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The Perils of Category Management: The Effect of Product Assortment on Multicategory Purchase Incidence

Retailers determine the assortment for a mix of product categories in a particular space (e.g., the checkout aisle, endcaps, freezer space). Within such a "target" space, shoppers are exposed to a selection of product categories that are not necessarily correlated in consumption. In this article, the authors examine whether the assortment of one category affects consumers' purchase incidence decision in another, independent category that shares a common display space (e.g., frozen meals and ice cream). They use a multivariate probit model of purchase incidence and incorporate assortment variety captured by an entropy measure. Results from analyses of IRI data and an online experiment provide strong evidence that consumers are less likely to purchase from a category of a given assortment when it is presented with another category assortment of greater variety and that this effect is driven by the display proximity. Furthermore, results from an eye-tracking study indicate consumers' allocation of limited attention to category assortments as an explanation for the finding. This work serves as one of the first studies to document the impact of product assortment beyond a focal category, and the results highlight a limitation of individual category management when grocery retailers make product assortment decisions.

Keywords: product assortment, aisle management, cross-category analysis, hierarchical Bayesian model, eye tracking

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Category product assortment refers to a set of products offered within a category by a retailer to consumers. Category product assortment planning is an important decision for retailers, and for several reasons, it often involves decisions on multiple product categories in a particular space. For example, grocers make use of their checkout aisle to entice shoppers in the queue to make impulse purchases. The retailers' objective is to maximize sales from such purchase incidences by displaying items from tempting product categories, such as chocolate bars and magazines. In the fixed space of the checkout aisle, the retailer needs to determine the assortment for each category to be displayed. A similar approach is required for the end-of-aisle shelves, or endcaps, where retailers generally offer promotional deals from a few categories. In some instances, the nature of the products requires the retailer to make assortment decisions for a group of categories in a common space—for example, freezer space in a supermarket. The assortment of frozen items is planned on the basis of available freezer space; as a result, shoppers are naturally exposed to the selection of frozen food categories while searching for any particular product.

In this article, we examine whether, in a retail space, the assortment of one category affects consumers' purchase incidence decisions in another category displayed nearby. In particular, we investigate whether the "display proximity" between the two category assortments can drive such intercategory purchase dependence. The grocer's assortment of multiple categories in a common display aisle makes a useful empirical context in which to study the cross-category effect of product assortment driven by display proximity. The fact that such multicategory assortments often comprise a set of categories that are not related in terms of consumption a priori (e.g., chocolates and magazines at the checkout aisle) enables us to identify the effect due to the display proximity separately from that due to correlations in consumption.

The findings from this study can guide retailers toward more effective assortment decisions. In the presence of the cross-category assortment effect, the assortment decisions should not be made independently (i.e., one category at a time). In addition to understanding the existence and the pattern of the effect, it is also important to identify potential factors that

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could trigger the effect. Given that retailers handle a large number of product categories in a store, there is a need to identify the boundary condition for the cross-category effect. Identifying the role of display proximity will inform retailers of the circumstances in which they should consider the effect of product assortment beyond a focal product category.

The existence of cross-category assortment effects is a largely unexplored empirical question. Early studies in the area of assortment research have focused on the benefits of large versus small assortments and supported a conventional belief that a larger product assortment will benefit consumers and lead to greater sales (Baumol and Ide 1956; Kahn and Lehmann 1991; McAlister and Pessemier 1982). Over the past decade, major retailers have questioned the strategy of offering a large number of products within each category and have rationalized their product assortments.[1] In line with this trend, industry and academic researchers have shown that consumers' purchase decisions are influenced by their "perception" of an assortment rather than by any objective characterization of the assortment (e.g., number of distinct options; Boatwright and Nunes 2001; Broniarczyk, Hoyer, and McAlister 1998; Chernev 2005; Drèze, Hoch, and Purk 1994; Gourville and Soman 2005; Iyengar and Lepper 2000; Kahn and Wansink 2004). In this stream of research, however, a large number of product categories have been studied independently, so the findings are limited to a single product category (for an in-depth review, see Chernev 2011).

The empirical findings from single product categories do, however, motivate inquiry into the effect of assortment across categories. Research has shown that the amount of shelf space allocated to a product category can shape consumers' perception of assortment and choices (Broniarczyk, Hoyer, and McAlister 1998). This is due to consumers' cognitive (shelf-space heuristics) and affective (ease of searching for favorite items) reactions. The finding suggests the presence of cross-category effects of assortment between categories that are related spatially. Indeed, in a related study, Bezawada et al. (2009) examine the impact of category aisle and display placements on multicategory sales using store-level planogram and sales data and confirm the important role of the category display location. Yet their approach is distinct from ours in two respects. First, their work follows the intuition that the impact of marketing activities for a set of substitutes (e.g., butter and margarine) or complements (e.g., pasta and pasta sauce) will go beyond a single product category.[2] By focusing on a priori defined consumption complements (cola and potato chips), the main interest of their study is to compare the magnitude of the cross-category effects due to the category placements with other known effects due to price and promotions between such pairs of complements. Our study focuses on cross-category effects even when there are no known complementary or substitution patterns across categories. In addition, Bezawada et al.'s use of aggregate data, as opposed to household panel data, makes it difficult to identify the impact on individual consumers' decision making.

Why and when can we expect the consumer's purchase decision in one category to be influenced by the assortment of another independent category? Although no direct theory from the assortment research can answer this question, we note that there are multiple mechanisms leading to the cross-category effects of product assortment. We focus on two explanations—one, economic, and the other, psychological—that make distinct predictions with respect to the boundary of the effects. First, such intercategory purchase dependence that results from product assortment may be attributed to a general competition among categories for consumers' finite shopping budget. When consumers face a binding budget constraint on a shopping trip, their demand for any one category will depend on marketing activities for all other categories, which in turn changes their purchase probability of the categories. A great assortment in one product category could make consumers spend more on that category and, thus, less likely to spend on the other categories.[3] This argument is also consistent with empirical evidence of consumers' mental accounting in a grocery shopping context (Heath and Soll 1996; Heilman, Nakamoto, and Rao 2002; Stilley, Inman, and Wakefield 2010). According to this account, cross-category effects occur as a result of any marketing activity—including the retailer's product assortment decisions. In particular, the effect of price will be the most evident, and the effect will exist across categories regardless of display locations in the store.

Second, psychological theories of a consumer's visual attention and perception processes predict the existence of cross-category effects between category assortments displayed in close proximity in a given space. Attention has been characterized with three properties of (1) a limited capacity, (2) a selective process, and (3) coordination of the perception-action cycle (LaBerge 1995). The first two properties imply that the consumers faced with multiple stimuli need to allocate their limited attention among the stimuli, and the third property emphasizes the role of attention beyond mere information acquisition. Research in marketing and psychology has advanced this idea and shown that consumers' visual attention to marketing stimuli reflects a higher-order cognitive process and can predict downstream actions such as product consideration, choices, and purchases (Janiszewski, Kuo, and Tavassoli 2013; Rizzolatti, Riggio, and Sheliga 1994; Russo 1978; see also Wedel and Pieters's [2006] review). According to this attention-based theory, consumers faced with multiple assortments in a given space would need to allocate their

[1]According to a survey released by ACNielsen (2010), more than 40% of U.S. retailers reduced the number of products on their shelves in 2009. The pharmacy chain Walgreens reduced the number of superglues in its assortment from 25 to 11, and Kroger delisted 30% of its cereal items. During the same period, Wal-Mart also announced its store remodeling program, which involved eliminating thousands of slow-selling items.

[2]This intuition has been tested empirically (Lee, Kim, and Allenby 2013; Manchanda, Ansari, and Gupta 1999; Russell and Petersen 2000; Song and Chintagunta 2006). In particular, research has shown that the cross-category price effects are significant between pairs of categories that exhibit interdependence in consumption, and their signs inform the nature of the relationship (positive cross-price effects between substitutable goods and negative effects between complementary goods).

[3]Alternatively, if consumers do not find their preferred option in one category, they are likely to spend more on the other categories.

limited attention among the stimuli, and their purchase decision on a certain product category could be negatively affected by greater assortments of surrounding categories that steal some of their attention. The cross-category effects of product assortment on their purchase incidence can, therefore, arise from consumers' limited attention (i.e., as opposed to the limited economic budget) and be unique to the category assortments that are displayed closely to each other. Other psychological theories of a consumer's context-dependent judgment and decision making generate similar predictions (Adaval and Monroe 2002; Nunes and Boatwright 2004).

In our empirical analysis, we extend a model of the household's multicategory purchase incidence (Chib, Seetharaman, and Strijnev 2002; Manchanda, Ansari, and Gupta 1999) to uncover the cross-category assortment effects, and we apply the model to two discretionary frozen food categories: frozen meals and ice cream. These two categories share the same display space but are neither explicit substitutes nor complements in consumption. We construct a comprehensive data set from both household scanner panel data and store-level sales and operationalize an assortment variable using an entropy measure (Hoch, Bradlow, and Wansink 1999; Kahn and Wansink 2004; Van Herpen and Pieters 2002). This measure has been shown to explain the bulk of consumers' perceived variety by capturing variations of two aspects of assortment: size and composition. We make use of this metric to link consumers' perception of the assortment to their category purchase likelihood in a grocery shopping context.

Our empirical results confirm that households perceive the two categories independently with regard to cross-category price effects. Yet their purchase decisions in each category are affected by the assortment of both categories—positively by own assortment and negatively by cross-assortment. This finding of the negative cross-category assortment effects in the absence of simultaneous significant price effects is new and refutes the economic argument that predicts cross-category effects of every marketing activity. Instead, it is consistent with the psychological argument.

To determine whether it is the display proximity between the categories that gives rise to the cross-category effects of assortment, we conduct additional analyses. First, using household purchase data, we estimate the assortment effects between other pairs of categories that do not compete for a particular space (frozen meals and paper towels). Second, we conduct an online experiment in which we manipulate the display proximity between a given pair of categories (chocolates and magazines). Results from both studies consistently point to the display proximity as a trigger of the effects. Given these results, we attempt to further test the psychological argument that the effects could be due to consumers' limited attention by measuring participants' attention to multicategory assortment in a given space using an eye tracker. The results indicate that the consumers' allocation of limited attention to multicategory assortment could account for why they are less likely to purchase from an assortment when it is presented with another large assortment.

Our results raise the question of whether retailers should employ individual category management in all circumstances. Category management is a practice in which retailers manage the performance of individual product categories as independent units, and it has been employed increasingly since the early 1990s; as of 2003, 96% of retailers in the United States reported that they applied the category management to their assortment planning (ACNielsen 2004). Our results challenge this notion of managing product categories independently, and we draw retailers' attention to the finding that their efforts to increase the variety of product categories independently could lead to adverse outcomes in some situations. The findings support some of their recent attempts at redesigning and managing each aisle as a "department" with a common theme instead of as a group of independent category assortments (Food Marketing Institute 2012).

The rest of the article proceeds as follows: In the next section, we develop the econometric model of multicategory purchase incidences by incorporating the key aspect of product assortment. The subsequent section describes the data and operationalization of variables, and the estimation results follow. The results are then complemented by two studies that identify the role of display proximity. Next, we attempt to understand the mechanism at the consumer level by conducting an eye-tracking study, and we close by offering conclusions.

