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By Scott A. Neslin and Harald J. van Heerde

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Scott A. Neslin[1] and Harald J. van Heerde[2]

[1] *Dartmouth College, Tuck School of Business, 100 Tuck Hall, Hanover, NH 03755, USA, scott.a.neslin@dartmouth.edu*

[2] *University of Waikato, Department of Marketing, Private Bag 3105, Hamilton 3240, New Zealand, heerde@waikato.ac.nz*

Abstract

Promotions affect sales after the immediate sales bump. In other words, they have dynamic effects on consumer purchase behavior outside the period of the promotional offer. The objective of this monograph is to present a comprehensive overview of the various dynamic effects of promotions. We believe there is an opportunity for such a monograph since the literature on dynamic promotion effects is vast and quite scattered. There have been so many researchers who have worked in this field across decades, using very wide-ranging terminologies, methodologies and data, that we believe there is a need to catalogue the current state of affairs. To keep the discussion centered on a common theme, we focus in particular on the dynamic effects of *price promotions*, (rather than non-price promotions) offered to *consumers* (rather than to the trade or to sales force).

1

Introduction

Firms spend a significant part of their marketing budgets on sales promotions. Promotion accounted for roughly 75% of marketing expenditures for US packaged goods manufacturers during 1997–2007, and the other 25% was for advertising (Trade Promotion, 2007). In 2007, 60% of the budget was spent on promotion to the trade (i.e., from manufacturers to retailers) and 14% on manufacturer promotions to consumers. Since the impact of promotions on sales is usually immediate and strong (Blattberg et al., 1995), promotions are attractive to results-oriented managers seeking to increase sales in the short term (Neslin, 2002). In a recent meta-analysis, Bijmolt et al. (2005) report that the average short-term sales promotion elasticity is -3.63, which implies that a 20% temporary price cut leads to a 73% rise in sales. There are few, if any, other marketing instruments that are equally effective.

Promotions also affect sales after the immediate sales bump. In other words, they have dynamic effects on consumer purchase behavior outside the period of the promotional offer. The objective of this article is to present a comprehensive overview of the various dynamic effects of promotions. We believe there is an opportunity for such an article since the literature on dynamic promotion effects is vast and quite scattered. There have been so many researchers who have worked in this field across decades using very wide-ranging terminologies, methodologies, and data that we believe there is a need to catalog the current state of affairs. To keep the discussion centered on a common theme, we focus in particular on the dynamic effects of *price promotions* (rather than non-price promotions) offered to *consumers* (rather than to the trade or to sales force). Price promotions are current-period temporary price reductions to enhance sales or loyalty. In contrast for example, loyalty programs often offer future discounts on a long-term basis. For a discussion of the particular dynamics that have been observed for loyalty programs, we refer to Blattberg et al. (2008).

We envision two target audiences for this article. The first is marketing students and marketing professionals seeking insights into the dynamic effects of promotions. For this audience, this article illustrates the dynamic effects with several graphs, shows what has been found in the literature, and indicates what managers can do with these findings. The second audience is academic researchers new to the promotions area who are interested in studying dynamic promotion effects. This audience hopefully not only benefits from model equations and the literature summary, but also derives inspiration from our suggestions for future research.

Our organization of the article reflects both these audiences. To illustrate the in-total six different dynamic promotion effects, we use as a device an econometric model of household purchase behavior. For each effect (each section) we follow the same structure. We start by showing the equation that accommodates the dynamic effect under consideration, and next we show in a graph how the effect shows up in simulations of the purchase behavior aggregated across households. Next we discuss the empirical findings on that effect based on the literature. Finally, we discuss each effect's managerial implications and future research avenues. Note that our emphasis is on discussing what the dynamic phenomena are and what we know about them. The econometric model serves as a vehicle for rigorously introducing each phenomenon. See Van Heerde and Neslin (2008) for a more detailed discussion of sales promotion modeling.

The dynamic effects covered in this article are the following. Promotions may lead to stockpiling and deceleration (Section 3) and state dependence (Section 4). Promotions may also affect reference prices, which affect subsequent purchase behavior (Section 5). Over time, after repeated exposure to price promotions, consumers may become more price sensitive (Section 6). Promotions may have permanent effects on consumer behavior (Section 7) and lead to competitive reactions (Section 8).

Before we start with discussing the different dynamic effects, we present in Section 2 the basic model without these dynamic effects. After that, we gradually expand the basic model with the components to capture each of the dynamic effects.

2

Basic Model Without Dynamic Effects

Promotions can influence category incidence, brand choice, and purchase quantity, and historically, these decisions have received the most attention. The models for these household-level decisions are based on household panel scanner data. Following Gupta (1988), we assume that the probability that household h buys q_{bt}^{h} units of brand b during week t is the product of three probabilities[1]:

$$P(Q_{bt}^{h} = q_{bt}^{h}) = P(I_t^h = 1) * P(C_t^h = b | I_t^h = 1) * P(Q_{bt}^{h} | I_t^h = 1, C_t^h = b), \tag{2.1}$$

where

$P(I_t^h = 1)$	is the probability that household h buys the category during week t (incidence),
$P(C_t^h = b \vert I_h^t = 1)$	is the probability that, conditional on incidence at t, household h buys brand b (choice), and

[1] We use "week" as the dynamic unit of analysis because we believe: (1) time is the best way to illustrate dynamics, (2) managers are more likely to see sales results in a time series, and (3) this provides a useful perspective relative to previous research that has often used purchase occasion or shopping trip as the unit of analysis.

$P(Q_{bt}^h = q_{bt}^h | I_h^t = 1, C_t^h = b)$ is the probability that, conditional on incidence and a choice to buy brand b during week t, the household buys q_{bt}^h units (quantity).

2.1 Incidence Model

Category incidence is modeled as a binary logit (e.g., Bucklin et al., 1998):

$$P(I_t^h = 1) = \frac{1}{1 + e^{-\,Utility\_of\_Incidence_t^h}}, \tag{2.2}$$

where the "utility of a purchase incidence" is given by:

$$Utility\_of\_Incidence_t^h = \gamma_0 + \gamma_2 \overline{CONS}^h + \gamma_3 INV_t^h, \tag{2.3}$$

where $\overline{CONS}^h$ is the household's average daily consumption, which is included to capture observed cross-sectional heterogeneity, and INV_t^h is the household's product inventory at the beginning of time t. We expect $\gamma_2 > 0$ because households with higher consumption rates should purchase more often, and $\gamma_3 < 0$ as a larger inventory decreases the necessity to buy from the category. We can operationalize INV_t^h as:

$$INV_t^h = INV_{t-1}^h + PurQty_{t-1}^h - \overline{CONS}^h, \tag{2.4}$$

where $PurQty_{t-1}^h$ is the category quantity purchased by household h during time $t - 1$.

In this simple initial model there is no effect of promotions on the incidence decision. Once we study the stockpiling effect (Section 3), we include a term that captures this effect.

2.2 Brand Choice Model

The probability that household h buys brand b at time t, conditional on buying in the category, is often given by a multinomial logit model (Guadagni and Little, 1983):

$$P(C_t^h = b | I_t^h = 1) = \frac{e^{Utility\_of\_Brand\_Choice_{bt}^h}}{\sum_{b'=1}^{B} e^{Utility\_of\_Brand\_Choice_{b't}^h}}, \tag{2.5}$$

where B is the number of brands and $Utility\_of\_Brand\_Choice_{bt}^{h}$ is the "deterministic component" of the utility of household h for brand b at time t (Guadagni and Little, 1983):

$$Utility\_of\_Brand\_Choice_{bt}^{h} = \beta_{0b}^{h} + \beta_{1b}^{h} Price_{bt}, \tag{2.6}$$

where β_{0b}^{h} is a brand-specific intercept (heterogeneous across consumers) and $Price_{bt}$ is the net price of brand b at time t. For expositional purposes, we assume that there are only price promotions (reflected in temporary decreases in the $Price_{bt}$ variable) and no non-price promotions such as feature and display. Of course, Equation (2.6) can easily be expanded to include non-price promotions.

2.3 Purchase Quantity Model

Given purchase incidence and choice of brand b, the probability that household h buys $q_{bt}^{h} = 1, 2, \ldots, n$ units in week t is captured by a Poisson model with a truncation at the zero outcome (Bucklin et al., 1998). This can be written as:

$$P(Q_{bt}^{h} = q_{bt}^{h} | I_t^h = 1, C_t^h = b) = \frac{\exp(-\lambda_t)(\lambda_t)^{q_{bt}^{h}}}{[1 - \exp(-\lambda_t)] q_{bt}^{h}!}, \tag{2.7}$$

where λ_t is the purchase rate (number of units) of household h for brand b in week t. This parameter is initially modeled as just an intercept for the selected brand:

$$\lambda_t = \phi_1. \tag{2.8}$$

This purchase quantity model does not yet include the effects of price promotions and so does not initially vary over time. When we add stockpiling to the model (Section 3), λ will vary over time.

We use models (2.1)–(2.8) to simulate purchases across 10,000 households. The appendix shows the parameter values we use in the simulation. Figure 2.1 shows the sales pattern of the focal brand and its single competitor over time, as well as total category sales, for *the basic model without any promotion dynamics*. During promotions, we can clearly identify peaks in the promoted brand's sales as well as

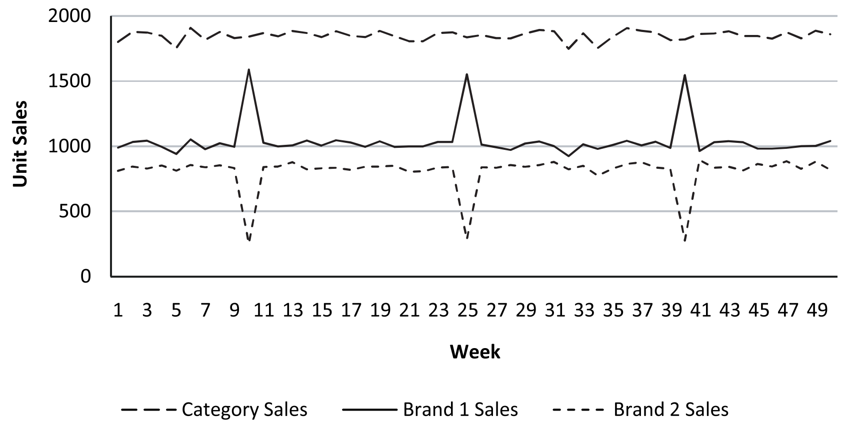

Fig. 2.1 Base case simulation of equations (2.1)–(2.8): No Dynamic Promotion Effects.

dips in the competitor's brand sales. Category sales are essentially flat, because there is no effect of promotions on the incidence or quantity decision in this initial model. Hence the promotional bumps comprise 100% brand switching effects in Figure 2.1.

