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Cross-Category Effects of Aisle and Display Placements: A Spatial Modeling Approach and Insights

Amid growing competition, retailers are increasingly interested in more effective aisle and display management strategies. These strategies involve placements of product categories in aisles and displays within each store to facilitate greater sales affinity (demand attraction) between categories to improve the store's share of customer wallet. The authors investigate the effects of aisle and display placements on the sales affinities between categories. They develop a spatial model of brand sales that allows for asymmetric store-specific affinity effects between two or more categories, while controlling for the effects of traditional merchandising and marketing-mix variables, such as price, feature, and display. They estimate the model on aggregate store-level data for regular cola and regular potato chip categories for a major retail chain, using hierarchical Bayesian methods. They show the usefulness and extension potential of the model through simulation of aisle placements for a third category. The results show that aisle and display placements have significant and sizable asymmetric effects on cross-category sales affinities comparable to those influenced by marketing-mix variables. Retail managers can use this detailed store-level model and subsequent insights to develop customized aisle and display management for their individual stores.

Keywords: cross-category sales, aisle management, display placement, spatial model, marketing mix

Retailers today face increasing competition in their markets, prompting them to focus on in-store merchandising (e.g., aisle and display placement decisions) and promotion (e.g., price and deal decisions) strategies to improve their shares of consumer purchases and wallets (Bolton, Shankar, and Montoya 2007; Kumar, Shah, and Venkatesan 2006). As much as 70% of consumer decisions for grocery products are made at the store, making these in-store merchandising decisions critical to retailers' performance (Aldata Solution 2007). To this end, retailers are going beyond category management to cross-category management initiatives involving merchandising and promotion (Basuroy, Mantrala, and Walters 2002; McTaggart 2005). Whereas the goal of category management is to maximize profits across brands within a product category, the objective of cross-category management is to optimize profits across categories.

At the heart of cross-category management lies a deep understanding of a cross-category sales affinity (demand attraction between categories) analysis that helps retailers identify the product categories that are likely to be purchased together (*Supermarket Business* 1999). More formally, the sales affinity of a focal product category to a second product category can be defined as the tendency for sales in the second product category to influence sales in the focal category. The observed sales affinity between any two product categories at a store may be due to (1) the aisle placement, (2) the location of displays, (3) marketing-mix decisions (e.g., prices, deals), and (4) purely coincident purchases for the two categories. The sales affinity due to the first three elements depends on the intrinsic or inherent tendency of the categories to be bought and consumed together in a usage situation or occasion. Retailers can use the results of affinity analyses to plan more effective in-store merchandising and promotion strategies to increase their customers' cross-buying of products, leading to greater purchases at their stores.

Retailers' embrace of cross-category management initiatives is also changing the way manufacturers market their products. To be more responsive to the retailers' emphasis on improving cross-category performance, manufacturers are paying greater attention to cross-category affinities in planning their marketing strategies (Dupre and Gruen 2004). For example, Pepsi and Frito-Lay jointly undertake integrated marketing campaigns together with extensive cross-category merchandising to boost sales and profits in both the soft drink and the snack categories (*The Wall Street Journal* 2003). Similarly, General Mills helps retailers improve merchandising strategies through analysis of purchases across categories (ACNielsen 2005). In addition to helping retailers, such strategies can also benefit the manufacturer by increasing the sales of multiple brands in disparate but related categories. The benefits are particularly high if a manufacturer is a category captain (typically a leading vendor of the category) that the retailer selects to plan merchandising and other marketing decisions for that category (Gray 2005).

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An important part of a retailer's cross-category management strategy is aisle management strategy. Aisle management involves the effective placement of categories in the store aisles to improve customers' shopping experience, sales of related categories, and overall store performance (Burke 2005; *Drug Store News* 1998). The relative aisle placement of two categories is typically represented by aisle adjacency, which refers to the proximity of aisles that stock the categories. Retailers can significantly benefit from effective aisle management decisions. For example, according to the director of category management at the SuperValu chain, the retailer used to stock boxed dinners in one aisle and rice mixes two aisles from it (*Progressive Grocer* 2004a). However, moving the products even closer may provide higher visibility for the products and a better shopping experience for the consumers.

Another critical part of retail cross-category management strategy is display placement strategy. The location and proximity of displays of one category with respect to another category can have a significant effect on the sales of both categories. A detailed understanding of such effects can help retailers better manage the placement of displays of different categories in the store.

Although analysis of the effects of aisle and display placements on cross-category sales is important to retailers, it is not an easy task for several reasons. First, these effects need to be estimated in the presence of other marketing-mix variables, such as price and feature advertising, which are important determinants of retail sales (Bolton and Shankar 2003; Kirande and Kumar 1995; Kumar and Leone 1988; Shankar and Bolton 2004; Walters 1991). Second, the analysis method should account for the spatial distances or differences in locations of aisles and displays. Third, the analysis should allow for potential asymmetries in these effects between product categories. Such asymmetry exists when the affinity of Category 1 (e.g., potato chips) to Category 2 (e.g., cola)—in other words, the effect of sales of Category 2 on sales of Category 1—is different from the affinity of Category 2 to Category 1 (i.e., the effect of sales of Category 1 on sales of Category 2). These asymmetries in the effects of aisle and display placements on the sales of two categories can have important implications for retailers. By knowing the categories whose aisle and display placements have strong effects on the sales of other categories, a retailer can choose the locations of aisles and displays for different categories to boost overall store sales.

Thus far, retail stores have adopted a macro approach to aisle and display management, grouping product categories into broad clusters for aisle location based on consumer expectations, shopping habits, store size, and area demographics (Goldschmidt 2007; McTaggart 2005; *Progressive Grocer* 1996). This approach typically focuses on optimal floor space allocations. For example, SuperValu practices a category space optimization approach in which the retailer decides retail floor space for a product category on the basis of its contribution to overall store sales (Tarnowski 2004).

However, such approaches or models have important limitations and are suboptimal. First, these approaches primarily focus on floor space allocation and do not account for spatial proximities between aisles and across display locations. Second, many aisle and display placement decisions are based on managerial judgment that may be suboptimal. A retailer-level model that captures the effects of spatial proximities can potentially enable retailers to improve their aisle and display placement decisions significantly, leading to sizable profit gains. The incremental annual profit from more effective aisle and display placements of two categories, such as cola and chips—typically among the top six categories of a supermarket chain in sales volume—could range from $10 to $15 million for a 200-store retail chain.[1]

In this article, we develop a spatial model to analyze the effects of aisles and display placements on the sales affinity between categories, while controlling for the effects of marketing-mix variables, such as price, feature, and display, on cross-category brand sales. We estimate our model on store-level brand sales data for regular cola and potato chip product categories, using the hierarchical Bayesian method. We show the usefulness and extension potential of the model through simulation of aisle and display placements of a third category. Our empirical analysis reveals important findings. It shows that aisle and display placements have significant and sizable asymmetric effects on cross-category sales affinities, comparable to those influenced by marketing-mix variables.

We believe that this research makes important contributions. First, to our knowledge, this is the first article to analyze empirically the effects of aisle and display placements on cross-category sales, providing important insights into these decisions. In doing so, our work extends prior research (e.g., Bultez and Naert 1988; Corstjens and Doyle 1981; Dréze, Hoch, and Purk 1994) on retail floor space and shelf space management and enables ease of analysis by using readily available store-level scanner data rather than costly in-store experiments that vary aisle placements. Second, this research offers a spatial statistical analysis tool that accounts for the distances across aisle and display locations to study the effects of aisle and display placements on cross-category sales, thus helping retailers improve their performance store by store. Third, we extend spatial modeling applications in marketing that use only a single spatial correlation parameter by allowing for asymmetric effects through the use of two parameters and by employing multiple spatial autoregressive structures to model disparate in-store category affinities. Our analysis incorporates both substitution effects within a category and complementary effects across categories, offering a comprehensive approach to measuring affinity effects.

Conceptual Development

Typically, the demand for two product categories is complementary when they are consumed together. Examples of pairs of complementary categories include toothpaste and toothbrush, cake mix and cake frosting, and detergent and fabric softener. The greater the intrinsic sales affinity

[1]This is based on conversations with senior executives of two leading retail companies that operate in the northeastern and southern parts of the United States.

between any two categories, the larger are the effects of aisle and display placements and promotional decisions across the two categories. Prior research in this realm has used both household-level (market basket) data and store-level data to empirically infer these complementarities through the correlation of preferences across categories. In general, studies that use market basket data investigate the problem at the category level, and those that use store-level data examine these effects at the brand level.

The relative aisle placement of categories in the store can affect the joint purchases of two or more categories. Although there is a dearth of studies on aisle placement, the related literature on retail floor space and shelf space management suggests that there could be cross-category affinities due to aisle placement. Several studies have developed algorithmic optimization approaches to shelf space allocations while considering cross-category effects (e.g., Borrin and Farris 1995; Bultez and Naert 1988; Corstjens and Doyle 1981; Curhan 1972; Thurik and Kooiman 1986; Urban 1998). Dréze, Hoch, and Purk (1994) report results from a field experiment about shelf placement, in which juxtaposing a product category, such as fabric softeners, between the shelves of the complementary categories of liquid and powder detergents resulted in a significant increase in the sales of the laundry care category as a whole.

Although these studies suggest the importance of floor space and shelf placements for cross-category sales, they do not examine the effects of aisle or display placements. Moreover, little is known about the potential asymmetry in the effects of both aisle and display placements across categories that makes the effect of aisle placement of one category on the sales of the other category different from that of the other category. For example, the likelihood of a toothpaste purchase evoking the chewing gum category in the consumer's mind and triggering the latter category's purchase may be higher than the converse event. Such differences have been attributed to the strength of the associations between categories under the associated network theory of category knowledge structures (Ratneshwar and Shocker 1991). Through its strong link to the oral care category in the consumer's mind, the toothpaste category can evoke a related category, such as chewing gum. However, the chewing gum category does not have oral care as its central benefit, because it is both an experience product and a social product that can be shared. Consequently, the purchase of chewing gum is less likely to evoke oral care and the toothpaste category to which it is linked in the consumer's associated network.[2] Furthermore, because traveling to a different aisle imposes a disutility to consumers, we expect that the affinities in both directions (toothpaste on chewing gum and chewing gum on toothpaste) are attenuated by the distance between the aisles.

