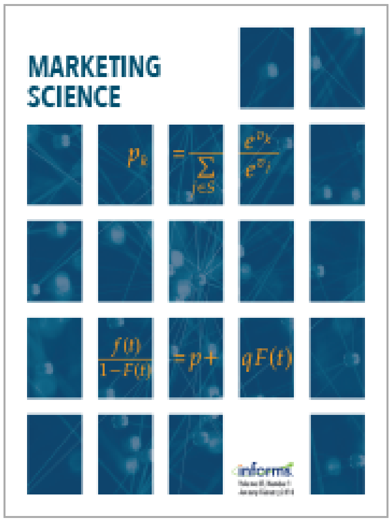

Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MARKETING SCIENCE
Vol. 23, No. 3, Summer 2004, pp. 317–334
ISSN 0732-2399 | EISSN 1526-548X | 04 | 2303 | 0317

DOI 10.1287/mksc.1040.0061

Decomposing the Sales Promotion Bump with Store Data

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Sales promotions generate substantial short-term sales increases. To determine whether the sales promotion bump is truly beneficial from a managerial perspective, we propose a system of store-level regression models that decomposes the sales promotion bump into three parts: cross-brand effects (secondary demand), cross-period effects (primary demand borrowed from other time periods), and category-expansion effects (remaining primary demand). Across four store-level scanner datasets, we find that each of these three parts contribute about one third on average. One extension we propose is the separation of the category-expansion effect into cross-store and market-expansion effects. Another one is to split the cross-item effect (total across all other items) into cannibalization and between-brand effects. We also allow for a flexible decomposition by allowing all effects to depend on the feature/display support condition and on the magnitude of the price discount. The latter dependence is achieved by local polynomial regression. We find that feature-supported price discounts are strongly associated with cross-period effects while display-only supported price discounts have especially strong category-expansion effects. While the role of the category-expansion effect tends to increase with higher price discounts, the roles of cross-brand and cross-period effects both tend to decrease.

Key words: econometric models; market response models; sales promotion; regression and other statistical techniques
History: This paper was received December 22, 2000, and was with the authors 21 months for 3 revisions; processed by Scott Neslin.

1. Introduction

Sales promotions often result in large sales effects for a promoted item (Neslin 2002, p. XI). However, this does not mean that the sales increase is truly beneficial. To help determine that, managers need a method that decomposes the effect of a price promotion into its constituent parts. These parts differ in attractiveness to the manufacturer and retailer. For example, at the store level the sales increase for a promoted brand could come from other brands losing sales within the same store, from selling less in other time periods (due to, for example, stockpiling) and from category expansion (due to, for example, increased consumption). The *retailer* obtains no benefit from cross-brand effects within the store, except for possible differences in margins. However, cross-brand effects could be beneficial for *manufacturers*. Neither retailers nor manufacturers generally derive benefit if the sales increase is borrowed from other time periods, unless they earn higher margins during the promotion or the corresponding stockpiling is intended to hinder a competitor's activity. Thus, it matters greatly what the constituent parts of sales effects are. With a model that decomposes the *unit sales* effects of price promotions, managers can evaluate past promotions so as to improve future decisions. For example, they could favor price promotions with the strongest category-expansion effects.

The current practice of evaluating price promotions includes baseline/incremental methods and regression analyses of store data (Bucklin and Gupta 1999). These methods allow managers to estimate the own- and cross-brand effects of promotions, but do not focus on a decomposition of price-promotion effects. Extant decomposition methods use elasticities based on household-level scanner data (Gupta 1988, Chiang 1991, Chintagunta 1993, Bucklin et al. 1998). They address important aspects, including differences in the nature of decomposition results between categories (Bell et al. 1999), and between short- and long-run results (Pauwels et al. 2002). However, none of the current decomposition models answers the key question: If the promoted brand gains 100 units, how many units do other brands loose, how many units come from other periods, and how many units represent category expansion? The answer is crucial for a determination of the profitability of promotions as well as their competitive impact (Neslin 2002).

We use store-level scanner data and provide a decomposition of the own-brand sales effect into net cross-brand, cross-period, and category-expansion effects. Our approach answers the call by Bucklin and Gupta (1999, p. 268): "Research is needed to develop simple, robust models that will provide better estimates of promotional sales that are truly incremental to the manufacturer, not borrowed from the future, from another store, or from a sister brand."

Our method is relevant for academic researchers and practitioners. We contribute to the sales promotion decomposition literature (see §2) both with respect to the methodology and the substantive results. In §3, we propose a store-level model, and describe how it provides the desired decomposition. We discuss four scanner datasets in §4, provide empirical results in §5, and present our conclusions in §6. We present model estimation details in the appendix.

2. Literature Review and Contributions

In this section, we briefly summarize extant decomposition approaches and identify our contributions. First, we use *net* unit sales effects instead of gross effects (§2.1). Second, we split *primary demand* effects into cross-period and category-expansion effects (§2.2). Third, we provide two *additional* decompositions, one pertaining to cross-store and the other to cannibalization effects (§2.3). Fourth, we allow the own-brand sales effect and the decomposition to *depend* on: (a) the type of support for a temporary price discount, and (b) the magnitude of the discount (§2.4). Fifth, our approach is based on *store* data (§2.5). Sixth, we present a *unified framework* that defines each decomposition effect precisely and ensures that the sum of the effects is by definition equal to the own-brand (item) effect (§2.6). Finally, in §2.7, we discuss how our research differs from Pauwels et al. (2002).

2.1. Net Sales Effect Decomposition

There are two approaches to obtain a decomposition of sales-promotion effects: *gross* (elasticity based) and *net* (unit sales based). Gupta (1988) introduces the gross approach, and it is used by Chiang (1991), Chintagunta (1993), Bucklin et al. (1998), and Bell et al. (1999). On average, Bell et al. (1999) show that the price promotion elasticity can be decomposed into 74% brand choice elasticity, 11% purchase incidence elasticity, and 15% quantity elasticity. The brand choice elasticity percentage is the part of the bump representing consumers switching away from other brands keeping everything else constant. Thus, if a promoted brand gains 100 units, the other brands together would loose 74 units *if the category does not grow*.

Our approach in this paper is consistent with the net approach proposed by van Heerde et al. (2003). We compute the net impact of a promotion on the sales of other brands, *accounting for category growth*. The key difference with the gross approach is the way the net approach accounts for the increase in purchase incidence that benefits all brands in the category. If a brand is promoted, the category purchase incidence probability in the household models increases. Because this increase also applies to the nonpromoted brands, it tends to compensate for the gross sales loss due to brand switching. Importantly, van Heerde et al. (2003) show that if one accounts for this compensating effect, the net sales loss of other brands is only 33 units on average. The gross decomposition describes the consumer choice process in detail but the net decomposition is required to assess the net losses in cross-brand sales and net growth in category sales. Because net effects are the bottom-line quantities, we also follow a net decomposition approach. We define secondary demand effects as the net effect of a promotion on the sales of nonpromoted brands in the same week, category, and store,[1] and primary demand effects as the net effect of a promotion on category sales within the same week in the same store.[2] In the next section, we present a way to split primary demand effects.

2.2. Split of Primary Demand Effects

Decomposition studies of household data (except for Pauwels et al. 2002; see §2.7) show to what extent the immediate primary demand elasticity is due to increased purchase incidence or to increased purchase quantity (e.g., Gupta 1988). Those results do not indicate whether such increases represent pure stockpiling (without increased consumption; see Bell et al. 2002) as opposed to other effects such as consumption increases. We decompose primary demand effects into cross-period effects and category-expansion effects. Cross-period effects are the part of primary demand effects that represent temporal shifts in sales, due to both lead effects (Doyle and Saunders 1985, Kalwani

[1] This definition differs from the one in Bell et al. (1999) because (1) we focus on sales effects instead of choice probabilities, and (2) we limit ourselves to sales in the same store.

[2] This definition differs from the one in Nijs et al. (2001) who use total national sales levels, and the one in Srinivasan et al. (2003) who look at total retailer sales at the chain level.

et al. 1990, Gönül and Srinivasan 1996, van Heerde et al. 2000, Macé and Neslin 2004) and lagged effects (e.g., van Heerde et al. 2000).[3] Category expansion is the part of the primary demand effect that is not due to temporal shifts, and it may include increased consumption (Assunçao and Meyer 1993, Ailawadi and Neslin 1998, Chandon and Wansink 2002), deal-to-deal purchasing (Krishna 1994), category switching (Walters 1991), and store switching (Bucklin and Lattin 1992).

2.3. Additional Decomposition Effects

One additional decomposition effect of interest is the separation of the cross-store effect from the category-expansion effect. Cross-store effects are related to store switching, which has two variants (Bucklin and Lattin 1992). The first is "direct" store switching that pertains if households use outside-store cues (e.g., featured price cuts) to decide where to purchase specific items. Direct store switching leads to net decreases in item sales in stores competing with the store promoting the item. The second is "indirect" store switching, which applies if a household visits multiple stores in a given week, and inside-store cues (e.g., displays with price promotions) influence which items are purchased in the different stores (Bucklin and Lattin 1992, Neslin 2002). Indirect store switching does *not* imply that store choice is driven by in-store activities. Instead, it requires autonomous cross-shopping, which is common for many households (Keng and Ehrenberg 1984). Kumar and Leone (1988) find evidence of indirect store-switching effects, because price cuts and displays in one store decrease sales in an adjacent store. We show how the category-expansion effect within a store can be split into a cross-store effect and a market-expansion effect (the category-expansion effect net of the cross-store effect) with data on multiple chains in a metropolitan area.

With SKU-level data, we can split the cross-item effect (effect on other SKUs) into cannibalization and cross-brand effects (net sales losses of nonpromoted items belonging to other brands). This distinction is especially relevant for manufacturers.

2.4. Decomposition as a Function of Promotion Characteristics

To evaluate price promotions we create a model that accomplishes the decomposition separately for four alternative support conditions. This is important because the price-discount effect is moderated by the type of support (Lemon and Nowlis 2002, van Heerde et al. 2001). To illustrate, it seems plausible for discounts that are only communicated within a store (e.g., by a display) to have strong cross-brand sales effects. By contrast, discounted items with out-of-store support (i.e., feature) have greater potential to create cross-store sales effects. To obtain a separate decomposition of the price-discount effect for different support conditions, we create four separate predictor variables for price discounts: (1) without support, (2) with feature-only support, (3) with display-only support, and (4) with feature-and-display support. We do not provide a decomposition of the effects of non-price promotions (such as features without price cuts), because these occur very rarely in our data.