3

Stockpiling and Deceleration

3.1 Illustration

Promotions can induce consumers to purchase earlier than otherwise (purchase acceleration), purchase extra quantity of the product, or defer purchase until a promotion is available (purchase deceleration). We refer to acceleration and quantity effects as *consumer stockpiling*.

3.1.1 Consumer Stockpiling

The theoretical motivation for stockpiling is that consumers' trade off inventory costs versus price (Blattberg et al., 1981; Krishna, 1992). If the discounted price is sufficiently low, consumers decide to purchase earlier or more than without the discount, and stock the extra product inventory in their homes.

Purchase Acceleration. To capture the purchase acceleration effect on incidence, we need to expand Equation (2.3) by adding the "inclusive value" $InclValue_t^h$, which in a nested logit framework is the maximum expected utility available to household h from buying a brand in the category in week t. It is given by the log of the denominator of the brand choice probability: $InclValue_t^h =$

$\ln\left(\sum_{b'=1}^{B} e^{Utility\_of\_Brand\_Choice_{bt}^{h}}\right)$ (see Equation (2.5).[1] This yields:

$$Utility\_of\_Incidence_t^h = \gamma_0 + \gamma_1 InclValue_t^h + \gamma_2 \overline{CONS}^h + \gamma_3 INV_t^h. \tag{3.1}$$

If $\gamma_1 > 0$ in Equation (3.1), promotions accelerate the purchase timing decision, which is one manifestation of stockpiling.

Figure 3.1 shows the results of the simulation that accounts for purchase acceleration by using Equation (3.1) for the incidence decision instead of Equation (2.3). One key change compared to Figure 2.1 without dynamic effects is that category sales now expand during promotions. Hence brand switching no longer constitutes 100% of the promotional bump. Moreover, the promotional spikes in brand sales promotions are now followed by post-promotion dips in category sales as well as brand sales. This is because several households have shifted purchases forward in time that would have occurred later but now occur in the promotion week. It is easier for households to do this who would have purchased in the next week after the promotion, because their

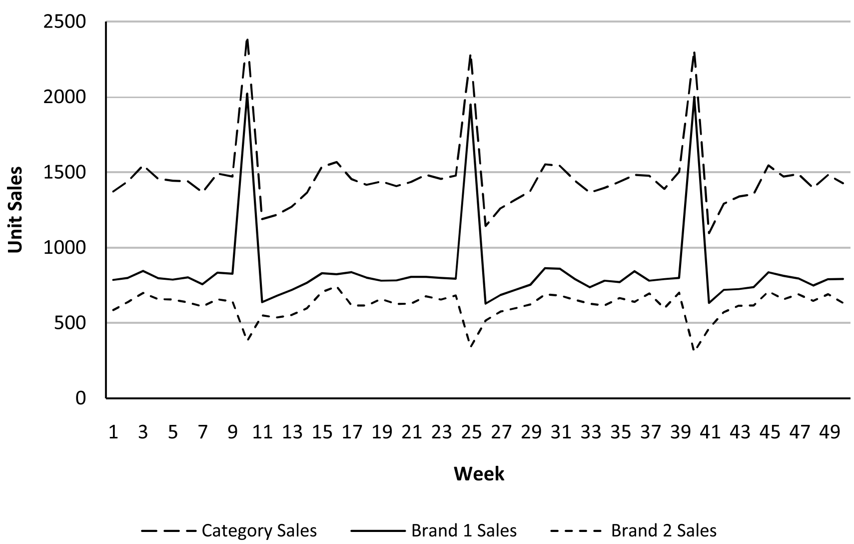

Fig. 3.1 Purchase acceleration effect.

[1] The derivation of the inclusive value and its place in the purchase incidence models can be derived from a "nested" logit framework (e.g., see Bucklin et al., 1998).

inventory levels dictated that they had almost run out of the product. This is why we get a dip immediately after the promotion.

Increased Purchase Quantity. The second manifestation of stockpiling is through increased purchase quantity. To capture this, we augment the purchase rate parameter λ_t at time t with the price of the selected brand:

$$\lambda_{bt} = \phi_1 + \phi_2 Price_{bt}. \tag{3.2}$$

A $\phi_2 < 0$ ensures that a price discount increases the purchase quantity.

Figure 3.2 shows simulated sales without an acceleration effect ($\gamma_1 = 0$) but allowing for an effect on purchase quantity via Equation (3.2). Again, a key change compared to Figure 3.1 without dynamic effects is that category sales now expand during promotions. Moreover, the promotional spikes in brand sales promotions are now followed by post-promotion dips. However, while purchase acceleration leads to dips right after the promotion (Figure 3.1), the dips due to the increased purchase quantity effect only happen a few weeks after the promotion (Figure 3.2). The reason for this difference is that as noted earlier, purchase acceleration brings in consumers who would have purchased right

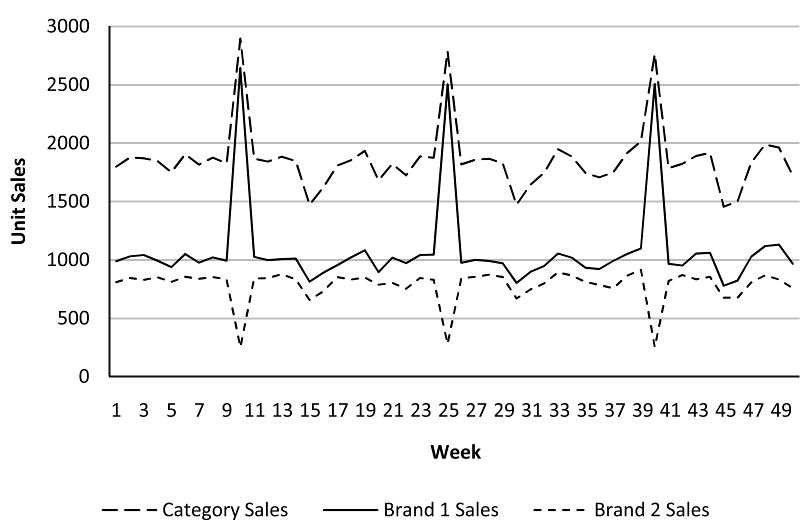

Fig. 3.2 Increased purchase quantity effect.

after the promotion (weeks $t+1, t+2, \ldots$). In contrast, the increased quantity effect does not mean that more consumers buy in the category. Instead, those consumers who already had decided to buy the category decide to buy more than otherwise due to the promotion. This sales increase displaces sales that would have occurred roughly one interpurchase time after the promotion. For example, the customer who would have purchased one unit in weeks 10, 15, 20, and 25, now purchases two units in week 10 (the promotion week), and can skip week 15, resuming again in week 20. As a result, the dip due to the increased quantity effect happens a few weeks after the promotion.

3.1.2 Increased Consumption

The most common assumption is that $\overline{CONS}^h$ represents the constant consumption rate of household h. However, Ailawadi and Neslin (1998) propose that the consumption rate for household h at time t ($CONS_t^h$) flexibly varies over time as a function of inventory:

$$CONS_t^h = INV_t^h \left[\frac{\overline{CONS}^h}{\overline{CONS}^h + (INV_t^h)^f} \right]. \tag{3.3}$$

This means that promotion-induced stockpiling can increase category consumption (see also Sun, 2005). If households stockpile on promotion but increase their consumption rates depending on their inventory levels, at the next purchase occasion these inventory levels could be down to similar levels as without a promotion. Hence increased consumption may lead to weaker post-promotion dips. We illustrate this point in Figure 3.3. To obtain this figure we have kept purchase acceleration intact by using Equation (3.1) with $\gamma_1 > 0$, but we replace the inventory model that assumes a fixed consumption rate (2.4) by an inventory model with the varying consumption rate $CONS_t^h$ from Equation (3.3):

$$INV_t^h = INV_{t-1}^h + PurQty_{t-1}^h - CONS_{t-1}^h. \tag{3.4}$$

Similar to Figure 3.1, Figure 3.3 shows a post-promotion dip, but category sales return more quickly to normal than in Figure 3.1. The reason is that additional consumption occurs in period $t+1$. That is, consumers buy in period t, boosting up their inventory for period

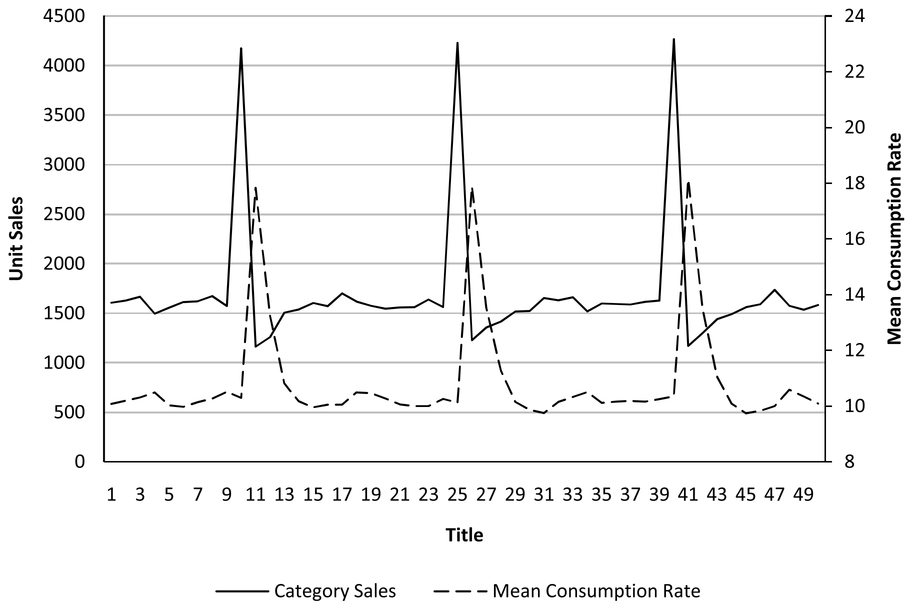

Fig. 3.3 Increased consumption effect.

$t+1$ so they don't buy in period $t+1$. However, they do consume in period $t+1$ so by period $t+2$, consumers are back to a normal buying pattern. In other words, while there is a dip during the week that people consume, they soon return to normal inventory and so the dip is not nearly as prolonged: consumers come back into the market sooner than in the pure purchase acceleration case (Figure 3.1).