The implication of the asymmetric affinities between the categories is that if a consumer visits the toothpaste aisle to make a purchase, he or she may decide to look for chewing gum as well. If chewing gum is available in an aisle nearby, the consumer may see it and buy it. However, the close proximity of chewing gum to toothpaste may not necessarily lead to the consumer buying toothpaste when he or she first visits the aisle containing chewing gum. Thus, there are strong theoretical reasons to expect the influence of aisle placements on cross-category affinities to be asymmetric.

The placement of displays for a category may also affect sales of another category. Displays serve as reminder advertising for a brand, a product category, and other product categories that might be related to that category in a consumer's categorization schema (Sujan and Dekleva 1987). As with aisle placement, display placement of product categories offers a goal-oriented shopper several benefits. It reduces information search complexity by making assortment assembly easier; it reduces acquisition efforts, enhancing convenience; it provides in-store cueing of forgotten needs relating to another category; and it facilitates variety seeking and new product choice to meet the goal (Ratneshwar, Pechmann, and Shocker 1996). Our purpose is to investigate such effects using store-level sales data to provide actionable implications for aisle and display placements. In addition to aisle and display placements, pricing and deal decisions in one category may affect purchase incidence in related categories.

Prior studies have used different models and data to estimate these effects. Manchanda, Ansari, and Gupta (1999) develop and estimate a multivariate probit model for purchase incidence decisions across cake mix, cake frosting, fabric detergent, and fabric softener categories, using market basket data. In a similar vein, Russell and Peterson (2000) assess cross-category dependence in consumer choice behavior using a multivariate logistic model. They estimate their model using market basket data on paper towels, toilet tissues, facial tissues, and paper napkins and find that these categories are characterized by inelastic own demands and mostly negative cross-price elasticities.[3] Heilman and Bowman (2002) examine segmentation of consumer purchasing across multiple categories using a logit-mixture model estimated on household purchases of three baby product categories. Using store-level data, Song and Chintagunta (2006) model both store choice and brand purchase incidence for four categories: analgesics, ready-to-eat cereals, laundry detergents, and toilet tissues. They find that cross-category price elasticities are much smaller than own-category price elasticities. Moreover, they identify some categories as complements and some as substitutes. Wedel and Zhang (2004) estimate within- and cross-category effects of regular and sale prices on brand sales for the refrigerated and frozen orange juice categories. Other researchers have investigated correlations in price sensitivity across categories without explicitly examining coincidence of purchases (e.g., Ainslie and Rossi 1998; Kopalle, Mela, and Marsh 1999; Russell and Kamakura 1997).[4]

[2]Similarly, a category commonly bought on a planned purchase or stock-up trip is more likely to trigger a purchase of a product category usually purchased on a fill-in shopping trip than vice versa.

[3]This statement implies that these categories are complements.

[4]For an extensive review of models pertaining to multicategory choice, see Seetharaman and colleagues (2005).

The effect sizes of aisle and display placements and of marketing-mix variables, such as price, feature, and display, in one category on the sales of another category may be different. Although the effects of such marketing variables on category sales have been shown to be significant (e.g., Kumar and Leone 1988), they may not necessarily be higher than those of aisle and display placements, because these in-store merchandising activities are becoming increasingly influential on sales (Dréze, Hoch, and Purk 1994). There is no strong theoretical rationale on the relative sizes of these effects, so we view them as empirical issues suitable for detailed investigation with appropriate models and data.

Model Development

To examine cross-category effects, we develop a model of cross-category sales using spatial statistics. Marketing researchers have used models based on spatial statistical methodology in other contexts (e.g., Bronnenberg and Mela 2004; Jank and Kannan 2005, 2006; Rust and Donthu 1995; Ter Hofstede, Wedel, and Steenkamp 2002; Yang and Allenby 2003).[5] However, to our knowledge, we are the first to use the spatial statistical methodology to study the effect of aisle and display placements on cross-category sales.

We can write our model as follows:

$$\text{(1)}\qquad \ln(S_{cjt}) = B + N_j \ln(p_{cjt}) + \Psi d_{cjt} + \Gamma f_{cjt} + \Pi d_{cjt} \times f_{cjt} + \chi \text{Season}_{cjt} + \eta \text{Holiday}_{cjt} + \theta_{cj} + \phi_{cjt} + \varepsilon_{cjt},$$

where $S_{cjt} = [S_{1cjt}, S_{2cjt}, \ldots]'$ is a stacked vector of brand sales such that S_{icjt} is unit sales of brand i in category c at store j in week t and p_{cjt}, d_{cjt}, and f_{cjt} are vectors of brand prices, displays, and features, respectively, stacked in a way similar to S_{cjt}, where $i = 1, \ldots, I_c$; $c = 1, \ldots, C$; $j = 1, \ldots, J$; and $t = 1, \ldots, T$.[6] Furthermore, Season is a vector of dummy variables capturing seasonality effects, and Holiday is a vector of dummy variables representing holidays, such as Memorial Day and Christmas. In addition, B, N_j, Ψ, Γ, Π, χ, and η represent vectors of coefficients for the corresponding variables; θ_{cj} is a vector of aisle placement–induced cross-category sales affinities (i.e., a function of observed aisle placements); ϕ_{cjt} is a vector of display placement–influenced cross-category sales affinities (i.e., a function of observed display locations); and ε_{cjt} is a vector of residual errors.

We use a double-log functional form for price and a log-linear form for display, feature, and their interaction (i.e., the dependent variable is in log form, but the independent variables are in linear form), consistent with prior studies (e.g., Kumar and Leone 1988; Shankar and Bolton 2004; Van Heerde, Gupta, and Wittink 2003). The double-log form for a variable such as price has the desirable property of the parameter estimate directly providing the elasticity for that variable. We can compare the price elasticities for different brands by directly comparing the parameter estimates. Moreover, the double-log form captures the diminishing-returns-to-scale property for the variable. The log-linear form is appropriate for dummy variables, such as those for display, feature, and their interaction, because these variables take the value of zero for several observations.

For parsimony, we examine two product categories in the model but can include more categories by expanding the number of rows and columns in the weighting matrices (we describe this in greater detail subsequently) in the model to accommodate affinities among multiple categories. Alternatively, we can analyze categories in a pairwise way, as we show subsequently in an extension to this model. In our empirical analysis, we consider two categories that are a priori expected to be complements: regular cola and potato chips; thus, in the rest of the article, we assume that the number of categories is C = 2. Our model incorporates both substitution effects between brands within a category and potential complementary effects across the categories. We present a more detailed specification of Equation 1 and the coefficient matrices in Appendix A.

Aisle Placement–Influenced Cross-Category Sales Affinities

In Equation 1, θ_{cj} is the store-specific cross-category sales affinities for category c and store j that are influenced by aisle placement. Let θ_j denote the vector that comprises θ_{cj} for both categories. We specify θ_j using a spatial autoregressive structure (Smith and LeSage 2004), as follows:

$$\text{(2)}\qquad \theta_j = \rho\left(\tau_1 W_{1j} + \tau_2 W_{2j}\right)\theta_j + u_j, \text{ and}$$

$$\text{(3)}\qquad \tau_1 + \tau_2 = 1.$$

In Equation 2, u_j is a stacked vector of nonspatial errors for the two categories at store j. Our specification estimates θ_j at the category level rather than at the brand level because the latter model is difficult to identify with our data. Appendix A provides additional details of the distribution assumptions for u_j. The sales affinity between the categories is captured by the spatial term, $\rho(\tau_1 W_{1j} + \tau_2 W_{2j})\theta_j$. We posit that the sales affinity between two categories depends on the distance between the aisles in which the categories are stocked in the store. Typically, cola and chips are located in different aisles in the store. However, in some stores, the categories face each other or are located on opposite sides of the same aisle. Because sales affinity may be greater in the latter case than in the former, we use separate weighting matrices, W_{1j} and W_{2j}, for store j to capture these two effects (i.e., aisle distances between the categories and whether they are on opposite sides of the same aisle, respectively). We describe W_{1j} and W_{2j} in greater detail in Appendix A. The terms τ_1 and τ_2 are weights (normalized to sum to one) attached to W_{1j} and W_{2j}, respectively, and they capture the relative influence of the two effects in explaining cross-category sales affinity. In Equation 2, we specify W_{1j} and W_{2j} on the basis of store planogram data, but we estimate the other parameters.

The spatial correlation parameter matrix ρ consists of two parameters, ρ_1 and ρ_2, that capture the directional affini-

[5]Other nonmarketing studies that use spatial statistics methodology to study various problems include Gelfand, Kottas, and MacEachern (2005).

