely to travel by car (Bhatnagar and Ratchford 2004).

Loyalty card penetration rates are higher for households with children than for couples and single-person households. This outcome is consistent with the results of Leenheer and colleagues (2007), who find that consumers compare the expected benefits and costs when deciding to participate in customer loyalty programs. In this view, larger households are more likely to benefit from such programs because of their higher demand levels, which will positively affect their adoption decision. On average, households with children visit the store more frequently than do singles, consistent with the results of Roy (1994), who notes that larger households buy more often than smaller households because of their higher demand levels.

The results also indicate that cannibalization between different stores may exist (Kalnins 2004), because we find a positive effect of distance to the next-nearest store on the average number of visits. That is, consumers living within the trade area of a particular store but close to another store of the same chain may visit the other store. Average expenditures per visit also are positively affected by the distance to the next-nearest store. Yet both cannibalization effects are small compared with the influence of the other factors.

## Table 3.3: Parameter estimates of models estimated at the store level

| Explanatory Variable | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Trade Area Perimeter | | % Unscanned Sales | | % Outside Trade Area | | Number of Competitors | |
| | **Coeff** | **t-value** | **Coeff** | **t-value** | **Coeff** | **t-value** | **Coeff** | **t-value** |
| Constant | 1.292 | 2.87*** | -2.800 | -0.83 | 3.723 | 0.82 | -1.176 | -0.45 |
| *Store characteristics* | | | | | | | | |
| Size (in 10,000 $m^2$) | 16.106 | 2.77*** | -2.083 | -0.25 | -8.448 | -0.79 | | |
| % female assortment | | | -3.445 | -1.63 | -2.685 | -1.01 | | |
| % children's assortment | | | -6.114 | -2.52** | -3.539 | -1.15 | | |
| Proportion of the year the store is open (in months) | 0.012 | 0.13 | -0.515 | -2.38** | -0.123 | -0.39 | | |
| Year of establishment (/100) | -0.242 | -0.42 | 0.269 | 0.34 | 1.472 | 1.44 | | |
| Distance to the nearest store (in miles) | 0.001 | 0.26 | 0.008 | 1.30 | 0.024 | 2.86*** | -0.009 | -2.20** |
| *Competitor characteristics* | | | | | | | | |
| Number of competitors (/100) | 0.923 | 1.72 | 2.304 | 3.29*** | 1.017 | 1.12 | | |
| *Consumer characteristics* | | | | | | | | |
| Population size (/100,000) | -0.175 | -1.05 | -0.308 | -1.29 | -0.208 | -0.67 | 0.452 | 7.59*** |
| % households with children | | | 3.979 | 1.34 | -1.681 | -0.42 | 1.283 | 0.74 |
| % couples without children | | | 6.924 | 1.81 | -6.100 | -1.18 | 5.388 | 2.39** |
| % households with high SES | | | 7.227 | 1.11 | 2.164 | 0.25 | -9.531 | -3.16*** |
| % households with above-average SES | | | -3.478 | -1.19 | 0.587 | 0.14 | 1.994 | 0.70 |
| % households with average SES | | | -3.773 | -1.25 | -0.013 | -0.00 | 1.940 | 0.62 |
| % households with low SES | | | 7.889 | 2.66*** | 6.002 | 1.48 | 2.078 | 0.70 |
| % of double-income families | | | -1.959 | -0.64 | 1.156 | 0.28 | -0.188 | -0.05 |
| Average number of low-educated | | | -0.001 | -0.00 | -2.071 | -1.55 | -0.668 | -0.65 |
| > average number of low-educated | | | -0.103 | -1.26 | -2.053 | -1.73 | 0.510 | 0.58 |
| Average number of middle-educated | | | -2.927 | -3.99*** | -2.571 | -2.57** | 2.116 | 3.22*** |
| > average number of middle-educated | | | -3.636 | -4.74*** | -2.579 | -2.45** | 1.068 | 1.10 |
| Average number of high-educated | | | 0.138 | 0.25 | -0.254 | -0.34 | 0.767 | 1.68 |
| > average number of high-educated | | | -0.810 | -1.56 | -0.040 | -0.06 | 0.863 | 1.32 |
| Time trend | 0.014 | 2.84*** | -0.025 | -0.39 | -0.032 | -0.39 | 0.100 | 2.58** |
| $R^2$ | 0.38 | | 0.48 | | 0.15 | | 0.58 | |
| Number of observations | 102 | | 102 | | 102 | | 102 | |