3.1.3 Deceleration

Deceleration is motivated by consumer expectations (Krishna, 1994a,a; Gönül and Srinivasan, 1996; Mela et al., 1998). When a consumer learns that promotions are regularly available, she/he can defer the purchase till the next promotion. To capture deceleration in our purchase model, we augment the incidence model with the effect of the time since the last promotion ($TimeSinceLastPromo$):

$$\begin{aligned} Utility\_of\_\text{Incidence}_t^h = {} & \gamma_0 + \gamma_1 InclValue_t^h + \gamma_2 \overline{CONS}^h + \gamma_3 INV_t^h \\ & + \gamma_4 TimeSinceLastPromo_t^h, \end{aligned} \tag{3.5}$$

where $TimeSinceLastPromo_t^h = \sum_{b=1}^{B} w_{hb}\, TimeSinceLastPromo_{bt}^h$, which is the weighted sum of the time since last promotion for each of the brands, weighed by the household's purchase share of each brand. The idea is that the longer ago there was a promotion in the category, the more likely it is that there will be one soon. $TimeSinceLastPromo_{bt}^h$ decreases the likelihood that the household wants to buy in the category now, and hence $\gamma_4 < 0$. The $TimeSinceLastPromo_{bt}^h$ variable is reset to zero in week t if there is a promotion for brand b in that week.

Figure 3.4 shows simulated sales when consumers decelerate their purchases prior to promotions. In the weeks immediately prior to the second and third promotions we can clearly see evidence for pre-promotion dips. As expected, there is no such pre-promotion dip before the first (ever) promotion as this promotion was not anticipated by consumers. Only after this first promotion, consumers start anticipating the next one, which is captured in our model via the time since last promotion variable. At the next promotion, so many consumers have postponed purchasing the product for so long that the response to the

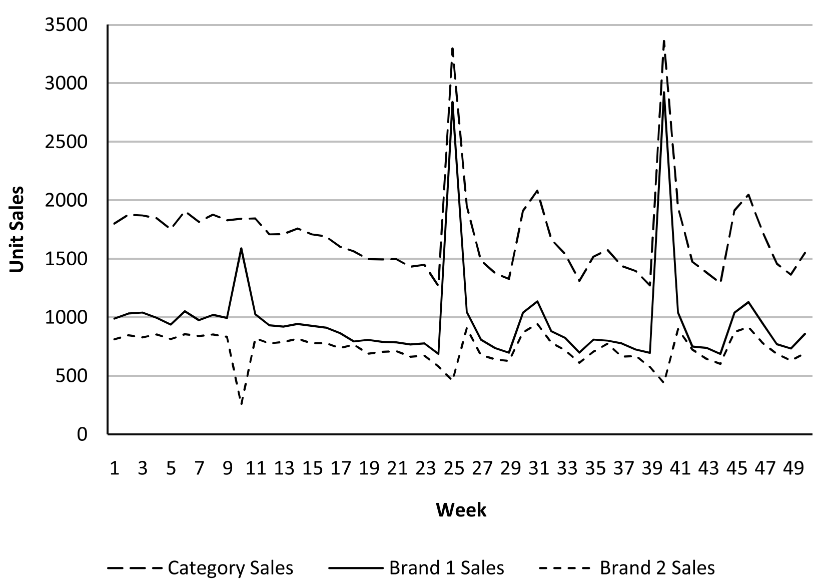

Fig. 3.4 Deceleration effect.

promotion is huge. That is the reason that the spike at the second and third promotion is considerably higher than for the first promotion.

Figure 3.5 shows what happens if we combine purchase acceleration, increased purchase quantity, and deceleration. Figure 3.5a shows the

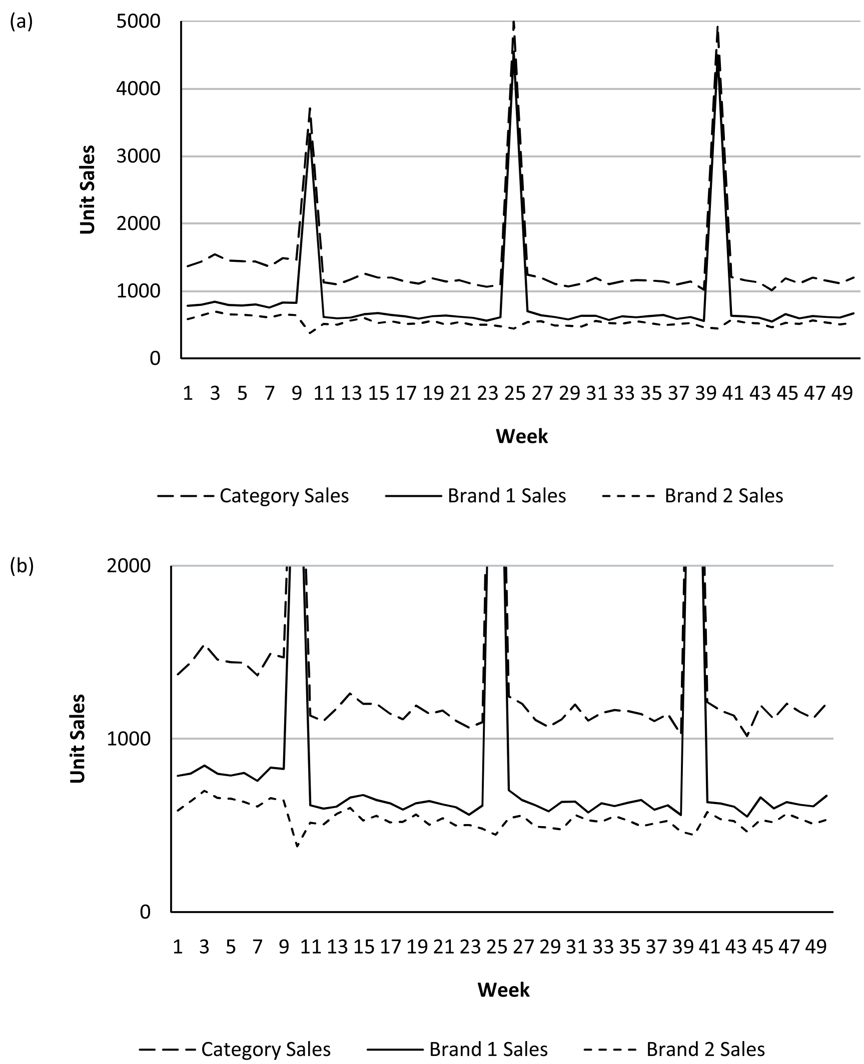

Fig. 3.5 Combined purchase acceleration, increased purchase quantity and deceleration effect. (a) Full view; (b) Zoomed view.

full view with very strong promotional spikes. The reason is that each of these three effects contributes to the current promotion effect. Due to the scale of the vertical axis, the dynamic pre- and post-promotion effects are not entirely evident. That is why Figure 3.5b provides a close-up view. Figure 3.5b shows some evidence for immediate post-promotion dips (due to purchase acceleration; Figure 3.1), for delayed post-promotion dips (due to increased purchase quantity; Figure 3.2) and for pre-promotion dips due to deceleration effects (Figure 3.4). As we required a "zoomed view" to begin to discern pre- and post-promotion dips when all stockpiling and deceleration effects are operative, statistical analysts using time series data must use large sample sizes and carefully craft lag structures that capture these effects (see e.g., Van Heerde et al., 2000).

3.2 Empirical Findings

3.2.1 Stockpiling

The empirical support for stockpiling is strong, and it is one of the few promotion effects that has been documented for durables as well as packaged goods. For durables, Doyle and Saunders (1985) found that promotions accelerate purchases of furniture, while Thompson and Noordewier (1992) found that rebates accelerated purchase of automobiles. For packaged goods, Shoemaker (1979) and Wilson et al. (1979) reported early evidence on stockpiling. They concluded that promotions were associated with shorter interpurchase times (from the previous purchase to the current promotion purchase) and larger purchase quantities. Similar evidence was found by Blattberg et al. (1981). Neslin et al. (1985) capture these results in a two-equation model:

$$\text{Purchase Quantity} = f(\text{Promotion}, \text{Inventory}, \text{Interpurchase Time})$$
$$\text{Interpurchase Time} = f(\text{Promotion}, \text{Inventory})$$

Purchase quantity was hypothesized to be positively related to promotion and interpurchase time, and negatively to inventory. Interpurchase time was hypothesized to be negatively related to promotion and positively to inventory. Neslin et al. (1985) found that featured price cuts increased purchase quantities and decreased interpurchase times.

Subsequent studies have developed more formal models for purchase incidence and quantity (Gupta, 1988; Jain and Vilcassim, 1991; Bucklin and Gupta, 1992; Chintagunta, 1993; Bucklin et al., 1998; Mela et al., 1998). These models also support the existence of stockpiling. Rather than studying interpurchase times, this research typically examines whether a category purchase occurs in a given time period (using a model for purchase incidence utility similar to Equation (3.1)). Note that a significant promotion effect (on either incidence or interpurchase time) is necessary evidence of acceleration, but not sufficient. This is because a significant incidence effect could represent an increase in category consumption (Neslin and Schneider Stone, 1996).

Inventory (INV_t^h) plays a key role in stockpiling. Through this variable, a larger promotion-induced inventory delays a household's first purchase incidence after the promotion. Chandon and Wansink (2006) question whether the actual inventory levels or estimated inventory levels are the best way to operationalize the inventory variable. Based on two lab experiments and two field studies across 29 product categories, Chandon and Wansink (2006) conclude that subjective inventory *estimates*, not actual inventory levels, drive subsequent purchase incidence.

While most studies look at the incidence and quantity effects of promotions for single items, Foubert and Gijsbrechts (2007) consider bundle promotions: discounts when a consumer purchases a set of products. For example, a yogurt brand could offer a discount if the consumer buys three units from a range of flavors. Foubert and Gijsbrechts (2007) find that bundle promotions have relatively weak effects on incidence and quantity decisions. Instead, promotional bundling is particularly effective for stimulating switching behavior.

3.2.2 Decomposition of the Promotional Bump

In a seminal paper, Gupta (1988) decomposed the sales elasticity due to promotion for coffee into brand switching (84%), purchase timing acceleration (14%), and increased purchase quantity (2%). Chiang (1991) obtains similar percentages. Bell et al. (1999) decompose the sales elasticity for 13 product categories and find that, on average, brand choice accounts for 75% of the total elasticity (range 49–94%). Thus, the percent attributable to purchase timing acceleration and increases in purchase quantity varies between 6 and 51%.

