Chapter 3

The Estimation of Pre- and Postpromotion Dips

3.1 Introduction

One of the key issues in sales promotion research is whether “there is a trough after the deal” (Blattberg, Briesch, and Fox 1995). The evidence from analyses of household-level panel data shows that consumers accelerate their purchases as a result of sales promotions. For example, Gupta (1988) decomposes the sales effect due to promotion for coffee into brand switching (84 percent), purchase timing acceleration (14 percent), and increased purchase quantity (2 percent). Chiang (1991) obtains similar percentages, while Grover and Srinivasan (1992, pp. 86-87) conclude that “one-fourth of the gain in a week’s product category sales resulting from a promotion is at the expense of the succeeding week’s sales”. Bell, Chiang, and Padmanabhan (1999) decompose the sales effect for thirteen product categories and find that, on average, brand choice accounts for 75 percent of the total elasticity (range 49-94 percent). Thus, the percent attributable to purchase timing acceleration and increases in purchase quantity varies between 6 and 51 percent.

At first sight one might think that the acceleration effects in timing and quantity evident at the household level should translate directly in a postpromotion dip in weekly store-level sales data. However, postpromotion dips are rarely detected in visual or (traditional) statistical analyses of store data. A resolution of this paradox is important for both researchers and managers. For researchers, a lack of convergent validity between the results from household-level panel data and weekly store-level sales data casts doubt

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about the nature of the acceleration phenomenon. Also, many managers say they use store-level (or more highly-aggregated) scanner data more frequently for analyses than household-level panel data (Bucklin and Gupta 2000). However, if the household results are accurate, then managers who rely on aggregated data for inferences about promotion effects will obtain incorrect conclusions. Unless stockpiling can be properly accounted for, managers will overestimate the effectiveness of promotions: they tend to classify all of the promotion-based sales spike as incremental (Neslin and Schneider Stone 1996). Since managers rely heavily on aggregated data, the most challenging part of the postpromotion dip paradox is the apparent lack of a dip in store-level data. We show two typical store-level sales graphs in Figure 3.1, from the data used in our empirical application (see below). Neither of these graphs shows any sales dip before or after a sales spike.

As far as we know, only Doyle and Saunders (1985), Leone (1987), Litvack, Calantone, and Warshaw (1985), and Moriarty (1985) studied acceleration based on store data. Doyle and Saunders (1985) demonstrated that lead effects of promotions, resulting from the anticipations of promotions by consumers and other economic agents, can be as important as lagged effects. They examined monthly gas appliance sales as a function of (a.o.) the commission structure for sales personnel, and analyzed whether salespeople move some customer purchases to the time period in which their commission rates are higher. Doyle and Saunders calculated that about 7 percent of total sales during an 8-week promotion period consisted of sales that would have taken place prior to the promotion period had commission rates not been increased during the promotion.

Leone (1987) applied intervention analysis on weekly sales data to evaluate a single “5 for $1.00” sale for wet cat food. The weekly sales data graph showed a clear postpromotion dip and the analyses confirmed this dip. Litvack, Calantone, and Warshaw (1985) observed the sales of many items before, during, and after a price cut. Interestingly, the authors did not observe a postpromotion dip in sales for the items that could have experienced purchase acceleration. Moriarty (1985) includes one-week lagged promotion variables in a sales response function. He finds significant postpromotion dips for only three of the fifteen cases.

Although a few of these studies obtain evidence of pre- or post-dips, Blattberg, Briesch, and Fox (1995, p. G127) mention that “examination of store-level POS data for frequently purchased goods rarely reveals a trough after a promotion. This anomaly is surprising and needs to be better
understood.” Neslin and Schneider Stone (1996) consider eight possible arguments for the apparent lack of postpromotion dips in store-level sales data. Their arguments imply that the dips may be hidden. As a result, dips will be difficult to detect by traditional models or by a visual inspection of the data. Since brand sales are the aggregate of purchases across heterogeneous households, both pre- and postpromotion sales data will have complex patterns.
Essentially, sales are shifted from multiple future- and past periods into a current, promotion-based sales spike in a nontrivial way.

Neslin and Schneider Stone (1996) suggest that researchers carry out “sophisticated distributed lag analyses of weekly sales data in the hope of measuring the postpromotion dip statistically.” We present a flexible modeling approach, and regress brand-level sales on current-, lead-, and lagged own-brand price indices using three different distributed lead and lag structures: an Almon model, an Exponential decay model, and an Unrestricted dynamic effects model. We distinguish four types of price discounts: ones without any support, ones with feature-only support, ones with display-only support, and price discounts with feature and display support.

The key contributions of this study are:

- We propose a store-level model specification explicitly based on the arguments for the apparent lack of a postpromotion dip in aggregate data;
- We show there is no postpromotion dip paradox: we obtain pre- and postpromotion dips that are comparable to those obtained with household data;
- We propose a new way of modeling the interaction effects between price cuts and various types of support (feature and/or display), and show differences in the magnitude of pre- and postpromotion effects between price cuts with alternative types of support.

In section 3.2 we review eight arguments for the apparent lack of a postpromotion dip in models of store sales, and derive implications from these arguments for the specification of pre- and postpromotion dips. In section 3.3 we show the model specification and discuss model calibration. We introduce store-level scanner data sets for two product categories in section 3.4, and provide empirical evidence for dynamic promotion effects for both categories in section 3.5. In section 3.6 we present our conclusions.

### 3.2 Arguments for the lack of a postpromotion dip, and implications for model specification

Neslin and Schneider Stone (1996) provide eight possible arguments for the apparent absence of postpromotion dips in store-level scanner data. We list these below, and identify implications for the specification of store-level brand sales models.
3.2. Arguments for the lack of a postpromotion dip, and implications for model specification

Figure 3.2: Nonresponding

(Normal: \(PQ = 2\) units, \(IT = 2\) weeks, \(CR = 1\) unit per week)

We also provide graphical illustrations of six of the eight explanations. As we will see below, these explanations (illustrated in Figures 3.2-3.9 and discussed below) are based on households’ responses to promotions. We simulate a promotion in week \(t\) for a brand in a single-brand product category. Figure 3.2 shows the hypothetical purchase timing, purchase quantity and inventory level of a household that does not respond to this promotion. This household serves as the base case, with an Interpurchase Time (IT) of two weeks, a Purchase Quantity (PQ) of two units, and a Consumption Rate (CR) of one unit per week. The households in Figures 3.3-3.9 are assumed to show the same purchase timing, purchase quantity, and consumption rate in the absence of promotions, unless indicated otherwise. We also compare the sales aggregated across these different households under two scenarios: with a promotion at \(t\) and without this promotion.

**a. Consumers purchase deal to deal**

Some consumers purchase a brand only in the promotional periods. If this were the only argument, there would be no dip in household- nor in store data.

Figure 3.3 shows the purchase and inventory characteristics for a deal-to-deal purchasing household.

**b. Increased consumption**

Consumers may stockpile in the presence of promotions, but if they consume excess inventory quickly, there will again be no dip in household- nor in store data.
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Figure 3.3: Deal-to-deal purchasing

(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)

![Bar chart showing deal-to-deal purchasing](image)

Figure 3.4 simulates a household that increases its consumption rate temporarily from one unit per week to two units per week as a result of the increased purchase quantity in promotional week $t$.

Figure 3.4: Increased consumption

(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)

![Bar chart showing increased consumption](image)

c. Competitive promotions mask the dip

If promotions for competing brands such as Coke and Pepsi are used in successive weeks, it will be impossible to disentangle the loss due to brand switching from the loss due to “within-brand quantity or timing acceleration”. Clearly, the model of brand sales has to incorporate current cross-brand promotion variables which in extreme cases may be collinear with own-brand postpromotion variables. This issue affects both household- and store data.
3.2. Arguments for the lack of a postpromotion dip, and implications for model specification

**d. Positive repeat purchase effects cancel the acceleration effect**

It is conceivable that some promotions increase repeat purchases. Even if this effect is unlikely to be the same in magnitude (with opposite sign) as a reduction due to purchase acceleration, any positive repeat purchase will complicate the diagnosis of a postpromotion dip. This complication applies to household- as well as store data.