Notes: SES = socioeconomic status; *** $p < 0.01$ ** $p < 0.05$

**Table 3.4: Parameter estimates of models estimated at the zip code level**

| **Explanatory Variable** | **Dependent Variable** | | | | | |
|---|---|---|---|---|---|---|
| | **Loyalty Card Penetration** | | **Visits** | | **Expenditures** | |
| | **Coeff** | **t-value** | **Coeff** | **t-value** | **Coeff** | **t-value** |
| Constant | -6.130 | -15.85*** | -0.803 | -2.43** | 4.890 | 5.06*** |
| *Store characteristics* | | | | | | |
| Size (in 10,000 $m^2$) | 2.236 | 2.40** | 2.964 | 1.86 | -0.252 | -0.11 |
| % female assortment | 3.938 | 6.04*** | 0.806 | 1.95 | -1.167 | -2.01** |
| % children's assortment | 5.890 | 9.39*** | 1.705 | 3.91*** | -1.402 | -2.29** |
| Proportion of the year the store is open (in months) | 0.907 | 12.45*** | 0.451 | 4.94*** | -0.144 | -1.37 |
| Year of establishment (/100) | -1.797 | -7.08*** | -0.071 | -0.45 | -0.457 | -2.05** |
| *Competitor characteristics* | | | | | | |
| Number of competitors (/100) | 1.732 | 9.52*** | -0.171 | -1.45 | 0.075 | 0.45 |
| *Consumer characteristics* | | | | | | |
| Distance to the store (in miles) | -0.103 | -60.14*** | -0.022 | -40.83*** | 0.003 | 3.00*** |
| Distance to next-nearest store (in miles) | 0.002 | 1.80 | 0.003 | 9.28*** | 0.003 | 5.17*** |
| % households with children | 0.553 | 4.52*** | 0.102 | 5.86*** | -0.013 | -0.21 |
| % couples without children | 0.295 | 2.32** | 0.018 | 0.89 | -0.025 | -0.33 |
| % households with high SES | 0.326 | 3.55*** | 0.003 | 0.18 | 0.153 | 2.34** |
| % households with above-average SES | 0.183 | 2.45** | 0.020 | 1.34 | 0.094 | 1.68 |
| % households with average SES | 0.061 | 0.87 | -0.014 | -0.97 | 0.131 | 2.31** |
| % households with low SES | -0.169 | -1.92 | -0.008 | -0.46 | -0.050 | -0.74 |
| % of double-income families | 1.205 | 6.91*** | -0.086 | -2.86*** | 0.074 | 0.68 |
| Average number of low-educated | 0.038 | 1.32 | -0.010 | -2.21** | 0.025 | 1.63 |
| > average number of low-educated | 0.109 | 3.18*** | -0.009 | -1.54 | 0.054 | 2.90*** |
| Average number of middle-educated | 0.085 | 3.86*** | 0.021 | 4.59*** | 0.044 | 2.90*** |
| > average number of middle-educated | 0.066 | 2.06** | 0.036 | 5.26*** | 0.038 | 1.64 |
| Average number of high-educated | -0.011 | -0.56 | -0.008 | -2.22** | -0.010 | -0.85 |
| > average number of high-educated | -0.130 | -4.55*** | -0.026 | -4.63*** | -0.031 | -1.76 |
| Time trend | 0.105 | 24.39*** | -0.012 | -3.41*** | -0.005 | -1.10 |
| Spatial autocorrelation coeff ( $\lambda$ ) | 0.163 | 9.04*** | 0.655 | 81.35*** | 0.082 | 5.82*** |
| $R^2$ | 0.52 | | 0.53 | | 0.04 | |
| Number of observations | 16,032 | | 11,104 | | 9,884 | |