Econometric Model

In this section, we present a model of consumers' multicategory purchase incidence decisions based on random utility theory. We first describe the specification of the utility function and build an econometric model for two product categories.

Utility Specification

On a given shopping trip, each consumer decides whether to purchase any product from each of two product categories, j (j = 1, 2). Formally, consumer i's decision on a given shopping trip t is represented by a vector $Y_{it} = \{y_{i1t}, y_{i2t}\}$, where $y_{ijt} \in \{0, 1\}$ refers to the consumer's purchase incidence decision on category j (1 if purchased and 0 otherwise). The utility that the consumer obtains from category j is specified as a linear function of three components:

$$U_{ijt} = \alpha_{ijt} + g_i(Z_{jt}) + \epsilon_{ijt}. \tag{1}$$

α_{ijt} is consumer i's time-dependent intrinsic preference for category j; $g_i(Z_{jt})$ is consumer i's evaluation of a set of attributes Z_{jt}, which determines the attractiveness of category j at a shopping trip t; and ϵ_{ijt} is a stochastic error component.

Intrinsic category preference. Acknowledging that consumers' preference for product categories can vary over time, we decompose the category preference to an individual fixed component and two time-varying components. First, our model captures seasonal changes in category demand by including a U.S. state–level monthly temperature.[4] This additional variable is also useful in capturing

[4]We collected the monthly state-level average temperature data from Earth System Research Laboratory, U.S. Department of Commerce (http://www.esrl.noaa.gov/psd/data/usclimate). As an alternative specification, we also considered quarterly fixed effects instead of the temperature variable and confirmed that the main results remained consistent.

contemporaneous state-level aggregate demand shocks that affect households in a similar fashion (Dubé 2004). Second, we complement the model by accounting for household inventory. For a repeatedly purchased product category, the amount of household inventory of the category can influence the purchase decision (Guadagni and Little 1998). Because we do not observe the data of each individual household's inventory, we use a variable of time since last category purchase (from any store) made by each household as a proxy. This time variable is operationalized as the number of weeks since each household's latest category purchase occasion. By including the variable, we attempt to identify indirectly whether the consumers' category purchase was induced by the lack of inventory at home.[5]

$$\alpha_{ijt} = \alpha_{0ij} + \alpha_{1j}\text{Temp}_t + \alpha_{2j}\text{Time}_{ijt}. \tag{2}$$

Category attributes. The explanatory variables we include as category attributes are prices, promotion intensity, and assortments of both categories. There are two main features in the proposed attribute selection. First, variables for category assortments are included. Consumers may experience additional utility from a larger assortment (Broniarczyk, Hoyer, and McAlister 1998; Kahn, Moore, and Glazer 1987; Oppewal and Koelemeijer 2005). In addition to assortment size, composition of the assortment could influence the consumers' perceived variety and, thus, their utility from the category. To capture the overall impact of the category assortment on consumers' purchase decisions through changes in their perceptions, we incorporate a metric for attribute-level frequencies (entropy) in each category assortment. The entropy measure has been shown to account for the bulk of consumers' perceived variety by capturing variations of two aspects of assortment: size and composition (Kahn and Wansink 2004; Van Herpen and Pieters 2002). In the "Data" section, we provide a detailed description of this variable. Second, the utility for one category is written as a function of various marketing activities in the other category as well. Traditionally, the rationale for this is that, for the categories whose consumptions are correlated (i.e., substitutes or complements), the utility that consumers obtain from one category is not independent of marketing activities in other related product categories. One parsimonious way of capturing such cross-category effects of the marketing mix variables is to include marketing variables in every relevant category in the utility specification (Duvuuri, Ansari, and Gupta 2007; Manchanda, Ansari, and Gupta 1999).[6] We follow this approach to capture any potential cross-category effects that result from marketing mix variables. In the present model of two product categories, therefore, both category utilities can be written as a function of the same set of marketing-mix variables: $\forall j = 1, 2$,

$$\begin{aligned} g_i(Z_{jt}) = {} & \beta_{1ij}\text{Price}_{i1t} + \beta_{2ij}\text{Price}_{i2t} + \beta_{3ij}\text{Promo}_{i1t} \\ & + \beta_{4ij}\text{Promo}_{i2t} + \beta_{5ij}\text{Assort}_{i1t} + \beta_{6ij}\text{Assort}_{i2t}. \end{aligned} \tag{3}$$

Stochastic component. Idiosyncratic error terms $\epsilon_{it} = \{\epsilon_{i1t}, \epsilon_{i2t}\}$ account for unobserved components of utility that consumers obtain from the two categories. If these error terms are assumed distributed i.i.d. standard normal distribution, consumers' purchase decisions for these two categories become independent after taking into consideration the cross-category effects from the selected marketing-mix variables. In reality, however, other potential factors could lead to consumers' joint category purchases (e.g., common category purchase cycle, consumer habits and mood, other economic reasons), and researchers have accounted for such unobserved sources of correlation by allowing the variance–covariance matrix of the error terms to have more flexible forms (Chib, Seetharaman, and Strijnev 2002; Manchanda, Ansari, and Gupta 1999). In our model, we also relax the assumption of independent errors by assuming

$$\epsilon_{it} \sim \text{MVN}(0, \Sigma), \tag{4}$$

where Σ is a 2×2 variance–covariance matrix. For the sake of identification of parameters, we model this further as a correlation matrix by setting its diagonal elements as 1.

Heterogeneity across households. To account for unobserved sources of heterogeneity across households, we introduce household-specific random coefficients. Specifically, an individual fixed component of category preference and coefficients for category attributes are assumed heterogeneous across households. To place our focus on the effects of marketing variables, we assume coefficients for temperature and inventory variables that are constant across households. Denote $\theta_i = \{\alpha_{0i}, \beta_{1i}, \ldots, \beta_{6i}\}$ as a vector containing these household-specific coefficients for both categories. Then the hierarchical structure for θ_i is specified as follows:

$$\theta_i \sim \text{MVN}(\bar{\theta}, \Omega), \tag{5}$$

where $\bar{\theta}$ is a 14-dimensional vector and Ω is a 14×14 variance–covariance matrix representing the overall covariation in individual responses to the included marketing-mix variables and intrinsic category preferences for the two product categories.

Modeling Multicategory Purchase Incidence

Following the latent utility approach, a household's category purchase incidence is determined by

$$y_{ijt} = 1[U_{ijt} \geq 0]. \tag{6}$$

Combined with the previous assumption that idiosyncratic error terms ϵ_{it} follow a multivariate (bivariate) standard normal distribution, this formulation becomes a bivariate probit model. Denote X_{it} as a vector containing covariates that correspond to a set of individual coefficients for household i at

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[5]As alternative operationalizations, we also considered this time variable normalized at the individual-household level (i.e., the absolute and relative deviation from each individual mean interpurchase time) and confirmed that the main empirical findings remained unchanged.

[6]Mehta (2007) developed an alternative model of category purchase incidence and brand choice decisions built on microeconomic principles of consumers' basket utility maximization behavior. By deriving that theoretically supported cross-category effects depend only on the menu of purchased categories, he showed that other models that disregard this property may overemphasize the cross-category effects.

time t. Then, the conditional probability that household i with known θ_i and $\{\alpha_1, \alpha_2\}$ makes a certain purchase decision $Y_{it} = \{y_{i1t}, y_{i2t}\}$ at shopping trip t is given by

$$P(Y_{it} = \{y_{i1t}, y_{i2t}\} | \theta_i, \alpha_1, \alpha_2, \Sigma) = \int_{C_1}\int_{C_2} \varphi(U_{it}|\theta_i, \alpha_1, \alpha_2, \Sigma)dU_{it}, \tag{7}$$

where $\varphi(U_{it}|\theta_i, \alpha_1, \alpha_2, \Sigma)$ is the density of a bivariate normal distribution with mean $(X_{it}\theta_{i1} + \alpha_{11}\text{Temp}_t + \alpha_{21}\text{Time}_{i1t}, X_{it}\theta_{i2} + \alpha_{12}\text{Temp}_t + \alpha_{22}\text{Time}_{i2t})$ and variance–covariance matrix Σ. C_1 and C_2 are two intervals corresponding to the observed purchase decisions for each category; $(0, \infty)$ if purchased and $(-\infty, 0)$ otherwise. The resulting probability that a randomly selected household i makes a certain sequence of purchase decisions for total T_i number of shopping trips, $Y_i = \{Y_{i1}, Y_{i2}, \ldots, Y_{iT_i}\}$ for the two categories is then written as the following:

$$\begin{aligned} &P\left(Y_i = \{Y_{i1}, Y_{i2}, \ldots, Y_{iT_i}\}|\alpha_1, \alpha_2, \bar{\theta}, \Omega, \Sigma\right) \\ &= \int \prod_{t=1}^{T_i} P(Y_{it}|\theta_i, \alpha_1, \alpha_2, \Sigma)\cdot\psi\left(\theta_i|\bar{\theta}, \Omega\right)d\theta_i, \end{aligned} \tag{8}$$

where $\psi(\theta_i|\bar{\theta}, \Omega)$ is the density of a multivariate normal distribution. This requires integration over multiple multivariate normal distribution of θ_i, which makes a direct estimation using likelihood infeasible. Following the previous estimation approach for multivariate probit model with consumer heterogeneity, we make use of Bayesian inference from the Markov chain Monte Carlo iterations with prespecified priors over the unknown parameters (Allenby and Rossi 1998).

Data

Category Selection and Households' Shopping History

We selected the product categories for our empirical analysis from one of our previous examples of frozen food categories: frozen meals and ice cream.[7] Because these two product categories must be displayed in a freezer, most grocers present them together in the freezer aisle. In general, grocers allocate each aisle to a set of substitutable or complementary product categories, such as "families" of paper goods or detergents, and many frozen items presented in this aisle may also be grouped as alternatives for daily meals (e.g., frozen meat, frozen poultry). Between frozen meals and ice cream, however, there is no such clear relationship in terms of consumption. Such a selection of categories enables us to investigate potential intercategory purchase dependence driven mainly by the assortment and not by correlations in consumption.

The empirical analysis of the two categories uses two different IRI data sets: (1) a household panel purchase data set and (2) a corresponding store panel sales data set. Both data span five geographical markets (California, Georgia, Illinois, Massachusetts, and Washington) and 56 weekly time periods (from January 30, 2006, to February 25, 2007). Previous research focusing on the effects of price and promotions on multicategory purchase incidences has used either household panel data (Bucklin and Lattin 1991; Chib, Seetharaman, and Strijnev 2002; Manchanda, Ansari, and Gupta 1999; Russell and Petersen 2000) or store panel data (Song and Chintagunta 2006). The identification of the effects of product assortments, however, requires comprehensive data that contain outcomes of both households' purchase decisions and the in-store product assortments available to the households.

The household panel data provide the information on weekly shopping behaviors for a sample of households. For the selected two categories, the data contain the history of shopping trips that result in purchases of either of the two categories and the information of each visited store. To obtain the record of shopping trips that involved no purchase of either category, we also examine each household's shopping history for eight other categories: analgesics, canned tuna, coffee, condiments, cookies, juice, paper towels, and toothpaste. By combining the information on all the shopping visits that each household made for these ten categories (including frozen meals and ice cream), we generate a comprehensive list of stores that the households visited during the period of observation. Given that these categories include ones that are purchased regularly and quite frequently (e.g., juice), the resulting list of stores should be a good representation of each household's shopping history.