Figure 3.5 shows a household that tries the brand at the promotion and demonstrates repeat purchase behavior. This explanation is likely to have relevance for new brands or for households unfamiliar with an existing brand.

**Figure 3.5: Trial and repeat purchase**

(Normal: PQ = −, IT = −, CR = −)

![Graph showing trial and repeat purchase over weeks](image)

**e. Retailers partially extend promotions beyond the first week**

Retailers may extend all or part of a promotion—in particular display activity—and thereby increase sales immediately following the initial promotion which will mask the dip (Blattberg and Neslin 1990, p. 358). In principle, this effect can be accounted for with expanded display variables in the model. However, it is possible that extensions are not captured. For example, display activity is measured by weekly store audits, say on Thursday. If a display is extended only during the first three days of a second week (Monday, Tuesday and Wednesday), the value of the display variable will not accurately reflect this second week’s situation. Therefore, we need lagged display variables to capture this display extension effect which should affect sales positively. The other common scanner data variables (sales, prices, feature activities) do not have this measurement error problem. This problem is common to household- and store data.
f. The combined effect of quantity and timing acceleration

Blattberg and Neslin (1990, p. 192) propose that these two aspects of acceleration steal sales from different sections of the interpromotion time period. Timing acceleration steals from the weeks immediately following the promotion, depressing sales in those weeks, while the effects of quantity acceleration are manifested during the next consumer purchase occasion, depressing sales often after a lag of a few weeks. In household-level models these effects can be measured separately. Our store-level model should account for flexible, multi-period postpromotion dips to capture these effects jointly.

Figure 3.6 illustrates the concept of quantity acceleration while Figure 3.7 shows the concept of timing acceleration. Note that in these figures quantity acceleration causes a household to repurchase later than timing acceleration does.

<table>
<thead>
<tr>
<th>Figure 3.6: Quantity acceleration</th>
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<tbody>
<tr>
<td>(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)</td>
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<tr>
<td><img src="image" alt="Diagram showing quantity acceleration" /></td>
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- begin-of-week units purchased
- end-of-week inventory level

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<td>t+4</td>
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2. Wansink, Kent, and Hoch (1998) demonstrate that especially anchor-based promotions—presented as multiple-unit prices, purchase quantity limits, and suggestive selling—can increase purchase quantities.

g. Lack of consumer inventory sensitivity

If consumers do not run their homes like warehouses, excess inventory will not affect the next purchase(s) as much as expected. Inventory may be reduced to its normal level only after an extended period. Hence, the postpromotion dip is dissipated into the future. In household-level models heterogeneity in inventory amounts and sensitivities can be accommodated, while a brand sales model should incorporate multi-period postpromotion dips.
3.2. Arguments for the lack of a postpromotion dip, and implications for model specification

Figure 3.7: Timing acceleration
(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)

Figure 3.8 shows a household with a low inventory sensitivity. It purchases four units as a result of the promotion in week $t$. Then, even though the inventory is still two units at the beginning of week $t+2$, the household purchases two more units (as regularly).

Figure 3.8: Low inventory sensitivity
(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)

h. Anticipatory responses
The literature suggests that consumers form price expectations for future periods (Winer 1986, Kalwani et al. 1990). If consumers expect a significant price reduction in the future they may defer or decelerate their purchases, causing prepromotion dips. In other words, an expected price decrease in period $t$ may decrease sales in period $t-k$, $k = 1, 2, \ldots$.

We assume (compare Winer 1986 and Kalwani et al. 1990, equation (8)) that price expectations are unbiased, and that actual prices capture price
expectations. Hence we propose that the sales of period $t - k$ is a function of the actual price in period $t$.

Since consumers are heterogeneous in the length of the period they are willing to defer purchases in anticipation of a price promotion, prepromotion dips are spread out over multiple prepromotion weeks. However, we do not know when a prepromotion dip will be the deepest. Hence the model should also account for flexible, multi-period prepromotion dips. We note that household-level models that include future expected prices implicitly account for prepromotion effects.

Figure 3.9 illustrates the purchase and inventory patterns for a household that shows anticipatory responses. The pre- (and the post-)promotion purchases by this household are lower than in the corresponding periods in the absence of a promotion.

Figure 3.9: Anticipatory responses

(Normal: PQ = 2 units, IT = 2 weeks, CR = 1 unit per week)

To summarize, arguments a-e complicate finding postpromotion dips in both household- and store data. In contrast, the distinction between these data types appears to be especially strong in arguments f, g, and h.

**Aggregated sales across the different households**

We assume that there exists one of each type of household shown in Figures 3.2-3.9. Figure 3.10 represents three aggregated quantities:

- the hypothetical weekly unit sales sold in the absence of a promotion in week $t$ (leftmost bar for a week);
- the sales due to a promotion in week $t$ (middle bar for a week);
- the difference between the weekly unit sales in the presence versus the absence of a promotion in week $t$ (rightmost bar for a week).
3.2. Arguments for the lack of a postpromotion dip, and implications for model specification

Figure 3.10: Sales aggregated across the eight households in Figures 3.2-3.9

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<tr>
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<th>t–4</th>
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<td>Without promotion in week t, with it, and difference)</td>
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<td>Sales without promotion in t (sum across 9 periods = 63 units)</td>
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<td>Sales with promotion in t (sum across 9 periods = 67 units)</td>
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<td>Sales gain (&gt; 0) or sales loss (&lt; 0) due to promotion in week t (sum across 9 periods = 4 units)</td>
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The resulting sales pattern due to the promotion (middle bar) shows quite complex pre- and postpromotion effects. The true aggregated sales at the store level are composed of purchases by many households who are likely to exhibit even more heterogeneous response behavior. Thus, the pre- and postpromotion sales patterns in sales data may be considerably more volatile than the pattern shown in Figure 3.10. We also note that the promotion in week t yields a net sales gain of 4 units across the nine weeks, given the behavior of the eight households.

3. Neslin and Schneider Stone (1996) simulated weekly unit sales based on explanation f only: households showing low inventory sensitivity. They proposed a household-level logit model for purchase incidence as a function of household inventory and promotions. After aggregation across heterogeneous households, the sales graph did not show consistent postpromotion dips. Instead, the simulated sales appeared to be parallel to and below the level of baseline sales that would occur if there were no promotions. If the magnitude of the inventory sensitivity parameter was increased, postpromotion dips became evident. Our “simulation” represents an unweighed combination of all six household-related explanations.
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The store-level model we want to develop should account for factors that can hide postpromotion dips in traditional store-level models and in a visual inspection of the data. The model should accommodate:

i) multiple-week own-brand postpromotion effects, negative (arguments f, g), or positive (arguments d, e) relative to the sales under the no-promotion scenario. The model includes lagged effects to capture postpromotion effects;

ii) multiple-week own-brand prepromotion dips (argument h). The model includes lead effects to capture prepromotion effects;

iii) flexible pre- and postpromotion effects (arguments f, g, and h);

iv) current cross-brand effects (argument c).