Notes SES = socioeconomic status; *** $p < 0.01$ ** $p < 0.05$

The results in Table 3.3 show that most consumer characteristics of the trade area do not have a significant impact on the percentage of unscanned sales or the percentage of sales outside the trade area. One exception to this trend is the proportion of zip codes belonging to the store's trade area with an average or higher-than-average number of middle-educated, for which all four effects are significant (Table 3.3). These findings indicate that if the chain's target customers (i.e., middle-educated) inhabit a large part of the trade area, sales to nonmembers and members living outside the store's trade area will be lower.

*Spatial Dependence*

The three spatial autoregressive coefficients of the spatial-error random-effects models are all positive and significantly different from 0 (Table 3.4), which indicates that the error terms are spatially correlated. This means, zip codes close to one another tend to have similar values for each sales component due to unobserved similarities in consumer characteristics, preferences, and behavior. The degree of spatial autocorrelation for the number of visits is much greater than that for the penetration rate and the average expenditures per visit.

### *3.4.4 Store Performance Evaluation*

We now know the effect of each variable on each sales component, but not the total effect on sales. To evaluate the predictive power of our decomposition framework, we calculate the predicted total sales and compare the obtained values with the actual sales figures for each store in the holdout sample (all stores in 2006). For this purpose, we follow the store site evaluation process presented in Figure 3.1. We first determine the geographical boundaries of store trade areas (which assigns those zip codes that reside closer to a store than the predicted value to that store) and the number of competitors, using the coefficients reported in the first and the last column of Table 3.3. Because these two variables are mutually dependent, we solve this problem iteratively. We next use the coefficients reported in Table 3.4 to predict the three sales components (i.e., loyalty card penetration rate, visit frequency, and average expenditures per visit) for each four-digit zip code in the store's trade area. Similarly, we use the coefficients reported in Table 3.3 to derive predictions of the percentage of sales to members living outside the store's trade area and the percentage of sales to nonmembers. We obtain the predicted values for each criterion variable by adding the average BLUP correction and Kelejian and Prucha (2007) terms based on Equations (3.11)–(3.13) to Equations (3.4), (3.6), and (3.8) and applying the correct transformations. When we obtain predictions for all these components, we can calculate total sales using Equations (3.1)–(3.3). As we show in Figure 3.4 (left panel), the model predicts total sales well. The correlation coefficient between observed and predicted sales equals 0.63. This correlation coefficient decreases to 0.60 when the trade area is reduced to zip codes responsible for 75% of total sales and to 0.51 when the trade area is enlarged to zip codes responsible for 95% of total sales. In sum, we conclude that the focus on the primary and secondary zones of a store's trade area produces the best results from a forecasting point of view.

For comparison, we estimated a benchmark model that ignores spatial autocorrelation, which can be obtained by substituting $\lambda = 0$ in Equations (3.5) and (3.7). The correlation coefficient decreases to 0.32 when spatial dependence between the error terms is not taken into account (right panel).[1] As expected, on the basis of econometric theory (Anselin 1988), the parameter estimates do not change dramatically when we ignore spatial autocorrelation, but the standard errors and tests based on them are substantially influenced. We find that all but one of the parameter estimates have the same sign in the proposed model as in the benchmark model without spatial effects. Hence, accounting for spatial autocorrelation leads to better results from a substantive as well as a methodological point of view. An

[1] The tables with the corresponding estimation results are available on request.

important feature of spatial models is that they borrow information from neighboring zip codes to predict each sales component at a particular location. Predictive performance of the proposed model is therefore considerably better than a model that ignores spatial dependence between zip codes in close proximity. These findings underline the usefulness of including spatial error correlation for store location and evaluation decisions.