While interpreting these results, it is important to note that there are two fundamental approaches to calculating the decomposition of sales promotion effects, the “elasticity” approach and the “unit sales” approach. The elasticity approach was originated by Gupta (1988). It is based on the mathematical relationship that the elasticity of the probability of buying brand b at time t with respect to price promotion equals the sum of the elasticities of brand choice, purchase incidence, and purchase quantity with respect to price promotion. So for example, a total elasticity of -3 may be decomposed into a -2.25 brand choice elasticity (75%), a $-.45$ incidence elasticity (15%), and a $-.3$ purchase quantity elasticity (10%).

Conversely, the unit sales decomposition splits the total sales promotion bump (measured in unit sales rather than elasticity) into sales losses of other brands in the category and growth in category sales (Van Heerde et al., 2003). So for example, a brand gains 100 units during a promotion, competitor brands lose 35 units, and the category expands by 65 units. The unit sales decomposition then attributes 35% of the bump to brand switching effects and 65% to category expansion effects.

Research that is based on decomposing the elasticity concludes that brand switching (brand choice elasticity) accounts for the major part of the bump (75%), whereas temporary category expansion (purchase incidence and quantity elasticities) comprises the remaining 25%. However, Van Heerde et al. (2003) argue that looking at elasticities does not give the full picture, and the opposite conclusion emerges when these results are expressed in unit sales.

The rationale is as follows. A promotion leads to a “bigger pie”: a temporary increase in that week’s sales for the entire category (captured via the incidence effect). During this week, competitor brands suffer from a “smaller slice of the larger pie”: a temporarily lower percentage share (captured via the brand choice effect). While the elasticity decomposition only looks at the change in the conditional choice share to calculate brand switching effects, the unit sales decomposition acknowledges that the counteracting force of the incidence effect mitigates the net sales loss for competitor brands. As a consequence, a 100-unit promotional sales bump for a brand only leads on average to a 33-unit (rather than 75-unit) sales loss for competitor brands and a 67-unit (rather than 25-unit) increase in category sales during the promotional week. Hence, Van Heerde et al. (2003) conclude that only 33% of the sales promotion bump is due to brand switching instead of 75%. The remaining 67% is due to incidence and quantity effects. Van Heerde et al. (2004), based on an aggregate model for the unit sales decomposition, arrive at very similar brand switching percentage (31%), while the cross-period effect (stockpiling and deceleration) constitutes 34% and the category expansion effect 33%. Steenburgh (2007) provides additional discussion of the difference between the elasticity and unit sales decompositions.[2]

3.2.3 Post-promotion Dips in Aggregate Data

Logic, as well as Figures 3.3 and 3.4, dictates that if consumers are stockpiling, there should be a dip in category or brand sales in the weeks following a promotion, as consumers work through their inflated inventory. A mystery in promotion analysis, however, was that studies of weekly supermarket scanner data often did not find such dips (Moriarty, 1985; Wittink et al., 1987; Abraham and Lodish, 1993; Neslin and Schneider Stone, 1996).

Neslin and Schneider Stone (1996) posited several potential explanations for the lack of a post-promotion dip. These included deal-to-deal buying, increases in consumption, competitive promotions, positive repeat-purchase effects canceling the post-promotion dip, retailers extending promotions beyond the period officially indicated in the data, mixing acceleration and quantity effects, lack of consumer inventory sensitivity, and deceleration masking acceleration. Undoubtedly all these phenomena are present in weekly data and make it difficult to measure post-promotion dips.

Work by Van Heerde et al. (2000) shows that careful time-series regressions with large sample sizes can uncover post- as well pre-promotion dips. Van Heerde et al. (2000) investigated nine brands in

[2] Van Heerde and Bijmolt (2005) present a unit sales decomposition that splits the promotional bump into contributions by members of a loyalty program and non-members.

two product categories. They found evidence for both stockpiling and deceleration. They found that the dynamic sales effect (stockpiling plus deceleration) ranged from 3.6%–25.1% of the average brand's current promotion effect.

Macé and Neslin (2004) used the same approach to study how UPC, category, and store clientele characteristics were associated with the degree of acceleration or deceleration. They examined over 30,000 UPCs in 83 stores in 10 categories. They found that both stockpiling and deceleration are stronger for high-priced, frequently promoted, and high market-share brands. They found that better educated households, households with cars, and households living in higher-valued housing are particularly prone to deceleration. Lower-income households, larger households, households with working women, and households with cars are heavier stockpilers. Chan et al. (2008) find that with price promotions, brand loyals mainly stockpile for future consumption, whereas brand switchers tend not to stockpile. They also find that in response to a price promotion, light users increase consumption more, whereas heavy users stockpile more for future consumption.

3.2.4 Deceleration

Doyle and Saunders (1985) found evidence for deceleration effects, which they attributed to salespeople telling their clients of an upcoming promotion. They examined monthly gas appliance sales as a function of 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% 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. Mela et al. (1998) found that consumers decreased their baseline purchase incidence rates and purchased greater quantities as promotion levels increased over time. This is consistent with deceleration. Moreover, the pre-promotion dips identified in Van Heerde et al. (2000) and Macé and Neslin (2004) are also consistent with deceleration effects. Notwithstanding these results, research studying deceleration effects at the individual level is very scarce.

3.2.5 Consumption

The mechanism for consumption rate is that promotion induces higher household inventories, which encourage consumers to use a product at a faster rate. If the household has one container of ice cream in the house, it may use ice cream at a rate of one container per week. However, if there are two containers in the house, the household might use one and a half containers per week. This mechanism is supported by several theories. Assunção and Meyer (1993) demonstrate that higher inventory levels allow the consumer to consume at any desired rate, without having to worry about going back into the store and possibly paying a high replacement price. Folkes et al. (1993) find support for scarcity theory, which states that smaller quantities are perceived as more valuable and therefore consumed more slowly (Wansink, 1996, see also). Wansink and Deshpande (1994) provide evidence that higher inventory levels create higher in-home awareness of the product, and therefore it is consumed more often. Soman and Gourville (2001) and Gourville and Soman (1998) propose that stockpiling can influence consumers' perceptions of the sunk costs of their inventory investment, and hence influence usage rates.

Ailawadi and Neslin (1998) attempt to investigate the usage-rate mechanism. Similar to other researchers, they calculate current consumer inventory as previous inventory plus new purchases minus consumption. However, while previous researchers assumed the consumption rate was constant, Ailawadi and Neslin allow consumption rate to be a function of inventory, reflecting the usage-rate mechanism (see also Equation (3.3)).

Ailawadi and Neslin (1998) find that yogurt consumption changes flexibly as a function of inventory, whereas ketchup consumption is less flexible. The authors conduct simulations that reveal for the yogurt category that 35% of the total effect of a promotion on brand sales represents increased consumption. This figure is close to the 43% increased consumption effect for yogurt reported by Sun (2005). Ailawadi and Neslin's (1998) corresponding figure for ketchup was 12%, while Sun's (2005) result for canned tuna was 33%. Silva-Risso et al. (1999) estimate Ailawadi and Neslin's model for spaghetti sauce and find consumption is not very flexible, similar to ketchup. Bell et al. (1999)

provide additional evidence for the usage-rate mechanism for bacon, potato chips, soft drinks, and yogurt.

Chan et al. (2008) complement the decomposition of the promotion bump by adding increased consumption effects. They use the unit sales decomposition method advocated by Van Heerde et al. (2003). For canned tuna (paper towels), the consumption effect is 29% (18%) of the bump, the brand switching effect is 28% (14%), and the stockpiling effect is 43% (69%). Hence, once again, the unit sales decomposition method estimates relatively small brand switching effects.

In sum, there is ample evidence for stockpiling in the literature and some evidence for increased consumption effects. While research on deceleration effects at the household level is very scarce, there is some evidence for its manifestation through pre-promotion dips at the aggregate level.

3.3 Managerial Implications

In its purest form, stockpiling implies that a brand is purchased during the promotion at the (lower) promotional price rather than at a (higher) non-promotional price after the promotion. Similarly, pure deceleration means that the consumer avoids paying the (higher) pre-promotional price and buys at the promotion with a discount instead. Hence, pure stockpiling and deceleration imply that purchases are shifted toward the promotional period either from the post-promotion period (due to stockpiling, see Figures 3.1 and 3.2) or from the pre-promotion period (due to deceleration, see Figure 3.4). As a consequence, over the full time horizon (pre-, during-, and post-promotion) there is little sales gain for the retailer or manufacturer, while there is a loss of profit margin due to the lower promotional price. From this point of view, stockpiling and deceleration are negative effects that manufacturers and retailers may want to avoid. Reducing the frequency and predictability of promotions are ways to achieve that (Foekens et al., 1999; Macé and Neslin, 2004).

However, there is a rationale why even pure stockpiling could be beneficial for retailers and manufacturers. It allows them to shift the costs of storing products to consumers (Blattberg et al., 1981). The decrease in storage costs may compensate for the loss of profit margin on promotional items.

This windfall is further enhanced if stockpiling is followed by an increase in the consumption rate. Increased consumption rates imply that the stockpiled inventory is consumed faster, and that the additional units sold on promotion are really providing net gains for retailers and manufacturers across the full time horizon (remember the relatively shallow post-promotion dips in Figure 3.3). Obviously, being aware of this possible benefit of promotions, historically retailers and manufacturers have been much more keen on promoting categories for which consumption rates can be easily accelerated (e.g., chocolate, ice cream, soft drinks) than categories with very little scope for increased consumption (e.g., salt, vacuum cleaner bags, coffee filters).

There is yet another way in which stockpiling may actually be beneficial for manufacturers and retailers, and that is through "preemptive switching". Preemptive switching means that the stockpiled inventory prevents consumers from buying competitor brands in the post-promotion period. As a consequence, only part of the post-promotion dip is felt by the focal brand, while the rest is spread across other brands. Similarly, extra inventory may prevent consumers from buying the same product category from other retailers, thereby mitigating the post-promotion dip felt by the focal retailer. This is why retailers often implore shoppers to "stock up and save." Further support for the positive side of stockpiling for manufacturers is that it may have a positive impact on brand loyalty (Ailawadi et al., 2007a; see discussion in Section 4.2).

In conclusion, while the common managerial point of view toward stockpiling is negative, there are several reasons why it should be viewed as positive, both for manufacturers and retailers. Further work is needed to weigh the plusses and minuses of stockpiling.

3.4 Future Research

It is fair to say that there has been a massive amount of research on stockpiling. Research on increased consumption is a bit more scattered. While Ailawadi and Neslin (1998), Sun (2005), and Chan et al.