The decomposition may also depend on the magnitude of a price discount. For example, Gupta and Cooper (1992) show that incremental stockpiling approaches zero when the price-discount level exceeds some value. Sethuraman (1996), Sethuraman et al. (1999), and van Heerde et al. (2001) show that cross-brand effects also strongly depend on the magnitude of the price discount. Consumers could have different reservation prices for the separate decisions underlying the decomposition. By using a nonparametric method (local polynomial regression; see §3.4) we obtain discount-dependent decomposition effects. Importantly, the nature of nonlinearity in the discount effect is allowed to differ between the four support conditions.

2.5. Store-Level Data

To decompose the promotional sales spike, we use store-level scanner data instead of household data. This choice is driven by the goal of this paper, which is to propose a simple yet managerially relevant decomposition method that is applicable to widely available store data. In addition, store data are in general more representative than household data (cf., Gupta et al. 1996, Bucklin and Gupta 1999). Further, we want the method to be applicable for all categories, including low-incidence product categories, where store data offer better coverage than household data. Finally, firms typically have access to and analysis capabilities only for aggregate data.

One important benefit of household data is that one can obtain insight into the underlying consumer responses (incidence, choice, and quantity) due to promotions (see, e.g., Zhang and Krishnamurthi 2004). This decomposition is not available from store data, because it is impossible to recover individual household decisions. In addition, it may be useful to understand to what extent households show responses that cancel each other. For example, a nonpromoting brand may gain 100 units due to an increase of customers in the category, induced by a promotion for another brand, but lose 100 units due to brand

[3] The cross-period effects are based on retail sales to consumers. In sales from manufacturers to retailers there may also be promotion-induced intertemporal shifts due to forward-buying by retailers (Drèze and Bell 2003).

switching. Household data also offer an important advantage with regard to the accommodation of heterogeneity. For store data this is still in its infancy, and we leave this for future research. We do note that because households are exposed to the same marketing mix in a given week and store, a primary source of aggregation bias is absent in nonlinear models of store data (Allenby and Rossi 1991, Gupta et al. 1996).

There exists considerable doubt about the possibility to decompose the sales effect of promotions based on store data (e.g., Bucklin et al. 1998). We show that: (1) it is possible to derive theoretically and substantively meaningful decompositions based on store data, (2) the substantive conclusions about primary and secondary demand effects are similar to corresponding inferences based on household data, and (3) our methodology provides a unique framework for a range of related questions.

2.6. Unified Framework

We show mathematically how current own-brand sales can be split into various decomposition components. By doing this, we present a unified framework that defines sales-promotion effects precisely. Our approach consists of specifying a separate criterion variable for the own-brand effect and for each decomposition effect. Initially, each of the different criterion variables is regressed linearly on the promotion variables of interest and appropriate covariates that are identical across the equations. Thus, the equations differ from each other only on the left-hand side. The decomposition of interest is obtained by relating the parameters for a given price promotion variable across the different equations. A linear additive specification (as opposed to a multiplicative one) allows us to derive a mathematically consistent decomposition in terms of unit sales. When we later relax the linearity assumption via nonparametric estimation (§5.3), we maintain this consistency by imposing certain constraints.

2.7. Positioning Relative to Pauwels et al. (2002)

Pauwels et al. (2002) focus on mean-reverting behavior of incidence, choice, and quantity after promotions. Their study differs from ours as follows. First, our primary goal is to quantify to what extent a current own-brand sales increase due to promotion can be attributed to cross-period and category-expansion effects. Second, we express the effects in *unit sales* rather than elasticities. Third, we study effects of sales promotions on own- and cross-brand sales, whereas Pauwels et al. (2002) consider own-brand effects only. Fourth, we also accommodate pre-promotion effects in the dynamic component. Fifth, we use store data whereas Pauwels et al. (2002) use aggregated household data.

3. Sales-Based Approach for Decomposition

We first present a "standard decomposition" in §3.1. In §§3.2 and 3.3, we introduce two extensions of the standard approach. In §3.4, we discuss estimation methods for constant and varying decompositions. In §3.5, we discuss the specification of dynamic effects.

3.1. Standard Decomposition

The standard decomposition splits the own-brand sales increase into three parts: cross-brand, cross-period, and category-expansion effects. We illustrate the standard decomposition in Table 1. In this example, the focal brand has baseline sales of 100 units. Consistent with the modeling approach presented below, we multiply own-brand sales by minus one. The other brands together have baseline sales of 400 units, and hence, baseline category sales are 500 units (not shown). The sales promotion for the focal brand in week six (coded for the promotion dummy as −1) leads to a 100-unit own-brand sales increase (−200 versus −100, in week six). Cross-brand effects are the net losses in other brands' sales in the week when the focal brand is promoted: 35 units (400 − 365, in column 2). Cross-period effects are the net losses in pre- and post-promotion own-brand (−30) and cross-brand sales (−10), so in total −40 units. Note that we include both own- and cross-brand sales changes in the surrounding weeks to determine the cross-period effect. Thus, the cross-period effect is specified at the category level. As a result, accelerated brand switches are included in the cross-period effect. Finally, the category-expansion effect is 25 units (100 − 35 − 40).

To show that we can retrieve this decomposition from simulated data, we estimate four linear regression models (see the middle panel of Table 1). Note that we decompose the unit sales effect of a promotion based on the same predictor variables for each of the four criterion variables. For the own-brand effect we use minus Own-Brand Sales (OBS_t) as the criterion variable, and for cross-brand effects we use Cross-Brand Sales (CBS_t). For cross-period effects, we use category sales in $t-1$ and $t+1$: $PPCS_t$, Pre- and Post-Category Sales. For category expansion, the criterion variable is minus Total Category Sales before, during, and after period t (TCS_t), in the example $[t-1, t+1]$. A change in the latter variable reflects expansion effects in own-brand sales that cannot be attributed to other brands nor to other periods. The decomposition is obtained from the effects of the promotion variable in period t on the four criterion variables.[4]

[4] We can refrain from estimating one of the models because one decomposition effect can be derived from the other effects. In the empirical applications we indeed omit one equation (see §3.4).

Table 1 **Illustration of Sales Decomposition**

	Data				
Time (t)	Minus own-brand sales (OBS)	Cross-brand sales (CBS)	Category sales in $t-1$ and $t+1$ (PPCS)	Minus category sales in $[t-1, t+1]$ (TCS)	Promotion dummy (Prom_t)
1	−100	400	—	—	0
2	−100	400	1,000	−1,500	0
3	−100	400	1,000	−1,500	0
4	−100	400	990	−1,490	0
5	−90	400	1,065	−1,555	0
6 (Promotion)	−200	365	960	−1,525	−1
7	−80	390	1,065	−1,535	0
8	−100	400	970	−1,470	0
9	−100	400	1,000	−1,500	0
10	−100	400	1,000	−1,500	0
11	−100	400	—	—	0

Linear regression models for $t = 3, \ldots, 9$ (All have $R^2 = 1.00$)

$\widehat{\text{OBS}}_t = -100 + 100\text{Prom}_t - 10\text{Prom}_{t+1} + 0\text{Prom}_{t+2} - 20\text{Prom}_{t-1} + 0\text{Prom}_{t-2}$

$\widehat{\text{CBS}}_t = 400 + 35\text{Prom}_t + 0\text{Prom}_{t+1} + 0\text{Prom}_{t+2} + 10\text{Prom}_{t-1} + 0\text{Prom}_{t-2}$

$\widehat{\text{PPCS}}_t = 1{,}000 + 40\text{Prom}_t - 65\text{Prom}_{t+1} + 10\text{Prom}_{t+2} - 65\text{Prom}_{t-1} + 30\text{Prom}_{t-2}$

$\widehat{\text{TCS}}_t = -1{,}500 + 25\text{Prom}_t + 55\text{Prom}_{t+1} - 10\text{Prom}_{t+2} + 35\text{Prom}_{t-1} - 30\text{Prom}_{t-2}$

Misspecified linear regression models for $t = 3, \ldots, 9$

$\widehat{\text{OBS}}_t = -95 + 105\text{Prom}_t$

$\widehat{\text{CBS}}_t = 398 + 33\text{Prom}_t$

$\widehat{\text{PPCS}}_t = 1{,}015 + 55\text{Prom}_t$

$\widehat{\text{TCS}}_t = -1{,}493 + 32\text{Prom}_t$

The promotion variable is a $(0, -1)$ dummy in the example, representing promotion at time t (Prom_t). Because pre- and post-promotion effects influence own-brand and cross-brand sales in other periods, we also need a lead promotion dummy (Prom_{t+1}) and a lagged promotion dummy (Prom_{t-1}) as covariates. In addition, because PPCS_t and TCS_t span the period $[t-1, t+1]$, they may also be affected by a two-week lead (Prom_{t+2}) and by a two-week lagged promotion dummy (Prom_{t-2}). Although these two extra variables are redundant in the equations for OBS and CBS (confirmed by the zero coefficients), we include the same predictors in all equations to ensure a mathematically consistent decomposition: the sum of the estimated decomposition effects necessarily equals the own-brand effect.

We show the OLS results for the four multiple regressions in the middle panel of Table 1. The coefficients for Prom_t in the four equations give the desired decomposition: the own-brand effect is 100 units, the cross-brand effect is 35 units, the cross-period effect is 40 units, and the category-expansion effect is 25 units. Thus, we obtain a consistent decomposition by estimating four regressions, and using only one coefficient from each regression. Importantly, the covariates (lead and lagged variables) are required to obtain unbiased effects of the current promotion variable. Excluding them would lead to misspecified models, with biased effect estimates for the decomposition as we show in the bottom panel of Table 1. All intercept and slope parameter estimates now differ from the correct values, and the mathematical consistency property is also violated.

For real-world applications with noisy data, we employ more complex models to obtain the desired decomposition. However, the principle illustrated in Table 1 remains the same. In general, there are J brands, the time window for which we define cross-period and category-expansion effects is $[t-T^*, t+T]$, and we estimate the models pooled across stores ($i = 1, \ldots, I$). Because stores differ in size, and it is inappropriate to assume equal absolute unit sales effects across stores, we transform all criterion variables so as to obtain equal effects across stores *proportional* to category volume.[5] Thus, we divide all criterion variables by the *average* category sales per store (CS_i).[6] If S_{ijt} is unit sales of brand j in

[5] Such a proportionality assumption is implicit in the multiplicative models commonly applied to pooled store data.