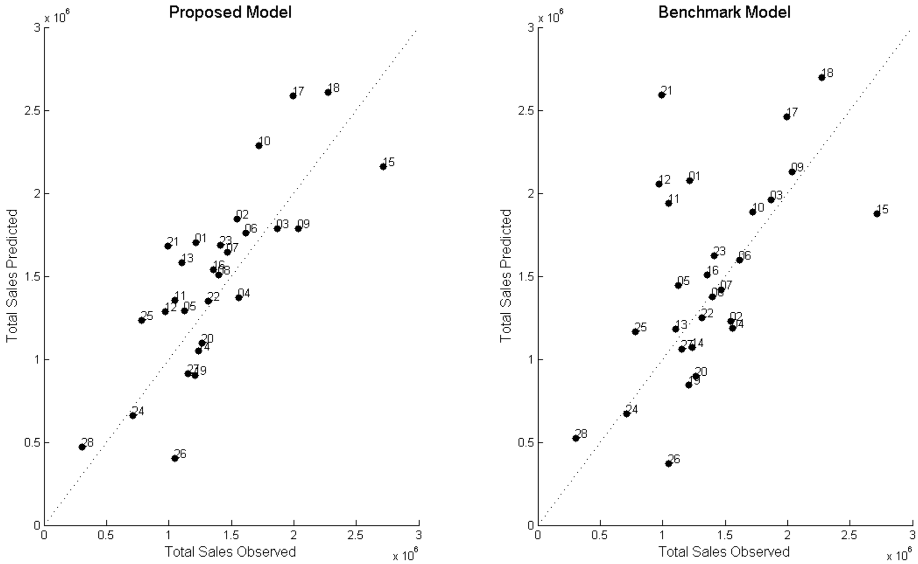


**Figure 3.4: Predictive validity of (a) the proposed model and (b) the benchmark model.** The data displayed in the scatterplots are observed and predicted values for total sales per store in 2006.

To illustrate how the retailer might use these results for store location evaluations, we use the estimated coefficients from Tables 3.3 and 3.4 to predict each sales component for two new stores (represented in Figure 3.4 by the numbers 27 and 28) and employ the obtained values to calculate their (potential) sales. These stores, opened in 2006, are similar to the existing stores. From Figure 3.4, we note that the decomposition framework predicts total sales for these stores quite well. Although the realized sales figures differ somewhat from the predicted figures, the model predictions are on the same order of magnitude as the observed values. The actual sales level of store 28 (€306,187), for example, is among the lowest of all stores; the same holds true for the predicted sales (€481,117). Similar conclusions apply to store 27 (€1,153,110), which belongs to a larger group of stores with average sales levels and is classified accordingly by the predicted sales figures (€929,543). Actually, predictions for all sales components, including the percentages of sales to nonmembers and members living outside the trade area, are close to the observed values. These results indicate that our modeling approach offers retailers an extremely useful tool for store location evaluation. Retailers that consider various candidate locations may want to use our proposed model to obtain estimates of potential sales for each site, which they then can employ to evaluate their entry decisions better.

By comparing the predicted and observed sales figures for each four-digit zip code, the retailer also can identify areas in which it can improve store performance. Our model predicts three sales components (i.e., loyalty card penetration rate, visit frequency, and average expenditures per visit) for each zip code in the store's trade area. Using the predicted values for each sales component, we calculate total sales to loyalty card holders (hereafter, total scanned sales) for each zip code and compare these values to the realized sales figures. We depict the results in Figure 3.5 by plotting the predicted values for each sales component and the total scanned sales for the trade area of store 27 (Figure 3.5a-d). Because the retailer also may want to know whether the store is currently over- or underperforming in certain areas, we plot the difference between the observed and predicted values for each sales component in Figure 3.5e-h. The colors of the zip codes represent predicted values for each sales component (Figure 3.5a-d) and the differences between observed and predicted values (Figure 3.5e-h). We represent the store itself by a black dot.