(2008) show encouraging evidence for the faster usage-rate mechanism, a large cross-category study is needed to generalize these results. Nijs et al. (2001) found that promotion increases category demand in 58% of the 560 product categories they analyzed. They did not investigate the various mechanisms for increasing consumption, but their results suggest that the effect of promotion on consumption is extensive.

Deceleration is an under-researched dynamic promotion effect. While Ailawadi and Neslin (1998), Sun (2005), and Chan et al. (2008) studying two dynamic effects (stockpiling and increased consumption), they do not explicitly measure deceleration effects. Capturing deceleration effects in a household-level study alongside stockpiling, increased consumption, and brand switching would allow us to assess their relative magnitudes. It would also help us to solve the puzzle of the empirical importance of preemptive switching.

A final important topic is to understand the dynamics of category complementarity and substitution due to promotion. Several papers (Leeflang et al., 2008; Ailawadi et al., 2006, 2007b; Song and Chintagunta, Song and Chintagunta (2006); Wedel and Zhang 2004; Manchanda et al., 1999; see Neslin, 2002 for further references), have demonstrated that promotions in Category A can increase sales in Category B (complementarity or halo effect) or decrease them in Category C (substitution effect) in the week of the promotion. Do the complementarity effects represent accelerated sales of Category B? For example, a promotion for spaghetti sauce may increase sales of spaghetti. Would those sales have occurred anyway in future weeks? Do the substitution effects represent decelerated sales of Category C? For example, the spaghetti sauce promotion may decrease sales of macaroni and cheese. But do those sales of macaroni and cheese simply take place next week rather than in the current week? The answers to these questions have important implications for the net store-wide profitability of promotions.

4

State Dependence

4.1 Illustration

State dependence is the degree to which current choice affects future utility. Choosing Brand A in this period may increase the utility provided by Brand A in the future, thus increasing the probability it will be purchased again. There are several reasons why consumers may exhibit state dependence: (1) *learning:* the customer learns more about the attributes and/or performance of Brand A after purchasing it, (2) *inertia:* it may be cognitively easier to stay with the brand last purchased; the consumer may not see the value of investigating another brand considering the effort involved, (3) *switching costs:* even if another brand appears to be better, it isn't worth the hassle costs of switching to it, and (4) *variety seeking:* consumers may innately derive pleasure from switching brands, just for the sake of trying something new. Inertia and switching costs result in positive state dependence: choosing Brand A now enhances the likelihood of choosing it at the next purchase occasion. Learning may increase or decrease the likelihood of subsequent purchase, depending on what is learned. Variety seeking by definition decreases the likelihood of purchasing Brand A at the next purchase occasion.

There are many ways to model state dependence, but probably the most common way is to include a lagged purchase indicator $Last_{bt}^{h}$ in Equation (2.6):

$$Last_{bt}^{h} = 1, \text{ if HH } h \text{ bought brand } b \text{ on the last purchase occasion;} \quad 0, \text{ otherwise.} \tag{4.1}$$

As a result, we have the following equation:

$$Utility\_of\_Brand\_Choice_{bt}^{h} = \beta_{0b}^{h} + \beta_{1b} Price_{bt} + \beta_{3} Last_{bt}^{h} \tag{4.2}$$

Figure 4.1 shows the simulated impact of state dependence on sales over time. Figure 4.1a shows three promotions when β_3 is set to 0.90.

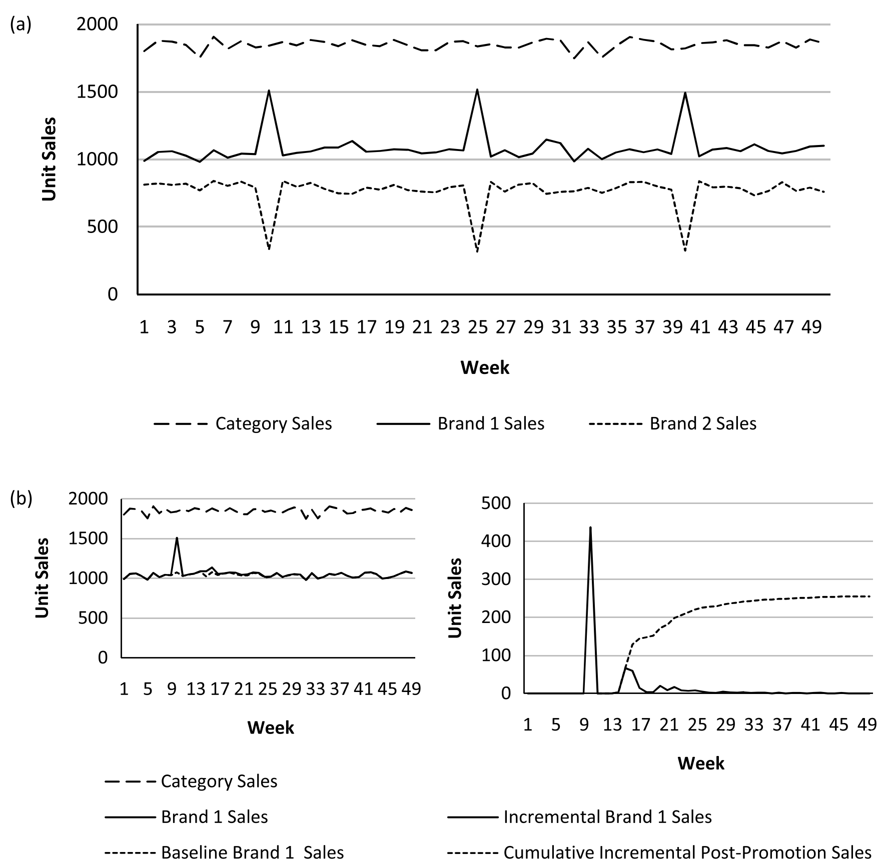

Fig. 4.1 The impact of promotion in the presence of state dependence. (a) Three promotions; (b) One promotion.

Sales increase roughly six weeks after the first promotion (one inter-purchase period), and in general increase throughout. By the end of the data, the gap between Brand 1 and Brand 2 has clearly widened. This is due to the buildup in repeat purchases for Brand 1 due to state dependence. Figure 4.1b shows more clearly the post - promotion incremental sales generated by a single promotion in the presence of state dependence. The left graph of Figure 4.1b shows the impact of the first promotion in Figure 4.1a. The solid line represents the simulated sales level. The dotted line visible in the week of the promotion, but difficult to discern in succeeding weeks, represents baseline sales (simulated sales without the promotion). The right graph of Figure 4.1b subtracts the baseline from simulated promotion sales to produce incremental sales. Figure 4.1b also shows cumulated incremental sales. We see (1) the post-promotion incremental sales are strongest roughly one interpurchase time after the promotion and decline thereafter, and (2) cumulative sales reach 254 units, more than half the promotion-period incremental sales. Thus, state dependence may be an important dynamic promotion effect for brands.

The existence of state dependence means that promotions have an impact on brand preference that goes beyond the promotion purchase occasion. This has crucial implications for the profitability of promotions as well as for overall promotion strategy. Therefore, it is not surprising that a huge amount of research has gone into verifying whether the phenomenon is real. The challenge is that it cannot be observed easily in aggregate data since the effect in a given week may not be particularly large, and therefore is easily masked by random variation (not to mention other phenomena such as reference prices or stockpiling). For this reason, state dependence is most commonly measured using household panel data. Even then, there are two potential confounds in estimating β_3: temporal and cross-sectional.

The temporal confounds include carryover from marketing instruments such as promotion or advertising and serial correlation in unobserved factors (e.g., the weather, advertising, or changes in the consumers' circumstance such as entertaining visitors for a sustained period of time). Three key studies have investigated these issues and still found β_3 to be statistically significant. Roy et al. (1996) partial out the impact of lagged choice variables from serial correlation and find both to be present. Erdem and Sun (2001) consider lagged choice variables and marketing carryover and find state dependence in five of six product categories. Seetharaman (2004) provides the most comprehensive analysis of potential temporal confounds to date. He considers lagged choice as well as marketing carryover and two forms of serial correlation, and still finds significant state dependence. It appears safe to conclude that findings state dependence exists apart from other dynamic effects. Having said this, Seetharaman warns that omitting other forms of dynamics can result in over-estimation of the state dependence effect.

The cross-sectional confound, also known as "spurious state dependence," is that heterogeneity in consumer preferences or even in marketing response can become confounded with state dependence. If one does not account for preference heterogeneity, the state dependence variable ($LAST$) will pick up that effect because there is a positive correlation between preference and $LAST$. In marketing, this issue was first discussed by Frank (1962) and Kuehn (1962) and elaborated by Neslin and Shoemaker (1989). The most vivid demonstration of the potential biases of not controlling for customer heterogeneity was the simulation work by Abramson et al. (2000). As a result, it is deemed a requirement in choice modeling to control elaborately for heterogeneity (both observed and unobserved).

Several papers have shown that state dependence still is found even after controlling for heterogeneity. Three of the most noteworthy are Keane (1997), Horsky et al. (2006), and Goldfarb (2006). Keane considered several forms of unobserved heterogeneity, e.g., heterogeneity in consumer tastes for various attributes, as well as serial correlation (see above discussion on temporal confounds). He tested 16 models in all. However, the coefficient for lagged choice remained significant and positive.[1] Horsky et al. (2006) considered both unobserved and observed preference heterogeneities. Key to their analysis was the availability of survey-based measures of brand preference. These measures are

[1] Keane used the $BLOY$ variable, an exponentially smoothed function of previous choices, proposed by Guadagni and Little (1983).

extremely valuable because they address the concern that controls for unobserved heterogeneity may themselves be inaccurate because they are still latent error terms that by definition are correlated with observed variables (e.g., $LAST$). Horsky et al. still find state dependence. Finally, Goldfarb (2006) provides even more transparent evidence for state dependence in the face of heterogeneity. He models Internet portal choice and has upwards of 1,000 observations per household. Therefore he had enough degrees of freedom to run separate choice models for each customer, eliminating the need for statistical controls for heterogeneity. He found that lagged portal choice was statistically significant for 74% of households, supporting state dependence.

In summary, state dependence appears to be a real phenomenon–current choice influences future choice.

4.2 Empirical Findings

4.2.1 State Dependence Is Positive

While as discussed earlier, state dependence could have either a positive or negative impact on future purchasing, the almost universal finding is that state dependence is positive ($\beta_3 > 0$, see the references in this section). One exception is the work of Bawa (1990). Another is Zhang and Krishnamurthi (2004) who allow state dependence to vary over time, and while it is usually positive, can dip into negative territory (see Figure 2.1, p. 571 of their paper). The predominance of positive state dependence suggests either that consumers learn positive things about the products they buy, or through either inertia or switching costs, become creatures of habit.