To obtain in-store marketing variables for each category, we use the information from the store panel data. The store panel data contain weekly price and unit sales for every Universal Product Code (UPC) along with detailed product descriptions. The data also include promotional information such as special displays and feature advertisement at the UPC level. Although we do not directly observe product assortments that were displayed on shelves in each store, we can infer such information using a union of UPCs sold during a certain period of time for which the sales have been recorded. This measure assumes that at least one unit of each displayed product is sold during the period. For example, Briesch, Chintagunta, and Fox (2009) used a union of weekly sales records when estimating the impact of product assortment on store choice.

A potential concern of the previous operationalization using weekly sales data are the presence of products on shelves that did not sell during a particular week. We operationalize category assortment using the union of UPCs sold from the category every four weeks so that the estimated effects are less likely to be influenced by the slow-selling items.[8] Combining the sales data with detailed descriptions of UPCs, we construct attribute-based entropy for category assortment and capture how the size and composition of the assortment change across stores over time.

We constructed the complete data set for our empirical study by merging both household and store panel data using unique store identification codes. We selected households with more than 10 shopping trips over a 56-week period, which

[7]We use the IRI data sets for frozen entrées/dinner and ice cream. Because the data contain various items of frozen entrées, dinners, and soups, we use the term "frozen meals" hereinafter for the sake of clarity.

[8]For a robustness check, we also estimated our model with assortment variables based on quarterly (i.e., every 13 weeks) UPC sales and confirmed that the main results remained consistent.

resulted in 16,781 shopping trips made by 727 households. The average number of shopping trips per household in our final data is 23.08, which translates to an inter-shopping-trip time of 15.8 days. In terms of store coverage, the data cover 60 stores from 30 retail chains in five geographical markets. During the observed period, each household visited 1.63 stores on average, and 53.0% of the total households visited only one store (i.e., no switching behavior between stores for selective category shopping).

Table 1 summarizes the observed category purchase patterns. In our sample, the average number of ice cream purchase occasions per household was roughly twice as many as that of frozen meals, and this is consistent with the data for U.S. households on average (source: Nielsen Consumer Panel Services [2001] and IRI Builders Suite [2008] data sets). Although our inference of households' shopping trips based on their purchase occasions for ten product categories may capture a fraction of their total shopping trips, the observed purchase pattern for the two categories is consistent with U.S. households on average. In addition, through a simplified simulation study, we confirmed that such data omission on "no-purchase" trips allowed unbiased estimation of the assortment effects (it could at best influence an estimate for an intercept term).

For both categories, a single item purchase was the most commonly observed, and this emphasizes the relevance of modeling households' purchase incidence decisions for these two categories. Table 2 provides frequencies of four possible shopping baskets, and we observe that the average purchase probability of one category varies depending on the purchase incidence of the other category. By modeling jointly the purchase incidences of both categories, our study helps uncover sources of such interdependence.

Operationalization of Marketing Variables

Price and promotion intensity. In operationalizing the category price and promotion intensity, we followed previous research. We generated household-level variables similar to those described in a previous study of households' multicategory purchase incidences (Manchanda, Ansari, and Gupta 1999). For category price, we first computed brand prices for each store-week unit as sales-weighted average price of UPCs in each brand. This allows brand prices to vary across stores over time. We calculated the household-specific category price as a weighted average price of brands in which the weights were the shares of brands purchased by a household for the entire period.[9] For households that never made a purchase in either category, we used store-level sales-weighted price. The IRI store panel data contain the information on promotions as indicator variables for special displays and feature advertisements at the UPC level. The data do not include price promotions, and any changes in prices are captured as variations in our price variable. We operationalize our promotion variable at the household level in a similar manner to our price variable. Because this value lies between 0 and 1, we define it as intensity.

TABLE 1
Descriptive Statistics of Households' Category Purchases

	Category Purchased		
	Frozen Meals	Ice Cream	Total Obs.
# of households	355	690	727
# of shopping trips	1,228	5,035	16,781
Mean (SD) purchase occasions per household	3.46 (3.76)	7.30 (6.77)	23.08 (10.65)
Mean (mode) units purchased per occasion	1.59 (1)	1.80 (1)	

TABLE 2
Purchase Frequencies by Shopping Basket

Category Purchase Decision			
Frozen Meals	Ice Cream	Frequencies	%
1	1	198	1.2
1	0	1,030	6.1
0	1	4,837	28.8
0	0	10,716	63.9
Total		16,781	100.0

Category assortment. For a comprehensive measure of a product category assortment, we considered previous metrics of perceived variety. Hoch, Bradlow, and Wansink (1999) developed a mathematical model for the assortment perception based on dissimilarity between pairs of options, and their model was later extended to an attribute-based model using entropy by Van Herpen and Pieters (2002). We followed the attribute-based approach and constructed entropy for each attribute selected in a category and aggregated them to obtain a category-level assortment variable. If a category assortment in a store comprises K number of attributes, and each attribute $k = 1, 2, \ldots, K$ varies with level l_k ($l_k = 1, 2, \ldots, L_k$), then the entropy of attribute K is defined as

$$\text{(9)} \qquad \text{Entropy}_k = -\sum_{l_k=1}^{L_k} p_{l_k} \times \ln p_{l_k},$$

where p_{l_k} is the proportion of UPCs of attribute level l_k in the category assortment. This shows how many different levels of a certain attribute are presented in the assortment. As an illustration for the ice cream category, if a store carries only sherbet items among the three available types—ice cream, sherbet/sorbet, and frozen yogurt/tofu—the entropy of this "type" attribute in that store will be zero. Conversely, the entropy will be largest if all types are equally present in the assortment. When the entropy is computed for each attribute

[9]We follow this two-step procedure using brand prices instead of direct operationalization using UPC prices for several reasons: (1) the operationalization of the household-specific category price using UPC prices becomes cumbersome for a category with a large number of distinct UPCs (e.g., ice cream), (2) the operationalization is not feasible if, for some weeks, there are stores that sell only UPCs that a certain household never bought, and (3) taking a similar approach to previous research renders our results comparable.

k, the in-store category assortment is represented as a sum of all entropy across K number of attributes. That is, the overall measure of product assortment for a category with K attributes at time t is

$$\text{Assort} = \sum_{k=1}^{K} \text{Entropy}_k. \quad (10)$$

The higher the degree of such attribute dispersion, the greater perception of variety consumers obtain from the assortment. Accordingly, in our model, we denote the product assortment for category j (j = 1, 2) faced by each household i in each shopping trip t as Assort_{ijt}.

For both categories, the entropy was operationalized using three attributes: product type, brand, and pack size. For the frozen meals category, types include breakfast entrée, hand-held nonbreakfast entrée, dinners, chili, and frozen soup. We segmented the size of the frozen meals items using the weight information (ounces) on the item description, grouping each 4 oz interval as one level of size. The size of the ice cream category was measured in pints, and we treated an interval of .5 pint as one level of size.

We note that product flavors would be another important attribute in both categories, and we also considered including flavors as an additional product attribute in operationalizing entropy. Unlike the other three product attributes, however, the inclusion of flavors came with two additional empirical challenges. First, flavors vary marginally across UPCs, resulting in an extensive number of flavors presented in each category assortment (e.g., an average store in the data carried an assortment of 311 ice cream UPCs with 105 distinct flavors). By looking at frequently used words in flavor descriptions, we defined and grouped UPCs into major flavor types to compute entropy. Second, the data on flavor are missing for all private label and few national brand UPCs, and we included a flavor type, "missing," to account for these items. Because this operationalization required more discretionary judgment (e.g., selection of major flavors), we present our empirical results using an assortment variable incorporating the other three attributes. However, we confirm that the empirical findings remained unchanged regardless of the inclusion of flavors and provide the complete analysis in the Web Appendix.

Descriptive Statistics

Table 3 provides some descriptive statistics by geographic market for the three marketing variables. We note that the category assortment variable exhibits a generally lower level of variation than price or promotions. Furthermore, this variation comes from across-store variation at a point in time as well as within-store variation over time. To estimate our model with household-specific parameters, we need a certain level of variation that comes from within-household variation over time. To determine the extent to which such variation exists in the data, we conducted the following analysis:

First, we obtained the household-level distribution of category assortment entropy to which each household was exposed during their entire shopping history and grouped the trips made by the household into high versus low levels of the assortment entropy (high: >80% quantile; low: <20% quantile). Then, we investigated each household's shopping trips in which high and low levels of entropy from the two categories interacted (i.e., high-high, high-low, low-high, and low-low), and computed the household's category purchase probability on each of the four occasions. Table 4 presents the mean of the households' purchase probabilities in each occasion.

From Table 4, we see that the category purchase probabilities vary with entropy of both assortments. In the ice cream category, consumers' higher purchase probability was associated with higher own- and lower cross-category entropy. We also observed the negative association between the purchase probabilities and the cross-category entropy in the frozen meals category. We note that these are only correlations because we do not control for other marketing variables and demand shifters. Nevertheless, the data in Table 4 provide some model-free evidence to motivate our formal analysis of the cross-category assortment effects.

As an alternative operationalization of assortment, we also constructed the category assortment size as the number of distinct UPCs sold in each four-week period to understand the

TABLE 3
Descriptive Statistics of Category Marketing Variables

	Price		Promotion Intensity		Assortment Entropy	
	M	SD	M	SD	M	SD
Frozen Meals						
California	6.03	(1.65)	.23	(.28)	4.44	(.24)
Georgia	5.39	(.98)	.06	(.14)	4.52	(.29)
Illinois	5.90	(1.42)	.16	(.22)	4.39	(.70)
Massachusetts	5.45	(.91)	.12	(.20)	4.24	(.35)
Washington	5.50	(1.47)	.07	(.16)	4.01	(.80)
Ice Cream						
California	1.93	(.98)	.29	(.29)	3.78	(.20)
Georgia	1.17	(.34)	.21	(.25)	4.41	(.10)
Illinois	1.37	(.70)	.44	(.31)	4.31	(.27)
Massachusetts	1.11	(.59)	.13	(.21)	4.76	(.15)
Washington	1.29	(.63)	.22	(.24)	4.12	(.33)

Notes: We obtained statistics for entropy from a unique set of store/four-week units.

TABLE 4
Variety of Category Assortment and Purchase Probability

	Ice Cream	
	High Entropy	**Low Entropy**
Frozen Meals		
High entropy (# of observations)	7.5%, 29.0% (731)	7.6%, 28.0% (1,120)
Low entropy (# of observations)	6.9%, 31.5% (1,407)	8.8%, 30.3% (951)

Notes: Purchase probabilities are presented in an order of [frozen meals, ice cream]. High (low) entropy refers to top (bottom) 20% quantile in assortment entropy.

correlations between these measures. We find that category entropy is positively correlated with the assortment size (frozen meals: .75, $p < .01$; ice cream: .57, $p < .01$) but the less-than-perfect correlation confirms that a larger assortment does not always exhibit higher entropy. The use of entropy (i.e., a measure for perceived variety) instead of the mere size, therefore, conceptually follows the previous finding that the assortment size will affect consumer choice only if it influences the perceived variety (Broniarczyk, Hoyer, and McAlister 1998). Another important observation is that although there is a positive correlation between the assortment sizes of the two categories (.48, $p < .01$), the correlation between entropy of each category assortment is not significantly different from zero (.02, $p = .68$). A positive correlation between the assortment sizes across the categories can be attributed to a store-level variation of freezer sizes; larger stores with more freezer space tend to stock more items of these two categories. The absence of significant correlation between the entropy measures implies that the variety (i.e., not size) of each category assortment changed independently. This finding highlights the advantage of using entropy measures that do not suffer from multicollinearity and confirms that our finding of cross-category assortment effects is not driven by a simple trade-off that stores with a larger ice cream assortment need to display fewer frozen meal products.[10]

Empirical Results

In this section, we present results from the complete model estimation. We obtained parameter estimates from the posterior distributions using Markov chain Monte Carlo iterations (50,000 iterations with first 20,000 draws as a "burn-in" period). Table 5 summarizes the parameter estimates for the effects of marketing-mix variables in the two product categories. With regard to intrinsic category preferences, there is no significant pattern consistent across households in either category. As we expected, temperature has a significant positive effect on the purchase incidence of ice cream, and time since each household's latest category purchases has positive effects on both category purchases.