From Figure 3.5a, we see that, in general, the loyalty card penetration rate relates negatively to distance to the store, apart from the northeastern part of the trade area in which a large city is located and where the number of loyalty card holders is substantially lower than in other zip codes at similar distances to the store. Visit frequency also decreases with distance to the store (Figure 3.5b), meaning that loyalty card holders living closer to the store visit it more often than do those living farther away. However, average expenditures per visit increase with distance to the store (Figure 3.5c), likely because members who live farther away buy in larger quantities and are more likely to travel by car. This finding holds true for the largest part of the trade area but, again, not for the northeastern part of the market, for which we predict relatively low expenditures per visit. From Figure 3.5d, we note that if any relationship exists between total scanned sales and travel distance, it tends to be negative, which indicates that the negative relationships between the loyalty card penetration rate and visit frequency and distance dominate the positive relationship between average expenditures and travel distance.

To determine if there is room for improvement at certain locations, we plot the difference between the observed and predicted values in Figure 3.5e–h. For a retailer, it is useful to know whether scanned sales in certain areas are lower than predicted and whether this difference is due to the number of loyalty card holders, the number of visits, or the expenditures per visit. From Figure 3.5e, we determine that loyalty card penetration is lower than predicted in a large part of the trade area; therefore, the retailer should try to enhance the number of loyalty card holders by, for example, mailing a door-to-door flyer that informs consumers about the advantages of the store and its loyalty program. The number of visits falls short of the predicted values mainly in the outer parts of the trade area (Figure 3.5f). To increase the number of times existing loyalty card holders visit the store, the retailer may want to reward existing customers according to the number of times they visit the store. The spatial pattern for the average expenditures per visit indicates, as we show in Figure 3.5g, that zip codes differ substantially in the extent to which they over- or underperform. In general, the difference between the observed and predicted values tends to increase in zip codes located farther away from the store, but in these areas, the variation in prediction errors is higher as well. In Figure 3.5h, we indicate the differences in observed and predicted values for total scanned sales. Scanned sales are lower than predicted mainly in some zip codes to the west of the store and in the outer parts of the trade area. The outlet manager could investigate the local situation further by, for example, conducting a customer survey. Combined with the model results, which help explain the causes for the (negative) differences in sales, the manager could use information from the survey to develop marketing strategies specifically for certain store locations or even certain zip codes.