4.2.2 The Impact of Promotion Purchases on State Dependence

Perhaps the most important empirical finding regarding promotions and state dependence is that the degree of state dependence changes if the consumer buys on promotion. This was first noted by Guadagni and Little (1983) and articulated by Blattberg and Neslin (1990) as the "purchase effect" (state dependence) and the "promotion usage effect" (impact of promotion on state dependence). There are several reasons to suspect that buying on promotion may affect the magnitude, and even sign, of state dependence. Self-perception theory suggests that if the consumer concludes he or she bought the brand because of the promotion rather than brand preference, purchase event feedback will be weakened (Dodson et al., 1978). Behavioral learning theory (Rothschild and Gaidis, 1981) suggests promotion purchasing could enhance or detract from purchase event feedback. The effect could be positive if the promotion serves as a reward and thus encourages future purchasing, or negative if promotion merely trains consumers to buy on promotion.

To investigate this, Gedenk and Neslin (1999) develop a feedback model that distinguishes whether or not the last purchase was made on promotion. They find that price promotions detract from feedback but the net effect is still positive. This finding is the same as originally reported by Guadagni and Little (1983)–a promotion purchase is less reinforcing than a non-promotion purchase, but better than no purchase at all. It is also the same as found by Seetharaman (2004). Gedenk and Neslin also find that non-price promotions do not detract from state dependence–feature promotions have no effect and product samples actually increase state dependence.

The simplest way to include the impact of promotion on state dependence is through by creating an interaction term between $LAST$ and lagged promotion, e.g.,

$$\begin{aligned}&\mathit{LastPromo}_{bt}^{h} = 1, \text{ if household } h \text{ bought brand } b \text{ at the last purchase}\\&\text{occasion } \mathit{and}\ (\mathit{Price}_{btprev(h)} - \mathit{Price}_{btprev(h)-1}) < 0\end{aligned} \tag{4.3}$$

where *tprev(h)* signifies the week in which the household's previous purchase occurred, so $\mathit{LastPromo}_{bt}^{h} = 1$ if the customer bought brand b at reduced price on his or her last purchase occasion. To fully capture state dependence, both Last_{bt}^{h} and $\mathit{LastPromo}_{bt}^{h}$ are included in the brand choice utility model:

$$\begin{aligned}\mathit{Utility\_of\_Brand\_Choice}_{bt}^{h} = {}&\beta_{0b}^{h} + \beta_{1b}\mathit{Price}_{bt} + \beta_3\mathit{Last}_{bt}^{h}\\&+ \beta_4\mathit{LastPromo}_{bt}^{h}\end{aligned} \tag{4.4}$$

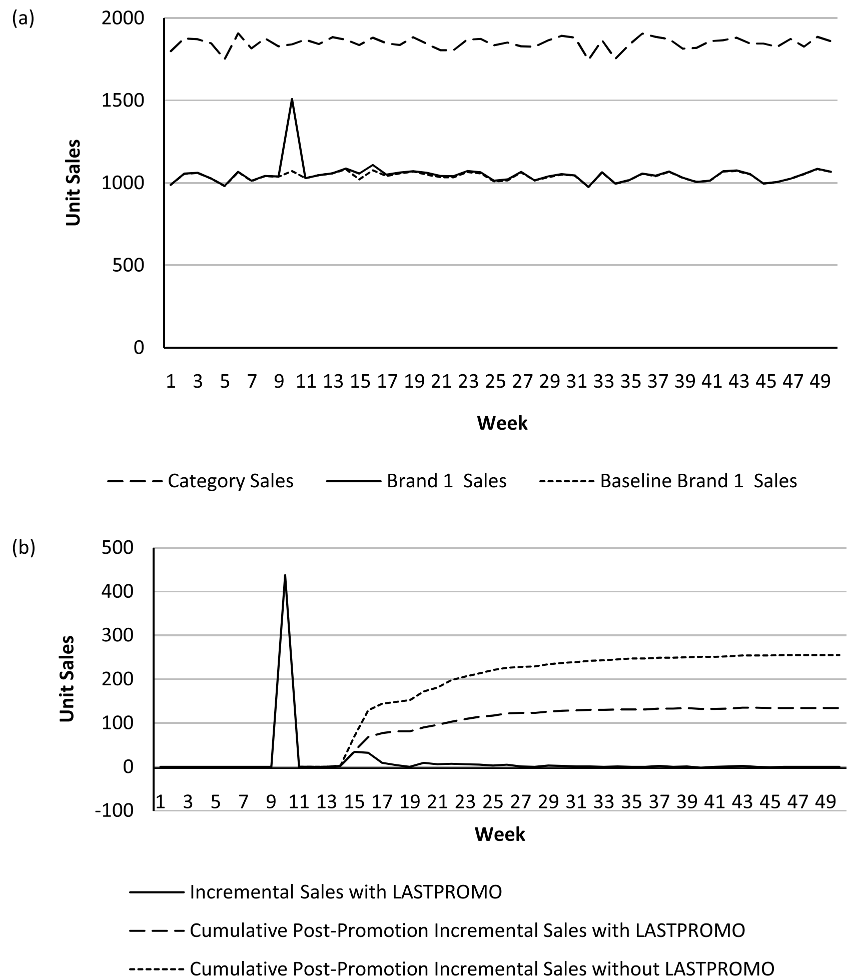

Fig. 4.2 Incremental sales due to one promotion when incorporating the impact of promotion on state dependence. Total sales; (b) Incremental sales.

Figure 4.2 shows the simulated impact of one promotion, where $\beta_3 = 0.9$ and $\beta_4 = -0.3$, i.e., promotions detract from state dependence. Figure 4.2(a) shows that promotion still increases long-term sales, although not as much as would be the case if promotion did not detract from state dependence (Figure 4.1). Figure 4.2b shows the incremental post-promotion impact is 134 units, less than the 254 units in Figure 4.1, but still a large percent of promotion-week incremental sales.

4.2.3 State Dependence Exists in Many Product Categories

Much of the choice modeling research in marketing focuses on scanner panel data from the Consumer Packaged Goods (CPGs) industry. This makes it difficult to generalize findings across other industries. However, in the case of state dependence, there is a myriad of evidence supporting its existence in other industries and contexts. These include choice of ski resorts (Moeltner and Englin, 2004), supermarket choice (Rhee and Bell, 2002), youth employment (Doiron and Gøgens, 2008), exporting behavior by firms (Kaiser and Kongsted, 2008), health status (Halliday, 2008), and Internet portal choice (Goldfarb, 2006). The wide variety of venues where researchers have found state dependence attests both that state dependence is a real phenomenon and shows its generality. Unfortunately, none of the above studies investigates the impact of promotions on state dependence, or with the exception of Rhee and Bell, even consider promotions among their independent variables. There is obviously ample opportunity to investigate the impact of promotions in more contexts than Consumer Packaged Goods (CPGs).

4.2.4 State Dependence As a Consumer Trait

Consumers intuitively should differ in the degree of state dependence present in their choice processes. This in turn begs the question of whether state dependence is a consumer trait. That is, is the consumer who is state dependent in Category A also state dependent in Category B? This was investigated by Seetharaman et al. (1999). The authors considered five categories: ketchup, peanut butter, margarine, toilet tissue, and canned tuna. Note while these are all CPG categories, they are quite different in terms of interpurchase time, storability, etc. Seetharaman et al. estimated consumer-specific state dependence terms (β_3's) and found that the average pair-wise correlation in these parameters between categories was 0.46 with a standard deviation of 0.04. This suggests that indeed state dependence is a consumer trait.

4.2.5 State Dependence and Consumer Stockpiling

Ailawadi et al. (2007a) propose yet another mechanism for state dependence effects of promotions. They postulate that promotion-induced stockpiling enhances state dependence because the household consumes more of the brand over a continuous period of time. They propose the following brand choice utility function:

$$\beta X_{bt}^h = \beta_1 Price_{bt} + \beta_2 Feature_{bt} + \beta_3 Display_{bt} + \beta_4 Last_{bt}^h + \beta_5 LastPromo_{bt}^h + \beta_6 \frac{Q_{bt}^h}{\bar{Q}^h}.$$

The $Q_{bt}^h/\bar{Q}^h$ term reflects the quantity purchased on the previous purchase occasion relative to the average purchase quantity. If consumers develop higher preference for brands they stockpile, $\beta_6 > 0$. Hence if $(Q_{bt}^h/\bar{Q}^h) > 1$, we have stockpiling and this yields more repeat purchases. On the other hand, if more consumption breeds boredom, stockpiling should result in less positive reinforcement and fewer repeat purchases ($\beta_6 < 0$). In the empirical application to yogurt and ketchup, Ailawadi et al. (2007a) find that stockpiling is associated with an increase in repeat-purchase rates, i.e., $\beta_6 > 0$.

The result has been found just by the above authors, albeit in two product categories, so by no means is generalized. However, this is a potentially important finding because it suggests that stockpiling enhances brand loyalty.

4.3 Managerial Implications

The implications of state dependence include: further justification for promotion as a competitive equilibrium outcome, optimal category pricing, personalized pricing, and promotion profitability. Freimer and Horsky (2008) show that in markets with state dependence, monopolists as well as duopolists will find themselves promoting in equilibrium, and depending on the demand function, will increase profits relative to the single-price equilibrium. The intuition is simple–with positive state dependence (even if reduced by promotion), the promoting firm obtains some monopoly power over the additional consumers who buy the brand. This monopoly power cushions price competition when the brand is not promoting. Obviously, the state dependence effect has to be strong enough. In addition, Freimer and Horsky only consider cases where the market is expandable, e.g., in the duopolist case, there is a benign outside good from which the brands can gain sales. It would be interesting to examine whether state dependence can lead to promotions in a non-expandable market.

Dubé et al. (2008) consider the impact of state dependence on a retailer's pricing of all brands in a product category. They do not consider the possibility of price promotions, but do show that the presence of state dependence influences everyday prices in an interesting way–namely, the prices of higher quality brands generally decline relative to lower quality brands. Che et al. (2007) also look at the impact of state dependence on everyday prices, and show empirically that manufacturers and retailers take into account state dependence in setting prices, although with a limited time horizon.