Cross-Category Effects of Marketing-Mix Variables

Effects of price and promotions. Own price and promotion effects are significant with expected signs in both categories; higher price significantly reduces the category purchase incidence probability while more promotions increase it. In examining the coefficients for cross-category effects, we find that there are no significant cross-category price effects between the two product categories. The absence of cross-category price effects leads us to conclude that consumers regard frozen meals and ice cream as neither complements nor substitutes. This is as we expected, given the characteristics of the two categories.

Effects of category assortments. The assortment coefficients capture the average effects of the category assortments on a household's category purchase incidence. Unlike the price coefficients, every assortment coefficient is significant with a consistent pattern. In both product categories, on average, a greater own-category assortment induces a higher probability of category purchases. This positive effect of own assortment coincides with the findings from the assortment research that the (perceived) variety is a significant driver of consumers' purchase decisions (e.g., Kahn and Wansink 2004).

The results show that there are significant negative cross-category effects between the two categories. In other words, households are less likely to purchase from a category of a given assortment when it is presented with the other category assortment of greater variety. Given the insignificant cross-price effects, such negative cross-assortment effects are driven neither by consumers' shopping budget constraints nor correlations in category consumption. These results, therefore, provide evidence that the product assortment alone can drive the intercategory purchase dependence through variations in variety.

This finding is notable in that it distinguishes the scope of retailers' multicategory product assortment policy from that of pricing policies, which have spanned groups of substitutes and complements. Our results show that the negative cross-category assortment effects can be present, independent of the cross-category effects that result from price or promotions. Among the included marketing variables for the frozen meals category, only the assortment has an impact on consumers' purchase decision for the ice cream category. For these two categories, pricing policy may be implemented independently, but the product assortment planning should take into account its implications beyond a single category.

Correlation among consumer responses. The model also reveals the pattern of correlations among consumers' sensitivities to various marketing variables through the variance–covariance matrix Ω. In particular, we find that the correlations within a set of a household's responses to the assortment exhibit a significance pattern. Table 6 presents the estimated correlations among household-level assortment coefficients. There is a significant negative correlation between

[10]We also estimated the complete model using the number of UPCs as an assortment variable instead of entropy and found that the model did not produce plausible and significant findings. Indeed, the model did not even capture a significant effect of own-category assortment consistent with previous literature, possibly because of the multicollinearity of the variables between categories.

TABLE 5
Posterior Means of Parameters for Marketing-Mix Variables

Purchase Incidence of…	Category Preference			Price		Promotions		Assortment	
	Intercept	Temp	Time	FM	IC	FM	IC	FM	IC
FM	–.718 (1.015)	–.002* (.001)	.006** (.002)	–.397** (.050)	.080 (.124)	.410** (.137)	–.351** (.123)	.314** (.133)	–.423** (.190)
IC	–.423 (.671)	.005** (.001)	.013** (.002)	.011 (.027)	–.507** (.086)	–.070 (.088)	.354** (.070)	–.312** (.079)	.244** (.123)

*Significant at the 10% level.
**Significant at the 5% level.
Notes: FM = frozen meals; IC = ice cream. Estimates are posterior means and standard deviations. Coefficients for temperature and time (since last category purchase) are constant across households.

coefficients for own- and cross-category assortments, indicating that consumers whose category purchase decisions are highly influenced by the own-category assortment also tend to be affected more negatively by the other categories in the aisle of display. In addition, there are positive signs both between own terms and between cross-terms across categories, implying consumers' consistent reaction to the category assortment, but neither of them are significant.

Correlation in stochastic errors. After accounting for the effects due to selected variables, we expect the effects of any unobserved sources of a household's intercategory purchase behavior to be captured through a correlation of the error terms. In the present context of the two frozen food categories, in addition to the effect of display proximity "in a store," the role of freezer space constraint "at home" could play a critical role in consumers' purchase decisions for the categories. More specifically, if households have only limited freezer space at home, greater variety of ice cream could not only increase their probability of purchasing ice cream but also decrease their probability of purchasing the other frozen meal products. Without capturing such an unobserved factor using a stochastic component, therefore, the model could attribute the impact of that factor to the effect of product assortment. Similarly, the household's caloric intake concern might lead to a misinference of the cross-category assortment effects. The estimated correlation in the error terms is negative and significantly different from zero (posterior mean = –.194, SD = .030). We find that this negative correlation is consistent with the aforementioned arguments

TABLE 6
Correlation Between Individual Responses to Own- and Cross-Category Assortment

	Frozen Meals Purchase		Ice Cream Purchase	
	Own	Cross	Own	Cross
Frozen Meals Purchase				
Own (FM)	1.00			
Cross (IC)	–.61**	1.00		
Ice Cream Purchase				
Own (IC)	.22	–.13	1.00	
Cross (FM)	–.26	.12	–.78**	1.00

**Significant at the 5% level.
Notes: FM = frozen meals; IC = ice cream.

based on the household's freezer space and calorie concerns.[11] Therefore, it demonstrates the importance of modeling unobserved sources of category purchase dependence between these two categories.

Elasticities

To understand the magnitude of the effect of each marketing variable, we compute elasticities using the data and household-specific estimates from the model. The elasticity is defined as the percent change in the aggregate category demand (in purchase incidence probability) in response to a 1% change in a corresponding marketing variable. We take into account heterogeneity across households by computing the purchase incidence probability of each household at each shopping occasion.[12]

Table 7 presents the elasticities with respect to price, promotions, and assortment following from the statistically significant coefficients from the model. The estimated category-level (i.e., not brand-level) price elasticities are in a range consistent with those in the literature (Andreyeva, Long, and Brownell 2010; Hoch et al. 1995). Purchase incidences for frozen meals are more elastic to changes in price than those for ice cream (–1.20% vs. –.47%). This could be explained by the notion that frozen meals have more direct substitutes (e.g., homemade dinners). Promotion elasticities are much smaller than price elasticities and lie in a range consistent with those from previous studies of consumers' category purchase incidences using similar nonprice (i.e., features and special displays) promotion variables (Manchanda, Ansari, and Gupta 1999; Mehta 2007).

To understand the managerial implications of the computed assortment elasticities, we discuss some retailers' actions that would have resulted in a 1% change in entropy in an average store in our sample. Unlike other marketing variables, changing assortment entropy involves structural changes to the overall assortment. The average store stocked 311 ice cream UPCs from 23 brands and 71 frozen meals

[11]The account based on freezer space was further supported by our complementary study of a pair of refrigerated dairy product categories (margarine and yogurt). We hypothesized that storage space at home is less of a constraint for these categories, and the estimated correlation of the errors was negative yet smaller in magnitude (posterior mean = –.083, SD = .018). The Web Appendix provides detailed results.

[12]A detailed procedure of estimating the empirical elasticity from the data is available on request.

TABLE 7
Elasticity of Category Purchase Probability to Changes in Marketing Variables

Purchase Probability of…	Price Elasticity: Own Category	Promotion Elasticity: Own Category	Assortment Elasticity: FM	Assortment Elasticity: IC
FM	–1.196** (.214)	.112** (.021)	2.171** (.621)	–1.589* (.903)
IC	–.472** (.072)	.096** (.015)	–.882** (.254)	.954** (.388)

*Significant at the 10% level.
**Significant at the 5% level.
Notes: FM = frozen meals; IC = ice cream. This table displays the effects of column variables on row category purchases. Standard deviations are in parentheses.

UPCs from 20 brands. In the ice cream category, a 1% increase in entropy could be obtained by adding ten sherbet items from the three largest national brands (Breyers, Ben & Jerry's, and Häagen-Dazs). Alternatively, without changing the size of the assortment, the store could obtain the same amount of increase by adjusting the product composition. The average store filled 30% of the ice cream assortment with bulky (3~4 pints) private label UPCs and could replace five private label UPCs with smaller UPCs (2 pints) from a leading national brand (e.g., Breyers). Similarly, in the frozen meals category, we found that the increase could be obtained either by adding one handheld entrée UPC (in the 12~20 oz size) from each of the three largest brands or by replacing eight UPCs from the largest brand with those from the second- and third-largest brands.

In these two product categories, adding more variety to a category assortment is effective in increasing a purchase frequency of that category, and frozen meals exhibit higher own-category elasticity than ice cream (2.17% vs. .95%, respectively). On the one hand, higher elasticity of the aggregate category demand with respect to the assortment may result (1) when each consumer has diverse preferences for multiple products and/or (2) when consumers have their own distinct favorite products. On the other hand, lower assortment elasticity of the demand may be associated with a higher concentration of the category sales by a relatively smaller set of popular items. To account for the lower own-assortment elasticity in the ice cream category, we examined this correlation in the data and found that the ice cream purchase incidences are indeed more likely to occur among items with certain product types, brands, and sizes compared with frozen meals. For example, in California, 77.6% of the ice cream category purchase incidences were generated among the top five brands, compared with 58.3% in the frozen meals category. We also observed this trend in other product attributes, such as product types and pack sizes.

With regard to the cross-category assortment elasticities, the magnitude of the negative impact from changes in the other category assortment is also greater in the frozen meals category (–1.59% vs. –.88%, respectively), suggesting that there are differences across product categories in the impact of assortment changes. In addition, we find that the magnitude of cross-category assortment elasticity can be as high as own-assortment elasticity: although the positive impact on its own category of increasing the frozen meals assortment (2.17%) could be greater than the negative impact from the ice cream category (–1.59%), the positive impact of increasing the ice cream assortment could be offset by the negative impact from the frozen meals category (.95% and –.88%, respectively). Previous empirical studies focusing on price effects between products related in consumption (based on an economic argument) have found that the own-price effects are generally greater than the cross-price effects (e.g., Berry, Levinsohn, and Pakes 1995). Our finding that the magnitude of the cross-category effects is comparable to that of the own-category effects is, therefore, an aspect that distinguishes the impact due to product assortment from that due to price. The finding indicates that adjacent category assortment can be as important as the own-category assortment in consumers' category purchases and suggests that it may not be due to indirect effects (as suggested by economic theory) but to context-dependent psychological effects. We investigate this aspect further in the subsequent sections.

As an extension of the analysis, we also investigated whether omitting the product assortment can be a source of mis-inference of the price effects between the pair of categories. We reestimated the multicategory purchase incidence model with all variables in the full model except the category assortment entropy. Previous multicategory purchase incidence models inferring the relationship between a pair of categories take this form (e.g., Manchanda, Ansari, and Gupta 1999). When omitting the assortment variables, both estimated cross-price elasticities become economically larger and statistically significant. This suggests that a mis-specified model that does not take into account any effects from the product assortment could lead researchers to incorrectly infer that these categories are substitutes in consumption.