It is clear that there is very limited opportunity to test the relevance of specific arguments on sales data. For example, several arguments can account for the occurrence of negative postpromotion effects. Thus, we do not propose to test the relevance of any arguments. Instead, our objective is to present and estimate a model which can accommodate complex pre- and postpromotion effects for managerial use, and to report the nature and magnitude of these effects in store data.4

4. There may be other, relevant differences between models of store sales and models of household purchases which pertain to the differential observability of postpromotion dips. For example, our model does not accommodate store switching. If the sales effect in a given store due to a promotion for a brand in that store partly reflects shifts in sales between stores, then the current effect that is potentially incremental to the manufacturer of the brand is overstated. Household models of brand choice typically focus on choices conditional upon a product category purchase in any of several stores. If the choice of store is not explicitly modeled, as a function of a.o. promotional activities, then the household models will be subject to similar problems (see Gupta et al. 1996 for a discussion of the conditions under which household choice models generate the same results as store sales models). Thus, we do not believe there is actually a difference between household- and store-level models on this aspect. Of course, households are unlikely to actively switch purchases between stores as a function of promotions for tuna or tissue, the product categories we study. Store switching does tend to occur for such items as soft drinks and disposable diapers (see Kumar and Leone 1988). Other relevant aspects are the following. One, household panel data could represent a nonrepresentative sample from store-level data. Two, household data involve the imputation of causal data for items not purchased whereas store-level data are complete. And three, the purchases for low-penetration categories may be unreliable with household data (see also section 1.6).
3.3 Model specification and calibration

We require a model that accommodates flexible lead- and lagged effects for multiple sales promotion variables over multiple weeks in a flexible manner. Basically, there are two approaches: econometric and time series. The econometric approach includes lead- and lagged sales promotion variables as predictors in a model of brand sales. The time series approach would use transfer function/intervention modeling. In the latter case, we would use ARIMA models for all variables, and estimate a transfer function (if the predictors are continuous) or an intervention model (if the predictors are binary) to relate the criterion variable to the predictors.

The traditional time series approach, used for example by Leone (1987), would have to be modified in four ways. One, we have multiple predictors instead of one used by Leone (1987). This implies that we would have to model the dynamic interactions between the predictors as well. Two, for a given predictor we have multiple promotional observations (see Tables 3.1-3.2 below), whereas Leone evaluated the effect of a single promotion. Three, we need to allow for lead- and lagged effects. While Doyle and Saunders (1985) used time series methods to identify lead- and lagged effects for multiple predictors, their final model (see Doyle and Saunders 1985, p. 59, equation (3)) is an econometric model. Four, we have time series observations for multiple stores. We are not aware of transfer function/intervention models for lead- and lagged effects of multiple predictors in a pooled data context. Although the development of such models may be a fruitful area for new research, the econometric approach appears to be equally promising and is straightforward to implement.

Our econometric model is a modification of the Scan*Pro model, also presented in (2.2) (Wittink et al. 1988, Fokens, Leeflang, and Wittink 1994, Christen et al. 1997). The original model includes own- and cross-brand effects of promotions, and is estimated with store-level scanner data provided by AC Nielsen. Our modification of the Scan*Pro model is related to: (1) variable choice, and (2) model specification.

3.3.1 Variable choice

In our model the criterion variable is log of unit sales of a brand in a specific store in a given week, as is true for the Scan*Pro model. The Scan*Pro model includes as predictors four current promotional instruments: discount, feature-only, display-only, and feature and display, for the brand and for other
brands. We modify this formulation for reasons explained below. We define: (1) own- and cross-brand discounts without support, (2) own- and cross-brand discounts with feature-only support, (3) own- and cross-brand discounts with display-only support, (4) own- and cross-brand discounts with feature and display support, (5) own-brand feature-only without price cuts, (6) own-brand display-only without price cuts, and (7) own-brand feature and display without price cuts.

We specify the instruments (1)-(4) as log price indices. We use logs so that the parameters are elasticities. We use price indices (ratio of actual to regular prices) to capture only the promotional price effects. For the instruments (1) we take the log price index observations and multiply these by one for observations with neither feature nor display activity for the brand, and by zero otherwise. The values of the instruments (2)-(4) are determined in an analogous way. We include instruments (5)-(7) as indicator variables since there is no price discount associated with those observations. Still, these activities can cause sales increases for the brand (Inman, McAlister, and Hoyer 1990).

Our approach has two advantages over the traditional approach of including log price index variables separately from the indicator variables for the non-price promotion variables. In our case, the set of own-brand variables is minimally correlated by definition (as is the set of cross-brand variables), whereas in the traditional approach, the log price index variable is often highly correlated with one or more of the non-price promotion variables. Also, the interpretation is straightforward: price cuts are the core of sales promotions, whereas feature and display are meant as communication devices. Importantly, our variable definitions capture any interaction effects between price cuts and the various types of support, which is one of the key issues within sales promotion research (Blattberg, Briesch, and Fox 1995). Our results show the own- and cross-brand price promotional elasticities for each of the four conditions of support.5

5. Our approach is somewhat similar to the one followed by Papatla and Krishnamurthi (1996, p. 23, equation (2)). They include interaction effects between indicator variables for price cut dummies, feature and display. However, their set of predictors is more correlated than our set, and their approach does not generate different price (promotion) elasticities for the promotion conditions. On the other hand, Narasimhan, Neslin, and Sen (1996) already provide survey-based elasticities for pure-, featured- and displayed price cuts.
3.3. Model specification and calibration

Of course, our model also includes variables for dynamic price promotion effects. Specifically, we use variables to capture lead- and lagged own-brand log price index effects under the four conditions of support.

3.3.2 Model specification

The current own- and cross-brand promotional instruments are included multiplicatively, as in the Scan*Pro model. The lead- and lagged own-brand log price indices with four different types of support are modeled with three alternative dynamic effects specifications:

- Unrestricted dynamic effects (Judge et al. 1985, pp. 351-356);
- Exponential decay dynamic effects (a finite duration version of the Geometric Lag Model in Judge et al. 1985, p. 388);

The Unrestricted dynamic effects approach approximates lead- and lagged effects by including the relevant predictors in lagged format \( t - 1, t - 2, t - 3, \ldots \), as well as in lead format \( t + 1, t + 2, t + 3, \ldots \). In this specification, all lead and lagged variables have unique parameters. Thus, if criterion variable \( y_t \) is explained by current, past and future values of one predictor variable \( x_t \), up to a maximum lag of \( s \) periods and a maximum lead of \( s' \) periods, then the Unrestricted dynamic effects model is

\[
y_t = \alpha_0 + \alpha_1 x_t + \sum_{u=1}^{s} \beta_{u} x_{t-u} + \sum_{v=1}^{s'} \gamma_{v} x_{t+v} + u_t,
\]

where

\[
t = s + 1, \ldots, T - s'.
\]

The lagged effect parameters (betas) capture postpromotion effects, whereas the lead effect parameters (gammas) capture prepromotion effects, which are caused by anticipatory responses.

The Exponential decay model imposes a specific structure on the dynamic effects (see also Blattberg and Wisniewski 1989):

\[
\beta_u = \lambda^{u-1} \beta \quad \text{and} \quad \gamma_v = \mu^{v-1} \gamma.
\]
As a result, the model with one predictor \( x_t \) is:

\[
y_t = \alpha'_0 + \alpha'_1 x_t + \sum_{u=1}^{s} \lambda_{u-1}^u \beta_{u-t} + \sum_{v=1}^{s'} \mu_{v-1}^v \gamma_{v+t} + u'_t,
\tag{3.2}
\]

\[t = s + 1, \ldots, T - s'.\]

The parameters \( \lambda \) and \( \mu \) are the decay parameters.