State dependence is also important for designing and evaluating promotion programs. Zhang and Krishnamurthi (2004) estimate a choice/incidence/quantity model for an online store that incorporates time-varying state dependence. The authors find that state dependence varies over time at the individual level, with the consumer cycling between mostly positive state dependence and sometimes negative state dependence (variety seeking). They then determine the optimal promotion using a three-purchase-occasion time horizon. Their optimization suggests that previous period buyers require a price cut only if they are variety seeking (to keep them in the franchise), while previous period non-buyers require a price cut if they have positive state dependence (to lure them into the franchise) (see Figure 3.1, p. 574 of their paper). The authors show that their prescriptions would have resulted in higher profits in a holdout period test. This is a very interesting and promising paper–it combines price personalization, dynamic optimization, and state dependence.

At an even more tactical level, many CPG firms calculate some measure of profitability for each of their promotions. To the authors' knowledge, these calculations typically do not take into account promotion dynamics, including state dependence. Yet as Figure 4.2 shows, state dependence can produce a significant number of incremental sales beyond the immediate promotion. Define the following:

$\Pi_0 =$ Manufacturer profits without promotion.

$\Pi_P =$ Manufacturer profits with promotion.

M_0 = Normal profit margin for manufacturer.

δ = Trade deal discount offered by manufacturer.

S_0 = Normal (baseline sales) per week.

Δ = Increase in sales per week during promotion.

S_{pp} = Sales per week in the periods following the promotion week.

T = Time horizon for the post-promotion period.

Following these definitions, we have:

$$\Pi_0 = S_0M_0 + TS_0M_0.$$
$$\Pi_P = (S_0 + \Delta)(M_0 - \delta) + TS_{pp}M_0.$$
$$\Pi_P - \Pi_0 = \Delta(M_0 - \delta) - S_0\delta + T(S_{pp} - S_0)M_0.$$

The first term is the increase in profits due to selling Δ more units during the promotion week, albeit at a reduced margin of $M_0 - \delta$. The second term reflects lost contribution from baseline sales during the promotion week (we've sacrificed δ per unit on those sales). The third term is the gain in sales from repeat purchases due to state dependence. $T(S_{pp} - S_0)$ is the total cumulative gain in repeat sales over the time horizon. Note these sales contribute full margin M_0.

In the example shown in Figure 4.2, we have $\Delta = 437$ units, $T(S_{pp} - S_0) = 134$ units, and $S_0 = 1072$ units (during the promotion week). Wholesale price is \$1.88 and let's assume \$1.25 of that is normal margin (this is a very high margin product). The discount offered is $\delta = \$0.94$. We therefore have,

$$\begin{aligned}\Pi_P - \Pi_0 &= 437(\$1.25 - \$0.94) - 1072(\$0.94) + 134(\$1.25)\\ &= \$135.47 - \$1007.68 + \$167.50 = -\$704.71\end{aligned}$$

The promotion is unprofitable, because the manufacturer sacrificed too much margin (\$0.94) on baseline sales. However, the loss is cushioned significantly by the 134 incremental post-promotion purchases due to state dependence. This contributes \$167.50 to the calculation, more than was contributed by the incremental sales generated in the week of the promotion. While the increase in post-promotion sales is smaller than the increase in promotion week sales (134 versus 437), the post-promotion sales are at full margin. The numbers of course could come out differently depending on the exact level of incremental sales, profit margins, etc., but in any case, the example shows the importance of including post-promotion sales impact due to sate dependence in the calculation.

4.4 Future Research

While we have learned much about the existence and measurement of state dependence, there are several avenues of research that need to be pursued. First, we need to understand more fully the impact of promotions on state dependence. Many of the applications include the *Last* variable but not the *LastPromo* variable, even though the evidence is clear that buying on promotion results in a different level of state dependence than buying not on promotion. More work along the lines of Gedenk and Neslin (1999) is needed, where we learn how different types of promotions (price/non-price, hedonic/utilitarian, etc.) impact future purchasing.

Second, we need to understand the impact of promotion on state dependence in more product categories. The research discussed earlier shows that indeed state dependence is a phenomenon that applies to other industries besides CPG. However, this research has not shown how promotion influences this state dependence. For example, how do various online promotions affect the tendency to use the promoted website?

Third, more work needs to be done on dynamic optimization of promotion policy in the presence of state dependence. Zhang and Krishnamurthi (2004) pioneered this area. However, their optimization has only a three-period time horizon and does not generate a stationary policy that can be implemented on an ongoing basis. Fourth and related to this, future research should build on the work of Freimer and Horsky (2008) and Dubé et al. (2008) and examine the impact of state dependence on equilibrium promotion outcomes, for example, when the market is not expandable.

Fifth, we need to understand better the potential bias in state dependence estimates from not including various other forms of dynamics. Seetharaman (2004), as well as Keane (1997), suggest that not including factors such as serial correlation can bias the state dependence estimate. There are also the dynamics directly related to promotion that are discussed in this article, such as reference price, stockpiling, and price sensitivity effects. Erdem et al. (2001) are relatively unique in including both state dependence and reference price effects in the same model (they find both to be significant), although they do not go into details such as investigating the impact of promotion on state dependence.

Sixth, work is needed to determine the underlying cause of state dependence. Is it learning, inertia, switching costs? The answer to this has important implications for strategies aimed at taking advantage of state dependence (see Moshkin and Shacher, 2002). Seventh, we reported two interesting findings — state dependence appears to be a consumer trait (Seetharaman et al., 1999), and stockpiling appears to enhance state dependence (Ailawadi et al., 2007a) — that need to be generalized. These are important findings yet have only been investigated each in one paper.

5

Reference Prices

5.1 Illustration

The reference price is the standard with which consumers compare the currently available price of an item in order to assess the attractiveness of the available price (Kalyanaram and Winer, 1995; Winer, 1986). If the comparison is highly favorable, i.e., the available price is lower than the reference price, the consumer is more likely to purchase the product. If the comparison is not favorable, the consumer experiences a "sticker shock" and will be less likely to purchase the product.

There are several justifications for the existence of reference prices and their impact on brand sales. First, a reference price may be an effective *heuristic* for the consumer faced with the daunting task of deciding what, when, and how much to buy. By comparing available price to a standard, the consumer avoids the details required to optimize utility using the standard economic model (see Thaler, 1985). Second, a reference price helps the consumer decide whether the available price is a *fair* price, i.e., whether the available price is a "rip-off". Third, the reference price helps the consumer to know whether the available price is a good *deal*. Fourth, the reference price may be a requirement for *optimal long-term decision making*, as captured in dynamic rational models. Under this framework, *expectations* of future prices play an important role in determining whether the consumer should buy now or later (Erdem et al., 2003). Fifth, reference is a *naturally occurring phenomenon* because the consumer gets accustomed to a given price level, and therefore uses this to judge any newly presented price level. The idea behind this is adaption-level theory (Helson, 1964, also see Blattberg and Neslin, 1990). Finally, prospect theory postulates that the *fundamental mechanism* by which customers make decisions is to compare where that decision will leave them relative to their status quo, to where they are now (Kahneman and Tversky, 1979; Thaler, 1985).

There are two forms of reference price–internal and external. Internal reference prices (IRPs) are formed based on temporal influencers such as previous prices. IRPs are also called memory-based or temporal reference prices. External reference prices (ERPs) are based on information available in the current purchase environment, e.g., price information provided at the point of purchase or prices of comparable products. Since IRPs are most directly related to dynamics — in their formation as well as their impact — our focus is on IRPs. For additional reading on ERPs, see Rajendran and Tellis (1994) and Mazumdar and Papatla (2000).

Illustrating reference price effects requires two models: reference price formation and reference price impact. We will use two common forms of these models to simulate the reference price effect. Briesch et al. (1997) conclude that brand-specific exponentially smoothed reference price formation provides the best-fitting model of reference price formation:

$$RefPrice^h_{bt} = \alpha RefPrice^h_{btprev(h)} + (1-\alpha)Price_{btprev(h)},$$

where

$RefPrice^h_{bt} =$ household h's reference price of brand b at purchase occasion t,

$\alpha =$ carryover parameter, $0 \leq \alpha \leq 1$, and

$tprev(h) =$ week in which the household's previous purchase occurred.

Briesch et al. identify several applications of the "sticker shock" model of reference price impact. Our model simply adds the difference $(Price_{bt} - RefPrice_{bt}^{h})$ as an extra independent variable in brand choice utility:

$$\begin{aligned} Utility\_of\_Brand\_Choice_{bt}^{h} = {} & \beta_{0b}^{h} + \beta_{1b} Price_{bt} \\ & + \beta_{2b}(Price_{bt} - RefPrice_{bt}^{h}). \end{aligned} \tag{5.1}$$

The notion is that, as usual, price has a negative effect on utility ($\beta_{1b} < 0$). A price that is higher than the reference price ($Price_{bt} - RefPrice_{bt}^{h} > 0$) will entail an additional loss in utility: $\beta_{2b} < 0$. This is the sticker shock effect. Conversely, a price discount, i.e., a price that is lower than the reference price ($Price_{bt} - RefPrice_{bt}^{h} < 0$) will increase the brand choice utility.

Figure 5.1 shows a simulation where brand choices have been generated with reference price effects according to Equations (5.1) and (5.2). Figure 5.1a shows that Brand 1 experiences sharp increases in sales during the promotion week, followed by a sharp decrease in sales roughly five weeks after, and a concomitant increase in sales for Brand 2. There is no impact on category sales, as we are only modeling the impact on brand choice.

Figure 5.1b shows Brand 1 sales in conjunction with average reference price as well as the sales level that would have occurred without the reference price effect. We see (1) the promotion spike is bigger with the reference price effect (Equation (5.1)) and (2) the mean reference price among all consumers decreases significantly in the week following the promotion, and begins to increase so that by the time of the next promotion, the size of the sales spike is the same as the first. The five-week lag before the sales decrease is due to the average inter-purchase time among buyers who purchased during promotion. These consumers re-enter the market to find an available price much larger than their reference price. The result is sticker shock and a decrease in sales.

In summary, the most apparent impacts of reference price are (1) larger than usual spikes in promotion sales and (2) decreased sales roughly one inter-purchase time after the promotion, due to sticker shock.