The Role of Category Display Proximity

Our empirical finding of the cross-category effects from product assortment without simultaneous significant price and promotional effects is novel, and it indicates that the effects are not due to the consumer's shopping budget constraint or correlations in category consumption. It emphasizes further that, unlike price and promotion policy, retailers should not determine each category assortment independently, even for a group of categories that are independent with respect to consumption (i.e., neither substitutes nor complements). However, given that retailers handle a large number of product categories in a store, the issue that arises is the boundary condition under which such cross-category effects hold. To address this issue, we ask in this section: Would these negative cross-category assortment effects be present among any pairs of categories in a store?

TABLE 8
Posterior Means of Parameters for Marketing-Mix Variables

Purchase Incidence of…	Category Preference			Price		Promotions		Assortment	
	Intercept	Temp	Time	FM	PT	FM	PT	FM	PT
FM	−1.399 (1.262)	−.002* (.001)	.010** (.002)	−.366** (.050)	.054 (.150)	.421** (.134)	.145 (.156)	.244* (.145)	−.211 (.288)
PT	−3.728** (.867)	.002* (.001)	.019** (.002)	−.030 (.043)	−.610** (.127)	−.146 (.136)	.724** (.128)	.041 (.124)	.536** (.215)

*Significant at the 10% level.
**Significant at the 5% level.
Notes: FM = frozen meals; PT = paper towels. Estimates are posterior means. Standard deviations are in parentheses.

The estimated negative sign and the magnitude of the cross-category effect comparable to the own-category effect suggest that the effect could be driven by a local context in which consumers make a purchase decision. If the effect is indeed due to the nature of multicategory assortment displayed in a common retail space, the magnitude of the effect will vary depending on the category display proximity. Our results from the frozen categories in a freezer space satisfy a necessary, but insufficient, condition to argue the role of category display proximity. Seeking supporting evidence on whether the display proximity matters for the effects to occur, we conducted additional studies using market data and an online experiment.

Analysis of Market Data

First, we estimated the model for frozen meals and paper towels as a falsification test. The selection of these two categories is consistent with our early empirical study in that they are expected to be independent with respect to consumption, but the selection differs in that they do not share a common shelf space. The absence of the cross-category assortment effects between these two categories will, therefore, support our hypothesis that such effects are attributed to consumers' context-dependent judgment of the multicategory assortment in a given space. In the paper towel category, we obtained variables for price and promotions in the same manner and operationalized assortment entropy using three corresponding attributes: product-type (ply), brand, and pack size (number of rolls).

Table 8 presents parameter estimates from the model. In both product categories, own price, promotions, and assortment affect the purchase likelihood of the category significantly, but there are no significant cross-category effects. In particular, the results show that the own assortment remains important in the paper towels category, but the cross-category effects are not significant. It is also noteworthy that the size of the own effects in the frozen meals category is consistent with those obtained from the analysis with the ice cream category (see Table 5).

In addition, using a different source of market data, we applied the model to two additional pairs of product categories that are neither substitutes nor complements in consumption yet are often displayed in close proximity to each other in stores: a pair from refrigerated dairy categories (margarine and yogurt) and another from sauce categories (pasta sauce and condiments). We found some more evidence of the positive own- and negative cross-category effects as a result of product assortment for these pairs. The Web Appendix provides a detailed description of the data and the analyses.

Analysis of Online Experiment

We obtained more direct evidence through an online experiment, in which we manipulated the (sequential) category display proximity between a fixed pair of product categories: chocolates and magazines. The following subsections provide the experiment details.

Procedure. We recruited 202 participants using Amazon Mechanical Turk (62.8% male; average age = 29.7 years). The study used a 2 (size of the magazine assortment: small vs. large) × 2 (multicategory display: joint vs. separate) between-subject design. Participants were randomly assigned to one of the conditions, and all participants read the following scenario:

> Imagine that you have had a slight headache for the whole day at work. After work, you stop by a shop. While browsing the store searching for a bottle of water and a box of painkillers, you also pass by aisles of some other product categories. On the following pages you will see the assortment for the product categories that you will be exposed to. You will be asked to choose water and painkiller items to buy, and indicate your intention to purchase from the other categories.

The purpose of this instruction was to provide the participants with a common shopping goal (purchase of water and painkiller items) and thus to make all the other purchases explicitly unplanned. It also put participants in the familiar situation of visiting a store with a shopping list. After reading the scenario, participants were presented with the product options for the four categories—bottled water, painkillers, chocolates, and magazines—and were asked to choose an item to purchase from the first two categories and indicate their likelihood to purchase from the second two categories. The dependent variable of our interest was their likelihood of purchase from the chocolate assortment (on a seven-point Likert scale of purchase likelihood; 1 = "very unlikely," and 7 = "very likely").

Assortment size condition. Unlike studies addressing the role of the assortment size, the assortment size of the chocolate was fixed at eight throughout the conditions. The assortment size of the other unplanned category, magazines, varied depending on the condition (3 vs. 12 options).[13] Thus,

[13]When increasing the number of magazines, we ensured that it would also diversify the attributes present in the assortment: while a small assortment included only magazines in fashion and politics, a large assortment included magazines in fashion, politics, automotive, entertainment, and lifestyle (for sample screenshots, see Appendix A).

even though the actual size of the chocolate assortment was constant across conditions, its relative size varied by condition. Our interest lies in whether consumers' likelihood of purchase from the chocolate assortment depends on the size of the magazine assortment. The size of the assortment of the two planned categories (i.e., water and painkillers) was fixed at five each.

Display condition. To test the role of category display proximity in consumers' purchase likelihood, we manipulated the display proximity between assortments of chocolates and magazines by showing the two categories either jointly or separately interspersed with the other categories. In the joint presentation condition, the respondents were presented with a set of two product categories at a time. Faced first with the water and painkiller assortment (i.e., planned purchases) together on a screen, they were asked to choose a specific item they would buy in each category. After making purchase decisions for these two categories, they were presented with two unplanned categories—chocolates and magazines—together. Appendix A provides this two-step procedure in the joint display condition. In the separate display condition, the respondents were presented with one category assortment at a time and display of the two unplanned categories was interposed by planned categories. More specifically, the respondents' product choices for water and painkiller items occurred between their evaluations of the two unplanned categories. The evaluation of chocolate assortment always took place at the end to make everyone aware of the assortment of the magazines. Our major interest with regard to this condition is, therefore, whether the size of potential cross-category assortment effects varies depending on the sequential proximity of the display.

Seven-point scale responses of likelihood. To identify the participants' preference shifts across conditions using a consistent approach, we modeled the latent random utility corresponding to each condition and mapped it to the observed discrete scales of likelihood. Formally, the utility that the participant i obtains from the selection of chocolates is specified using dummy variables indicating each condition:

$$(11)\qquad \begin{aligned} U_i = \beta_0 &+ \beta_1 \times [\text{Separate Disp. \& Large Assort.}] \\ &+ \beta_2 \times [\text{Joint Disp. \& Small Assort.}] \\ &+ \beta_3 \times [\text{Joint Disp. \& Large Assort.}] + \epsilon_i, \end{aligned}$$

where ϵ_i is a stochastic component assumed to follow the standard normal distribution. Then, we determined the participant's choice over a seven-point scale likelihood y_i by the following rule.

$$(12)\qquad y_i = \begin{cases} 1 & \text{if} \quad U_i \le \alpha_1 = 0 \\ j & \text{if} \quad \alpha_{j-1} < U_i \le \alpha_j \\ \vdots & \qquad \vdots \\ 7 & \text{if} \quad \alpha_6 \le U_i \end{cases}.$$

This is an ordered probit model, in which we estimate parameters of the utility together with boundary parameters α_j ($j = 2, \ldots, 6$).

Results. Figure 1 presents the mean purchase likelihood from the given chocolate assortment in each condition. Table 9 summarizes the main results of our model estimation. As illustrated, β_0 refers to the average baseline utility that the participants obtain from the condition in which they face the chocolate assortment separately from the assortment of three magazines. The estimates β_1~β_3 indicate whether there are any significant changes in utility deviating from the baseline condition, and they confirm that there is a significant decrease in utility from the given chocolate assortment when it is presented jointly with a large magazine assortment (β_3).[14] This replicates our finding from the study of two frozen food categories. In addition, the results show that no other changes are significant. In particular, there is no significant difference in utility between small and large magazine assortment conditions when the two category assortments are interposed by other categories (β_1). This not only

FIGURE 1
Mean Purchase Likelihood by Condition

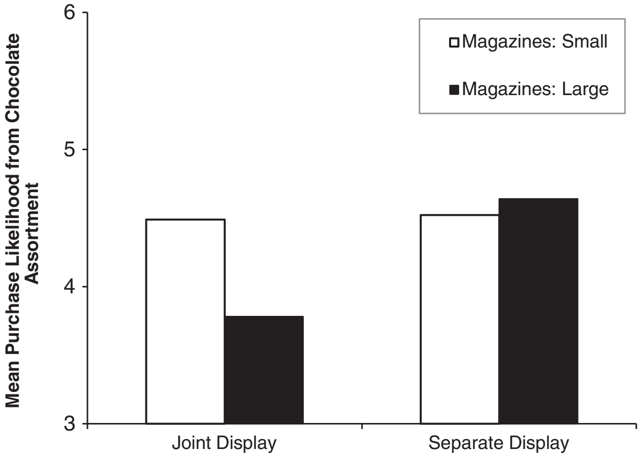


TABLE 9
Utility Parameter Estimates from Ordered Probit Model

Parameter	Interpretation	Estimate	SD
β_0	Utility from the chocolate assortment when presented separately from small magazine assortment	1.197**	(.172)
β_1	Utility shift when presented separately from large magazine assortment	–.019	(.214)
β_2	Utility shift when presented jointly with small magazine assortment	–.041	(.213)
β_3	Utility shift when presented jointly with large magazine assortment	–.423**	(.208)

**Significant at the 5% level.

[14]The decrease was significant at the 10% level regardless of choices of the baseline condition.

replicates our finding from the study of the frozen meals and paper towels categories but also provides direct evidence that the negative cross-category assortment effects are due to joint display of the categories.

In our analysis on frozen meals and ice creams, we have shown that it is less plausible that the negative cross-category assortment effects are due to the consumers' budget constraints, given the insignificant cross-category price effects. The experimental results also enable us to test the economic argument on the basis of consumers' budget constraints. Under a (mental) budget assigned to a given shopping trip, consumers may be more likely to choose one over the other depending on the category appeal. If this is the case, we should have observed such a tendency to purchase either of the two categories rather than both regardless of the types of display we manipulated. The results from the large magazine assortment condition refute this argument. We first confirm the main effect of the magazine assortment size on the respondents' purchase likelihood from the magazine assortment: the larger the magazine assortment, the more likely consumers were to purchase from it. Although every respondent in the large magazine condition saw the same assortments of magazines and chocolates, only the respondents who saw both together on a screen expressed a lower intent to purchase chocolates. When they were presented with the two assortments separately, they did not necessarily do so.[15]

Consumers' Attention to Multicategory Assortment

What might be a plausible explanation for the observed negative cross-category assortment effects? One explanation stems from the research on consumers' visual attention and perception processes and their impact on consumers' choices. Research in marketing and psychology has documented that consumer's visual attention to marketing stimuli reflects higher-order cognitive process and can predict downstream actions such as product consideration, choices, and purchases (Janiszewski, Kuo, and Tavassoli 2013; Rizzolatti, Riggio and Sheliga 1994; Russo 1978; see also Wedel and Pieters's [2006] review). Because of this important impact of visual attention on consumers' decision making, recent literature on advertising has focused on identifying various elements in a print advertisement (e.g., surface sizes) that affect consumers' attention (Pieters and Wedel 2004, 2007; Pieters, Wedel, and Zhang 2007).