[6]In our case, $I_c = 4$, C = 2, J = 79, and T = 108.

ties between the two categories, where $\{\rho_1, \rho_2\} \in (-1, 1)$. Thus, ρ_1 measures the affinity of sales in Category 1 to sales in Category 2. In other words, ρ_1 is a measure of the influence of sales in Category 2 on sales in Category 1. Similarly, ρ_2 measures the affinity of sales in Category 2 to sales in Category 1. Because we consider cola and chips complements, we expect both ρ_1 and ρ_2 to be positive. Moreover, because the affinity of cola to chips can be different from that of chips to cola, we allow for two spatial correlation parameters in the form of ρ_1 and ρ_2. As we noted previously, this step is a significant extension of prior research, which has used only a single spatial correlation parameter.[7]

Display Placement–Influenced Cross-Category Sales Affinities

The term ϕ_{cjt} in Equation 1 captures the cross-category sales affinity influenced by the distance of display placements (e.g., wing/end-of-aisle displays) from the aisles containing the categories. Because the location of the display placements can vary from week to week within a store, we have the time subscript t for ϕ_{cjt}. As with the aisle placement affinity parameter, θ_{cj}, we estimate ϕ_{cjt} using a spatial autoregressive structure at the category level rather than at the brand level for similar reasons. In addition, we estimate a single spatial correlation parameter (ρ_3) for ϕ_{cjt}. We define ϕ_{jt} to be the vector of the category-level parameters, ϕ_{cjt}. We specify ϕ_{jt} using the following spatial autoregressive structure:

$$\phi_{jt} = \rho_3 W_{3jt}\phi_{jt} + \upsilon_{jt}. \tag{4}$$

The spatial error term, $\rho_3 W_{3jt}\phi_{jt}$, in Equation 4 represents the cross-category sales affinities influenced by display placements, where ρ_3 is the spatial correlation parameter that indicates the strength of such affinities, $\rho_3 \in (-1, 1)$. Because we expect the two categories to be complements, we anticipate ρ_3 to be positive. We construct the weighting matrix W_{3jt} using the observed distance of a display location from the aisle of the other category so that it reflects our assumption that the influence of displays on cross-category sales affinities is inversely related to this distance. We provide additional details about the specification of W_{3jt} in Appendix A.

Cross-Category Sales Affinities Due to Purchase Coincidence

The last term, ε_{cjt}, in Equation 1 is a stacked vector of residual errors, ε_{icjt}, in the response equations for all brands in category c—that is, $\varepsilon_{cjt} = (\varepsilon_{11jt}, \varepsilon_{21jt}, ..., \varepsilon_{I_1 1jt}, \varepsilon_{12jt}, \varepsilon_{22jt}, ..., \varepsilon_{I_2 1jt})'$. We estimate the full variance–covariance matrix of these residuals in which ε_{icjt} in any store j and week t is assumed to follow a multivariate normal distribution: $\varepsilon_{icjt} \sim N(0, \Sigma)$. The off-diagonal elements in Σ represent residual covariances among sales of different brands. Following Manchanda, Ansari, and Gupta (1999), we view these covariances as "sales coincidences" that are not explained by any of the effects that are controlled for in the model—namely, marketing-mix, aisle placement, and display placement effects.

[7]For a review of such models, see Anselin (1988).

Heterogeneity

Note that our specification of the spatial terms in Equation 1 incorporates heterogeneity across stores in the category-level intercepts through θ_{cj} and ϕ_{cjt}. In addition, for parsimony, we incorporate heterogeneity in only the price response parameters (Hoch et al. 1995; Manchanda, Ansari, and Gupta 1999), as Appendix A specifies.

Consistent with our discussion in the "Conceptual Development" section, our model breaks down the observed sales affinity into four components. The first component is the spatial term, $\rho(\tau_1 W_{1j} + \tau_2 W_{2j})\theta_j$, in Equation 2, which captures the extent to which sales affinity is affected by relative aisle placements in a store. The second component is the term $\rho_3 W_{3jt}\phi_{jt}$, which accounts for the influence of display placement of one category on the sales of another. The third component is the cross-category sales affinity induced by marketing-mix effects. These effects are captured by the cross-category terms in the brand price and brand display parameter matrices, N_j and Ψ. The final component of affinity that is independent of in-store merchandising and marketing-mix efforts is the covariance terms in the residual error matrix, Σ. For example, we might observe affinity between two categories because consumers may purchase them together when they undertake stock-up trips (sales coincidence).

The magnitude of the observed affinity between the categories as captured by the first three components is influenced by the intrinsic affinity between the categories. Thus, although we may induce an (observed) affinity between potato chips and detergent, for example, by placing them in adjacent aisles in a store, the magnitude of this affinity will be tempered by the intrinsic affinity between these products. Among the four components, the first three are managerially actionable because they capture the combined impact of managerial actions (e.g., aisle, display placements) and the intrinsic affinity between the categories.

A spatial model, such as the one we specify here, is appropriate for analyzing affinities between categories because affinity can be viewed as autoregression between the errors in the sales equation for the two categories. Because this autoregression is moderated by the spatial distance between the categories in a retail context, the specification in Equation 2 is referred to as a spatial autoregressive error structure.

Data and Estimation

Data

We use a store-level scanner data set provided by a supermarket chain in the United States to estimate our model. The data are available for two categories, regular cola and regular potato chips, for a period of roughly 108 weeks from November 1996 to December 1998 for 160 stores. They include information on prices, displays, and features. In addition, they contain information on aisle and display placements for the categories in each store.

These categories are prominent drivers of supermarket sales. For example, in 2005, the supermarket sales of carbonated soft drinks and potato chips were $12 billion and

$3 billion, respectively.[8] Moreover, sales of soft drinks and salty snacks, such as potato chips, dominate supermarket sales, accounting for 21.5% and 13.2% of supermarket sales, respectively, during April 2006–March 2007 (*Nation's Restaurant News* 2007). Although we estimate the model using only two categories, we subsequently show how our methodology can be extended to include other important categories sold by the retailer when making overall decisions on aisle and display placements.

We select the top four brands in each of these categories for analysis. In the case of cola, we include the three national brands, Coca-Cola, Pepsi, and RC Cola, and a store brand (SCola). In the case of chips, we chose Lay's and Ruffles, the top two national brands; RChips, a strong regional brand; and SChips, a store brand. In both categories, the four chosen brands account for more than 90% of the total sales. We randomly select 79 stores from the 160 stores for estimating the model. The price, feature, and display variables are aggregated at the brand level using the Divisia method (Hoch et al. 1995). The display (feature) variable is defined as the percentage of all Universal Product Codes (UPCs) of the brand that are on display (feature) during a given week in a store.

PepsiCo and the retailer own brands in both categories. PepsiCo owns the Pepsi brand in the cola category and the Lay's and Ruffles brands in the chips category. The retailer owns SCola and SChips. The remaining manufacturers manage brands in only one of the categories we analyze. Table 1 presents a descriptive summary of the two categories. In the regular cola category, Coke, Pepsi, and RC Cola are the premium brands and have similar average prices, though RC Cola has a much lower market share. Coke and Pepsi are displayed and featured heavily, whereas the cheaper store brand, SCola, is displayed and featured much less frequently. The regular potato chips category presents a different, idiosyncratic scenario. In this category, Lay's and Ruffles are the most expensive brands. Moreover, the mean sales of Lay's are higher than those of Ruffles, and Lay's is displayed and featured more often than Ruffles. However, a regional brand, RChips, has the largest market share. It is competitively priced and featured the most. SChips is the cheapest brand, is displayed relatively heavily, and has the lowest market share.

In our data, aisle placements are measured by the distance between aisle locations of the two categories in the store, whereas display placements are represented by the distance of a brand's displays from the aisles containing the product categories. The aisle and display placements vary from store to store. For the aisle distances, the mean distance between the beverage and the snack aisles for all the stores is approximately 3.03 aisles, with a standard deviation of 2.72 aisles. The maximum separation between the aisles is 17. The minimum separation between them occurs when cola and chips categories are stocked facing each other on opposite sides, and this is the case for 16 stores. In another 10 stores, the two categories are located on neighboring aisles. In the case of display placements, there is both interstore and intertemporal variation. The mean distance of display placements from the cola aisle to the chip display is 12.36, with a standard deviation of 3.10 aisles. The maximum and minimum distances are 21 and 3 aisles, respectively. The mean distance between the snack aisle and the cola display is 14.36, with a standard deviation of 5.01. In this case, the maximum and minimum aisle separations are 23 and 7, respectively. We use the distances measured in aisles in the weighting matrices for the spatial error terms in our model.

Estimation

We estimate our model as a hierarchical Bayesian model, using Markov chain Monte Carlo techniques. In general, prior research has found hierarchical Bayesian models to be advantageous when modeling heterogeneity in response coefficients, as in Equation 5. For the hierarchical Bayesian model, we specify the prior distributions for the parameters of the model by using diffuse priors and conjugate distributions whenever possible.[9] We use a total of 30,000 iterations for the Markov chains with a "burn-in" of 27,500. We use the last 2500 to calculate the posterior means and the standard deviations of the model parameters. We also graphically monitor the chains for convergence.[10]

Results and Discussion

In this section, we present and discuss the results from the proposed model. We begin with a discussion of the sales affinities induced by aisle placement. Subsequently, we discuss the affinities influenced by display placement. Finally, we elaborate on the affinities due to marketing-mix variables and cross-category coincidences.

Aisle Placement–Influenced Cross-Category Sales Affinities

Table 2 presents the results on cross-category affinities obtained from the spatial component of the model. From this table, cross-category affinities influenced by aisle placements across categories are asymmetric, as measured by the correlation parameters, ρ_1 and ρ_2. Because the aisle placements influence the actual realized values of the affinities through the weighting matrices, retailers need to pay attention to the location of the categories within a store.

[8]See *Progressive Grocer* (2005) and *Advertising Age* (2004).

[9]Details are available on request. We also performed a simulation study to check whether the model is identified and whether the parameters are recovered as per Equation 1. The parameter estimates recovered were close to the true values and lie within the 95% highest posterior density intervals. Moreover, the correlation between the true and the recovered values is high, and the mean square error (MSE) is low. For example, for the marketing-mix coefficients, the correlation is in the range of .97–.99, and the MSE is approximately .30. Similarly, for θ, the correlation between the true and the estimated values is .99, and the MSE is .20. In case of ϕ, this correlation is .80, and the MSE is 1.3. In addition, when we increase the sample size, the estimates improve for all the parameters, and the correlations between their true and their estimated values increase considerably, and the MSE drops. These findings suggest that the model is identified and that our procedure can recover the parameters successfully.