The Almon model approximates the dynamic effects in (3.1) with polynomials. The lagged effect parameters are:

\[
\beta_u = \sum_{m=0}^{r} \phi_m (u - 1)^m; \quad (u = 1, \ldots, s; \ r < s).
\]

The lead effect parameters are:

\[
\gamma_v = \sum_{m=0}^{r'} \theta_m (v - 1)^m; \quad (v = 1, \ldots, s'; \ r' < s').
\]

In this manner, the Almon model is:

\[
y_t = \alpha''_0 + \alpha''_1 x_t + \sum_{u=1}^{s} \sum_{m=0}^{r} \phi_m (u - 1)^m x_{t-u} + \sum_{v=1}^{s'} \sum_{m=0}^{r'} \theta_m (v - 1)^m x_{t+v} + u''_t,
\tag{3.3}
\]

\[t = s + 1, \ldots, T - s'.\]

Our use of these three alternative dynamic effect specifications differs in three respects from the standard way they are used in the econometric literature. One, rather than only lagged effects, our approach includes lead effects as well. Two, instead of modeling the dynamic effects of just one variable, we model the dynamic effects of multiple variables. And three, the standard way is for researchers to use the Exponential decay- and the Almon models by imposing a structure in which the dynamic effect parameters are linked to the current effect parameter. Our approach relaxes this assumption: i.e., we let the current effect parameter be estimated independently of the lead-

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6. For \( u = 1 \) the first element of this sum is defined as \( \phi_0 (0)^0 \equiv \phi_0 \).
3.3. Model specification and calibration

and lagged effect parameters. We do this because current price promotion effects are expected to be much larger than (week-specific) lead- and lag effects. In addition, we use separate approaches for lead- and lagged effects for all models since we should incorporate flexible dynamic effects (implication iii). For the Exponential decay model, this means that the lagged effect decay parameter $\lambda$ may differ from the lead effect decay parameter $\mu$. For the Almon model, this means that the degree of the lagged effect polynomial ($r$) may be different from the degree of the lead effect polynomial ($r'$).

It is clear that the Unrestricted dynamic effects approach defined in equation (3.1) offers the highest degree of flexibility. However, it involves many lead- and lagged variables, which may lead to multicollinearity. In contrast, the Exponential decay model (3.2) uses few variables (and thus: parameters), but is relatively inflexible. In model (3.2), the dynamic effect is assumed to be largest in the weeks immediately after (lagged effect) or before (lead effect) the promotion. This may be restrictive, because of the multitude of factors causing pre- and postpromotion effects (see section 3.2). The Almon approach (3.3) is between these two approaches: it is more flexible than the Exponential decay model, but more parsimonious than the Unrestricted model.\footnote{Blattberg and Neslin (1990, p. 190) say: “While there are no published examples of using polynomial lags to measure the lag effects of promotion, the technique appears to be promising.”}

For brand $k, k = 1, \ldots, J$, the most general model is:

$$
\ln S_{ik,t} = \sum_{j=1}^{J} \sum_{l=1}^{4} \alpha_{jkl} \ln(P_{ijl,t}) + \alpha_{Fk} F_{ik,t} + \alpha_{Dk} D_{ik,t} + \alpha_{FDk} F D_{ik,t} + \sum_{s=1}^{s} \sum_{l=1}^{4} \beta_{kl,u} \ln(P_{i(k-l),t-u}) + \sum_{s'=1}^{s'} \sum_{l=1}^{4} \gamma_{kl,v} \ln(P_{i(k+l),t+v}) + \psi_{ik} R_t + \xi_{ik} W_t + u_{ik,t} \quad (3.4)
$$

with the lagged effect parameters $\beta$ and lead effect parameters $\gamma$ either kept unrestricted as in (3.1), modeled as an Exponential decay model (3.2), or modeled as an Almon model (3.3); and where:

$\ln S_{ik,t}$ is log unit sales of brand $k$ in store $i$ in week $t$;
\[ \ln(P_{ijl,t}) \] is log price index (ratio of actual to regular price) of brand \( j \) in store \( i \) in week \( t \); \( l=1 \) denotes that the observation is not supported by feature nor display; \( l = 2 \) that it is supported by feature-only; \( l = 3 \): supported by display-only, and \( l=4 \): supported by feature and display;

\( F_{ik,t} \) is a feature-only indicator variable for non-price promotion observations; \( = 1 \) if brand \( k \) is featured, but not displayed nor price promoted, by store \( i \) in week \( t \), \( = 0 \) otherwise;

\( D_{ik,t} \) is a display-only indicator variable for non-price promotion observations; \( = 1 \) if brand \( k \) is displayed, but not featured nor price promoted, by store \( i \) in week \( t \), \( = 0 \) otherwise;

\( FD_{ik,t} \) is an indicator variable for combined use of feature and display for non-price promotion observations; \( = 1 \) if brand \( k \) is featured and displayed by store \( i \) in week \( t \), but not price promoted, \( = 0 \) otherwise;

\( R_i \) is a store indicator variable; \( = 1 \) if observation is from store \( i \), \( = 0 \) otherwise;

\( W_t \) is a weekly indicator variable; \( = 1 \) if observation is from week \( t \), \( = 0 \) otherwise;

\( \alpha_{jkl} \) is the elasticity of brand \( k \)'s sales with respect to brand \( j \)'s price index in the current week; supported by neither feature nor display for \( l =1 \), by feature-only for \( l = 2 \), by display-only for \( l = 3 \), by feature and display for \( l = 4 \);

\( \alpha_{Fk}, \alpha_{Dk}, \alpha_{FDk} \) are the current-week effects on brand \( k \)'s log sales resulting from brand \( k \)'s use of feature-only (F), display-only (D), and feature and display (FD); each is the effect in the absence of a discount for brand \( k \);

\( \beta_{kl,u} \) is the elasticity of brand \( k \)'s sales in week \( t \) relative to brand \( k \)'s price index with support \( l \) in week \( t - u \);

\( \gamma_{kl,v} \) is the elasticity of brand \( k \)'s sales in week \( t \) relative to brand \( k \)'s price index with support \( l \) in week \( t + v \);

\( \psi_{ik} \) and \( \xi_{tk} \): store intercept for store \( i \) \( (i = 1, \ldots , N) \), brand \( k \), and week intercept for week \( t \) \( (t = 1, \ldots , T) \), brand \( k \), respectively;

\( u_{ik,t} \) is a disturbance term for brand \( k \) in store \( i \) in week \( t \).

Weekly indicator variables are included to account for seasonal effects and the effects of missing variables (e.g. manufacturer advertising and coupons).

To summarize our approach to measure pre- and postpromotion dips: we presented arguments why dips may not show in traditional store-level models and nor in visual displays of the data; for each argument we derived its
model implication; and we presented an extended model that accounts for all model implications in (3.4). This model includes flexible, multiple-week, pre- and post price promotion own-brand variables (implications i-iii), and it incorporates current cross-brand price-promotional instruments (implication iv). The dynamic structure is approximated by three alternative models, presented in (3.1)-(3.3).

Through use of separate price discount variables for four promotion conditions, the model accommodates a.o. lagged price cut with feature effects, which were found to be significant in prior research (Papatla and Krishnamurthi 1996). In summary, the model includes lead- and lagged variables for temporary price discounts with four types of support: no support, feature-only, display-only, and feature and display. Thus, our model also accounts for dynamic effects for features and displays (documented also by Lattin and Bucklin 1989), to the extent that these promotions were accompanied by price discounts.8

We note that the model implicitly accounts for a decrease in promotional effectiveness during a multiple-week price promotion. This occurs if the first week’s price promotion causes a dip in the second week’s sales, which then takes away from the second week’s price promotion effect, etc. In other words, the current effect of the promotion in this second week effect equals the current-week parameter (alpha, negative if \( j = k \)) plus the one-week postpromotion parameter (beta, generally positive). One rationale is that households who purchased promotional items in week one will be less responsive to the same promotion in a second week. Another rationale is that consumers who engage in deal-to-deal purchasing will have reduced motivation to participate if a promotion is extended. We note that there are other ways of modeling the effect of past and future deals on current price response. For example, Foekens, Leeflang, and Wittink (1999) use a varying-parameter approach, i.e., the alphas are a function of past promotions.

### 3.3.3 Model alternatives

We consider various alternatives to approximate the dynamic structure, separately for each of the brands. For example, we have to choose between

---

8. We also considered the existence of dynamic effects for feature and/or display activity without promotional price cuts. However, as consumers have no monetary incentive to accelerate their purchases in case of “value-less” promotions, we expect little or no dynamic effects. To check, we included dynamic effects for these variables in the models. The effects were significant in only a few cases so that parsimony justifies constraining them to be zero.
three alternatives for the dynamic effect specification: the Almon-, Exponential decay-, and Unrestricted models. In addition, for each of these specifications we estimate the durations of the lag period \( s \) and lead period \( s' \). Moreover, for the Exponential decay model, we need to find the best values for the lagged effect decay parameter \( \lambda \) and lead effect decay parameter \( \mu \). Finally, for the Almon model we have to determine the best degrees for the lagged effect polynomial \( r \) and for the lead effect polynomial \( r' \).