[6] The CS_i variable includes both regular and promotional sales. Thus, this variable might depend on the promotional intensity in store i. In §5.1, we show that this issue is of limited concern.

store i in week t, we define the criterion variables for the standard decomposition as

$$\mathrm{OBS}_{ijt} = -\frac{S_{ijt}}{\mathrm{CS}_i}, \qquad \mathrm{CBS}_{ijt} = \sum_{\substack{k=1\\k\neq j}}^{J} \frac{S_{ikt}}{\mathrm{CS}_i},$$

$$\mathrm{PPCS}_{it} = \sum_{\substack{s=-T^*\\s\neq 0}}^{T} \sum_{k=1}^{J} \frac{S_{ikt+s}}{\mathrm{CS}_i}, \quad \mathrm{TCS}_{it} = -\sum_{s=-T^*}^{T} \sum_{k=1}^{J} \frac{S_{ikt+s}}{\mathrm{CS}_i}.$$

These definitions allow us to write

$$\mathrm{OBS}_{ijt} = \mathrm{CBS}_{ijt} + \mathrm{PPCS}_{it} + \mathrm{TCS}_{it}. \tag{1}$$

We use a price index variable to separate promotional price from regular price effects. This variable is defined as the actual price for an item divided by its regular price. It equals one in nonpromotional weeks and is less than one if the actual (shelf) price is below the regular price. If the regular price changes, then the price index is defined relative to the new regular price (and it remains one if only the regular price changes). Thus, the price index captures temporary price discounts only. This variable is also used in ACNielsen's Scan*Pro model (Wittink et al. 1988).

Typical sales promotions consist of temporary price discounts that may be supported by feature advertising and/or (special) displays. Based on prior research, it appears to be meaningful to allow the effects of interest to depend on the type of support for a price discount (see §2.4). Nevertheless, extant decomposition research rarely focuses on empirical differences in effects between sales promotion types. Researchers who do, report that the support variables (Gupta 1988: feature-and-display, feature-or-display, and price cut; Chiang 1991: feature, display) are highly correlated because they are often used at the same time. To circumvent this problem, we define the variables in such a way that they are by definition uncorrelated. Our perspective is that price promotions have a price reduction as their core, and a communication device with four mutually exclusive options: (1) price index without support, (2) price index with feature-only support, (3) price index with display-only support, and (4) price index with feature-and-display support. The variables so constructed also allow for four separate decompositions. Given that the regular price may also change over time, we include separate own- and (average) cross-brand regular price variables as covariates.

For the standard decomposition, the models are specified as follows:

$$\begin{aligned}\mathrm{OBS}_{ijt} = \alpha_j &+ \sum_{l=1}^{4} \beta_{\mathrm{ob},lj} \mathrm{PI}_{ijlt} + \sum_{l=1}^{4} \gamma_{1,lj} \mathrm{CPI}_{ijlt} \\ &+ \sum_{m=1}^{3} \gamma_{2,mj} \mathrm{D}_{ijmt} + \sum_{m=1}^{3} \gamma_{3,mj} \mathrm{CD}_{ijmt} + \gamma_{4j} \mathrm{RP}_{ijt} \\ &+ \gamma_{5j} \mathrm{CRP}_{ijt} + \sum_{\tau=T+T^*+1}^{T_{\max}-T-T^*} \gamma_{6,\tau j} \mathrm{W}_t \\ &+ \sum_{\tau=1}^{T+T^*} \gamma_{7,\tau j} \mathrm{PI}_{ijlt+\tau} + \sum_{\tau=1}^{T+T^*} \gamma_{8,\tau j} \mathrm{PI}_{ijlt-\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma_{9,\tau j} \mathrm{CPI}_{ijlt+\tau} + \sum_{\tau=1}^{T+T^*} \gamma_{10,\tau j} \mathrm{CPI}_{ijlt-\tau} + u_{ijt},\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{CBS}_{ijt} = \alpha'_j &+ \sum_{l=1}^{4} \beta_{\mathrm{cb},lj} \mathrm{PI}_{ijlt} + \sum_{l=1}^{4} \gamma'_{1,lj} \mathrm{CPI}_{ijlt} + \sum_{m=1}^{3} \gamma'_{2,mj} \mathrm{D}_{ijmt} \\ &+ \sum_{m=1}^{3} \gamma'_{3,mj} \mathrm{CD}_{ijmt} + \gamma'_{4j} \mathrm{RP}_{ijt} + \gamma'_{5j} \mathrm{CRP}_{ijt} \\ &+ \sum_{\tau=T+T^*+1}^{T_{\max}-T-T^*} \gamma'_{6,\tau j} \mathrm{W}_t + \sum_{\tau=1}^{T+T^*} \gamma'_{7,\tau j} \mathrm{PI}_{ijlt+\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma'_{8,\tau j} \mathrm{PI}_{ijlt-\tau} + \sum_{\tau=1}^{T+T^*} \gamma'_{9,\tau j} \mathrm{CPI}_{ijlt+\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma'_{10,\tau j} \mathrm{CPI}_{ijlt-\tau} + u'_{ijt},\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{PPCS}_{ijt} = \alpha''_j &+ \sum_{l=1}^{4} \beta_{\mathrm{cp},lj} \mathrm{PI}_{ijlt} + \sum_{l=1}^{4} \gamma''_{1,lj} \mathrm{CPI}_{ijlt} \\ &+ \sum_{m=1}^{3} \gamma''_{2,mj} \mathrm{D}_{ijmt} + \sum_{m=1}^{3} \gamma''_{3,mj} \mathrm{CD}_{ijmt} + \gamma''_{4j} \mathrm{RP}_{ijt} \\ &+ \gamma''_{5j} \mathrm{CRP}_{ijt} + \sum_{\tau=T+T^*+1}^{T_{\max}-T-T^*} \gamma''_{6,\tau j} \mathrm{W}_t \\ &+ \sum_{\tau=1}^{T+T^*} \gamma''_{7,\tau j} \mathrm{PI}_{ijlt+\tau} + \sum_{\tau=1}^{T+T^*} \gamma''_{8,\tau j} \mathrm{PI}_{ijlt-\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma''_{9,\tau j} \mathrm{CPI}_{ijlt+\tau} + \sum_{\tau=1}^{T+T^*} \gamma''_{10,\tau j} \mathrm{CPI}_{ijlt-\tau} + u''_{ijt},\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{TCS}_{ijt} = \alpha'''_j &+ \sum_{l=1}^{4} \beta_{\mathrm{ce},lj} \mathrm{PI}_{ijlt} + \sum_{l=1}^{4} \gamma'''_{1,lj} \mathrm{CPI}_{ijlt} + \sum_{m=1}^{3} \gamma'''_{2,mj} \mathrm{D}_{ijmt} \\ &+ \sum_{m=1}^{3} \gamma'''_{3,mj} \mathrm{CD}_{ijmt} + \gamma'''_{4j} \mathrm{RP}_{ijt} + \gamma'''_{5j} \mathrm{CRP}_{ijt} \\ &+ \sum_{\tau=T+T^*+1}^{T_{\max}-T-T^*} \gamma'''_{6,\tau j} \mathrm{W}_t + \sum_{\tau=1}^{T+T^*} \gamma'''_{7,\tau j} \mathrm{PI}_{ijlt+\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma'''_{8,\tau j} \mathrm{PI}_{ijlt-\tau} + \sum_{\tau=1}^{T+T^*} \gamma'''_{9,\tau j} \mathrm{CPI}_{ijlt+\tau} \\ &+ \sum_{\tau=1}^{T+T^*} \gamma'''_{10,\tau j} \mathrm{CPI}_{ijlt-\tau} + u'''_{ijt}\end{aligned} \tag{5}$$

for $i = 1, \ldots, I$ (stores), $j = 1, \ldots, J$ (brands), and $t = T + T^* + 1, \ldots, T_{\max} - T - T^*$ (weeks), where

PI_{ijlt} = price index for brand j in store i in week t; $l = 1$ indicates "no support," $l = 2$ feature-only support, $l = 3$ display-only support, and $l = 4$ feature-and-display support; PI_{ijlt} equals $1 - d/100$ if there is a d percent discount for brand j with support l in week t in store i, and 1 otherwise.

CPI_{ijlt} = average price index across brands k, $k = 1, \ldots, J$, $k \neq j$, for support type l.

D_{ijmt} = dummy for a nonprice promotion for brand j in store i in week t; $m = 1$ for feature-only without price discount, $m = 2$ display-only without price discount, and $m = 3$ feature-and-display without price discount.

CD_{ijmt} = average dummy for a nonprice promotion across brands k, $k = 1, \ldots, J$, $k \neq j$, for support type m.

RP_{ijt} = regular price for brand j in store i in week t.

CRP_{ijt} = average regular price across brands k, $k = 1, \ldots, J$, $k \neq j$.

W_t = week dummy: 1 for week t, 0 otherwise.

u_{ijt}, u'_{ijt}, u''_{ijt}, u'''_{ijt} = disturbance terms for brand j in store i in week t in Equations (2)–(5).

T^* is the number of leads, T is the number of lags, and $T_{\max}$ is the total number of weeks.

The parameter $\beta_{\mathrm{ob},\,lj}$ in (2) is the effect on minus *o*wn-*b*rand sales of the price index for brand j with support l, $\beta_{\mathrm{cb},\,lj}$ in (3) is the *c*ross-*b*rand effect of this price index, $\beta_{\mathrm{cp},\,lj}$ in (4) represents the *c*ross-*p*eriod effect, and $\beta_{\mathrm{ce},\,lj}$ in (5) is the effect on minus category sales in a time window (*c*ategory-*e*xpansion effect). All parameters are expected to be positive. Because we use the same set of predictors for (2)–(5), the identity in Equation (1) leads to the result:

$$\beta_{\mathrm{ob},\,lj} = \beta_{\mathrm{cb},\,lj} + \beta_{\mathrm{cp},\,lj} + \beta_{\mathrm{ce},\,lj}. \tag{6}$$

Importantly, everything required for the decomposition is contained in these parameter estimates. This allows us to test the statistical significance of each part of the decomposition with a single t-test. In words, Equation (6) says

own-brand effect
= cross-brand effect + cross-period effect
+ category-expansion effect.