[10]In addition, we estimated parallel chains with different starting values, but the results remain unchanged.

TABLE 1
Descriptive Statistics for Sales and Marketing Variables

A: Regular Cola Category

	Mean Weekly Sales per Store (in 10,000 Ounces)				Average Price (Cents/Ounce)				Mean Percentage of UPCs Featured			Mean Percentage of UPCs Displayed			Mean Percentage of UPCs Featured and Displayed		
Brands	M	SD	Minimum	Maximum	M	SD	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
Coke	119.58	112.73	26.78	263.24	1.87	.40	1.07	2.57	37.15	0	99.99	36.63	0	99.71	20.72	0	82.61
Pepsi	138.92	106.68	60.30	323.81	1.67	.23	1.10	2.04	51.79	0	99.99	31.65	0	99.85	25.50	0	85.30
RC Cola	1.38	1.68	.53	5.34	1.89	.32	1.23	2.14	2.24	0	100.00	1.79	0	100.00	.79	0	4.75
SCola	3.74	3.71	1.26	10.50	1.34	.22	.83	1.59	6.67	0	98.12	11.73	0	98.40	4.23	0	55.50

B: Regular Chips Category

	Mean Weekly Sales per Store (1000 Ounces)				Average Price (Cents/Ounce)				Mean Percentage of UPCs Featured			Mean Percentage of UPCs Displayed			Mean Percentage of UPCs Featured and Displayed		
Brands	M	SD	Minimum	Maximum	M	SD	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
Lay's	1.43	1.47	.45	5.46	22.10	3.02	13.8	32.8	9.78	0	100.0	9.59	0	98.2	3.91	0	84.17
Ruffles	.76	1.03	.26	5.10	23.14	3.04	17.20	28.5	3.90	0	97.4	2.17	0	91.9	1.09	0	40.32
SChips	.49	.51	.18	2.03	14.15	2.01	10.01	16.6	5.90	0	97.3	8.67	0	79.9	3.20	0	42.00
RChips	2.35	1.28	.96	4.36	18.37	1.05	13.40	22.5	15.80	0	100.0	3.21	0	100.0	2.17	0	53.57

TABLE 2
Posterior Mean of Affinity Parameters

Parameter	Posterior M	Posterior SE
Aisle Placement–Influenced Affinity		
ρ_1 (affinity of cola to chips)	.745	.143
ρ_2 (affinity of chips to cola	.501	.172
τ_2 (weight due to same side)	.685	.201
σ_2 (ailse error)	.221	.027
Display Placement–Influenced Affinity		
ρ_3 (display placement affinity)	.205	.090
ξ_2 (display error)	.008	.000

Thus, locating the aisles containing the cola and chips categories closer to each other can increase cross-category affinities, leading to a greater share of customer wallet. The higher value of τ_2 relative to τ_1 (which equals $1 - \tau_2$) indicates that having the chips and cola categories facing each other across the same aisle has a greater impact on cross-category sales affinity than moving the aisles of the two categories closer together by one aisle.

The relative magnitudes of ρ_1 and ρ_2 suggest that the affinity of cola to chips is 49% higher than the affinity of chips to cola. Typical consumption behavior may explain such an asymmetry. Consumers typically feel the need to consume a drink such as cola when eating a snack such as a potato chip, but they may not feel the need to eat chips when consuming a drink. Thus, from a marketing perspective, sales of chips can more effectively drive sales in the cola category than vice versa. This finding implies that promotion and merchandising in the chips category may be more effective from the perspective of maximizing sales across multiple categories. This implication is valuable to retailers and manufacturers in implementing cross-category management with respect to these categories. Finally, σ^2 is statistically significant, suggesting that there are significant variations in category sales across stores that are not explained by affinities induced by aisle placements. We subsequently discuss these residual variations across stores.

Display Placement–Influenced Cross-Category Sales Affinities

From Table 2, the effect of display placements on cross-category sales affinities, as denoted by ρ_3, is also significant. The implication is that retailers can use displays more effectively by positioning them closer to complementary categories to increase cross-category sales. Moreover, manufacturers such as PepsiCo, which sells products in both the chip and the cola categories, should be willing to pay more for displays of their brands that are located closer to their brands' complementary category.

When we compare the magnitude of ρ_3 with those of ρ_1 and ρ_2, the placement effects due to aisle distance are more prominent than those due to display placements. A possible reason for this result is as follows: In the case of display placement, because only one or two brands in a category are displayed at any time, only the sales from the displayed brands can create a cross-category affinity. In the case of aisle placement, however, the cross-category affinity is influenced by all the brands in the aisles.

Marketing-Mix Effects

Average category effects. Before discussing the brand-level estimates, we consider category averages of the marketing-mix effects to understand the relative magnitudes of the effects. Table 3 presents the category averages for the within- and cross-category effects for price and display and for the own-category effects of feature advertising. The signs of the averages of the own-category effects conform to expectations: negative price coefficients and positive display and feature coefficients. Moreover, the averages for the own-category cross-effects show positive signs for price effects and negative signs for display effects, as we expected. In general, the magnitude of the own-category effects is larger for the potato chips category than for the regular cola category. This finding suggests that marketing-mix variables have a greater effect in the potato chips category than in the cola category.

We now consider the cross-category effects reported in Table 3. The results are consistent with the pattern for own-category results in that the cross-effects of potato chips are larger than those of cola. Thus, prices in the chips category have a greater effect in stimulating sales in the cola category than vice versa. Among the cross-category effects included in the model, price effects are the most prominent, followed by display effects. Comparing the own- and cross-category effects, we find that, in general, the own-category effects are larger than the cross-category effects, consistent with our expectation.

Brand-level estimates. Tables 4 and 5 report the mean parameter estimates across stores. There are wide asymmetries in the effects across various brands in both categories. In the cola category, for the price effects, the store brand has a greater influence on the national brands in the same category than vice versa. This result is a departure from prior literature, which finds that the national brands typically steal more from lower-priced store brands than vice versa (e.g., Blattberg and Wisniewski 1989; Sethuraman, Srinivasan, and Kim 1999). The price cross-elasticities in the chips category are significantly different from zero for most brand pairs, suggesting greater perceived substitutability of the brands in this category than in the cola category. Furthermore, in this category, a price hike by Lay's, Ruffles, or SChips increases the sales of RChips more than any other brand. RChips is the competitively priced, largest-selling brand. It also has the highest price elasticity (in absolute value). It appears that customers prefer it more for its value proposition—namely, reasonable quality at reasonable price. Thus, RChips benefits the most if the rival brands increase their prices, but it also loses the most if it increases its own price. In contrast, Lay's, the most expensive and least price-elastic brand, may be viewed as a higher-quality brand. In addition, this pattern of results holds for the cross-category price effects in Table 5. Pepsi and RChips gain the most from a price cut in their complementary categories of potato chips and cola, respectively.

TABLE 3
Posterior Mean Estimates of Within- and Between-Category Effects (Simple Averaged Across Brands)

A: Price Elasticities for Regular Cola

Within-Category Effects						Between-Category Effects		
Own			Cross			Cross-Effects of Regular Potato Chips		
M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
–2.109	–1.486	–2.567	.068	–.385	.967	–.152	.322	–1.596

Price Elasticities for Regular Potato Chips

Within-Category Effects						Between-Category Effects		
Own			Cross			Cross-Effects of Regular Cola		
M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
–2.358	–1.562	–2.819	.406	–.442	1.472	–.051	.612	–.745

B: Display Effects for Regular Cola

Within-Category Effects						Between-Category Effects		
Own			Cross			Cross-Effects of Regular Potato Chips		
M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
.350	.216	.559	–.123	.025	–.463	.023	–.437	1.129

Display Effects for Regular Potato Chips

Within-Category Effects						Between-Category Effects		
Own			Cross			Cross-Effects of Regular Cola		
M	Minimum	Maximum	M	Minimum	Maximum	M	Minimum	Maximum
1.572	.293	4.195	–.317	.293	–1.084	.067	–.285	.395

C: Feature Effects for Regular Cola

	M	Minimum	Maximum
Own-Effects	.283	.022	.585

Feature Effects for Regular Potato Chips

	M	Minimum	Maximum
Own-Effects	.285	.083	.570

Notes: In some cases (e.g., price elasticities for regular cola and cross-effects of regular potato chips), the maximum has a negative sign because that is the expected direction of effect.

The display effects in Table 4 indicate that sales of Lay's and Ruffles benefit strongly from displays. The results (in Table 5) of the cross-category display effects illustrate how firms can use brands in multiple categories to compete effectively. For example, when Coke is on display, Pepsi's sales are hurt more disproportionately than Coke's sales are when Pepsi is on display. However, PepsiCo can mitigate this effect through cross-category display and price promotion of Lay's. Moreover, although the sales of Pepsi drop when Coke is on display, the sales of Lay's increase, benefiting PepsiCo. The display × feature interaction effect is significant only for SCola and RC Cola in the cola category and Lay's, SChips, and RChips in the chips category. In general, the display × feature interaction effects are more prominent for the store brand. Among the holiday and season dummies, Super Bowl, Memorial Day, Independence Day, and summer season have significant effects on sales.