To accomplish this, we let the maximum lag period vary from zero to six weeks \( (s = 0, 1, 2, \ldots, 6) \) and also let the maximum lead period vary from zero to six weeks \( (s' = 0, 1, 2, \ldots, 6) \), for the three specifications. Both maxima are six weeks so that they are close to the average interpromotion period in the data sets (see section 3.4). For the Exponential decay model we let each decay parameter vary independently from 0.1, 0.2, \ldots up to 0.9. For the Almon model, we consider polynomials up to degree three for both the lag polynomial \( (r = 0, 1, 2, 3) \) and, independently, for the lead polynomial \( (r' = 0, 1, 2, 3) \). We note that the polynomial degree must be smaller than the maximum lead or lag length \( (r < s \text{ and } r' < s') \).

For a given brand, we proceed as follows:

1. We estimate model (3.4) by OLS for all alternatives. Since the Almon- and Exponential decay models impose constraints on the parameters of successive periods, we have to impose these constraints during estimation. To accomplish this, we compute linear combinations of both lead- and lagged predictors, using polynomial coefficients as weights for the Almon model and geometrically declining weights for the Exponential decay model (see also Judge et al. 1985, p. 357 and p. 388). The Unrestricted model does not impose constraints, and we estimate it by just including untransformed lead- and lagged predictors. Within each of the three dynamic effect specifications, we vary the lead and lag duration as well as the values of the decay parameters (for the Exponential decay model) or the polynomial degrees for the lead and lagged effects (for the Almon model). Next, we choose among all alternatives the model that minimizes Akaike’s Information Criterion: 

\[
AIC = \ln(SSR/n) + 2p/n, \text{ where } SSR = \text{Sum of Squared Residuals}
\]

for a given model, \( n \) = number of observations used to estimate this model, and \( p \) = number of predictors included in this model. We use AIC because it can be used to compare the nonnested models and it ranked high in a comparison of 11 model selection criteria (Rust et al. 1995). While the Schwarz criterion ranked first overall (Rust et al.
Data

We use weekly store-level scanner data from AC Nielsen for two product categories to calibrate the models. We use pooled data to estimate the effects across all stores. The first data set of 52 weeks pertains to the three largest national brands in the 6.5 oz. canned tuna fish product category in the USA ($T=52, J=3$). The data are from 28 stores belonging to one supermarket chain in a metropolitan area ($N=28$). We show descriptive statistics based on 1456 observations for each of these tuna brands in Table 3.1. The average interpromotion time varies from 3.2 to 9.9 weeks across the brands. Each brand is promoted frequently.

---

9. Burnham and Anderson (1998, pp. 68-69) see little utility in the Schwarz criterion in many applications, because it assumes the existence of a “true model”. They view modeling as an exercise in the approximation of the explainable information in the empirical data, and do not think a “true model” exists.
Table 3.1: Descriptive statistics for tuna category

<table>
<thead>
<tr>
<th>Tuna brand</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of stores</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>Number of weeks</td>
<td>52</td>
<td>52</td>
<td>52</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1456</td>
<td>1456</td>
<td>1456</td>
</tr>
<tr>
<td>Brand share percentage</td>
<td>46.6</td>
<td>30.8</td>
<td>22.5</td>
</tr>
<tr>
<td>Average regular price</td>
<td>0.86</td>
<td>0.87</td>
<td>0.86</td>
</tr>
<tr>
<td>Average interpromotion period in weeks (standard deviation)</td>
<td>3.2 (2.5)</td>
<td>9.9 (10.7)</td>
<td>5.9 (5.0)</td>
</tr>
<tr>
<td># Price promotions w/o support</td>
<td>245</td>
<td>101</td>
<td>220</td>
</tr>
<tr>
<td># Price promotions with feature-only</td>
<td>65</td>
<td>70</td>
<td>16</td>
</tr>
<tr>
<td># Price promotions with display-only</td>
<td>59</td>
<td>18</td>
<td>77</td>
</tr>
<tr>
<td># Price promotions with feature and display</td>
<td>241</td>
<td>79</td>
<td>112</td>
</tr>
<tr>
<td># Non-price promotions with feature-only</td>
<td>8</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td># Non-price promotions with display-only</td>
<td>44</td>
<td>23</td>
<td>47</td>
</tr>
<tr>
<td># Non-price promotions with feature and display</td>
<td>22</td>
<td>11</td>
<td>10</td>
</tr>
</tbody>
</table>

The second data set (also 52 weeks) pertains to the six largest national brands in the toilet tissue product category in the USA ($T=52$, $J=6$). Each brand is composed of a number of SKU’s, representing different sizes and forms. The database contains data aggregated across these SKU’s to define brand-level variables. Unit sales is defined as the total number of sheets per package sold, and unit price is the price per thousand sheets. We developed a procedure to impute the weekly regular prices required for the price index variables, since these were not included in this data set. The data are from 24 stores of different chains in one region of the USA ($N=24$). We show descriptive statistics based on 1248 observations for each of the toilet tissue brands in Table 3.2. The average interpromotion period for the toilet tissue brands varies from 4.8 to 8.2 weeks. The frequencies with which the brands are promoted is somewhat lower for this category than for tuna.

We note that Narasimhan, Neslin, and Sen (1996) obtained consumer-based ratings of “ability to stockpile” for 108 product categories. In their listing tuna fish is rated first and toilet tissue rated fourth. Although their measure is incomplete with regard to actual stockpiling of products, and is subject to an unknown degree of error, these two product categories provide excellent opportunities to examine the postpromotion dip controversy.

10. Details about this procedure are available in Appendix F.
3.5. Results

We estimate the models with data pooled across stores. Since promotional effects may differ between stores, we test the null hypothesis of parameter homogeneity. To do this, we (also) estimate the best models with store-specific current and dynamic effect parameters, but homogenous weekly effects. We report the p-values of the Chow test in the panel headed “Pooling test” in the lower part of Tables 3.3-3.4. We do not reject the null hypothesis for any of the nine brands.
Table 3.3: Tuna model calibration results

<table>
<thead>
<tr>
<th>Model selection</th>
<th>Tuna brand 1</th>
<th>Tuna brand 2</th>
<th>Tuna brand 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC Almon model (A)</td>
<td>-2.008</td>
<td>-1.967</td>
<td>-1.703</td>
</tr>
<tr>
<td>AIC Exponential decay model (E)</td>
<td>-1.994</td>
<td>-1.967</td>
<td>-1.693</td>
</tr>
<tr>
<td>AIC Unrestricted model (U)</td>
<td>-2.002</td>
<td>-1.967</td>
<td>-1.693</td>
</tr>
<tr>
<td>Model choice</td>
<td>A</td>
<td>A/E/U</td>
<td>A</td>
</tr>
<tr>
<td>Lead period s' (weeks)</td>
<td>4</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Lag period s (weeks)</td>
<td>3</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Re-Estimation results

<table>
<thead>
<tr>
<th>estimation procedure</th>
<th>IGLS-AH</th>
<th>IGLS-AH</th>
<th>IGLS-AH</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of observations for estimation</td>
<td>1260</td>
<td>1456</td>
<td>1260</td>
</tr>
<tr>
<td>number of parameters</td>
<td>104</td>
<td>91</td>
<td>103</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.941</td>
<td>0.834</td>
<td>0.915</td>
</tr>
</tbody>
</table>

Pooling test

| p-values Chow test | 0.986 | 1.000 | 0.996 |

Error assumption tests

| p-value simultaneous test (\( \alpha = 0.05 \)) | 0.000 | 0.000 | 0.000 |
| p-value zero autocorrelation (\( \alpha = 0.025 \)) | 0.000 | 0.000 | 0.000 |
| p-value homoscedasticity (\( \alpha = 0.025 \)) | 0.000 | 0.000 | 0.000 |

To test the error assumptions, we use the Bera-Jarque test (Körösi, Mátyás, and Székely 1992, pp. 173-180). We first test the error assumptions simultaneously, and report the p-values in the panel headed “Error assumption tests” of Tables 3.3-3.4. If the outcome is a rejection (i.e., a p-value lower than 5 percent), the hypotheses of zero autocorrelation and homoscedasticity are also tested separately. We use a significance level of 2.5 percent for these tests (based on Bonferroni’s rule). We report the p-values for these tests also in Tables 3.3-3.4. We find four cases of non-zero autocorrelation and seven cases of heteroscedasticity.