Van Heerde et al. (2003) define the fraction secondary demand effect as the ratio of the negative of the cross-brand sales decrease to the own-brand sales increase. For our model, this is equivalent to

$$\text{fraction cross-brand effect} = \frac{\beta_{\mathrm{cb},\,lj}}{\beta_{\mathrm{ob},\,lj}}.$$

In addition, van Heerde et al. (2003) define the primary demand effect as the ratio of the current category sales increase to the own-brand sales increase. Our approach expands on this framework by writing current category sales as $-\mathrm{PPCS}_{it} - \mathrm{TCS}_{it}$, which allows us to separate the primary demand effect into

$$\text{fraction category-expansion effect} = \frac{\beta_{\mathrm{ce},\,lj}}{\beta_{\mathrm{ob},\,lj}},$$

and

$$\text{fraction cross-period effect} = \frac{\beta_{\mathrm{cp},\,lj}}{\beta_{\mathrm{ob},\,lj}}.$$

The large number of covariates serves to minimize the possible occurrence of biased parameter estimates if relevant predictors are omitted. The example in Table 1 shows that we do not use the covariates' effects for the decomposition. We control for cross-brand price-promotion effects (via CPI_{ijlt}), for own-brand and cross-brand features and/or displays *without* price discounts (D_{ijmt} and CD_{ijmt}), and for regular price effects (RP_{ijt} and CRP_{ijt}). In addition, we include weekly indicator variables W_t to allow for seasonal differences in sales and as a proxy for missing brand-level variables such as advertising. We also include lead and lagged own-brand and cross-brand price index variables analogous to the example in Table 1. Although we assume that promotions can at maximum be anticipated T^* periods ahead, and their effects last at most T periods after the promotion, we have to include lead variables indexed $t+1, \ldots, t+T+T^*$, and lagged variables indexed $t-1, \ldots, t-T^*-T$.[7] We include the same set of lead and lagged variables for all criterion variables so as to obtain a mathematically consistent decomposition. We note that the total number of predictor variables is high, although not relative to the total number of observations, except for one dataset (see Table 2).

3.2. Extended Decomposition of the Category-Expansion Effect

The category-expansion component may include cross-store effects. With data for stores belonging to other chains, we can extend the decomposition of (6) by separating a cross-store effect from a market-expansion effect. The cross-store effect is defined as the impact of the price promotion on the sales of the

[7] We assume that a sales variable in period t is affected by lead variables indexed $t+1, \ldots, t+T^*$ and by lagged variables indexed $t-1, \ldots, t-T$. However, we have to add extra lead variables indexed $t+T+1, \ldots, t+T+T^*$, and lagged variables indexed $t-T^*-1, \ldots, t-T^*-T$ for a criterion variable that is defined as the sum of sales across the period $t-T^*$ through $t+T$ (TCS_{it}). This is necessary to accommodate leads and lags for the extreme weeks ($t-T^*, t+T$) in TCS_{it}. Recall that in the example of Table 1, although the sales effects are simulated to occur in the interval $[t-1, t+1]$, we require lead variables indexed $t+1$, $t+2$, and lagged variables indexed $t-1$, $t-2$.

Table 2 Description of Product Categories

Category	Tuna	Tissue	Shampoo	Peanut butter
Country	USA	USA	The Netherlands	The Netherlands
Data level	Brand	Brand	Brand	SKU
Unit sales measurement	6.5 oz. can	1,000 sheets	1 liter	1 kilogram
Number of stores	28	24	48	49
Number of weeks	104	52	109	144
Number of items with price promotions	4	6	5	3
Number of items without price promotions	1	0	6	2
Number of observations for each equation	2,240	672	4,043	5,591
Number of predictor variables in each equation	288	236	293	328
Number of SUR equations	16	18	15	12

brand in the same week in other stores. The market-expansion effect is the category-expansion effect minus the cross-store effect. We accomplish this split by first defining an "Extended Total Category Sales" variable ETCS_{ijt}, which is TCS_{it} minus the sales of focal brand j in competing stores $h = I+1, \ldots, I+Q$, SCS_{ijt} (all variables divided by average category sales in store i, CS_i):

$$\mathrm{ETCS}_{ijt} \equiv \mathrm{TCS}_{it} - \mathrm{SCS}_{ijt} = -\sum_{s=-T^*}^{T}\sum_{k=1}^{J}\frac{S_{ikt+s}}{\mathrm{CS}_i} - \sum_{h=I+1}^{I+Q}\frac{S_{hjt}}{\mathrm{CS}_i}.$$

Rewriting this equation as $\mathrm{TCS}_{it} = \mathrm{ETCS}_{ijt} + \mathrm{SCS}_{ijt}$, we decompose the category-expansion effect into a market-expansion effect $\beta_{\mathrm{me},\,lj}$ and a cross-store effect $\beta_{\mathrm{cs},\,lj}$:

$$\beta_{\mathrm{ce},\,lj} = \beta_{\mathrm{me},\,lj} + \beta_{\mathrm{cs},\,lj}. \tag{7}$$

In words, Equation (7) says

category-expansion effect = market-expansion effect
+ cross-store effect.

To estimate the cross-store and market-expansion effects, we regress respectively SCS_{ijt} and ETCS_{ijt} on exactly the same set of predictors as in previous equations (see (2)–(5)).

3.3. Extended Decomposition of the Cross-Item Effect

Extant decomposition research does not distinguish between cross-item effects within brands (cannibalization) and cross-item effects between brands. With SKU-level data it is possible to separate these effects. Define SKU m belonging to brand j ($m = 1, \ldots, M_j$), to distinguish cross-item effects that involve SKUs of the same brand from those of other brands. We define the sales of SKU m analogous to (1), i.e., also relative to average category store sales (CS_i):

$$\mathrm{OBS}_{ijmt} = -\frac{S_{ijmt}}{\mathrm{CS}_i}, \qquad \mathrm{CBb}_{ijt} = \sum_{\substack{k=1\\k\neq j}}^{J}\sum_{n=1}^{M_k}\frac{S_{iknt}}{\mathrm{CS}_i},$$

$$\mathrm{CBw}_{ijmt} = \sum_{\substack{n=1\\n\neq m}}^{M_j}\frac{S_{ijnt}}{\mathrm{CS}_i}, \quad \mathrm{PPCS}_{it} = \sum_{\substack{s=-T^*\\s\neq 0}}^{T}\sum_{k=1}^{J}\sum_{n=1}^{M_k}\frac{S_{iknt+s}}{\mathrm{CS}_i},$$

$$\mathrm{TCS}_{it} = -\sum_{s=-T^*}^{T}\sum_{k=1}^{J}\sum_{n=1}^{M_k}\frac{S_{iknt+s}}{\mathrm{CS}_i},$$

so that $\mathrm{OBS}_{ijmt} = \mathrm{CBw}_{ijmt} + \mathrm{CBb}_{ijt} + \mathrm{PPCS}_{it} + \mathrm{TCS}_{it}$, where current *cross-item within-brand* sales is indicated by CBw (Cross-*B*rand *w*ithin), and current *cross-brand* sales by CBb (Cross-*B*rand *b*etween). Note that the definitions of PPCS and TCS are the same as before, except that a brand may consist of multiple SKUs. We can now decompose the cross-item effect ($\beta_{\mathrm{cb},\,lj}$) into a within-brand ($\beta_{\mathrm{cbw},\,lj}$) and a between-brand effect ($\beta_{\mathrm{cbb},\,lj}$):

$$\beta_{\mathrm{cb},\,lj} = \beta_{\mathrm{cbw},\,lj} + \beta_{\mathrm{cbb},\,lj}. \tag{8}$$

In words, Equation (8) says

cross-brand(item) effect = within-brand effect
+ between-brand effect.

To estimate these effects, we regress respectively CBw_{ijmt} and CBb_{ijt} on the same set of predictors.

3.4. Estimation Methods for Constant and Flexible Decompositions

We first discuss the estimation method to obtain a decomposition that is constant across price discount depths. We then relax this constraint and allow all effects to depend on the magnitude of the price discount. We use linear regression models for the constant decomposition in (2)–(5) and for the extended decompositions in (7) and (8). We note that it is impossible to obtain a logically consistent unit-sales-based decomposition for the semilog or log-log models that are common for store data (e.g., Wittink et al. 1988, Blattberg and Wisniewski 1989, van Heerde et al. 2000). However, a multiplicative model does provide a mathematically consistent elasticity decomposition.[8] Note that we obtain one critical property of

[8] In an earlier version of this paper we decomposed elasticities and found the average cross-brand elasticity fraction to be almost 80%

the multiplicative model, proportionally equal effects across stores, by scaling all criterion variables by CS_i. We relax the linearity assumption later by nonparametric estimation of the price-discount effects in a manner that still yields a mathematically consistent decomposition.

For the constant decomposition of the own-brand effect into cross-brand, cross-period, and category-expansion effects, we estimate Equations (2)–(4) simultaneously across all items in a category. Equation (5) is redundant, because the parameter estimates can be derived from (2)–(4). We use iterative SUR-GLS to allow for contemporaneous correlation between the errors for all decomposition components for all brands (the SUR-part). In addition, we allow for first-order autocorrelation for all error terms (the GLS-part). For the criterion variable in Equation (4), this autocorrelation is at least partly induced by summations over time. We describe the estimation procedure in detail in the appendix. Our use of linear models (and flexibly estimated nonlinear effects) avoids the possibility of bias inherent in the application of nonlinear models to linearly aggregated data (Christen et al. 1997). We next turn to the assumption of linear deal effects.