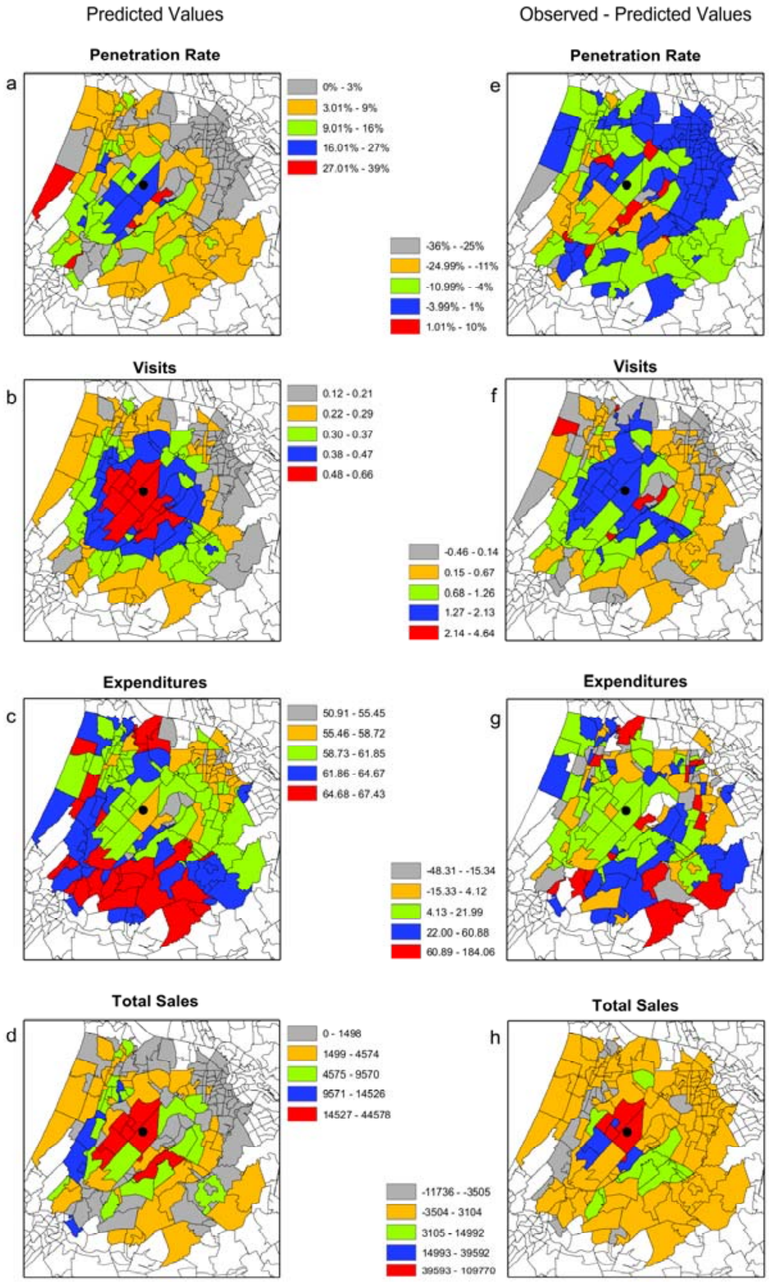


**Figure 3.5: (a-d) Predicted sales components for each zip code in the store's trade area. (e-h) Differences between observed and predicted sales components for each zip code in the store's trade area.**

### 3.4.5 Scenario Analysis

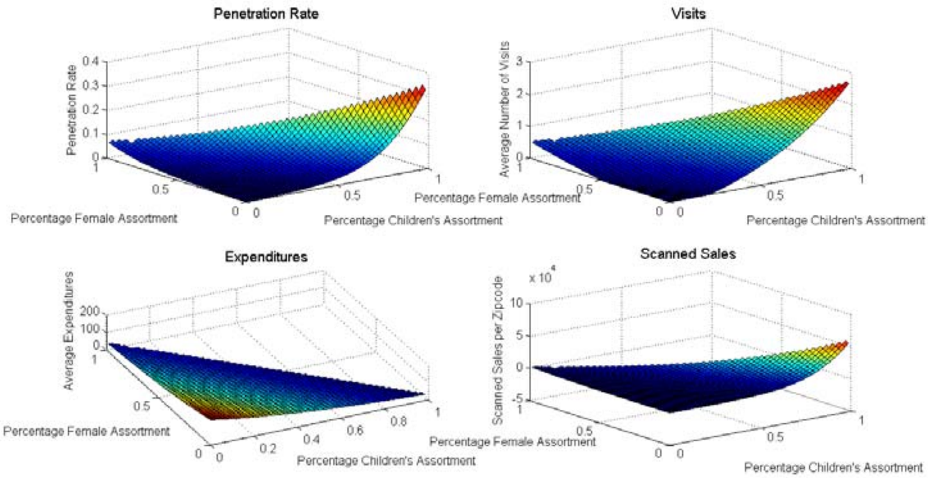


**Figure 3.6: Response patterns of different sales components to a change in the relative size of the children's and women's department.**

The proposed modelling approach also can answer other "what-if" questions, beyond store site evaluations. To determine the results if, for example, the relative sizes of the children's and women's departments were to change, we use the established parameter estimates, BLUP and Kelejian and Prucha (2007) correction terms to investigate the response patterns of different sales components (Figure 3.6). For this analysis, we change only the variables of interest (i.e., relative sizes of the children's and women's departments) and set all other predictor variables to their average values. Because store size is fixed, we define the relative size of the men's department as 1 minus the sum of the relative sizes of the children's and women's departments.