Given some error-term assumption violations, we re-estimate the models where necessary, using Iterative GLS (IGLS). Kmenta (1986, pp. 609-622) describes IGLS accounting for non-zero autocorrelation (IGLS-A), for heteroscedasticity (IGLS-H), or both (IGLS-AH). We iterate the GLS-procedure until convergence. In the panel headed “Re-estimation results” in Table 3.3-3.4 we show the estimation procedure used for each brand.

---

\( a \) We show the AIC for the specification that minimizes AIC across the alternatives considered for each of the three specifications.

\( b \) The models are exactly the same in this situation.

\( c \) IGLS-A = Iterative GLS that accounts for non-zero autocorrelation, IGLS-H = IGLS that accounts for heteroscedasticity, and IGLS-AH accounts for both.
### Table 3.4: Tissue data model calibration results

<table>
<thead>
<tr>
<th>Tissue brand</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model selection</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC Exponential decay model (E)</td>
<td>–1.268</td>
<td>–2.166</td>
<td>–1.917</td>
<td>–2.338</td>
<td>–2.842</td>
<td>–2.6632</td>
</tr>
<tr>
<td>AIC Unrestricted model (U)</td>
<td>–1.283</td>
<td>–2.195</td>
<td>–1.917</td>
<td>–2.369</td>
<td>–2.855</td>
<td>–2.630</td>
</tr>
<tr>
<td><strong>Model choice</strong></td>
<td>A</td>
<td>A</td>
<td>A/E/U</td>
<td>U</td>
<td>U</td>
<td>E</td>
</tr>
<tr>
<td><strong>Lead period s’ (weeks)</strong></td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>5</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td><strong>Lag period s (weeks)</strong></td>
<td>6</td>
<td>5</td>
<td>1</td>
<td>6</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td><strong>Re-Estimation results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>estimation procedure</td>
<td>OLS</td>
<td>OLS</td>
<td>IGLS-H</td>
<td>IGLS-H</td>
<td>IGLS-H</td>
<td>IGLS-AH</td>
</tr>
<tr>
<td>number of observations for estimation</td>
<td>1104</td>
<td>1008</td>
<td>1224</td>
<td>1008</td>
<td>1104</td>
<td>1032</td>
</tr>
<tr>
<td>number of parameters</td>
<td>111</td>
<td>116</td>
<td>105</td>
<td>132</td>
<td>120</td>
<td>103</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.883</td>
<td>0.929</td>
<td>0.957</td>
<td>0.975</td>
<td>0.987</td>
<td>0.947</td>
</tr>
<tr>
<td><strong>Pooling test</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-values Chow test</td>
<td>1.000</td>
<td>1.000</td>
<td>0.995</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td><strong>Error assumption tests</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value simultaneous test ($\alpha = 0.05$)</td>
<td>0.074</td>
<td>0.020</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>p-value zero autocorrelation ($\alpha = 0.025$)</td>
<td>–</td>
<td>0.057</td>
<td>0.657</td>
<td>0.060</td>
<td>0.846</td>
<td>0.005</td>
</tr>
<tr>
<td>p-value homoscedasticity ($\alpha = 0.025$)</td>
<td>–</td>
<td>0.035</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
</tr>
</tbody>
</table>

We note, however, that the IGLS parameter estimates are very close to the OLS-estimates (the primary benefit of IGLS lies in obtaining more valid estimated standard errors). In the same panel we report the number of observations used for estimation and the number of parameters. The number of observations used differs from the original number, due to the inclusion of lead- and lagged variables. For example, tuna brand 1 has a lead effect of four weeks and a lagged effect of three weeks. Hence we can only use weeks 4 through 48 of the 52 weeks for each store. The number of observations is 28 (stores) times 45 weeks or 1260 for this brand. The number of parameters includes the indicator variables for store and week. Below these numbers we show the $R^2$ values which are between 0.834 and 0.941 for tuna, and between 0.883 and 0.987 for toilet tissue.11

11. We also performed multicollinearity analyses. We computed the condition indices from the predictor matrices for the “best models”. They were higher than 30 for four brands. Hence there is a substantial amount of multicollinearity in the data, for those brands. This multicollinearity stems from the allowance for multiple and flexible lead- and lagged promotion effects, combined with weekly indicator variables. Therefore, individual parameter estimates...
We provide summary statistics for the OLS estimation results of (3.4) for the nine brands in the panel headed “Model selection” in Tables 3.3-3.4. Specifically, we report the AIC for the AIC-minimizing alternative of each of the three specifications. For each brand, we then choose the model specification that minimizes AIC (underlined values), and find dynamic price promotion effects for eight out of nine brands (tuna brand 2 being the exception). For the tuna brands, the preferred model on average has a longer lead- than lag length. For tissue brands, the lag period tends to be longer than the lead period. We also see in Tables 3.3-3.4 that the AIC-values for the Almon model are lowest for four out of nine brands. The Unrestricted model has the lowest AIC for two brands, and the Exponential decay model for one brand. For the two remaining brands, the three models are exactly the same: tuna brand 2 (no dynamic effects), and tissue brand C (one-week lagged effect). In the former case, the model without dynamic effects is best, and in the latter case, the lagged effect lasts one week only, so that there is no opportunity to consider alternative ways to describe dynamic patterns.

The lead- and lag lengths vary across the brands. However, for a given brand, the three dynamic-effect specifications often yield the same lead and lag lengths (not shown). Across the nine brands, 83 percent of the lead and lag lengths are exactly the same for the three AIC-minimizing specifications. For all brands we find that if one AIC-minimizing specification yields a non-zero lead- or lag length, the other specifications also do.

We present estimated effects averaged across brands from the best individual models, which have been re-estimated with IGLS if appropriate, in Tables 3.5 and 3.6. We take the average across all relevant estimates, whether they are significant or not. We report four current price index elasticities for each category, averaged across the brands, in Tables 3.5.a and 3.6.a: price cut without support, price cut with feature-only support, price cut with display-only support, and price cut with feature and display support. For both product categories, the price elasticity is the lowest for unsupported price cuts and the highest for price cuts with feature and display support, exactly as we would expect. Except for price cuts without support, the average own-brand price elasticities are larger for the tissue category than for the tuna category. However, these results are not comparable, because there are differences in the recency of the data (the tuna data are from 1986/1987, whereas the tissue

12. We present the model results in full detail in Appendix G.
3.5. Results

Table 3.5: Tuna data: current-, dynamic-, and net sales promotion effects, averaged across the three brands

<table>
<thead>
<tr>
<th>support type</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current sales effect</td>
<td>126</td>
<td>190</td>
<td>222</td>
<td>284</td>
</tr>
<tr>
<td>Dynamic sales effect (lead + lag)</td>
<td>-28</td>
<td>-24</td>
<td>-8</td>
<td>-21</td>
</tr>
<tr>
<td>Net sales effect (=current+dynamic)</td>
<td>98</td>
<td>165</td>
<td>214</td>
<td>263</td>
</tr>
</tbody>
</table>