The current literature assumes that the decomposition effects are the same across price discount magnitudes. Yet it is likely that the relative sizes of the effects depend on the price discount magnitude (see §2.4). To allow for a flexible decomposition we use a semiparametric model (partly nonparametric, partly parametric) that allows for flexible main effects for the predictor variable of interest, and assumes fixed parameters for the other variables. For example, for the own-brand effect of a price discount with support l (represented by variation in PI_{ijlt}), we replace (2) by the following semiparametric model:

$$
\begin{aligned}
\text{OBS}_{ijt} = {} & \alpha_j + m_{\text{ob},\,lj}(\text{PI}_{ijlt}) + \sum_{\substack{l'=1\\ l'\neq l}}^{4} \beta_{\text{ob},\,l'j}\text{PI}_{ijl't} \\
& + \sum_{l=1}^{4} \gamma_{1,\,lj}\text{CPI}_{ijlt} + \sum_{m=1}^{3} \gamma_{2,\,mj}\text{D}_{ijmt} \\
& + \sum_{m=1}^{3} \gamma_{3,\,mj}\text{CD}_{ijmt} + \gamma_{4j}\text{RP}_{ijt} + \gamma_{5j}\text{CRP}_{ijt} \\
& + \sum_{\tau=1}^{T_{\max}-T-T^*} \gamma_{6,\,\tau j}\text{W}_t + \sum_{\tau=1}^{T+T^*} \gamma_{7,\,\tau j}\text{PI}_{ijlt+\tau} \\
& + \sum_{\tau=1}^{T+T^*} \gamma_{8,\,\tau j}\text{PI}_{ijlt-\tau} + \sum_{\tau=1}^{T+T^*} \gamma_{9,\,\tau j}\text{CPI}_{ijlt+\tau} \\
& + \sum_{\tau=1}^{T+T^*} \gamma_{10,\,\tau j}\text{CPI}_{ijlt-\tau} + u_{ijt},
\end{aligned}
$$

where $m_{\text{ob},\,lj}(\text{PI}_{ijlt})$ is a nonparametric function. We replace (3)–(5) by analogous specifications (same functional form, same set of predictors) to obtain $m_{\text{cb},\,lj}(\text{PI}_{ijlt})$, $m_{\text{cp},\,lj}(\text{PI}_{ijlt})$, and $m_{\text{ce},\,lj}(\text{PI}_{ijlt})$. We use local linear regression to estimate the nonparametric functions (Fan 1992). The key benefit of local linear regression is that it allows for any degree of nonlinearity while maintaining the mathematical consistency of the decomposition for each level of the price index variable (see the appendix):

$$m_{\text{ob},\,lj}(\text{PI}_{ijlt}) = m_{\text{cb},\,lj}(\text{PI}_{ijlt}) + m_{\text{cp},\,lj}(\text{PI}_{ijlt}) + m_{\text{ce},\,lj}(\text{PI}_{ijlt}).$$

We create this decomposition separately for each brand, for each decomposition effect, and for each of the four price index variables. Other reasons why we use local polynomial regression are that it is very flexible, free from boundary problems (see van Heerde et al. 2001), design adaptive, and easy to implement (see §3.1 in Fan and Gijbels 1996). We do not use (global) polynomial regression (addition of squares or higher-order powers of selected predictors) because polynomial functions are not flexible, individual observations can have a large influence on remote parts of a curve, and the polynomial terms can be highly correlated, especially when many powers are needed (Fan and Gijbels 1996). We note that in the estimation of nonparametric effects, we also account for contemporaneous correlation and for autocorrelation (see the appendix for details).

3.5. Determination of the Time Window for Dynamic Promotion Effects

We now consider how to specify T for post-promotion and T^* for pre-promotion effects. This time window should be large enough so that it includes all possible dynamic effects of price promotions. For the proper calculation of the effect size of these dynamic effects it does not matter if the time window is larger than necessary, because the estimates of interest will be equal to those for properly shorter windows. However, increasing the time window decreases the number of degrees of freedom very rapidly because the number of predictor variables increases and the sample size decreases as T and T^* increase. Thus, we want to use the smallest possible values to capture the dynamic effects. We use $T = T^* = 6$, based on van Heerde et al. (2000), Macé and Neslin (2004), Nijs et al. (2001), and Pauwels et al. (2002).

Van Heerde et al. (2000) found that a six-week lead and lag length sufficed for the vast majority of

which is similar to the average secondary demand elasticity result based on household data.

brands. Macé and Neslin (2004) analyzed more than 30,000 SKUs in 83 stores and obtained "similar estimates of stockpiling or deceleration elasticity whether they were calculated based on 4, 5, or 6 period lags." Nijs et al. (2001) studied dynamic promotion effects at the category level for 560 product categories. They had comparable elasticity estimates for four, six, and eight lags, and noted that the impulse response functions for these three alternative lag specifications are highly correlated. Finally, Pauwels et al. (2002) report 90% duration intervals for post-promotion effects on incidence, choice, and quantity that range from zero to eight weeks. The average duration interval is approximately two weeks. Thus, it appears that a time window choice of $[t-6, t+6]$ is justified. Nevertheless, we also estimate models with a larger time window $[t-8, t+8]$ as well as smaller windows, and we report on the sensitivity of results below (§5.2).

4. Data

We apply the models to two American (tuna, tissue) and two Dutch (shampoo, peanut butter) weekly, store-level, scanner datasets. The tuna, tissue, and shampoo datasets are at the brand level, obtained via aggregation across SKUs with homogeneous marketing activities. We provide descriptive statistics in Tables 2 and 3. The first American dataset, from ACNielsen, contains five brands in the 6.5 oz. canned tuna fish product category. For the standard decomposition, we have 104 weeks of data for each of the 28 stores of one supermarket chain in a metropolitan area. Due to the inclusion of 12 lead and 12 lagged effects the effective sample size for each item is $28*(104-2*12)=2{,}240$. In this sample, brands 1–4 used price promotions (see Table 3) while brand 5 did not. Therefore, we can only estimate price-promotion effects for brands 1–4. We do, however, include the sales data for brand 5 in the criterion variables relevant to the decomposition: CBS_{ijt}, PPCS_{it}, and TCS_{it}. Thus, brand 5 may experience a change in sales when other brands are promoted, and this change is part of the decomposition. We note that the tuna dataset is the only one for which we can use the extended decomposition of the category-expansion effect into cross-store and market-expansion effects, because we have data for stores of other chains located in the same geographic area. For the estimation of cross-store effects, we assume that within-chain cross-store effects are zero.

The second dataset (52 weeks) pertains to the six largest national brands in the tissue product category in the United States. The data (also from ACNielsen) are from 24 widely dispersed stores located in the eastern United States. For some brands the number of price promotions is very small (see Table 3). For example, brand 6 has only one price promotion supported with display-only. As a result, we anticipate that the estimation of some decomposition effects for tissue will be difficult, and we report results only for promotion variables with at least 24 price promotion observations (there are 24 stores).

Table 3 Price Promotions for Individual Items

		Price promotions without support				Price promotions with feature-only support				Price promotions with display-only support				Price promotions with feature-and-display support			
Category	Item	#	Avg %	Min %[a]	Max %	#	Avg %	Min %	Max %	#	Avg %	Min %	Max %	#	Avg %	Min %	Max %
Tuna	1	520	23	5	51	97	29	6	47	90	25	6	44	317	31	5	63
	2	299	22	5	44	150	26	6	60	28	22	8	37	202	31	7	60
	3	352	22	5	41	76	24	7	45	97	28	7	45	142	31	7	40
	4	370	17	5	34	77	17	7	34	64	17	6	34	113	21	6	38
Tissue	1	47	16	8	32	29	26	10	40	34	26	22	42	35	30	16	44
	2	32	14	8	22	5	32	21	38	3	19	13	24	73	32	22	65
	3	14	12	9	19	10	28	17	43	3	21	15	25	81	26	17	38
	4	11	12	8	18	12	19	8	40	25	26	9	43	78	26	8	44
	5	4	13	10	17	33	18	8	33	5	18	15	22	58	22	10	38
	6	39	19	14	27	5	26	22	32	1	37	37	37	48	27	19	54
Shampoo	1	35	17	5	37	53	34	18	39	48	13	6	26	181	31	6	39
	2	586	17	5	59	86	34	5	64	40	24	9	60	64	36	18	61
	3	120	12	5	29	35	16	6	21	67	15	6	21	88	18	7	21
	4	66	12	5	65	36	13	13	13	61	12	6	63	79	13	7	42
	5	151	13	5	27	43	23	14	25	70	19	5	37	47	23	14	25
Peanut Butter	1	8	7	5	8	40	6	5	9	13	6	5	8	22	6	5	8
	2	123	14	5	27	120	13	5	40	101	16	5	73	281	20	5	66
	3	131	13	5	33	76	12	5	28	88	14	6	40	177	15	5	33

[a] In this table a price promotion is defined as a price 5% or more below the regular price (Rao et al. 1995).

The first Dutch dataset (from ACNielsen) consists of 11 shampoo brands, of which the five largest engage in promotional activities. For this product category we have 109 weekly observations for almost all 48 stores in a national sample from one large supermarket chain. This provides a net sample size of 4,043 observations for each of the five brands. As before, the six other brands are included in relevant criterion variables for the decomposition.

The second Dutch dataset (from ACNielsen) contains five items of peanut butter. In contrast to the other three datasets, this dataset contains multiple SKUs per brand, which enables us to separate the secondary demand effect into within-brand and between-brand effects, as in Equation (8). For this product category we have 144 weekly observations for almost all 49 stores in a national sample from one large supermarket chain. The net sample size is 5,519 observations. Three SKUs experienced price discounts. Data on the two remaining SKUs are included in the appropriate decomposition criterion variables. We note that the number of SKUs is modest so that we use a separate intercept for each SKU. With a larger number of SKUs we would use attribute-specific intercepts (see Fader and Hardie 1996).

Table 3 shows that there is a lot of variation in the price discounts offered by the individual items. For example, tuna item 1 was price promoted without support in 520 store-weeks. The discount was 23% on average with a range of 5% to 51%. With feature-only support the discount range is 6% to 47%, with display-only 6% to 44%, and with feature-and-display support 5% to 63%. Thus, the amount of variation in the price discount offered is substantial for each support condition. This is critical for the reliable estimation of nonparametric, price-discount-dependent demand curves and decomposition effects, separately for the four price index variables. A detailed examination of Table 3 suggests that both the frequency and range of discounts are poor for the tissue brands and one peanut butter brand.

5. Results

We obtain results through a series of model estimation and validation steps. We present results for the "standard decomposition" from Equation (6), and, where appropriate, the "extended decomposition" from Equations (7) and (8) in §5.1. We validate the time window choice in §5.2. In §5.3, we present RESET test results and, given the rejection of constant effects, we show flexible decomposition results based on local polynomial regression.

5.1. Standard Decomposition

We obtain a separate decomposition of own-brand sales effects for each of the four different support types. We use a pooling test to determine whether it is appropriate to postulate one common effect across the support types. The tests show that for all brands this homogeneity assumption is rejected ($p < 0.01$). Hence, we allow for separate effect sizes for the different support conditions.