Pieters, Wedel, and Zhang (2007) study the determinants of consumers' visual attention to a certain (target) ad item in a feature ad and find that consumers are more likely to visually attend to the target item when the item is more distinct from the other items in the feature and when the other items (distractors) in the feature are less heterogeneous. This finding that the consumer's visual attention to a target option is positively influenced by "target distinctiveness" as well as negatively by "distractor heterogeneity" may also hold when consumers evaluate multiple category assortments. Indeed, in their study, both constructs of target distinctiveness and distractor heterogeneity were operationalized through entropy, similar to our measure of assortment variety. If the variety of the other category assortment displayed in close proximity to a target assortment negatively affects the consumers' attention to the target assortment, it could account for why the consumers are less likely to purchase from the target assortment when it is presented with the other large assortment.

In addition, a feature-integration theory of attention (Treisman and Gelade 1980) also suggests that such a consumer's selective attention process can be relevant to our context of multicategory assortments in a given space. The theory emphasizes the role of focal attention for consumers to perceive objects correctly when the objects in a display contain multiple characteristics: the individual characteristics are perceived early and automatically, whereas objects are identified later, through more focused attention. This focal attention is then critical for the objects to be correctly perceived. This implies that consumers would need to pay more focal attention to a certain category assortment for an accurate evaluation of an assortment that comprises product options with varying attributes.

Building on the theory of attention and the aforementioned empirical finding of the positive impact of own distinctiveness and the negative impact of the distractor heterogeneity on the attention to a target item in a fixed space, we test whether consumers' attention to a certain category assortment can be influenced by variety of category assortments that share a display space. The study uses visual manipulation of the assortment as in our online experiment, and we measure the consumers' attention to a category assortment using eye-tracking technology.

Experiment Procedure

We conducted the eye-tracking study using 80 participants recruited by a behavioral lab in London Business School (30.0% male; average age = 28.4 years). We dropped observations from five participants because of low quality of eye-tracking calibration. Each participant was invited to a room with an eye tracker for their hypothetical weekly shopping tasks. They were presented with three pairs of product category assortments on a computer screen and asked to indicate their intention to purchase from each category assortment (seven-point Likert scale measure of likelihood). Each pair of category assortments was displayed on a screen, and the displayed categories and their order were as follows: (1) chocolates and magazines, (2) ice cream and frozen meals, and (3) mint drops and yogurt. Consistent with our other empirical studies, we paired the product categories that are a priori neither explicit substitutes nor complements. In addition, to minimize any effect of previously presented assortments on participants' evaluation of the subsequent pair of assortments, we added a filler task between the displays of the assortment pairs: after completing the hypothetical purchase intention task for a pair of assortments, the participants watched a five-minute viral video ad campaign from major toiletries brands and described their perception of the advertised brands before and after watching the videos. The selected advertisements

[15]The Web Appendix provides detailed results from analyzing the respondents' purchase likelihood for magazines.

were mostly narrative and did not contain any scenes that demonstrated actual products.[16]

Assortment Manipulation

The study used two conditions. We fixed one product category assortment in each pair (chocolates, ice cream, and mint drops) and displayed the same assortment for these categories to every participant. We refer to these categories as the "focal" categories in each pair. The number of options in the focal category assortment was fixed at nine. The two conditions therefore correspond to the size of the other category in each pair. Depending on the condition, the participants saw the focal category assortment together with either a small (3 options) or a large (12 options) other assortment. The stimuli used in the study were similar to those in the joint display condition in our previous online experiment. A notable distinction is, however, that this experiment captured individual observations for multiple pairs of assortments. The complete data from the experiment provided us with 450 observations of purchase likelihood for six categories.

In addition to between-subjects variations of their purchase intention, our experimental design enabled us to exploit within-subject variations by counterbalancing the size of the nonfocal category assortments that a participant faced: if a participant was presented with a given focal category assortment and small other assortment in the first pair, in the subsequent pair, (s)he was presented with the focal category and large other assortment. Then, the size of the other category switched again for the third pair of assortments.

Attention Data Collection

The eye tracker captured participants' eye movements on the presented screen and recorded their fixations (i.e., when the eyes are relatively still with an average duration of 100~500 ms) and saccades (i.e., fast movements of the eyes between fixated spots).[17] Consistent with previous research, we focus on the fixations for a measure of consumers' attention to a category assortment (e.g., Pieters, Wedel, and Zhang 2007). The focus of our study is to identify the pattern of their attention among the two category assortments on a screen, and thus we treat the entire selection of product options in each category as the unit of visual stimuli. As a composite measure of the attention to a category assortment, we counted the number of fixations made within a region of that category assortment on a screen.[18] Appendix B depicts the assortments displayed in each condition and the region of each assortment. The surface sizes of the overall assortment varied with the number of product options, but they remained constant for a given number of options. Surface size has been found to be an influential factor affecting consumers' attention, and any impact of the assortment changes we observe will, therefore, include the effects from the surface sizes.

[16]The two advertisements used in the filler tasks were Dove's "Love your Curl" campaign and Old Spice's "Dad Song" campaign.

[17]We followed the standard definitions set by an eye-tracker provider (Tobii Studio 3.3.1).

[18]This measure was highly correlated with the total duration (in seconds) of fixations made within the region (.90, $p < .01$).

Results

Using 450 observations of the attention paid to the six category assortments, we test whether assortments of both categories on a screen affect consumers' attention to each category assortment. In analyzing the number of fixations, we used a Poisson model because it is one of the most commonly used count models. Our main goal is to identify the impact of own and other assortments presented on a screen; as corresponding assortment variables, we use the number of product options in each assortment (i.e., assortment size). Table 10 presents the estimated parameters.

The results show that consumers paid more attention to a greater category assortment yet, given the own-assortment size, they paid less attention to the assortment when it was presented with the other large assortment. Treating each category assortment as a unit of visual stimuli, this finding is consistent with the positive impact of distinctiveness of target stimulus (driven by variety of the own category assortment) and distractor heterogeneity (driven by the variety of the other category assortment on the same screen). This finding remains consistent with a set of additional control variables taking into consideration fixed effects for each participant and for each category.

Table 10 also presents the result of analyzing the assortment effect on consumers' category purchase likelihood using the ordered probit model. The result replicates the main finding of the positive own- and the negative cross-category assortment effects (the effects were not statistically significant after including the category fixed effects, as a result of a loss in data variability).

While the results from the previous studies using market data and an online experiment identify the existence, pattern, and boundary condition of the cross-category assortment effects between categories that are independent in consumption, the results from the eye-tracking study provide a behavioral explanation of the effects. They demonstrate collectively that a greater variety of the other assortment, presented together with the focal category, has a negative impact on both consumers' attention to and purchase likelihood of the focal category.

Conclusion and Directions for Further Research

Research in marketing and operations has developed models of the retailer's product assortment planning and has guided practices such as category management, under which each category manager is responsible for the performance of each assigned category on the basis of decisions relating to the choice of assortment, pricing, and promotions (Basuroy, Mantrala, and Walters 2001). One challenge in category management, including assortment planning, comes from the fact that the retailer needs to make these decisions under spatial and other constraints. Thus, decisions regarding the management of one category often have to be made in the context of other categories that share a given space within the store.

The notion of aisle management has recently emerged, acknowledging the weakness of earlier tools that disregarded

TABLE 10
Parameter Estimates from Eye-Tracking Study

	DV: Attention to Category Assortment			DV: Category Purchase Likelihood		
Model Type	**(I) Poisson**	**(II) Poisson**	**(III) Poisson**	**(I) O-Probit**	**(II) O-Probit**	**(III) O-Probit**
Own assortment size	.077** (.004)	.078** (.005)	.078** (.004)	.062** (.015)	.076** (.016)	.052** (.017)
Adjacent assortment size	–.010** (.004)	–.009** (.004)	–.010** (.004)	–.029* (.015)	–.035** (.016)	–.004 (.017)
Controls						
Individual fixed effects		✓	✓		✓	✓
Category fixed effects			✓			✓
Observations	450	450	450	450	450	450

*Significant at the 10% level.
**Significant at the 5% level.
Notes: DV = dependent variable; O-Probit = ordered probit model.

potential cross-category effects from in-store marketing activities (Larson 2006). For example, General Mills, one of the world's largest food companies, has made an effort to build a platform to design the assortment in the overall refrigerated dairy sections instead of individual categories such as yogurt (ACNielsen, Heller, and Karolefski 2006). Indeed, a recent report by the Food Marketing Institute (2012) highlighted retailers' transformation of an aisle of multiple assortments into a "department" with a common theme as a key merchandising innovation.

In this article, building on prior findings that consumers' purchase decisions are driven by their perception of assortment and that consumers' judgment and decisions are often context-dependent, we show that there exists intercategory purchase dependence driven by the assortment between categories with no correlation in consumption. We provide insights into the pattern (positive own- and negative cross-effects) and boundary of the effects (the role of category display proximity) by analyzing data from IRI and an online experiment. Finally, a study using an eye tracker shows that the consumer's allocation of limited attention among category assortments in a given space accounts for the observed negative cross-category assortment effects.

The insights developed herein can be useful in various marketing practices in and beyond the retail industry. Among others, our empirical findings have a direct application to retailers' store layout. For example, by presenting a group of nonstaple (or less frequently purchased) product categories together in the same aisle, retailers might decrease their likelihood of selling from more diverse categories. By locating some of the categories with a smaller selection remotely, retailers could avoid potential negative effects from categories with a greater selection. This idea is also related to a recent study showing that the longer a customer travels within a store, the more likely (s)he is to purchase on a given shopping trip (Hui, Fader, and Bradlow 2009). Indeed, the study finds some evidence that customers who visit more aisles tend to make more impulsive purchases. By combining these effects on the demand side with each store's cost information on the supply side (e.g., slotting allowances), retailers can understand implications for store profitability. An area to explore, therefore, would be to integrate these factors into a multicategory assortment planning model. For example, the trade-offs between positive and negative marginal contribution of adding variety to a product category can be built in the model.

The implications of our findings can extend beyond retail category assortment planning to, for example, the variety of items offered on a restaurant menu. Some restaurants present a single menu listing a set of entrées, main courses, and desserts, whereas others have a separate menu for dessert to be presented at the end of the meal. Our findings provide reasons why restaurant owners may want to follow the latter practice, especially when they offer only a limited selection of dessert items relative to a larger list of entrées and main courses. By presenting the small selection of dessert items separately from the main menu, they may benefit from customers' choices that are not influenced by the variety of less relevant items.