Table 3.5.a: average parameter estimates for best models

<table>
<thead>
<tr>
<th>support type</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average current own-brand price elasticity</td>
<td>-3.1</td>
<td>-4.0</td>
<td>-4.5</td>
<td>-5.2</td>
</tr>
</tbody>
</table>

Table 3.5.b: simulated sales effects using best models

<table>
<thead>
<tr>
<th>sales impact of a 20 % price cut supported by</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current sales effect</td>
<td>126</td>
<td>190</td>
<td>222</td>
<td>284</td>
</tr>
<tr>
<td>Dynamic sales effect (lead + lag)</td>
<td>-28</td>
<td>-24</td>
<td>-8</td>
<td>-21</td>
</tr>
<tr>
<td>Net sales effect (=current+dynamic)</td>
<td>98</td>
<td>165</td>
<td>214</td>
<td>263</td>
</tr>
</tbody>
</table>

Table 3.5.c: percent net gains\(^c\) for all models

<table>
<thead>
<tr>
<th>support type</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best model(^a)</td>
<td>78%</td>
<td>87%</td>
<td>96%</td>
<td>93%</td>
</tr>
<tr>
<td>Almon model(^d)</td>
<td>78%</td>
<td>87%</td>
<td>96%</td>
<td>93%</td>
</tr>
<tr>
<td>Exponential decay model(^d)</td>
<td>86%</td>
<td>84%</td>
<td>102%</td>
<td>91%</td>
</tr>
<tr>
<td>Unrestricted model(^d)</td>
<td>79%</td>
<td>88%</td>
<td>98%</td>
<td>93%</td>
</tr>
</tbody>
</table>

\(^a\) The best models are the brand-specific AIC minimizing specifications, shown in Table 3.3.
\(^b\) no F, no D = neither feature nor display, F-only = feature-only, D-only = display-only, F and D = feature and display.
\(^c\) The percent net gain is the ratio of the net sales effect over the current sales effect.
\(^d\) We apply the same model type for all brands.

Data are from 1992, the regions represented (the data are from different USA regions), the store types, etc.

We also present the results from simulation exercises. We use the brand-specific current-, lead- and lagged effect parameter estimates from the best individual models to calculate the current sales effect and the pre- and postpromotion sales effects for a 20 percent promotional price cut for each of the four types of support. A 20 percent price cut is typical in both product categories. We obtain the current sales effect for an brand by subtracting the model-based sales level for this brand if all predictor variables are at their regular levels from the sales level if the relevant current price index variable is reduced by 20 percent while the other predictors are constant. The lead- and lagged effects are computed analogously. To illustrate, we present a visual representations for the model-based dynamic sales promotion effects for the same two brands as in Figures 3.1 and 3.2. For tuna brand 1 (Figure 3.11) we simulate a 20 percent price discount with feature-only support in week 1,
Table 3.6: Tissue data: current-, dynamic-, and net sales promotion effects, averaged across the six brands

Table 3.6.a: average parameter estimates for best models

<table>
<thead>
<tr>
<th>support type</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average current own-brand price elasticity</td>
<td>−2.9</td>
<td>−5.4</td>
<td>−5.2</td>
<td>−5.7</td>
</tr>
</tbody>
</table>

Table 3.6.b: simulated sales effects using best models

<table>
<thead>
<tr>
<th>sales impact of a 20% price cut supported by</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current sales effect</td>
<td>227</td>
<td>542</td>
<td>529</td>
<td>689</td>
</tr>
<tr>
<td>Dynamic sales effect (lead + lag)</td>
<td>−57</td>
<td>−72</td>
<td>50</td>
<td>−84</td>
</tr>
<tr>
<td>Net sales effect (=current+dynamic)</td>
<td>170</td>
<td>470</td>
<td>579</td>
<td>605</td>
</tr>
</tbody>
</table>

Table 3.6.c: percent net gains for all models

<table>
<thead>
<tr>
<th>support type</th>
<th>no F, no D</th>
<th>F-only</th>
<th>D-only</th>
<th>F and D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best model\textsuperscript{a}</td>
<td>75%</td>
<td>87%</td>
<td>110%</td>
<td>88%</td>
</tr>
<tr>
<td>Almon model\textsuperscript{d}</td>
<td>70%</td>
<td>89%</td>
<td>111%</td>
<td>88%</td>
</tr>
<tr>
<td>Exponential decay model\textsuperscript{d}</td>
<td>110%</td>
<td>96%</td>
<td>117%</td>
<td>93%</td>
</tr>
<tr>
<td>Unrestricted model\textsuperscript{d}</td>
<td>75%</td>
<td>86%</td>
<td>110%</td>
<td>87%</td>
</tr>
</tbody>
</table>

\textsuperscript{a} The best models are the brand-specific AIC minimizing specifications, shown in Table 3.4.
\textsuperscript{b} no F, no D = neither feature nor display, F-only = feature-only, D-only = display-only, F and D = feature and display.
\textsuperscript{c} The percent net gain is the ratio of the net sales effect over the current sales effect.
\textsuperscript{d} We apply the same model type for all brands.

whereas for tissue brand E (Figure 3.12) we present the results for a 20 percent price discount with feature and display support in week $t$.

We show in Tables 3.5.b and 3.6.b in units the average current sales effect as well as the average dynamic sales effect, which is the sum of the pre- and postpromotion sales effects. We then combine the current and dynamic effects into a net sales effect, which is the total promotion effect over time.\textsuperscript{13} The

\textsuperscript{13} We do not report separate lead- and lagged effects, because they may be confounded. For example, one postpromotion period may interfere with the prepromotion period of the next promotion, if these promotions are close in time. In addition, lagged terms can capture prepromotion dips since these dips are due to anticipatory responses that consumers may base on current- and lagged prices. We do not exclude lead effects from our model, however. First, since the length of the interpromotion period varies, pre- and postpromotion periods do not necessarily interfere. Second, lag terms capturing prepromotion dips should be modeled differently from lag terms capturing the effects of purchase acceleration and lack of consumer inventory sensitivity. For example, the sales pattern including pre- and postpromotion dips may look as follows: promotional sales spike (week 1) - postpromotion dip (weeks 2-3) - regular sales (week 4) - prepromotion dip (weeks 5-6) - promotional sales spike (week 7). We prefer
3.5. Results

Figure 3.11: Tuna brand 1, model-based dynamic promotion effects

20 percent price discount in week $t$ with feature-only support

Figure 3.12: Tissue brand E, model-based dynamic promotion effects

20 percent price discount in week $t$ with feature and display support

percent net gain is obtained by the ratio of the net sales effect to the current sales effect. The results in Tables 3.5.b and 3.6.b show that the difference to model such a pattern with a lagged effect specification (for weeks 2 and 3) and a lead effect specification (for weeks 5 and 6) over a model with a highly irregular five-week lagged effect. However, for the purpose of understanding the magnitudes of dynamic effects, it is sufficient to combine these effects into a “total dynamic sales effect”.
between current- and net sales effects can be quite large, so that the profit implications may change greatly if dynamic effects are taken into account. The percent net gain is obtained by the ratio of the net sales effect to the current sales effect.

Tables 3.5.b and 3.6.b show that more (feature/display) support produces larger own-brand current sales effects, for both product categories. The dynamic sales effects, however, do not show a similar pattern. For example, a 20 percent price cut with display has a relatively small negative dynamic effect for tuna (-8 units), and even a positive dynamic effect for tissue (+50 units). A display extension effect (argument e) is perhaps the most plausible explanation for this phenomenon. In any event, the net sales effect is a managerially more relevant measure than the current sales effect. For instance, if we use the current sales effects only for the tissue category, a manager may believe a price cut with feature-only has a larger sales effect than a price cut with display-only support (542 vs. 529 units). However, the net sales effect indicates that the contrary is true (470 vs. 579 units).