We show the standard decomposition of the own-brand sales effect into cross-brand, cross-period, and category-expansion effects in Table 4. The fit of all standard decomposition models is excellent.[9] The R-square for the whole SUR-system (Judge et al. 1985) ranges from 0.90 to 0.96. Across all brands in the four categories, 98% of all own-brand effects, 70% of all cross-brand effects, 46% of the category-expansion effects, and 33% of the cross-period effects are statistically significant (two-tailed, $p < 0.05$), as indicated in the last row of the top panel in Table 4. The reduced frequency of significant primary demand effects is consistent with Neslin et al. (1985, Figure 2), who find reduced power in models of purchase quantity and interpurchase time. Similarly, Bell et al. (1999) report a low signal-to-noise ratio for the quantity portion of primary demand effects in the elasticity decomposition based on household data. We note that although the promotional frequency for the tuna data is high (see Table 1), we still find that 63% of the cross-period effects are significant for this category.

The results shown here are the simple averages of brand-specific estimates (independent of the p-values). In the first column of Table 4 we show the average result for the own-brand sales Equation (2). The next columns show the percentage cross-brand effect from Equation (3), the percentage cross-period effect from Equation (4), and the percentage category-expansion effect from Equation (5). The top panel shows average results across the four product categories. Because all effects are relative to store-specific average category sales, the parameter estimates are also comparable across product categories. All average parameter estimates have the expected signs.

The parameter estimates represent the effect of the price index on the criterion variable (relative to average category sales in a store).[10] To illustrate, a 20% deal means that the price index variable goes from 1

[9] The average OLS-based autocorrelation coefficient (across brands of all categories) is 0.23 for the OBS equation, 0.18 for CBS, and 0.90 for PPCS. The large value for PPCS is due to the moving window summations. The SUR-GLS estimation procedure accounts for these autocorrelations.

[10] Differences in promotional intensity between stores affect the CS_i variable used for obtaining proportional effects across stores (see Footnote 6). To contemplate the magnitude of this issue we assume a 20% discount and the presence of display and feature. The average effect on own-brand sales is 1.82 times average category sales, of which 35% represents category expansion (Table 4). Consider an extreme case in which store 1 always promotes one of the brands in a category, and store 2 never promotes any brand. Even in that case,

Table 4 Average Decomposition of Constant Price Effects

	Standard decomposition				Extended decomposition	
	Own-brand effect $\hat{\beta}_{ob}$	Cross-brand effect $\hat{\beta}_{cb}/\hat{\beta}_{ob}$	Cross-period effect $\hat{\beta}_{sp}/\hat{\beta}_{ob}$	Category-expansion effect $\hat{\beta}_{ce}/\hat{\beta}_{ob}$	Cross-store effect $\hat{\beta}_{cs}/\hat{\beta}_{ob}$	Market-expansion effect $\hat{\beta}_{me}/\hat{\beta}_{ob}$
Averages across categories						
Price index						
Without support	0.44[a]	35%	44%	20%	—	—
With feature-only	1.24	32%	39%	29%	—	—
With display-only	1.16	38%	15%	44%	—	—
With feature and display	1.82	28%	36%	36%	—	—
Average	1.16	33%	32%	35%	—	—
Percentage significant (two sided, $p < 0.05$)	98%	70%	33%	46%	—	—
Tuna; $R^2 = 0.90$						
Price index						
Without support	0.46 (0.03)[b]	37% (9%)	57% (25%)	6% (21%)	0% (55%)	6% (71%)
With feature-only	1.03 (0.05)	30% (7%)	58% (14%)	12% (11%)	9% (46%)	3% (51%)
With display-only	0.98 (0.04)	36% (6%)	10% (23%)	54% (20%)	43% (35%)	11% (53%)
With feature and display	1.74 (0.05)	29% (4%)	36% (8%)	35% (6%)	31% (25%)	4% (28%)
Average	1.05	31%	38%	31%	25%	6%
Tissue; $R^2 = 0.96$						
Price index						
Without support	0.36 (0.06)	17% (61%)	73% (122%)	9% (90%)	—	—
With feature-only	1.24 (0.09)	18% (9%)	37% (33%)	45% (29%)	—	—
With display-only	1.07 (0.04)	29% (14%)	14% (37%)	57% (31%)	—	—
With feature and display	1.53 (0.03)	19% (5%)	41% (15%)	41% (12%)	—	—
Average	1.05	21%	35%	43%	—	—
Shampoo; $R^2 = 0.90$						
Price index						
Without support	0.46 (0.03)	24% (12%)	26% (31%)	50% (25%)	—	—
With feature-only	1.14 (0.05)	30% (6%)	58% (21%)	13% (17%)	—	—
With display-only	1.34 (0.04)	44% (6%)	30% (20%)	19% (16)	—	—
With feature and display	1.89 (0.04)	24% (4%)	25% (12%)	51% (11)	—	—
Average	1.21	31%	34%	33%	—	—
					Within-brand effect $\hat{\beta}_{cbw}/\hat{\beta}_{ob}$	Between-brand effect $\hat{\beta}_{cbb}/\hat{\beta}_{ob}$
Peanut butter; $R^2 = 0.95$						
Price index						
Without support	0.49 (0.06)	60% (16%)	26% (35%)	14% (24%)	33% (13%)	26% (14%)
With feature-only	1.54 (0.10)	47% (8%)	14% (26%)	39% (19%)	43% (5%)	4% (7%)
With display-only	1.26 (0.09)	42% (8%)	4% (27%)	54% (19%)	29% (6%)	12% (7%)
With feature and display	2.10 (0.11)	38% (6%)	42% (19%)	21% (14%)	31% (4%)	7% (6%)
Average	1.35	43%	24%	33%	34%	9%
Validation for time window $[t-8, t+8]$: Average effects						
Tuna	1.03	23%	40%	37%		
Tissue	0.99	39%	75%	−14%	—	—
Shampoo	1.13	32%	39%	27%	—	—
Peanut butter	1.50	47%	20%	33%	—	—
Validation for time window $[t-8, t+8]$: Correlation with $[t-6, t+6]$-based parameters						
Tuna	0.96	0.75	0.80	0.91	—	—
Tissue	0.98	0.19	0.27	0.36	—	—
Shampoo	0.92	0.89	0.62	0.95	—	—
Peanut butter	0.92	0.98	0.78	0.67	—	—

[a]Effect of price index on dependent variable proportional to average category sales.
[b]Standard deviation reflecting uncertainty in the estimate of the average (and not the variation across brands).

to 0.80. The parameter estimate of 0.46 for the own-brand effect of an unsupported price cut for tuna (second panel of Table 4) implies that a 20% price cut leads to an estimated increase in unit sales of $0.20 * 0.46 * 100\% = 9.2\%$ of average weekly category sales in a store. This own-brand effect is decomposed into 37% cross-brand, 57% cross-period, and 6% category-expansion effects.

The standard deviations in Table 4 reflect the uncertainty in the estimated average effect. To illustrate, an approximate 95% confidence interval for the unsupported price cut effect for an average tuna brand is $[0.46 - 2 * 0.03, 0.46 + 2 * 0.03] = [0.40, 0.52]$. The standard deviations show that the parameters are most reliably estimated for own-brand effects, next for cross-brand effects, then category-expansion effects, and finally, cross-period effects. For tissue we find an extraordinarily large standard deviation for cross-period effects in the without support condition (122%), pointing to a potential problem for this dataset (see §5.2). The variation in the parameter estimates across brands is not reported in Table 4. However, based on pooling tests, we find that in all categories the effects are heterogeneous across brands.

The results in Table 4 appear to show meaningful patterns. For each product category the estimated own-brand sales effect is smallest when there is no support (ranging from 0.36 to 0.49) and largest with feature and display (ranging from 1.53 to 2.10). For feature-only, the range is 1.03 to 1.54 and for display-only it is 0.98 to 1.34. In the first panel of Table 4, we see that the dominant decomposition component for discounts with feature-only support is the cross-period effect (39%). In absolute as well as in percentage terms, the cross-period effect is much stronger for feature-only ($0.48 = 39\%$ of 1.24) than for display-only ($0.17 = 15\%$ of 1.16). This is consistent with the idea that feature-only support is more likely than display-only support to induce stockpiling. Perhaps households that carefully plan inventories use features. Display-only yields relatively strong cross-brand (38%) and category-expansion effects (44%). This is consistent with the notion that special displays primarily affect the brand choice within the store and perhaps stimulate impulse purchases.

Interestingly, across the four support conditions, we find that the three parts account for about one third each of the own-brand unit sales effect. There is also a fair amount of consistency between the product categories in these percentages. Importantly, the cross-brand unit sales effect is, with the exception of peanut butter without support, always less than half of the own-brand effect. This differs strongly from the elasticity decomposition results in Gupta (1988), Chiang (1991), Chintagunta (1993), Bucklin et al. (1998), Bell et al. (1999), and Pauwels et al. (2002). However, our result is consistent with van Heerde et al. (2003), who show that an elasticity component of 3/4 translates to a net cross-brand effect of about 1/3.

It is also noteworthy that the cross-period effect accounts on average for about 1/3 of the unit sales effect. Until a few years ago researchers experienced great difficulty finding evidence consistent with stockpiling effects in models of store data (Neslin and Schneider Stone 1996). By allowing for extended periods of lead and lagged effects, van Heerde et al. (2000) found cross-period effects to account for up to 25% of the sales increase in two product categories. The primary reason for the higher percentage in our results is that we consider pre- and post-promotion dips in category sales, whereas van Heerde et al. (2000) only consider these dips in brand sales. Macé and Neslin (2004), using different data, different models, and different measures, report pre- and post-promotion unit sales dips that are also about 1/3 of the own-brand effect on average.

For tuna we show the decomposition of the category-expansion effect into cross-store[11] and market-expansion effects in the last two columns of Table 4. These results are quite unreliable, because only four out of 16 cross-store effects are significant. Nevertheless, the results suggest that cross-store effects occur for price promotions with feature support (feature-only, feature and display) as well as for price promotions communicated inside the store. This is consistent with respectively "direct" and "indirect" store switching (Bucklin and Lattin 1992, Kumar and Leone 1988). On average, the cross-store effect is four times as large as the market-expansion effect.