Model Validation

We compare the performance and the fit of the proposed model (full model) with those from several alternative models. We report the alternative model descriptions and the fit statistics, as measured by the log Bayes factor for the in-sample fit and the mean square error for the out-of-sample fit, in Table 6. For each alternative model specification, the log Bayes factor reflects the ratio of the posterior odds of the full model to that of the alternative model (West and Harrison 1997). A log Bayes factor value greater than two indicates strong evidence in favor of the full model over the alternative specification. For computing the out-of-sample

TABLE 4
Brand-Level Within-Category Posterior Mean Estimates of Marketing Effects and Control Variable Effects

A: Mean Price Coefficients (Elasticities)

Regular Cola

	Coke	Pepsi	RC Cola	SCola
Coke	–2.567**	–.163	–.385	.446*
Pepsi	.596**	–1.486**	.283*	.967**
RC Cola	–.067	–.120	–2.342**	.159**
SCola	–.080	–.0495	–.358	–1.672**

Regular Potato Chips

	Lay's	Ruffles	SChips	RChips
Lay's	–1.562**	.163*	.410*	.213*
Ruffles	.162*	–2.399**	–.442	–.223*
SChips	–.015	.393**	–2.655**	.117*
RChips	1.472**	1.228**	1.397**	–2.819**

B: Display Coefficients

Regular Cola

	Coke	Pepsi	RC Cola	SCola
Coke	.338*	–.023	–.180*	–.021
Pepsi	–.301*	.216*	–.047	.025
RC Cola	–.207*	–.127	.290*	–.463**
SCola	–.017	–.015	–.102*	.559**

Regular Potato Chips

	Lay's	Ruffles	SChips	RChips
Lay's	1.177**	–.225*	–.462*	–.033
Ruffles	–.570**	4.195**	–.346*	–.140*
SChips	–.366*	.142*	.293	.047
RChips	–.665**	–.111*	–1.084**	.623*

C: Feature Coefficients: Own-Effects Only

Regular Cola		Regular Potato Chips	
Coke	.022	Lay's	.192*
Pepsi	.237	Ruffles	.292*
RC Cola	.585*	SChips	.570*
SCola	.290*	RChips	.083

D: Display–Feature Interaction Coefficients: Own-Effects Only

Regular Cola		Regular Potato Chips	
Coke	.389	Lay's	.734*
Pepsi	.306	Ruffles	–.0684
RC Cola	.605*	SChips	1.042**
SCola	.702**	RChips	.571*

E: Holiday and Seasonal Dummies

New Year's	.015	Halloween	.016
Super Bowl	.201**	Thanksgiving	.085
Easter	.005	Christmas	–.001
Memorial Day	.135**	Summer	.036**
Independence Day	.102**	Fall	.003
Labor Day	.095*	Winter	–.005

*$p < .10$.
**$p < .05$.
Notes: For the cross-elasticity estimates, the column represents the brand whose price or display variable is changed. For example, in the first row of the price elasticity table (Panel A), the elasticity of Coke's sales to price change of SCola is given by .446.

TABLE 5
Brand-Level Between-Category Posterior Mean Estimates of Marketing Effects and Control Variables

A: Price Coefficients (Elasticities) Cross-Effects of Chips on Cola

	Lay's	Ruffles	SChips	RChips
Coke	–.266*	–.005	–.230*	–.146*
Pepsi	–1.596**	–.097	.322	–.147*
RC Cola	.036	–.092	–.075	–.078
SCola	–.271*	.045	–.035	–.082

Cross–Effects of Cola on Chips

	Coke	Pepsi	RC Cola	SCola
Lay's	–.140*	.026	–.343*	.028
Ruffles	–.175*	.144	.251	–.512**
SChips	–.033	.152*	–.745**	.085
RChips	–.329**	–.172*	.612	.344*

B: Display Coefficients Cross-Effects of Chips on Cola

	Lay's	Ruffles	SChips	RChips
Coke	.176*	–.199	–.117	–.012
Pepsi	1.129*	–.137	.104	.007
RC Cola	.236	–.437	–.059	–.304
SCola	–.062	.014	.042	–.025

Cross-Effects of Cola on Chips

	Coke	Pepsi	RC Cola	SCola
Lay's	.117*	–.047	–.285	–.106
Ruffles	.063	–.058	.140*	.149*
SChips	–.010	.018	.314**	.083
RChips	.245**	–.185	.395**	.229**

*$p < .10$.
**$p < .05$.

fit, we first divide the data for each store into two halves, each comprising 54 weeks. We reestimate the models on the first half and use the second half for prediction. From the fit statistics, we find that the full model outperforms all the other model specifications for both in-sample and out-of-sample statistics. Moreover, the null model, which does not include cross-category sales affinities as influenced by aisle and display placements, performs substantially worse than the other models that incorporate such effects. We conclude that aisle and display placement–influenced cross-category affinities are important in explaining the data.

Managerial Implications

The Impact of Aisle and Display Placements Across Categories

Both retailers and manufacturers can benefit from an increased understanding of the impact of in-store merchandising decisions on cross-category sales. Indeed, in many instances, the same manufacturer markets complementary categories and also serves as the category captain, helping the retailers manage those categories in the store (*Convenience Store News* 2007; *Progressive Grocer* 2004b).

To analyze the cross-category impact of aisle management, we compute the effect of aisle placements on sales (for the results, see Table 7; for details on how we compute effects and elasticities, see Appendix A).[11] We calculate the elasticities and effects for four scenarios: In Case 1, we move the categories of chips and cola one aisle closer in all the stores in the chain; in Case 2, we move the categories of chips and cola one aisle farther in all the stores; in Case 3, we move the categories of chips and cola so that they face each other in 55% of the stores; and in Case 4, we move the categories so that they face each other in 55% of the stores and are one aisle closer in the remaining stores.[12]

Table 7 shows that moving the categories one aisle closer results in a modest increase in sales. However, moving the categories so that they face each other in 55% of the stores leads to a substantial increase in mean sales.[13] More-

[11]Both retailers and manufacturers can estimate our model using a standard statistical package, such as SAS with a manager-friendly interface in Excel or Visual Basic.

[12]In our data, the categories face each other in an aisle in approximately 20% of the stores (16 of the 79 stores). For the sales impact analysis, we consider the case in which the categories are relocated to face each other in an additional 27 stores, leading to 55% (or a majority) of stores with the categories facing each other in an aisle. For simplicity, we do not consider the effects on the categories displaced by moving the cola and chips aisles closer.

[13]Note that the increase in the sales of Case 4 is not the sum of the increases in Cases 1 and 3, because the specified model is not

TABLE 6
Model Equations and Fit Statistics of Proposed and Alternative Models

Model	Model Equation	In-Sample Model Fit (Log Bayes Factor)	Out-of-Sample Model Fit (Mean Square Error)
Proposed model: asymmetric aisle and display placement effects (full model)	$\ln(S_{cjt}) = B + N_j \ln(p_{cjt}) + \psi d_{cjt} + \Gamma f_{cjt} + \Pi d_{cjt} \times f_{cjt} + \chi Season_{cjt} + \eta Holiday_{cjt} + \theta_{cj} + \phi_{cjt} + \varepsilon_{cjt}$	N.A.	.799
Alternative Model 1: no display placement effects	$\ln(S_{cjt}) = B + N_j \ln(p_{cjt}) + \psi d_{cjt} + \Gamma f_{cjt} + \Pi d_{cjt} \times f_{cjt} + \chi Season_{cjt} + \eta Holiday_{cjt} + \theta_{cj} + \varepsilon_{cjt}$	28.895	.854
Alternative Model 2: no asymmetric effects in aisle placement and no display placement effects	$\ln(S_{cjt}) = B + N_j \ln(p_{cjt}) + \psi d_{cjt} + \Gamma f_{cjt} + \Pi d_{cjt} \times f_{cjt} + \chi Season_{cjt} + \eta Holiday_{cjt} + \theta_{cj} + \varepsilon_{cjt}$ with $\rho_1 = \rho_2$	31.857	.873
Alternative Model 3: no aisle placement effects and no display placement effects (null model)	$\ln(S_{cjt}) = B + N_j \ln(p_{cjt}) + \psi d_{cjt} + \Gamma f_{cjt} + \Pi d_{cjt} \times f_{cjt} + \chi Season_{cjt} + \eta Holiday_{cjt} + \varepsilon_{cjt}$	860.013	.988

Notes: N.A. = not applicable.

over, the increase in mean weekly sales is considerably different across brands. For example, in Case 1, the sales of Coke and Pepsi rise appreciably, whereas those of RC Cola change negligibly. In the chips category, the sales of RChips increase the most. Similar patterns can be observed for other cases as well. Thus, stronger brands benefit more than weaker brands from these aisle placement changes.

We perform a similar analysis for display adjacencies. However, the effects of display adjacencies are not substantial because of the smaller magnitude of the display spatial correlation parameter ρ_3, as we discussed previously.

Our analysis considers the effect of aisle and display changes on the sales of only the two focal categories. To make comprehensive decisions on aisle and display placements, a retailer needs to consider the effects of aisle and display changes on the sales of other key product categories as well. In such a situation, our model can be extended to analyze the affinities related to these additional categories.

The Impact of Aisle Placements on Sales of a Third Category

In this section, we show how the inclusion of other categories in the analysis modifies the previous results on the sales impact of moving the aisle locations of cola and chips closer together. We illustrate this analysis by simulating the effects of a third category, nonrefrigerated/shelf juice (e.g., cranberry juice). The simulation consists of the following steps: In Step 1, with the third juice category under consideration, we simulate a model similar to Equation 1 for the two category pairs, juice–cola and juice–chips, to supplement our analysis of the cola–chips pair. We use the proposed model pairwise across categories because this approach is reasonable and avoids the risk that specification error in one category will contaminate the results for all the categories. Because we could not obtain real data on the juice category for the same period as that for cola and chips, we assume "reasonable" parameters for the model for the category pairs (i.e., juice–cola and juice–chips). We base these reasonable parameters (elasticities) on current juice category data that we obtained from another source.[14]

In Step 2, in the models for the juice–cola and juice–chips pairs, we add a separate weighting matrix whose elements take the value of one if the juice aisle is located between the cola and chips aisles and zero if otherwise. We describe this model in greater detail in Appendix B. By adding a separate weighting matrix to indicate the location of the juice category between the chips and cola categories, we can incorporate the juxtaposition effects on the juice category similar to those that Dréze, Hoch, and Purk (1994) observe for shelf locations within an aisle. We further assume that the juxtaposition effects are not important for cola and chips because of the strong complementarities that exist between them. In other practical applications, managerial judgment can help make such simplifications in the model.