A limitation of our study is that our model, which is conditional on a consumer's shopping trip, considers the consumer's visit to stores as exogenous and does not fully capture the overall cross-category effects of assortment through store traffic. Previous models of store choices have found that the category assortment is an influential factor in consumers' store choices (Briesch, Chintagunta, and Fox 2009). We could have mitigated this concern by including household-/store-fixed effects in our econometric model; however, because of an issue of statistical power of estimation, we could not estimate this alternative specification further. When estimating our model with store-specific fixed effects, we lost statistical significance of assortment effects for the frozen meals category. Although the previous approach accounting for the effect of product assortment on consumers' store choices assumes that the category demand arises prior to a shopping trip, our approach is more appropriate for product categories on which consumers often make purchase decisions in the store (e.g., categories at the checkout aisle).

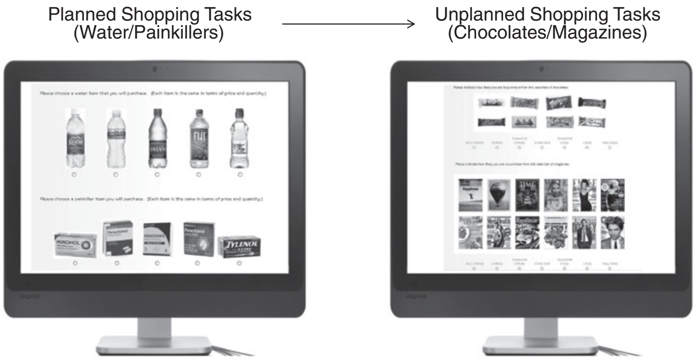
In summary, we show that the display proximity between category assortments is another important driver of consumers' intercategory purchase dependence, in addition to the correlation in consumption. Our results collectively demonstrate the importance of the retailer's holistic assortment planning over a group of neighboring product categories and highlight additional advantages of the retailer's aisle management over category management.

Appendix A: Online Experiment: Conditions and Questionnaires

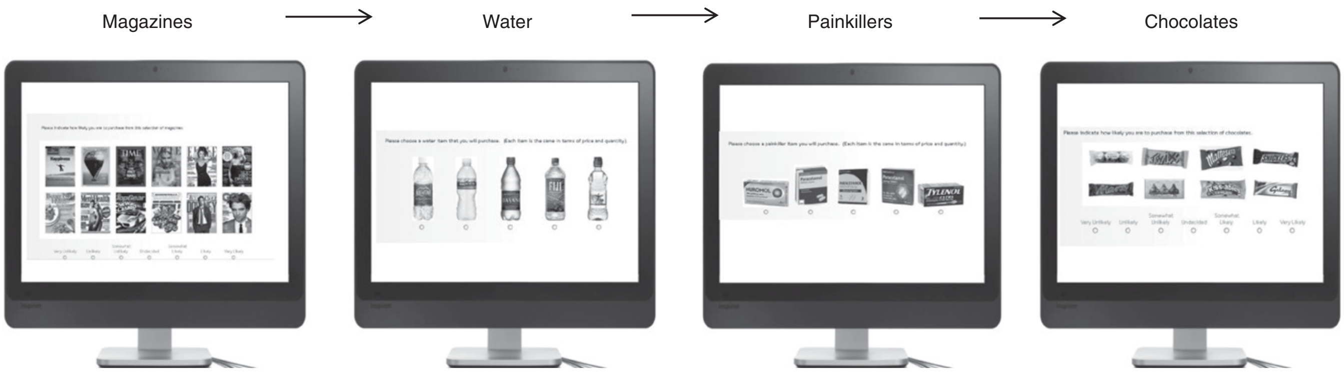
FIGURE A1
Factor 1: Magazine Assortment Condition (Small vs. Large)

FIGURE A2
Factor 2: Display Condition (Joint vs. Separate)

A: Joint Display Condition



B: Separate Display Condition



Notes: Participants were given the following instructions: (1) "Please choose a water (painkiller) item you will purchase"; and (2) "Please indicate how likely you are to purchase from this selection of magazines (chocolates)."

Appendix B: Eye-Tracking Experiment: Conditions and Regions of Interest

A: Pair 1: Chocolates and Magazines

Condition 1 | Condition 2

B: Pair 2: Frozen Meals and Ice Cream

Condition 1 | Condition 2

C: Pair 3: Mint Drops and Yogurt

Condition 1 | Condition 2

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The Perils of Category Management: The Effect of Product Assortment on Multicategory Purchase Incidence

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Web Appendix

In this appendix, we provide detailed descriptions of complementary analyses of IRI data and online experiment which are not included in the main paper. The IRI data analyses consist of a series of robustness checks we conducted with respect to operationalization of category assortment and household inventory variables, and an application of our model to new pairs of product categories. The following analysis of the online experiment data presents the result focusing on respondents' utilities from magazine assortments.

Operationalization of Category Inter-Purchase Time

In the main analysis presented in the manuscript, we included in the model a variable of each household's time since last category purchase. This variable is to capture indirectly the household's purchase incidence induced by the lack of inventory at home. In this section, we present the result from the model using alternative operationalization of this variable: we normalize this time variable to ensure that the identification of the effect comes from "within-household" variations as opposed to the variations across-households. We normalize the variable in two different ways; (1) constructing the relative percent difference from the average household inter-purchase time (by dividing the variable by each individual mean), and (2) constructing the absolute difference from the average household inter-purchase time (by subtracting each individual mean from the original time variable). The results from these two approaches are presented in Table W1. The results confirm that the implication of the estimates for the inter-purchase time remained unchanged and other parameter estimates are not distinguishable from those presented in the manuscript.

Operationalization of Category Assortment

In this section, we consider an alternative operationalization of an assortment entropy variable incorporating the flavor information. In our ice cream data, we have 2,400

Table W1. Parameter Estimates Using Normalized Category Inter-Purchase Time

1. The relative percent difference from the household mean

Purchase Incidence	*Category Preference*			*Price*		*Promotions*		*Assortment*	
of	*Intercept*	*Temp*	*Time*	*FM*	*IC*	*FM*	*IC*	*FM*	*IC*
FM	−0.699	−0.003**	0.119**	−0.384**	0.064	0.405**	−0.366**	0.339**	−0.405**
	(0.701)	(0.001)	(0.031)	(0.050)	(0.119)	(0.135)	(0.121)	(0.120)	(0.162)
IC	−0.520	0.006**	0.173**	0.016	−0.495**	−0.059	0.360**	−0.304**	0.255**
	(0.551)	(0.001)	(0.019)	(0.027)	(0.079)	(0.086)	(0.072)	(0.075)	(0.112)

2. The absolute difference from the household mean

Purchase Incidence	*Category Preference*			*Price*		*Promotions*		*Assortment*	
of	*Intercept*	*Temp*	*Time*	*FM*	*IC*	*FM*	*IC*	*FM*	*IC*
FM	−0.795	−0.002**	0.016**	−0.407**	0.068	0.389**	−0.345**	0.298**	−0.329*
	(1.028)	(0.001)	(0.002)	(0.050)	(0.125)	(0.143)	(0.126)	(0.130)	(0.192)
IC	−0.250	0.006**	0.023**	0.013	−0.505**	−0.068	0.360**	−0.318**	0.263**
	(0.548)	(0.001)	(0.002)	(0.028)	(0.078)	(0.091)	(0.070)	(0.076)	(0.110)

** Significant at 5% level; * Significant at 10% level

Notes: FM (Frozen Meals); IC (Ice Cream). Estimates are posterior means and standard deviations.

Coefficients for temperature and time (since last category purchase) are constant across households.

distinct product IDs which are unique by UPC code. Of these IDs, 574 are private label products for which the data of flavors are not available. Thus we make use of flavor descriptions from the remaining 1,826 product IDs to define major flavors for the category. We note that among these products, there are 324 products with missing flavor (these products account for 13% of the total sales). Together with private label products, therefore, we include a flavor type, "missing" for these products with missing data.

The remaining 1,502 product IDs with valid flavor descriptions exhibit 428 distinct flavors. Based on these descriptions, we classified major flavors as: chocolate (containing the word: "choc"), vanilla (containing the word "vanilla"), fruit (containing any of "berry" "orange" "cherry" "banana" or "apple"), nut (containing any of "nut", "almond", "pecan" or "praline"), and coffee/ cookie (containing any of "cookie", "coffee", "mocha"). For any description that contained more than one of the above words together, we classified it as "Multiple" and for any other flavor descriptions that contained none of the words above were classified as "other." Table W2 summarizes the distribution of the selected major flavors (in count) among the 1,502 product IDs.

We followed a similar process for the frozen meals assortment and classified major flavors as Beef, Pork, Chicken/ Turkey, Seafood, Others and Missing. Among total 931 unique product IDs, 565 product IDs had valid flavor descriptions and the distribution of the selected major flavors (in count) is also presented in Table W2. Given more individually varied menus for frozen meals than for ice creams, a higher portion of frozen meals products fell into "other."

Using this classification of flavors in both product categories (including all products and a "missing" flavor), we computed entropy of the flavor attribute in each category assortment and included it when operationalizing the category-level assortment entropy. We re-ran our model with this new assortment measure, and results of the estimation are presented in Table W3. The estimated parameters are statistically indistinguishable from those presented in the main manuscript. Overall, this result confirms that our main finding of the negative cross-category assortment in the absence of simultaneous price effect is robust to alternative operationalization of entropy measures incorporating flavors in both frozen meals and ice creams.

Table W2. Distribution of Selected Flavor Types by Product Category

Product Category	*Flavor Type*	*% Count**
Frozen Meals	Vanilla	17%
	Chocolate	16%
	Fruit	13%
	Multiple	9%
	Coffee/ Cookie	9%
	Nut	6%
	Other	31%
Ice Cream	Chicken/ Turkey	25%
	Beef	15%
	Pork	6%
	Seafood	4%
	Other	50%

*The percent count is computed among UPCs with valid flavor descriptions.

Table W3. Parameter Estimates Using Category Assortment Entropy

Purchase Incidence	*Category Preference*			*Price*		*Promotions*		*Assortment*	
of	*Intercept*	*Temp*	*Time*	*FM*	*IC*	*FM*	*IC*	*FM*	*IC*
FM	−1.108	−0.002*	0.009**	−0.386**	0.099	0.401**	−0.370**	0.289**	−0.360*
	(1.467)	(0.001)	(0.002)	(0.051)	(0.130)	(0.143)	(0.123)	(0.130)	(0.205)
IC	−0.742	0.006**	0.015**	0.012	−0.553**	−0.060	0.349**	−0.277**	0.259**
	(0.746)	(0.001)	(0.002)	(0.026)	(0.088)	(0.087)	(0.071)	(0.072)	(0.110)

** Significant at 5% level; * Significant at 10% level

Complementary Applications of Pairwise Category Purchase Analysis

The objective of this study is to test the generalizability of our empirical findings from two frozen food categories in a broader grocery context. We apply the proposed multicategory purchase incidence model to two more pairs of product categories and investigate within each pair the cross-category effects due to product assortment. We select pairs of product categories which are; 1) often displayed in close proximity to each other in stores, and 2) neither substitutes nor complements in terms of consumption. We expect refrigerated dairy food categories to satisfy generally these requirements and select margarine (including other butter substitutes) and yogurt. Another pair is pasta sauce and condiments (including mustard and ketchup), chosen from sauce categories. While we do not have access to store-level planogram data, it seems plausible that these pairs are displayed in the common aisle in most stores.