For peanut butter we show the decomposition of the cross-SKU effect into within-brand and between-brand effects. On average, we find that the cross-SKU effect is largely explained by the within-brand effect: 79% (34/43). Thus, the vast majority is attributable to cannibalization. The relative amount of cannibalization is highest with feature-only support: 91% (43/47) and next highest with feature and display: 82% (31/38). This is consistent with results reported by Kalyanam and Putler (1997, Figures 2 and 3).

store 1's average category sales will be only 13% greater ($20\% * 1.82 * 0.35$) than store 2s. We conclude that the impact of heterogeneity in promotional intensity between stores is slight.

[11] The cross-store amount captures within-brand, same-week effects. We correct for promotions by other chains and use the residuals of those models. We note that households could switch brands, stores, and periods simultaneously. Although this seems unlikely, we tested for this by also relating the residuals from total category sales at other chains to the appropriate predictor variables. Those results were statistically insignificant.

5.2. Validation of the Time Window

The cross-period and category-expansion effects are based on a time window of $[t-6, t+6]$ surrounding week t. To determine whether this time window is adequate, we also used $[t-8, t+8]$. This entails three changes in the model: (a) the criterion variables for the cross-period and category-expansion effects are obtained by summing across this larger time window; (b) the predictor variable set includes lead and lagged variables from the window $[t-16,\ t+16]$; and (c) the number of observations available for estimation is reduced due to the additional lead and lagged variables. We report the results in the last two panels of Table 4. Except for tissue, the average parameter estimates for the own-brand effects and the three decomposition percentages are not very sensitive to this alternative time window. For three product categories the correlations across the brand-specific parameter estimates are high, ranging from 0.62 to 0.99. Thus, the time window choice of $[t-6,\ t+6]$ seems appropriate for tuna, shampoo, and peanut butter.

For tissue the comparison is much less satisfactory. The average decomposition effects are dissimilar across the two window specifications, and the correlations between the parameter estimates, except for the own-brand effects, are low as well. The tissue data suffer from a small number of observations relative to the number of parameters, in part because there are just 24 stores and 52 weeks. Most critically, for the time window $[t-6, t+6]$, the effective number of observations per store is 28, and this reduces to 20 for the time window $[t-8, t+8]$.[12]

5.3. Flexible Decomposition

To determine the suitability of nonparametric analyses, we use the RESET test for the assumption of constant decomposition effects (Stewart 1991, pp. 71–72). It is a general procedure designed to detect an inappropriate functional form. To maximize the comparability across categories we focus on the standard decomposition effects from Equation (1). We compute RESET test-based p-values for each brand and separately for each of the Equations (2)–(4). The results show that all but one p-value is below 0.01 (the exception being the cross-period component for one of the shampoo brands). Thus, it is meaningful to allow for flexible estimation and decomposition of the own-brand sales effect so that the decomposition percentages may depend on the magnitude of a price discount.

We estimate the effects, separately for each support type, and flexibly by local polynomial regression.[13] The amount of flexibility in local polynomial regression is determined by the bandwidth parameter, which reflects a trade-off between bias and variance. With a very large bandwidth parameter, local polynomial regression is equivalent to estimating a regular global polynomial regression model (high bias, low variance). If the bandwidth parameter is small, there can be much variation in the response estimate and the decomposition (low bias, high variance). To obtain an acceptable trade-off, we apply the following set of rules for the bandwidth choice. First, we want a bandwidth that is small, to minimize the bias, but large enough to avoid inconceivable patterns such as effects with implausible signs or nonmonotonic patterns. Second, we want one common bandwidth across all criterion variables, across all instruments, across all brands, and across all categories. This ensures that the sum of the component effects always equals the effect on own-brand sales, as is the case for the constant decomposition. The use of a single bandwidth value also allows the results across instruments and categories to be maximally comparable. We choose $h = 0.3$ after considering other values such as 0.2 and 0.4. We note that $h = 0.3$ leads to curves that are less flexible than we could have justified, with a smaller bandwidth value, for the own- and cross-brand effects (see also van Heerde et al. 2001). However, a lower value provides an unacceptable number of nonmonotonic relationships, especially for cross-period effects. Thus, we ignore some potentially relevant nonlinearities to maintain consistency in the results relevant to the decomposition, and to maintain comparability across product categories.

We report the average own-brand effects and decomposition percentages across categories for selected price discount values in Table 5. We observe similar phenomena across the four support types (except for display-only): the percentage attributable to cross-brand effects tends to decrease for higher discounts, as does the percentage attributable to cross-period effects (consistent with Gupta and Cooper 1992). By implication the percentage attributable to category expansion tends to increase with higher discounts. This dependence is especially strong for feature-only supported price discounts: category expansion accounts for 21% at a 5% discount but

[12] We also analyzed what happens with shorter time windows. We started with the window $[t-0, t+0]$ (i.e., no dynamic effects), next $[t-1, t+1]$, up to $[t-6, t+6]$, but in all cases using the same set of predictor variables and the same data. We observe that both the size of the own-brand effect and the percentage cross-brand effects are very stable. The percentage cross-period effect increases initially, as one would expect, but starts to stabilize at $[t-5, t+5]$. The percentage category-expansion effect decreases initially and also starts to stabilize at $[t-5, t+5]$.

[13] Van Heerde et al. (2001) find that nonparametric regression for a sales response model predicts better in hold-out samples than parametric regression.

Table 5 Decomposition of Flexible Price Effects: Averages across Brands[a]

	Standard decomposition			
Price discount (%)	Own-brand sales effect	Percent cross-brand effect (%)	Percent cross-period effect (%)	Percent category-expansion effect (%)
Without support				
5	0.02[b]	36	34	30
10	0.05	35	34	30
15	0.07	35	34	31
20	0.10	35	34	32
25	0.13	33	32	35
30	0.16	31	28	41
Feature-only support				
5	0.06	32	48	21
10	0.12	32	48	21
15	0.18	32	48	21
20	0.23	32	48	21
25	0.29	32	47	21
30	0.37	34	47	19
35	0.43	32	45	24
40	0.50	26	40	35
Display-only support				
5	0.06	40	20	41
10	0.12	40	20	41
15	0.18	39	19	41
20	0.24	39	19	42
25	0.31	38	19	43
30	0.38	38	19	43
35	0.41	41	21	38
40	0.43	43	22	35
Feature-and-display support				
5	0.10	27	32	42
10	0.19	27	31	42
15	0.29	26	31	42
20	0.39	26	31	43
25	0.50	26	30	44
30	0.61	25	30	45
35	0.71	25	30	45
40	0.82	20	28	52

[a]We exclude the tissue brands and peanut butter brand 1 due to lack of variation in their price index variables.

[b]Effect of a 5% price discount on own brand sales, proportional to average category sales.

35% for a 40% discount. The most dramatic shifts occur for the highest price discounts. To illustrate, for a 35% feature-only supported discount the category-expansion effect is 24%, whereas it is 35% for a 40% discount, implying a much stronger absolute effect (a higher percent of the own-brand effect multiplied by a higher own-brand effect).

6. Conclusions

We propose a unit-sales-based decomposition approach for store data. Although store data do not allow us to model the disaggregate consumer responses due to price promotions, we do show how we can obtain substantively relevant decomposition effects. On average across four categories, we find that if a price promoted brand gains 100 units, the net loss for other brands is 33 units, so the secondary demand effect is about 1/3. This is very consistent with the net cross-brand sales effect derived from the elasticity decomposition for household data (van Heerde et al. 2003). Hence, there is high convergent validity with extant decomposition models. In addition, the large short-term primary demand effects (2/3) are consistent with Nijs et al. (2001).

An important aspect of our approach is that we split the primary demand effect into a cross-period and a category-expansion effect. Both of these effects on average also capture about 1/3 each of the own-brand effect. We obtain the relevant effects directly as response parameters associated with a single predictor variable (for each support condition), while controlling for covariates. This is accomplished by deliberate construction of the criterion variables. A requirement for a consistent decomposition is that each criterion variable is regressed on the same (large) set of predictor variables. In this sense, we favor model robustness (consistent decomposition) over model simplicity (few predictors).

We also extend the decomposition approach in several ways. One is that we allow a cross-item effect to be decomposed into within-brand (cannibalization) and between-brand effects for SKU-level data. For peanut butter, cannibalization effects dominate. Another extension is that we further decompose the category-expansion effect into a cross-store and a market-expansion effect. Our results for tuna indicate that the cross-store effect accounts on average for most of the category-expansion effect. We find that the decomposition results are moderated by characteristics of the price promotion. We accomplish the dependence on the type of support by a deliberate choice of variable definitions, and the dependence on the discount magnitude by local polynomial regression. The nonparametric response curves allow us to assess the cross-brand effect, the cross-period effect, and the category-expansion effect for each support type separately for relevant price discount levels. Our empirical results suggest that with more support (feature, display), the own-brand sales effects are stronger. In the decomposition percentages, we find that discounts with display-only support yield relatively more cross-brand and category-expansion effects. With higher discounts, the relative contributions of cross-brand and cross-period effects tend to decrease for all support types (except for display-only), while the relative contribution of category expansion tends to increase with higher discounts.

We provide the following validation and robustness checks of our results. First, the face validity is high.

We find average decomposition percentages that are similar to those obtained when household-level elasticity results are transformed into net sales effects. Second, we find statistical support for the dependence of effect sizes on support types, based on pooling test results. Third, all average parameter estimates have the expected signs. Fourth, we validate our choice of the time window by estimating models for a wider time window. We obtain similar results, except for tissue where the sample size is small. Fifth, the RESET test results indicate that the assumption of constant decomposition effects is untenable. Thus, it is attractive and appropriate to use the flexible approach of local polynomial regression so as to obtain more refined insights.

What are the managerial implications? Our results can be used to infer net sales effects of price promotions. From a retailer perspective, a 100-unit increase for the promoted brand causes on average a net 33-unit decrease for other brands in the category and a net 32-unit decrease in pre- and post-promotion category sales (Table 4). This leaves a potentially beneficial 35-unit increase for the retailer due to category-expansion effects. For the manufacturer, cross-period effects are also not beneficial unless those effects minimize sales opportunities for other brands. Therefore, a conservative estimate of the net effect for the manufacturer is the sum of cross-brand and category-expansion effects: 68 units on average. Because cross-brand effects may cause competitive reactions, the net benefit for manufacturers may also represent category expansion, to the extent that this component excludes cross-store effects. Overall, from a category management perspective jointly pursued by manufacturers and retailers, category-expansion effects are potentially the most desirable among the three standard decomposition effects.