We now reconsider our analysis of Case 3 in Table 7 by including the juice category. Recall that in this case, the chips and cola categories are moved so that they face each other in 55% of the stores. We assume that the relative location of the juice category with respect to the cola and chips categories in these target stores conforms to one of three possible layouts: (1) cola–juice–chips, (2) cola–chips–juice, and (3) juice–cola–chips in equal proportion. These layouts differ in the identity of the middle category among the three categories. Thus, a store with the first layout has the juice aisle located between those of the cola and potato chips categories. Because we do not consider shopping paths, we are agnostic to the order of these three categories (i.e., left

strictly linear. For example, both the distance measures are inverse exponential.

[14]We obtained the current juice data from another northeastern U.S. supermarket chain that operates approximately 70 stores.

TABLE 7
Effects of Changes in Aisle and Display Placements on Store Unit Sales and Revenues

Case	Brand	Mean Total Change in Weekly Sales (Quantity in Ounces)	Mean Change in Total Category Weekly Sales (Percentage)	Mean Total Change in Weekly Revenues ($)
Case 1: moving the potato chips and regular cola categories one aisle closer in all the stores in the chain	Coke	92,358	.76%	1,727
	Pepsi	107,299		1,792
	RC Cola	1067		20
	SCola	2887		39
	Lay's	628		138
	Ruffles	333		77
	SChips	217		30
	RChips	1031		186
	Total	205,820		4,009
Case 2: moving the potato chips and regular cola categories one aisle farther in all the stores in the chain	Coke	–145,200	–1.452%	–2,715
	Pepsi	–168,689		–2,817
	RC Cola	–1678		–32
	SCola	–4538		–61
	Lay's	–2757		–607
	Ruffles	–1461		–336
	SChips	–953		–133
	RChips	–4527		–815
	Total	–329,803		–7,516
Case 3: moving the potato chips and regular cola categories so that they face each other in 55% of the stores in the chain	Coke	1,122,845	9.23%	20,997
	Pepsi	1,304,489		21,785
	RC Cola	12,975		245
	SCola	35,095		470
	Lay's	878		193
	Ruffles	465		107
	SChips	303		42
	RChips	1441		259
	Total	2,478,492		44,100
Case 4: moving the potato chips and regular cola categories so that they face each other in 55% of the stores and are closer by one aisle in all other stores in the chain	Coke	1,287,761	10.59%	24,081
	Pepsi	1,496,083		24,985
	RC Cola	14,881		281
	SCola	40,250		539
	Lay's	1994		439
	Ruffles	1057		243
	SChips	690		97
	RChips	3274		589
	Total	2,845,989		51,254

to right versus right to left). Conforming to the assigned layout, we randomly generate the aisle location of the juice category for the different stores. Unlike the two-category Case 3 in Table 7, the results of the three-category Case 3 may depend on whether the chips or the cola category is moved. Furthermore, the implications may depend on the specific layout (1, 2, or 3) in the given store.

Table 8 presents the modified simulation results for Case 3 when the juice category is included. The baseline result represents the Case 3 values from Table 7, except that these values are now broken down by the store layout. Note that the Layout 3 stores have a greater improvement in revenues in the baseline case than the other two layouts. The greater improvement in these stores is simply a chance variation because stores were assigned randomly to the three layouts. Below the baseline results, we separately present the simulation results for moving the cola category to face the chips category (Scenario 1) and for moving the chips category to face the cola category (Scenario 2). Note that the spatial parameters assumed in our simulation (for the parameter values, see Appendix B) imply that there is a positive affinity (as influenced by aisle placement) between juice and chips and between juice and cola. However, the assumed affinity is greater for the juice–chips pair than for the juice–cola pair. A comparison of the results in Table 8 for both scenarios with the baseline results shows that the improvement in revenues is slightly higher when the juice category is included in the analysis. However, this overall improvement masks differences across stores with different layouts. When the cola category is moved, it has an adverse effect on the juice category in stores with Layout 3. The rationale is that the cola category is moved away from the juice aisle in stores with Layout 3, causing a decrease in cola-affinity-driven juice sales in these stores. However, juice sales are not adversely affected in stores with Layout 1, though the juice category is no longer juxtaposed between cola and chips. This result shows that the juxtaposition effect (based on the value of τ_3 in Appendix B) is not

TABLE 8
Simulation Results for Case 3 with a Third Category (Juice)

		Mean Total Change in Weekly Revenues ($)			
Simulation	**Store Layout**	**Cola**	**Chips**	**Juice**	**Total**
Baseline	Layout 1 stores	13,081	149	N.A.	13,230
	Layout 2 stores	13,952	160	N.A.	14,113
	Layout 3 stores	16,569	189	N.A.	16,758
	Total	43,602	498	N.A.	44,100
With juice (Scenario 1)	Layout 1 stores	13,170	164	67	13,400
	Layout 2 stores	14,033	161	64	14,257
	Layout 3 stores	16,386	188	–75	16,500
	Total	43,588	512	56	44,157
With juice (Scenario 2)	Layout 1 stores	13,170	164	182	13,515
	Layout 2 stores	14,033	161	–248	13,945
	Layout 3 stores	16,386	188	199	16,773
	Total	43,588	512	133	44,233

Notes: N.A. = not applicable.

high enough to adversely affect juice in stores with Layout 1.

In Scenario 2, in which we move the chips category, we observe an adverse effect on juice in stores with Layout 2 because chips move away from the juice aisle in these stores. Furthermore, because the affinity between juice and chips is stronger than that between juice and cola (for parameter, see Appendix B), the effects, both positive and negative, on juice are stronger when chips are moved (Scenario 2) than when cola is moved (Scenario 1). Indeed, Table 8 suggests that we can obtain better overall results by implementing Scenario 1 in stores with Layout 2 while adopting Scenario 2 in stores with Layouts 1 or 3. Overall, the simulation results of this section show that our methodology is fairly robust and can be extended to accommodate more categories.

Comparison of the Effects of Aisle Placements and Marketing-Mix Variables

An issue of managerial significance is the magnitude of the sales effects of aisle adjacencies compared with those of the traditional marketing-mix variables. For this comparison, we compute the elasticities with respect to the merchandising and marketing-mix variables (i.e., price, feature, and displays). In each of these cases, we change the relevant variable by 1% and calculate the corresponding change in sales. Because we operationalize the display (feature) variable as the percentage of all UPCs of the brand on display (feature), a unit percentage increase in this variable corresponds to a 1% increase in UPCs displayed (featured).

The results of the comparison of elasticities of merchandising and marketing variables appear in Table 9. To achieve the same change in sales produced by a unit decrease in interaisle distance, the retailer needs an overall price cut of 3.84% (.48% per brand). Similarly, to mimic the same increase in sales as in Case 3 (55% of stores with categories facing each other), the retailer requires a price cut of 37.07% per brand. Likewise, for merchandising variables, the retailer needs to increase display frequency by 11.52% per brand and feature frequency by 59.42% per brand to achieve the same sales as that achieved by moving the categories closer by an aisle. These results indicate that aisle placements and adjacencies can have as much an influence on sales as traditional marketing-mix variables, such as price, display, and feature. Thus, both retailers and manufacturers should pay close attention to aisle placements to increase sales, share of the customer wallet, and total profit.

Customizing Aisle Placement Strategies to Stores

Our analysis does not consider the costs of making changes in aisle placements. These costs may vary across stores. However, if we have access to the costs of changing aisle placements for each store, we can make customized recommendations on aisle placements for each store because we estimate the affinities induced by aisle placements at the individual store level (in θ_{cj}). Furthermore, because our model also identifies marketing-mix effects at the individual store level, we can identify stores that are more prone to aisle placement–induced affinities than to marketing-mix effects. Therefore, the results of our model calibration can be used to achieve a broader profit optimization through customized aisle placement and marketing-mix strategies for each store, depending on the store's responsiveness to these two variables. For example, depending on the relative responsiveness to these variables and the costs that might be incurred in implementing the store layout changes, certain stores may be targeted for better implementation of aisle management programs, and others may be selected for campaigns involving conventional merchandising/marketing-mix variables.