As we show in Figure 3.6, increasing the size of the children's or the women's department compared with the men's increases the number of loyalty card holders and visit frequency. However, the average expenditures per visit decline. To investigate the changes in scanned sales (per zip code), we determine the sales impact of an increase in the relative size of each department with an average number of households (bottom right graph, Figure 3.6)[2]. The overall effect of an increase in the size of either the children's or the women's department is positive and quite substantial. Therefore, the negative effect of an increase in the size of these departments on average expenditures per store visit is outweighed by its positive effects on the loyalty card penetration rate and the number of visits. We also find that an increase in the size of the children's department has a substantially larger sales impact than does a similar enlargement of the women's department. It therefore seems reasonable to conclude that stores belonging to this particular chain can increase their sales to loyalty card holders by enlarging the children's assortment and by reducing the fraction of floor space devoted to men's clothing.

## 3.5 Conclusions and Discussion

Store location is crucial to store performance because it determines store attractiveness and thus consumers' shopping decisions and spending patterns. The key objective of this chapter is to provide a general modeling approach to store location evaluation. The proposed model contributes to store location literature in several important ways. First, we use a decomposition framework to split store sales into their constituent parts, which leads to insights that remain unavailable with a model of just sales. Second, we use longitudinal customer data at the zip code level and thereby can explain differences in store performance across the trade area and over time. Third, we account for spatial dependence by specifying and estimating spatial-error models for panel data. We show how to estimate these models using longitudinal data pertaining to stores, purchase behavior, and consumer demographics.

In the empirical study, we apply our decomposition framework to 28 clothing stores of a Dutch retail chain. The customer database, supplemented with survey

[2] The number of households per zip code ranges from 0 to 11,960, with an average of 1,750.

data describing the retail environment of individual stores and commercially available geodemographic information, enables us to estimate spatial-error random-effects models that explain a substantial amount of variance in store sales. We identify several important drivers of store sales, such as travel distance, number of double-income families, and assortment composition. In particular, we find that the effect of predictor variables differs between the loyalty card penetration rate, the average number of visits, and the average expenditures per visit. For example, distance to the store negatively affects the penetration rate and the average number of visits but has a positive relationship with average expenditures per visit. We find empirical evidence of spatial dependence between the observations for each sales component as a result of unobserved similarities in consumer characteristics, preferences, and behavior.

The high predictive performance of our decomposition model underlines its usefulness for store location and evaluation decisions. Retailers who consider a number of candidate locations may want to use our proposed model to obtain estimates of potential sales for each site, which they can use to decide whether to invest in the proposed locations or not. The proposed model also makes it possible to develop criteria to evaluate the performance of existing stores. Furthermore, it can predict the sales impact of future changes within particular markets. Some of these factors entail management decisions (e.g., store location, composition), whereas other factors pertain to exogenous variables.

We acknowledge several limitations of our study that suggest directions for further research. The first limitation exists because we consider only one store chain. Although some of the findings therefore are peculiar to the retailer under consideration, the proposed store location evaluation model can be applied to other retailers or other settings that require evaluations of the location of facilities, such as health clubs, restaurants, banks, or public facilities.

Next, previous research suggests that our empirical findings might change if we choose another operationalization of the spatial weights matrix (Anselin 2002; Leenders 2002; Pace and LeSage 2004). However, in a recent study, Stakhovych and Bijmolt (2009) show that spatial models that use a first-order contiguity weight matrix perform better on average than do those that use other weight matrix specifications, due to their higher probabilities of detecting the true model and the lower mean standard error of the spatial and regression parameters. We are therefore confident in our results and do not consider other specifications.

Notwithstanding these limitations, we believe our modeling approach offers an extremely useful tool for store location evaluations. We also hope this chapter stimulates further research in this area.