Table 4 shows that on average the largest category-expansion effects occur for price cuts supported with feature and display (35% of $1.82 = 0.66$), followed by display-only supported discounts (0.52), feature-only-supported discounts (0.36), and finally, unsupported price discounts (0.09). Thus, although feature-only support has a higher own-brand effect than display-only support (1.24 versus 1.16), the category-expansion effect favors display-only. This is because features generate much stronger cross-period effects. Such insights require a decomposition approach. We note that a limitation is that we cannot generate profit implications because we lack data on the costs of features and displays, and we do not have access to profit margins of the products.

The net benefit of promotions is also affected by competitive reactions, which is currently not included in our model. For example, for manufacturers strong cross-brand effects are beneficial in the short run, but these could evoke severe competitive reactions after some time that nullify the initial benefit (Leeflang and Wittink 1996). To further enhance this research, one could extend the models to include competitive reactions as a function of the decomposition.

Our flexible decomposition results might understate the true nonlinearity in effects. To maintain consistency in the estimates across the criterion variables, we forced strong smoothness in the estimated curves based on requirements for the "weakest" criterion variable. With more data we can accommodate greater flexibility in all estimated effects. In general, the decomposition models require extensive datasets, both due to the large number of control variables and the loss of observations due to the lead and lag covariates. The relatively poor results for tissue suggest that one should have at least two years of weekly data for at least 25 stores, leading to a minimal sample size of 2,600 observations ($=2*52*25$). A high promotional frequency such as for tuna seems to lead to more reliable results. Multicollinearity is not a problem, due to the mutually exclusive definitions of the price index variables.

A further limitation is that our approach is applicable for the decomposition of sales bumps in stable environments. Our model is not intended to suggest what will happen if promotional intensities change. The method needs to be extended for evolving environments with persistent effects (Dekimpe and Hanssens 1999), which may result from free sample promotions for new products (Bawa and Shoemaker 2004) or from promotions directed to new customers (Anderson and Simester 2004). For mature categories, persistent effects of promotions seem to be rare (Nijs et al. 2001, Pauwels et al. 2002).

In our approach, accelerated switches are counted as cross-period effects. Sun et al. (2003) show that in household data it depends strongly on the model specification how these switches are categorized. To shed further light on this issue, it would be of interest to extend our model to separate cross-period effects into within-brand and between-brand components. This should be of interest to a brand manager whereas a retailer may be indifferent between these two types of stockpiling. In our model we could split the criterion variable for cross-period effects ($PPCS_{ijt}$) into (1) own-brand sales before and after period t, and (2) cross-brand sales before and after period t. Similarly, the category-expansion effect is further decomposable with respect to cross-category effects. For example, it would be useful to determine to what extent sales increases for a tuna brand may be attributable to sales decreases in other food categories.

Acknowledgments
The authors thank ACNielsen (USA and The Netherlands) for providing the data, and the editor, the area editor, the

reviewers, and seminar participants at Carnegie Mellon University, University of Chicago, Dartmouth College, Duke University, Erasmus University (Rotterdam), Harvard Business School, INSEAD, University of Leuven, London Business School, NYU's Stern School of Business, University of Texas, Tilburg University, UCLA, the Yale School of Management, and the Wharton School for comments. Professor van Heerde thanks the Netherlands Organization for Scientific Research for research support.

Appendix

The system of Equations (2)–(5) can be summarized as $y_{jkit} = X'_{jkit}\beta_{jk} + \varepsilon_{jkit}$, where j is the index for brand $(j = 1, \ldots, J)$, k is the index for the decomposition component ($k = 1$ for $y_{j1it} = \mathrm{OBS}_{ijt}$, $k = 2$ for $y_{j2it} = \mathrm{CBS}_{ijt}$, $k = 3$ for $y_{j3it} = \mathrm{PPCS}_{ijt}$, and $k = 4$ for $y_{j4it} = \mathrm{TCS}_{ijt}$), i is the index for store $(i = 1, \ldots, I)$, and t is the index for week $(t = 1, \ldots, T_{\max})$. The error is distributed as

$$\varepsilon_{jkit} = \rho_{jk}\varepsilon_{jkit-1} + u_{jkit}, \quad k = 1, \ldots, K \quad \text{(autocorrelation)},$$

$$\mathrm{Cov}[u_{jkit}, u_{j'lit}] = \sigma_{jkj'l} \quad \text{(contemporaneous correlation)}.$$

We delete one equation (e.g., for $y_{j4it} = \mathrm{TCS}_{ijt}$) because it is redundant. With iterative GLS, it does not matter which equation we drop (Greene 2000). We estimate the model in three consecutive steps (Greene 2000):

Step 1. Use OLS to obtain $\hat{\beta}^{\text{ols}}_{jk} = (X'_{jk}X_{jk})^{-1}X'_{jk}y_{jk}$. Compute $e_{jk} = y_{jk} - X_{jk}\hat{\beta}^{\text{ols}}_{jk}$ and

$$\hat{\rho}_{jk} = \frac{\sum_{i=1}^{I}\sum_{t=2}^{T_{\max}} e_{jkit}e_{jkit-1}}{\sum_{i=1}^{I}\sum_{t=1}^{T_{\max}} e^2_{jkit}}$$

(Greene 2000).

Step 2. Apply the Praise-Winsten transformation to the criterion and predictor variables (Greene 2000):

$$\tilde{y}'_{jk} = \Big(\sqrt{1-\hat{\rho}^2_{jk}}\,y_{jk11}, y_{jk12} - \hat{\rho}_{jk}y_{jk11}, \ldots, y_{jkIT_{\max}} - \hat{\rho}_{jk}y_{jkIT_{\max}-1}\Big), \quad \text{and}$$

$$\widetilde{X}'_{jk} = \Big(\sqrt{1-\hat{\rho}^2_{jk}}\,X_{jk11}, X_{jk12} - \hat{\rho}_{jk}X_{jk11}, \ldots, X_{jkIT_{\max}} - \hat{\rho}_{jk}X_{jkIT_{\max}-1}\Big).$$

Use OLS a second time to obtain $\tilde{\beta}^{\text{ols}}_{jk} = (\widetilde{X}'_{jk}\widetilde{X}_{jk})^{-1}\widetilde{X}'_{jk}\tilde{y}_{jk}$. Compute $\tilde{e}_{jk} = \tilde{y}_{jk} - \widetilde{X}_j\tilde{\beta}^{\text{ols}}_{jk}$. A consistent estimator of $\sigma_{jkj'l}$ is based on this least squares residual: $\hat{\sigma}_{jkj'l} = \tilde{e}'_{jk}\tilde{e}_{j'l}/\mathrm{IT}_{\max}$ (Greene 2000). Define the $jkj'l$th element of the inverted covariance matrix by $\hat{\sigma}^{jkj'l}$.

Step 3. The SUR-GLS estimator is given by (Greene 2000):

$$\hat{\beta} = \begin{bmatrix} \hat{\sigma}^{1111}\widetilde{X}'_{11}\widetilde{X}_{11} & \cdots & \hat{\sigma}^{11J3}\widetilde{X}'_{11}\widetilde{X}_{J3} \\ \vdots & \ddots & \\ \hat{\sigma}^{J311}\widetilde{X}'_{J3}\widetilde{X}_{11} & & \hat{\sigma}^{J3J3}\widetilde{X}'_{J3}\widetilde{X}_{J3} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \sum_{j'=1}^{J}\sum_{l=1}^{3}\hat{\sigma}^{11j'l}\widetilde{X}'_{11}\tilde{y}_{j'l} \\ \vdots \\ \sum_{j'=1}^{J}\sum_{l=1}^{3}\hat{\sigma}^{J3j'l}\widetilde{X}'_{J3}\tilde{y}_{j'l} \end{bmatrix}. \quad \text{(A.1)}$$

Now use this estimator to compute residuals, which are used in Step 1 again, etc., until convergence. This iterated SUR-GLS estimation procedure gives the maximum likelihood estimates (Greene 2000).

We next postulate that each criterion variable is a nonparametric function of the price discount level, while we control for constant effects of other covariates. We use the transformed predictor and criterion variables from the final iteration of the GLS-SUR estimation to account for contemporaneous correlation and autocorrelation. Define $\hat{\beta}$ in (A.1) as $(X^{*'}X^*)^{-1}X^{*'}y^*$, where y^* and X^* are $\tilde{y}$ and $\widetilde{X}$ pre-multiplied with the Cholesky decomposition of the inverse of the contemporaneous covariance matrix. This choice ensures that if we smooth the nonparametric function to a large extent, we obtain exactly the GLS-SUR estimates. We can now write the semiparametric version of the linear regression model as $y^*_{jkit} = m_{k,lj}(\mathrm{PI}_{ijlt}) + X^{*'}_{jkit(l)}\beta_{jk(l)} + \varepsilon_{jkit}$, where $X^{*'}_{jkit(l)}$ is the vector of all predictors excluding PI_{ijlt}. For price index level $\mathrm{PI}_{ijlt} = P_0$, we postulate a locally weighted polynomial regression (Fan and Gijbels):

$$\sum_{i=1}^{I}\sum_{t=1}^{T_{\max}}\left[\left\{y^*_{jkit} - \sum_{q=0}^{d}[\beta_{k,ljq}(\mathrm{PI}_{ijlt} - P_0)^q] - X^{*'}_{jkit(l)}\beta_{jk(l)}\right\}^2 \cdot K_h(P_{ijlt} - P_0)\right],$$

where $K_h(\cdot)$ denotes a Kernel function and h is a bandwidth. We use $\hat{\beta}_{jk(l)}$ from the GLS-SUR regression and next minimize this equation by using weighted least squares, and thus obtain the set $\{\hat{\beta}_{k,ljq}\ (q = 0, \ldots, d)\}$. The estimate for $m_{k,lj}(\mathrm{PI}_{ijlt})$ at $\mathrm{PI}_{ijlt} = P_0$ equals $\hat{\beta}_{k,lj0}$. Kernel $K(\cdot)$ determines the weight of neighboring observations. We use the quartic kernel: $K_h(u) = (15/16)\big[1 - (u/h)^2\big]^2 \mathrm{I}\{|u/h| \le 1\}$. The bandwidth parameter is 0.3 for all datasets (see §5.3 main text). The choice of a common bandwidth parameter across the equations for a particular brand and price index variable ensures a consistent decomposition, because it leads to the same set of regressors across the local polynomial regression equations. We take a first-order polynomial $(d = 1)$, hence the method we use is local linear regression. This choice is based on Fan and Gijbels (1996, §3.3).

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