Analysis of Residual Effects for Affinities

Aisle adjacencies are only one aspect of a store that affects sales affinities between categories. Other features, such as aisle width, store lighting, ease of navigation, and store congestion, may also affect the sales affinities between categories. Although our model accounts for aisle adjacencies through the weighting matrices in Equation 2, it absorbs the affinity induced by other store factors in the residual store effects, u_j. It may be useful for retail chain managers to ana-

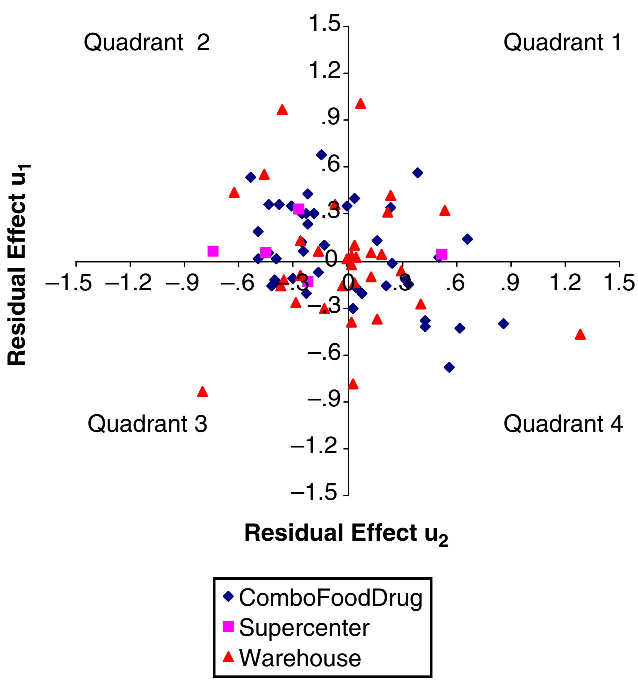
TABLE 9
Comparison of Required Changes in Merchandising and Marketing Variables for Desirable Outcomes

Variable	Brand	Elasticity	Average Change in Variable to Achieve the Same Effect as That by Bringing Aisle Closer by One	Average Change in Variable for the Same Effect if Categories Face Each Other in 55% of Stores
Price	Coke	2.567	3.84% (.48% per brand)	37.07% (4.63% per brand)
	Pepsi	1.486		
	RC Cola	2.342		
	SCola	1.672		
	Lay's	1.567		
	Ruffles	2.395		
	SChips	2.655		
	RChips	2.819		
	M	2.187		
Display	Coke	.112	92.19% (11.52% per brand)	892.43 (111.55% per brand)
	Pepsi	.069		
	RC Cola	.009		
	SCola	.065		
	Lay's	.110		
	Ruffles	.090		
	SChips	.025		
	RChips	.020		
	M	.063		
Feature	Coke	.004	475.32% (59.42% per brand)	4235.75% (529.47% per brand)
	Pepsi	.075		
	RC Cola	.002		
	SCola	.016		
	Lay's	.018		
	Ruffles	.014		
	SChips	.042		
	RChips	.050		
	M	.028		

lyze further the estimated residual store effects, $\hat{u}_j$, to identify stores that are underperforming or overperforming with regard to aisle placement affinities. Such an analysis can help managers identify the actionable conditions associated with overperforming stores and implement them in other stores.

An example of such an analysis appears in Figure 1, which plots the residual store effects for each category along the two axes. The stores in Quadrant 1 have positive residuals for the effects of both cola on chips ($\hat{u}_1$) and chips on cola ($\hat{u}_2$). The positive residuals suggest that sales in both categories in these stores exceed those predicted by the affinity influenced by aisle placements. Moreover, because residuals are higher in both categories, there is affinity between the categories in these stores due to factors other than aisle placements alone. For these reasons, the stores in Quadrant 1 can be viewed as performing better in inducing affinities between the two categories. The individual characteristics of these stores can be explored to develop prescriptions to improve the performance of other stores in the chain. Further analysis reveals that this quadrant consists of approximately 21% of the total stores. The frills-free warehouse format is the predominant format (56%) among these stores. The other types of stores in the data include a combination of food and drugstores and supercenters, which typically sell a wider range of merchandise.

FIGURE 1
Plot of the Residual Store Effects



In contrast, stores in Quadrant 3 can be viewed as underperforming with respect to cross-category affinities because sales of both categories in these stores are below the levels predicted by the aisle placements. Thus, both the internal and the external environments for these stores need further investigation to pinpoint the factors that might be contributing to their below-average performance. Stores in Quadrants 2 and 4 represent stores that perform well in one category but are below average in the other category.

To increase affinity-driven sales in the underperforming category of stores in Quadrants 2 and 4 and to improve cost efficiency across stores, a retail chain could incorporate the features of the overperforming stores of Quadrant 1. Burke and Payton (2006) note several store characteristics beyond aisle placements that may increase purchases of complementary products. These factors include having good store signage, reducing clutter, and having wide aisles to facilitate shopper navigation. Retailers could pay attention to these additional factors in underperforming stores to improve cross-category performance. As another example, warehouse format stores stock a narrow assortment of large pack sizes of adjacent categories that could make them salient in shopper consideration and induce high sales affinities. Retailers could suitably modify the assortment and pack sizes on the shelves in underperforming stores to improve salience and cross-category affinity.

Conclusions, Limitations, and Further Research

In this article, we develop and estimate a spatial model using store-level data to study the effects of aisle and display placements on cross-category brand sales, while controlling for the effects of marketing-mix activities. Our results show that the effects of aisle and display placements on cross-category sales are significant and asymmetric. Among the two placement variables, the effect of aisle adjacencies is stronger than that of display adjacencies. Importantly, the sizes of these effects match or exceed those of marketing-mix variables (i.e., price, feature, and display).

This research has important implications for both retailers and manufacturers because cross-category marketing programs depend on both manufacturers' incentives and retailers' willingness to implement such programs. Retailers can use the model results to make better aisle location and display decisions to increase overall sales and profitability. Moreover, they can exploit asymmetric sales affinities by making appropriate trade-off decisions. For example, if bringing the aisles of two categories (e.g., cola and chips) closer together to leverage sales affinities results in overcrowding of the aisles, the retailer can decide on the level of aisle separation required to achieve the desired overall sales lift by focusing on the sales of the category that benefits more from the asymmetry. Our simulation results with three categories show that asymmetric effects can be critically important in deciding which of two categories to move toward the other because each category may differentially affect a third category as a result of asymmetric effects. Furthermore, by comparing the differences in the aisle-induced affinities and marketing variables–induced affinities for the two categories, the retailer can better evaluate the payoffs from changing the aisle locations of the two categories compared with those from changing the marketing mix.

Manufacturers can use the results to better coordinate cross-category marketing programs and to cooperate effectively with retailers to encourage sales across their multiple brands. Given that current cross-category management initiatives tend to be more at a macro level and less detailed, our research can provide the necessary tool for manufacturers and retailers to apply detailed analysis to two or more selected categories to realize the value potential from such initiatives.

This research has certain limitations that further research could address. First, we performed the empirical analysis for two categories and a simulation for a third category. Other researchers could extend this analysis across more high-volume categories, for example, to a retailer's decision-support system for store layout decisions. Second, we consider only the effects of relative aisle placements on cross-category sales. Managers would also need to decide the absolute location of the aisles in the store (e.g., the direction and distance from store entrance). We could not obtain such data in our study, but future studies could collect such data and develop models to aid absolute aisle placement decisions. Third, although we glean insights into the effects of aisle and display placements on cross-category affinities using sales data, some researchers are beginning to examine customers' shopping paths for additional insights into store layout decisions (Hui, Fader, and Bradlow 2007). If such data were more readily available, researchers could seek triangulation of the affinity analysis results we illustrate herein with those from the analysis of shopping paths. Fourth, in some cases, aisle and display placement decisions may be influenced by factors such as trade deals and local market conditions. Further research could explore this endogeneity if relevant data on these factors are available. Finally, retailers are testing or using newer in-store technologies, such as radio frequency identification–enabled shopping carts, personal shopping assistants, and electronic displays, to improve shopability. The importance of these technologies in enhancing shopability may depend on consumers' perceptions of their values, both independently and in their interactions with merchandising decisions, such as those regarding aisle and display placements. Future studies could investigate the role of these technologies in influencing cross-category sales.

Appendix A

The matrix details of Equation 1 are specified in Table A1. In Equation 1, N_j and Ψ are $(I_1 + I_2) \times (I_1 + I_2)$ matrices, and $\Gamma = \gamma_i \mathbf{I}$, where $\mathbf{I}$ is an identity matrix of dimension $(I_1 + I_2) \times (I_1 + I_2)$, where I_1 and I_2 are the numbers of brands within each of the two categories. Note that our specification allows for a full unrestricted matrix of cross-brand estimates for prices and displays in the form of N_j and Ψ, respectively, while we estimate own effects using Γ and Π for feature and display $\times$ feature interaction, respectively (Manchanda, Ansari, and Gupta 1999; Montgomery 1997). We also estimated an alternative model in which we allow

TABLE A1
Matrix Details of Equation 1

$$\begin{bmatrix} \ln(S_{1cjt}) \\ \ln(S_{2cjt}) \\ \cdot \\ \ln(S_{1'c'jt}) \\ \ln(S_{2'c'jt}) \\ \cdot \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \\ \\ \cdot \end{bmatrix} + \begin{bmatrix} \eta_{11cj}\ \eta_{12cj}\ \dots\ \eta_{11'c'j}\ \eta_{12'c'j}\ \cdot \\ \eta_{21cj}\ \eta_{22cj}\ \dots\ \eta_{21'c'j}\ \eta_{22'c'j}\ \cdot \\ \cdot \\ \eta_{1'1cj}\ \eta_{1'2'cj}\ \dots\ \eta_{1'1'c'j}\ \eta_{1'2'c'j}\ \cdot \\ \eta_{2'1'cj}\ \eta_{2'2'cj}\ \dots\ \eta_{2'1'c'j}\ \eta_{2'2'c'j}\ \cdot \\ \cdot \end{bmatrix} \begin{bmatrix} p_{1cjt} \\ p_{2cjt} \\ \cdot \\ p_{1'c'jt} \\ p_{2'c'jt} \\ \cdot \end{bmatrix} + \begin{bmatrix} \phi_{11c}\ \phi_{12c}\ \dots\ \phi_{11'c'}\ \phi_{12'c'}\ \cdot \\ \phi_{21c}\ \phi_{22c}\ \dots\ \phi_{21'c'}\ \phi_{22'c'}\ \cdot \\ \cdot \\ \phi_{1'1c}\ \phi_{1'2'c}\ \dots\ \phi_{1'1'c'}\ \phi_{1'2'c'}\ \cdot \\ \phi_{2'1'c}\ \phi_{2'2'c}\ \dots\ \phi_{2'1'c'}\ \phi_{2'2'c'}\ \cdot \\ \cdot \end{bmatrix} \begin{bmatrix} d_{1cjt} \\ d_{2cjt} \\ \cdot \\ d_{1'c'jt} \\ d_{2'c'jt} \\ \cdot \end{bmatrix}$$