Data. The analyses make use of the IRI academic data set (Bronnenberg et al. 2008), and the period of investigation is set similarly to the previous study as 53 weeks from 26 December 2005 to 31 December 2006. However, some difference between the data sets should be noted. Compared to the previous household panel data, the new data track a greater number of households in a narrower scope of geographic markets: The raw data contain 5,553 panelists in 2 cities (Eau Claire, WI and Pittsfield, MA). Thus we begin by restricting our sample to 500 randomly selected households in these two markets.

The panel data for each category provide the households' shopping trips in which they purchased from the category, and to obtain the trips in which they purchased neither of the categories, we use additional data from the IRI academic data set. A unique feature of this data set is that it provides an extensive record of each household's store visit for every shopping occasion with their total spending per visit. On average, the household made 103 shopping trips to 6 different stores for 53 weeks.

Such a detailed shopping record might include the household's shopping visits made for quick, fill-in trips for daily essentials. In order to study the effect of product assortment on the households' category purchase decisions made in the store, we would ideally need to account for shopping trips where the households spend sufficient time browsing aisles.

Kollat and Willett (1967) classify shopping trips as "major" trips and "quick" trips based on the shopping expenditure, and conjecture that shoppers are more likely to be receptive to in-store stimuli during the major trips. In fact, it has been supported empirically that quick trips are more focused and generate fewer unplanned category purchases (Bell, Corsten and Knox 2011). Taking an approach similar to Kahn and Schmittlein (1989) in the absence of the information on the households' shopping goals, we distinguish the major trips from quick trips using the household's spending per shopping visit. More specifically, we use the trips where their spending exceeded the individual mean level of spending. In addition, we focus on stores where each household purchased the categories at least once.

Finally, the pairwise category purchase incidence model is applied to households that purchased each of the two categories under study at least once and that recorded at least 20 shopping trips. The final data set for dairy categories contain 16,376 shopping occasions made by 429 households. For sauce categories, the set contains 16,987 trips made by 470 households. Category purchase frequencies in both data sets are summarized in Table W4.

Descriptive Statistics. Table W5 presents some descriptive statistics of key variables in the final data sets. Every marketing variable was operationalized in the same manner as in the previous study, and assortment entropy was measured using three attributes; product type, brand and pack size. Margarine and butter substitutes comprise spread

Table W4. Summary of Category Purchase Incidence Frequency

Refrigerated Dairy Categories			*Sauce Categories*		
Purchase Incidence		*Total Obs. (%)*	*Purchase Incidence*		*Total Obs. (%)*
Margarine	*Yogurt*		*Pasta Sauce*	*Condiments*	
1. Aggregate Category Purchase Frequency					
3,690	5,448	16,376	3,081	2,187	16,987
2. Frequency by Shopping Basket					
1	1	1,072 (6.5)	1	1	1,687 (9.9)
1	0	2,618 (16.0)	1	0	2,581 (15.2)
0	1	4,376 (26.7)	0	1	500 (2.9)
0	0	8,310 (50.7)	0	0	12,219 (71.9)

Table W5. Descriptive Statistics of Category Marketing Variables

		Price		*Promotion Intensity*		*Assortment Entropy*	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Dairy	Margarine	1.82	(0.47)	0.13	(0.20)	2.74	(0.14)
	Yogurt	1.79	(0.30)	0.26	(0.28)	3.67	(0.45)
Sauces	Pasta Sauce	1.28	(0.34)	0.20	(0.26)	3.75	(0.47)
	Mustard & Ketchup	1.64	(0.68)	0.19	(0.23)	4.61	(0.33)

and liquid types, and yogurt has three types of regular, drinks, and smoothies. For pasta sauce, we manually classify the type into red (tomato-based), green (pesto) and white sauces, and for condiments, we use the data on whether each product belongs to ketchup, mustard, horseradish or condiment combo-packs. Between dairy categories, yogurt was generally supported by stronger promotions and had more diverse assortment - on average 34% more in entropy. Between sauce categories, condiments offered 23% more variety of products on average.

Model. The purchase incidence model follows largely the specification in the previous study. Given the less seasonal characteristics of the product categories, we do not use temperature variable and thus include a variable of time since last category purchase only in this study.

Results. Table W6 presents the main results. First, coefficients for time since last purchase are positive and significantly different from zero for most product categories, and demonstrate the importance of accounting for individual purchase cycle for those categories. Purchase incidence probability for yogurt, however, is not accounted for by this variable, possibly due to the discretionary nature of category purchases. Marketing variables for own categories have an impact on purchase incidences with anticipated signs. In particular, consistent with the previous study, greater variety of own assortment tends to induce more frequent category purchases although the effects for sauce categories are not significant at the 10% level. The cross-category effects due to the assortment between the pairs of categories are of major interest to us, and we find some evidence that there are significant negative cross-category effects. Yet, the estimated effects are not symmetric

Table W6. Posterior Means of Parameters for Marketing Variables

1. Refrigerated Dairy Categories

Purchase Incidence	*Category Preference*		*Price*		*Promotions*		*Assortment*	
of	*Intercept*	*Time*	*MG*	*YG*	*MG*	*YG*	*MG*	*YG*
Margarine	−2.174**	0.025**	−0.338**	0.122	0.469**	−0.024	0.771**	−0.219**
(MG)	(0.494)	(0.002)	(0.093)	(0.111)	(0.094)	(0.085)	(0.204)	(0.107)
Yogurt	−1.194**	0.003	−0.005	−0.351**	0.003	0.222**	0.133	0.201*
(YG)	(0.508)	(0.002)	(0.089)	(0.114)	(0.090)	(0.086)	(0.202)	(0.116)

2. Sauce Categories

Purchase Incidence	*Category Preference*		*Price*		*Promotions*		*Assortment*	
of	*Intercept*	*Time*	*PS*	*CD*	*PS*	*CD*	*PS*	*CD*
Pasta Sauce	0.141	0.020**	−0.548**	−0.171**	0.635**	−0.395**	0.084	−0.171*
(PS)	(0.491)	(0.002)	(0.129)	(0.086)	(0.082)	(0.084)	(0.084)	(0.106)
Condiments	−2.206**	0.027**	−0.106	−0.184**	−0.009	0.907**	0.022	0.168
(CD)	(0.495)	(0.002)	(0.137)	(0.091)	(0.089)	(0.090)	(0.088)	(0.111)

** Significant at 5% level; * Significant at 10% level

Notes: *Time* variable denotes the number of weeks since last category purchase.

between these categories.

Households are less likely to purchase from margarine when it is presented with a greater variety of yogurt items. Similarly, a more variety of condiments in a store tends to reduce the demand for pasta sauce. These effects are significant after accounting for individual household's category purchase cycle. Unlike the case of the two frozen food categories, however, the significant negative cross-effects are observed in only one category in each pair. In addition, we find that such a presence of asymmetric cross-category assortment effects is associated with difference in the level of assortment variety. We noted earlier that yogurt and condiments offered distinctly more variety than their neighboring categories did. A paired t-test over the unique set of observed category assortments confirmed this: The difference was significant both between margarine and yogurt (t =−33.792, df = 177, $p < 0.001$) and between pasta sauce and condiments (t =−26.568, df = 179, $p < 0.001$). We also conducted the test for a pair of frozen meals and ice cream, by state, given the much wider scope of markets in the sample. Despite some variations by state, variety in both categories generally lied in a similar range and the difference was not significantly different from zero in Illinois and Washington, which covered 53% of the total observations. This implies that the negative impact of the adjacent categories on the focal category is less likely to be present when the focal

Table W7. Pairwise Correlations in Stochastic Errors

Frozen Categories	*Refrigerated Categories*	*Sauce Categories*
−0.194**	−0.083**	0.082**
(0.030)	(0.018)	(0.021)

Posterior standard deviations are in parentheses. ** Significant at 5% level

category offers much larger variety compared to the neighboring category.

Correlations in errors. Table W7 presents the correlations in stochastic error terms in each pairwise analysis for a comparison. The effects of any unobserved sources of households' category substituting or complementing behaviors are captured via correlation of the error terms. In the main paper, we explain that the freezer space constraint which the households face at home could contribute to the negative correlation between the error terms in the case of frozen food categories. We expect that storage space at home is less of a constraint for smaller refrigerated items, and this is supported by the present result. The more the category purchases are subject to space constraint at home (frozen vs. refrigerated), the stronger the negative correlation becomes. The correlation becomes positive between sauce categories, which may be accounted for by the households' need for variety in the kitchen.

Complementary Analysis of Online Experiment

This section presents the results from the experimental data focusing on the respondents' purchase likelihood for magazines. The analysis tests primarily the effect of a change in the own assortment, since it is only the size of the magazine assortment (i.e., own assortment) that varied depending on the condition. It also serves as a manipulation check to confirm whether the larger magazine assortment was appealing enough to influence the respondents' perception of the overall assortments. Applying the ordered probit model, we found a positive main effect of a larger own assortment on the consumer's utility (posterior mean and SD: 0.272 and 0.153 respectively); the larger the assortment is, the more likely the consumers are to purchase from it. In addition, we also find a negative main effect of the joint display with the chocolate assortment on the utilities from magazines (posterior mean and SD: -0.273 and 0.153 respectively).

The magnitude of the own-assortment effect varied depending on the display condition. In the separate display condition, the respondents were presented with a magazine assortment in the beginning of the study and were not aware of the chocolate assortment when they evaluated the magazine assortment. This renders the context comparable to previous studies investigating the impact of the assortment size within a single category, and the results in this condition replicated the positive effect of the size. In the joint display condition, however, such a positive impact of the large assortment size was supported only directionally. We expect the presence of a negative impact due to the joint display with an assortment of eight chocolates, and it might have offset the positive impact of the large own assortment, which the consumers would have experienced otherwise. Although we also expect such a negative impact for the small magazine assortment presented together with the chocolate assortment, we did not observe a significant decrease in utility. Given the already low purchase intent from the assortment of three magazines when presented alone, this could be attributed to the floor effect.

The mean purchase likelihood for magazines by condition and estimates from the ordered probit model are presented in Figure W1 and Table W8.

Figure W1. Mean Purchase Likelihood for Magazines by Condition

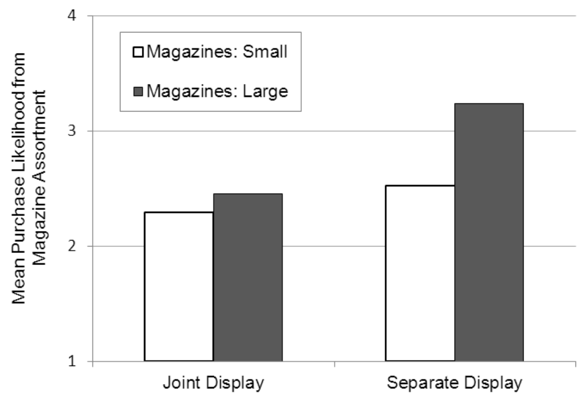

Table W8. Magazines Utility Parameter Estimates from Ordered Probit Model

Interpretation	*Estimate*	*SD*
Utility from a small magazine assortment presented alone	0.137	(0.169)
Utility shift when a small magazine assortment is presented jointly with chocolates	−0.061	(0.224)
Utility shift when a large magazine assortment is presented alone	0.475**	(0.221)
Utility shift when a large magazine assortment is presented jointly with chocolates	0.020	(0.220)

** Significant at 5% level

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