If we had to recommend one of the three model specifications to a manager, we would choose the Unrestricted model, although Tables 3.3 and 3.4 indicates no single specification can be considered best. One reason is that the substantive results from the Unrestricted model applied for all brands are the closest to those of the brand-specific best models. This can be inferred from the results in Tables 3.5.c and 3.6.c, in which we report average percentages net gain for the price cuts with different types of support. The first line shows these percentages based on the results for the best model in Table 3.5.b and 3.6.b. The second line shows the percentages for the Almon model, the third line for the Exponential decay model, and the fourth line for the Unrestricted model. Although the Almon model and the Unrestricted model give very similar results, the average absolute percent deviation in the percent net gains (from the results for the best model) is slightly smaller for the Unrestricted model than for the Almon model: 1.2 percent (tuna) and 0.6 percent (tissue) for the Unrestricted model, versus 0.0 percent (tuna) and 2.6 percent (tissue). For the Exponential decay model, the deviations in net percent gain from the best model are much larger: 5.1 percent (tuna) and 13.4 percent (tissue). Hence, the Exponential decay model gives very different conclusions about the percent net gain from these promotions. Another reason is the ease of implementation of the Unrestricted model. Whereas the Almon- and Exponential decay model require transformations of lead- or lagged predictor variables, the Unrestricted model only requires that the user provides lead- and lagged predictor variables.
3.5. Results

In addition, the Almon- and Exponential decay model require a grid search, across polynomial degrees (Almon), or across decay parameters (Exponential decay), on top of a search for lead- and lag lengths. The Unrestricted model only requires the latter search.

We see that the percent net gain figures for the best model are quite consistent across the two categories. For an unsupported price cut we have 78 percent (tuna) and 75 percent (tissue), for a feature-only supported price cut 87 percent for both categories, for a display-only supported price cut 96 percent (tuna) and 110 percent (tissue), and for a feature-and-display supported price cut it is 93 percent (tuna) and 88 percent (tissue). The percent net gains lower than 100 reflect pre- and/or postpromotion dips. For these cases, the purchase acceleration effects vary between 4 and 25 percent. These numbers appear to be consistent with the results from household-level studies.

We illustrate the performance (of the best model) by plotting actual and fitted sales. Instead of showing the graphs for all brands in all stores for all weeks (28 stores with 3 tuna brands with 52 observations each, and 24 stores with 6 tissue brands with 52 observations each), we select two illustrative examples. We take the same brands and stores as in Figure 3.1. Figure 3.13 shows actual and fitted sales for tuna brand 1 in store 28 for weeks 35-45. Fitted sales are obtained by using the model that includes current and dynamic effects (model (3.4)), and separately a model that includes current effects only. The latter “no-dynamic-effects model” was rejected in favor of the dynamic-effects model (see Table 3.3). Both models track actual sales quite well up to week 42. However, the dynamic-effects model shows a much smaller effect for the price promotion in week 43 than the no-dynamic-effects model. This store had a price promotion for week 41 as well, causing negative postpromotion effects which are captured by the dynamic-effects model but not by the no-dynamic-effects model.14

The second example is from tissue brand E sold in store 21, shown in Figure 3.14. In this figure we see that the dynamic-effects model approximates the postpromotion dip better than the no-dynamic-effects model does (see weeks 37 and 38). Again, the no-dynamic-effects model was rejected (Table 3.4). This graph illustrates the subtleness of dynamic promotion effects, and it is more representative of brand sales graphs than the one in Figure 3.13.

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14. The decreased effectiveness of the price promotion in week 43 is not due to prepromotion effects, since the brand was not price promoted after week 43.
3.6 Conclusions

We investigated one of the mysteries of sales promotion research: the lack of postpromotion dips in store data. From studies of household panel data it is known that consumers often accelerate their purchases in time and/or quantity due to promotions, which should result in a dip in purchases in the weeks
3.6. Conclusions

Following a promotion, this dip, however, is rarely observed in sales data. Extant arguments for the apparent lack of postpromotion dips imply that the dips may be difficult to detect by traditional models. Since brand sales are the aggregate of purchases across (heterogeneous) households, both pre- and postpromotion sales data may have complex patterns. Essentially, sales are shifted from multiple future- and past periods into a current, promotion-based sales spike in a nontrivial way. Neslin and Schneider Stone (1996, p. 92) suggested that researchers “... conduct sophisticated distributed lag analyses on weekly sales data in the hope of measuring the postpromotion dip statistically”. Our modeling approach reflects the multitude of factors pertaining to dynamic promotion effects, and we obtain these effects convincingly.

We use an econometric model to regress brand-level sales on current-, lagged-, and lead price discount variables (price indices) for three different distributed lead- and lag structures: an Almon model, an Unrestricted dynamic effects model, and an Exponential decay model. The Unrestricted dynamic model is very flexible but not parsimonious. The Exponential decay model is the least flexible and the most parsimonious one, while the Almon polynomial model is in between these extremes. Importantly, we distinguish the effects of four types of price discounts: without support, with feature-only support, with display-only support, and with feature and display support.

We applied the models to nine brands in two product categories: tuna fish and toilet tissue. Within each of these three models, we varied lead and lag lengths as well as the parameters describing the lag structure. For each brand, we selected the model specification that minimizes Akaike’s Information Criterion. We tested the assumption of parameter homogeneity among stores (no evidence of heterogeneity), and re-estimated models by accounting for nonzero autocorrelation or heteroscedasticity where necessary.

Our main findings across two product categories are:

- Significant dynamic promotion effects exist (for eight of the nine brands);
- The dynamic effects can be substantial. Negative dynamic effects are indicative of acceleration effects which vary between 4 and 25 percent of the current sales effect, across the two categories and across different support activities for discounts. These numbers are consistent with the

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15. Although household-level data have their shortcomings (see also Table 1.6), it seems unlikely that these shortcomings would cause postpromotion dips. Therefore, we think it is appropriate to believe that purchase acceleration is a real phenomenon at the household level.
results from household-level studies which have found the acceleration effect to vary between 6 and 51 percent;

- The conclusion for researchers is that the postpromotion dip paradox does not have to exist: household-level studies and this store-level study find acceleration effects of comparable sizes;

- For managers, our results suggest that the results from models that accommodate only current sales effects from a promotion may be quite misleading. Managers should insist on obtaining the sum of the current and dynamic effects from a model that accounts for (1) purchase acceleration effects and (2) display extension effects.

- Given the complexity of dynamic sales promotion effects, it is advisable to use a flexible specification, such as the Unrestricted model or the Almon model. We find that the percent net gains (Tables 3.5.c and 3.6.c) are very similar for the Almon-, and Unrestricted models (while the Exponential decay model produces very different results). Overall, the Unrestricted model is the closest to the “best model” results. It is also the model that is easiest to implement.

A fundamental question is whether our methodology can show spurious dips, i.e., find dips when these dips do not exist in reality. This will not happen for theoretical and empirical reasons. The theoretical reason is that if there are no real dips, our model selection criterion (AIC) will choose the most parsimonious specification, i.e., the specification without dynamic effects. The empirical reason is that the graphs with actual and predicted sales do not show evidence of overestimation of the size of pre- and postpromotion dips.

An interesting future research issue in this context is the accommodation of within-store and between-store heterogeneity in models of store sales. Within-store heterogeneity can occur due to changes in the composition of the set of households that purchase items from the product category over time. The use of time-varying response parameters is one way to account for such effects. Between-store heterogeneity may result from customer-, assortment-, and other differences between stores. Even though we found no evidence in favor of this type of heterogeneity, it may be relevant for other categories. Hsiao, Appelbe, and Dineen (1993) provide a general framework for varying parameter panel data models.

From a substantive perspective, it will be useful to apply distributed lead- and lag models to other product categories to discover commonalities and idiosyncrasies. With results on a much larger number of items it should be
3.6. Conclusions

instructive to explore the effects of product category and brand measures, marketing activities (e.g., interpromotion periods and depth of price cuts) and consumer characteristics on the observed dynamics.