$$+ \begin{bmatrix} \gamma_{11c}\ 0\ \dots\ 0\ \dots\ 0\ \dots \\ 0\ \dots\ \gamma_{22c}\ \dots\ 0\ \dots\ 0\ \dots\ . \\ \cdot \\ 0\ \dots\ 0\ \dots\ \gamma_{1'1'c'}\ \dots\ 0 \\ 0\ \dots\ 0\ \dots\ 0\ \dots\ \gamma_{2'2'c'}. \\ \cdot \end{bmatrix} \begin{bmatrix} f_{1cjt} \\ f_{2cjt} \\ \cdot \\ f_{1'c'jt} \\ f_{2'c'jt} \\ \cdot \end{bmatrix} + \begin{bmatrix} \pi_{11c}\ 0\ \dots\ 0\ \dots\ 0\ \dots \\ 0\ \dots\ \pi_{22c}\ \dots\ 0\ \dots\ 0\ \dots\ . \\ \cdot \\ 0\ \dots\ 0\ \dots\ \pi_{1'1'c'}\ \dots\ 0 \\ 0\ \dots\ 0\ \dots\ 0\ \dots\ \pi_{2'2'c'}. \\ \cdot \end{bmatrix} \begin{bmatrix} d_{1cjt} \times f_{1cjt} \\ d_{2cjt} \times f_{2cjt} \\ \cdot \\ d_{1'c'jt} \times f_{1'c'jt} \\ d_{2'c'jt} \times f_{2'c'jt} \\ \cdot \end{bmatrix} + \chi \begin{bmatrix} 1 \text{ or } 0 \\ 1 \text{ or } 0 \\ \cdot \\ 1 \text{ or } 0 \\ 1 \text{ or } 0 \\ \cdot \end{bmatrix} + \eta \begin{bmatrix} 1 \text{ or } 0 \\ 1 \text{ or } 0 \\ \cdot \\ 1 \text{ or } 0 \\ 1 \text{ or } 0 \\ \cdot \end{bmatrix} + \begin{bmatrix} \theta_{cj} \\ \theta_{cj} \\ \cdot \\ \theta_{c'j} \\ \theta_{c'j} \\ \cdot \end{bmatrix} + \begin{bmatrix} \phi_{cjt} \\ \phi_{cjt} \\ \cdot \\ \phi_{c'jt} \\ \phi_{c'jt} \\ \cdot \end{bmatrix} + \begin{bmatrix} \varepsilon_{1cjt} \\ \varepsilon_{2cjt} \\ \cdot \\ \varepsilon_{1'c'jt} \\ \varepsilon_{2'c'jt} \\ \cdot \end{bmatrix}$$

for the full matrix of responses in case of display × feature interaction. The results were similar.

Additional Details Regarding Equations 2–4

Formally, $\theta_j = [\theta_{1j}, \theta_{2j}]'$ and $u_j = [u_{1j}, u_{2j,}]'$ in Equation 2. We assume that $u_j \sim N(0, \sigma^2\mathbf{I})$, where $E(u_ju_k) = 0$ for $j \neq k$. We specify the spatial correlation parameter matrix ρ as follows: $\rho = [\mathbf{R}_1\mathbf{R}_2]$, where $\mathbf{R}_1$ is a $I_1 \times 1$ vector whose elements are all equal to ρ_1 and $\mathbf{R}_2$ is a $I_2 \times 1$ vector whose elements are all equal to ρ_2 with $\{\rho_1, \rho_2\} \in (-1, 1)$. In Equation 4, $\phi_{jt} = [\phi_{1j}, \phi_{2j}]'$ and υ_{jt} is a 2×1 vector of nonspatial errors, one for each category, with each error assumed to be independently distributed as $N(0, \xi^2)$.

Description of the Weighting Matrices

The weighting matrices, W_{1j} and W_{2j}, used in Equation 2 have the following structure to reflect aisle placements of the categories:

$$W_{1j} = \begin{pmatrix} \mathbf{O}_1 & \mathbf{D}_{1j} \\ \mathbf{D}_{2j} & \mathbf{O}_2 \end{pmatrix} \qquad W_{2j} = \begin{pmatrix} \mathbf{O}_1 & \mathbf{S}_{1j} \\ \mathbf{S}_{2j} & \mathbf{O}_2 \end{pmatrix},$$

where $\mathbf{O}_1$ and $\mathbf{O}_2$ represent square matrices of zeroes with dimensions I_1 and I_2, respectively, and $\mathbf{D}_{1j}$ and $\mathbf{D}_{2j}$ are matrices of dimensions $I_1 \times I_2$ and $I_2 \times I_1$, respectively, whose elements are all equal to $1/\exp(d_j)$ (Yang and Allenby 2003), where d_j is the distance between the aisle locations of the two categories in store j. Thus, in line with the practice in the spatial modeling literature, the diagonal matrices in W_{1j} are zero because they correspond to brands in the same category and do not pertain to cross-category sales affinities. In contrast, the cross-category sales affinities are allowed to vary inverse exponentially with the distance between the aisle locations of the two categories through the off-diagonal matrices, $\mathbf{D}_{1j}$ and $\mathbf{D}_{2j}$. Similarly, in the weighting matrix W_{2j}, the off-diagonal matrices, $\mathbf{S}_{1j}$ and $\mathbf{S}_{2j}$, are indicator matrices of dimensions $I_1 \times I_2$ and $I_2 \times I_1$, respectively, whose elements equal one if both Categories 1 and 2 in store j are on opposite sides of the same aisle and zero if otherwise. Thus, the matrix W_{2j} captures the cross-category affinities that arise from both categories being on the opposite sides of the same aisle.

We specify the weighting matrix W_{3jt} used in Equation 4 as follows:

$$W_{3jt} = \begin{pmatrix} 0 & \dfrac{1}{\exp\delta_{2jt}} \\ \dfrac{1}{\exp\delta_{1jt}} & 0 \end{pmatrix}.$$

Again, only the off-diagonal elements of W_{3jt} interact with cross-category components of ϕ_{jt}, so the diagonal elements are set to zero. For store j in week t, the off-diagonal element above the diagonal in W_{3jt} is inverse exponentially related to the distance, δ_{2jt}, of the display in Category 2, as measured from the aisle in which Category 1 is stocked. This element captures variation in cross-category sales affinity induced in Category 1 due to changes in display placements in Category 2. The interpretation of the other off-diagonal element in W_{3jt} is analogous. In computing δ_{1jt} and δ_{2jt} for a given week t, we average the distance measures of all the displayed brands in a category if more than one brand is displayed. However, in our data, only one brand is displayed per week approximately 80% of the time. Moreover, we find that for some store weeks, none of the brands in a category are on display. For these store weeks, we let the corresponding off-diagonal element of W_{3jt} have a very small value of the order of .0005. This is equivalent to assigning a large value to δ_{1jt} or δ_{2jt}.

Heterogeneity

To specify heterogeneity in the price parameters, let $\boldsymbol{\beta}_j' = [\text{vec}\ (N_j)']$. Our specification for heterogeneity in $\boldsymbol{\beta}_j$ is as follows:

$$\boldsymbol{\beta}_j = Z_j\Delta + K,\ K \sim N(0, V_\beta),$$

where the matrix Z contains demographic and competitor variables apart from the constant term and Δ is the corresponding matrix of coefficients. We mean-center the demographic and competitor variables so that we can interpret the constant term as the response for an average store. Furthermore, for parsimony, we allow all the price effects to have the same set of demographic estimates (Montgomery 1997).

Computation of Elasticities

We compute the elasticities with posterior draws used in the estimation of the model parameters (Allenby and Lenk 1994) per Equation 1, with the following expressions for the spatial error components:

$$\theta_{new} = (I_\theta - \rho W_{new})^{-1}\hat{u},\ \text{and}\ \phi_{new} = (I_\phi - \rho_3 W_{3new})^{-1}\hat{\upsilon},$$

where $\hat{u}$ and $\hat{\upsilon}$ are computed from Equations 2 and 4, respectively (Case 1991). When we compute the effect of changes in aisle or display placements, such changes result in a revision of the appropriate weighting matrices; these are indicated by W_{new} and W_{3new} in the preceding expressions.

Appendix B

Augmented Model Assumed for Cola–Juice and Chips–Juice

The augmented model assumed for the affinity between cola and juice and chips and juice is similar to Equation 1, except that display distances were not modeled; thus, $\phi_{cjt} = 0$. Furthermore, we modify Equation 2 as follows:

$$\theta_j = \rho\left(\tau_1 W_{1j} + \tau_2 W_{2j} + \tau_3 W_{4j}\right)\theta_j + u_j.$$

Thus, we assume a third weighting matrix, W_{4j}, in the formulation for θ_j to account for juxtaposition effects. Furthermore, we assume that $\tau_1 + \tau_2 + \tau_3 = 1$. We specify the matrix W_{4j} analogous to W_{2j}, except that the off-diagonal elements equal one in the case of W_{4j} if the drink category is juxtaposed between the cola and chips categories and zero if otherwise.

Key Simulation Parameters

Parameter	Cola–Juice	Chips–Juice
ρ_1 (e.g., cola–juice affinity)	.30	.55
ρ_2 (e.g., juice–cola affinity)	.20	.35
τ_2	.30	.30
τ_3	.20	.20

We assume that the strength of the complementarity between the juice–chips category pair is higher than that for the juice–cola category pair. This assumption is based on the reasoning that consumers might purchase a drink when they buy chips, though such behavior might not exist for juice–cola purchases. However, the purchases in these categories might still be positively related because of the location of these categories within the store and because consumers might buy both juice and cola together. Thus, we assume that the affinity due to aisle distances is stronger (and positive) for juice–chips and weaker (and positive) for juice–cola. We also assume that the magnitude of the affinity due to the juice category juxtaposed between chips and cola is lower than the affinity due to both the respective aisle distances and their presence on the same side of the aisle.

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