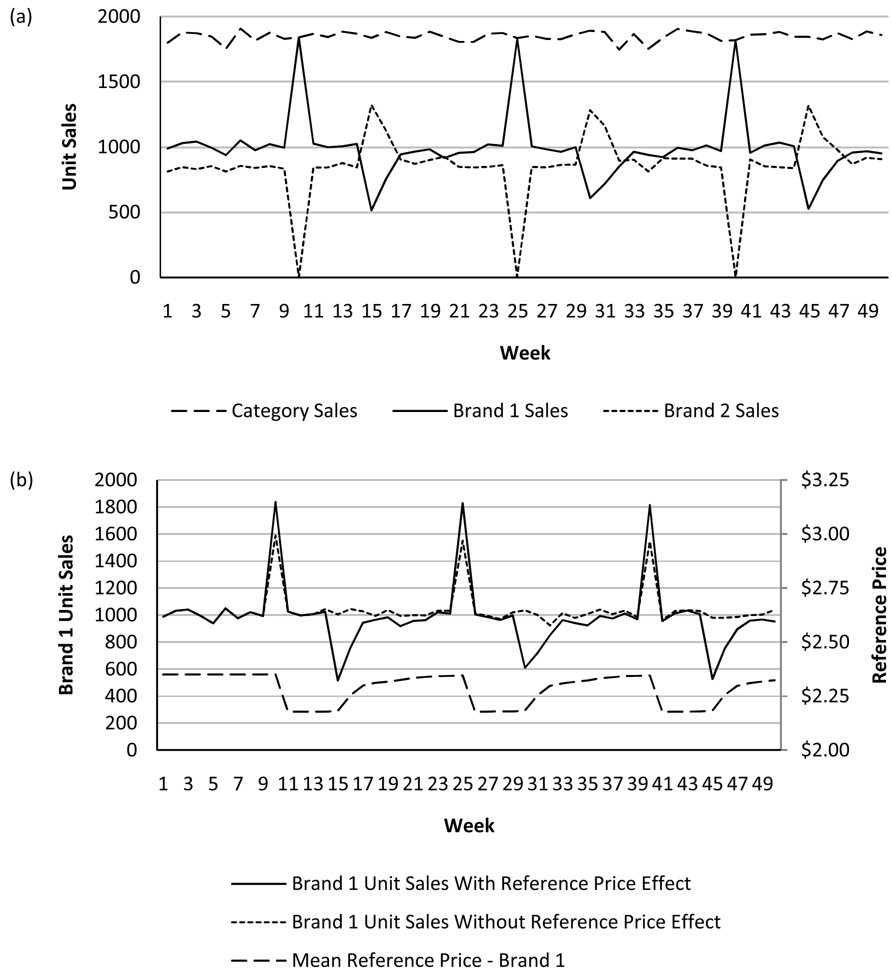

Fig. 5.1 Reference price effects. (a) Sales impact; (b) Mean reference price and sales impact with and without reference price effect.

5.2 Empirical Findings

5.2.1 Existence

Evidence of the existence of reference prices and their impact on brand sales comes from statistical modeling and laboratory experiments, or from their combination (e.g., Wedel and Leeflang, 1998). The modeling evidence comes mostly from models of consumer brand choice, virtually all of which are of consumer packaged goods. Researchers have estimated a variety of reference price formation and reference price impact models, and uniformly found significant effects (Mazumdar et al., 2005). Chang et al. (1999), however, propose a significant challenge to this work. The authors argue that price-sensitive consumers time their purchases so as to buy at low prices (i.e., they accelerate and decelerate). As a result, price-sensitive consumers have low reference prices, and because they are more price sensitive, the impact of the reference price effect is over-stated.

Despite the importance of this argument, it has not been addressed often in subsequent empirical work. One important exception is Bell and Bucklin (1999). These authors model purchase incidence and brand choice and account for segmentation in price response via latent class segments. They find important reference price effects in purchase incidence, i.e., reference "category value" influences purchase incidence. However, their results for reference price effects at the brand level are largely insignificant (p. 137, footnote 9). This work is very interesting – it is a precursor to the more systematically formulated dynamic structural models that now permeate the literature (e.g., Erdem et al., 2003). However, their lack of findings with regard to reference price effects at the brand level may reinforce rather than refute Chang et al.'s challenge.

The experimental evidence for reference price effects often investigates ERPs rather than IRPs, but there is evidence for IRPs. For example, Kalwani and Yim (1992) estimated a logit choice model with reference prices measured by consumer self-report. More recently, Wolk and Spann (2008) showed in a laboratory experiment that IRPs can influence Internet auction bidding behavior. The main challenge to papers of this genre is that the IRPs are solicited via self-report. This can create a demand of effect whereby the mere solicitation of IRPs makes them salient to the consumer, resulting in an artificially induced reference price effect. Perhaps the most convincing evidence of the existence of reference price effects comes from the ground-breaking work of Della Bitta and Monroe (1974; see discussion in Blattberg and Neslin, 1990, pp. 42–43). These researchers showed that a price is viewed more favorably if preceded by exposure to a series of higher prices, and less favorably if preceded by exposure to a series of lower prices. Reference prices best account for the observed results. Although this work does not measure reference price directly, that in fact is its strength because it rules out a demand effect.

5.2.2 Reference Price Formation

A large body of literature has focused on the mechanism by which consumers form IRPs. Mazumdar et al. (2005) summarize this work nicely. Briesch et al. (1997) provide what still is considered the definitive work in this area. They compared the predictive ability of three basic models: (1) The single-comparison model, which assumes that consumers use the price of a previously purchased brand as the single standard for judging all prices on the current purchase occasion, (2) The multiple-brand exponential smoothing model, which assumes that consumers form reference prices for all brands and the reference price for Brand A serves as the standard for comparing the current price of Brand A, (3) The rational expectations model, which assumes that consumers form reference prices for all brands based on the pricing history, trend, and deal frequency, as well as consumer characteristics such as deal proneness. Briesch et al. find that most convincing support, in terms of predictive ability, for the multiple-brand exponential smoothing model, which is why we use it in Equation (4.4).

While the Briesch et al.'s study is convincing and carefully executed, one can argue that its conclusion is difficult to accept literally. The multiple-brand exponential smoothing model assumes that customers form reference prices for *all* brands in the category, even ones they have never purchased before. Considering the number of categories the consumer purchases, this assumes a huge amount of information processing and ultimately, a highly involved customer (see Vaidyanathan and Aggarwal, 2001 for support for the role of involvement). It is possible that a compromise might be a consideration set model, whereby consumers judge whether the prices for a subset of brands are different from usual. This may not require that the consumer literally calculates Equation (4.4) for these brands, but merely that the consumer "knows" when a price is different from the past (Monroe and Lee, 1999, see) for a provocative discussion on "remembering" versus "knowing".

5.2.3 Impact on Sales

The major issue in empirical assessments of the impact of reference price on sales is "loss aversion." Based largely on prospect theory, which suggests that losses loom larger than gains (Thaler, 1985), the sticker shock effect should be greater than the promotion-impact effect (see Kalwani et al., 1990). That is, rather than one term for (Available Price − Reference), we need two terms, the gain term, with parameter β_G, which is non-zero only if Available Price < Reference Price, and the loss term, with parameter β_L, which is non-zero only if Available Price > Reference Price. The hypothesis is that $\beta_L > \beta_G$ in magnitude.[1] See also Pauwels et al. (2007) for more extensive analysis.

As summarized by Mazumdar et al. (2005), the evidence on this hypothesis is mixed. Moreover, Bell and Lattin (2000), propose a methodological challenge, similar to Chang et al.'s regarding the existence of reference price effects in the first place. Bell and Lattin suggest that heterogeneity in price responsiveness across customers can create apparent loss aversion. The argument again is that price responsive customers see lower prices when they purchase[2] and hence have lower reference prices. As a result, the curve of reference price versus choice is "kinked", with a steeper slope for lower reference prices, which are more likely to be associated with reference price losses than gains. The answer is to account adequately for price sensitivity heterogeneity when estimating choice models with reference price effects. For example, Erdem et al. (2001) do so and find consumers vary widely in loss sensitivity. Klapper et al. (2005) also control for heterogeneity and find some loss aversion, but while they also observe ample heterogeneity, "on average, we find no or only very moderate loss aversion" (p. 244).

[1] In our case, since we have defined the reference price term so that the parameter should be negative, β_L would be less than β_G in nominal measure.

[2] Note, however, that Bell and Lattin do not explicitly model purchase incidence in this paper.

5.2.4 Market Segmentation

An important and growing literature looks at market segmentation and reference prices, e.g., which consumers are more susceptible to reference price effects. Mazumdar and Papatla (2000) find that consumers who are more susceptible to IRP effects tend to focus their purchases on fewer brands and pay less attention to displays. Erdem et al. (2001) find that consumers susceptible to reference price effects, whether they be gain-sensitive and loss-sensitive, are more price sensitive than average, reinforcing Mazumdar and Papatla. However, they also find these consumers are more display and feature oriented, opposed to the findings of Mazumdar and Paptala. Moon et al. (2006) find that IRP-sensitive consumers are more price sensitive than average. Vaidyanathan and Aggarwal (2001) find that high involvement consumers use market prices to form their reference prices while low involvement consumers are more likely to use external information to form their reference prices. All these results make sense in characterizing the IRP-prone consumer as very price sensitive, highly involved in the category, and focused on fewer brands. This provides the motivation and ability for these consumers to utilize internal reference prices.

Another set of literature attempts to characterize the loss-averse consumer, i.e., the consumer who is more susceptible to loss aversion. Erdem et al. (2001) find that loss-sensitive consumers tend to represent larger families, with heads of household fully employed, and are less susceptible to prior purchase "state dependence" effects. They are less able to characterize the gain-sensitive consumer. Klapper et al. (2005) examine two product categories and find that loss-sensitive consumers are older, employed, and have children. These results are largely consistent with Erdem et al., although the reason for the positive relationship between employment and loss aversion is not clear. One would more likely expect that unemployment would be associated with loss aversion. Klapper et al. also examine psychographics and purchase behavior. They find for example that loss averse consumers are more price conscious and less quality conscious. It makes sense that these consumers would be more susceptible to sticker shock. In terms of purchase behavior, the authors find in one category that focus on fewer brands is associated with more loss aversion. Also, longer interpurchase times are associated with more loss aversion. The authors note that this could be due to the ability of high-interpurchase time consumers to postpone purchase in the face of sticker shock.

Overall, the ability of researchers to find segmentation relationships provides evidence of construct validity for the existence of reference price effects.

5.2.5 IRP versus ERP

Our focus is on internal reference price (IRP), but an obvious question is what is the relative importance of IRP versus external reference prices (ERPs). The answer appears to be that both forms are important, that there are segments that favor one over the other, and that some segments utilize both forms. Mayhew and Winer (1992) and Rajendran and Tellis (1994) included both IRP and ERP in a brand choice model. They found both effects to be significant. Mazumdar and Papatla (2000) segment consumers in four product categories based in part on the relative emphasis they put on ERP and IRP. The authors find some segments put more weight on IRP; others put more weight on ERP. Moon et al. (2006) reach similar conclusions. In short, both temporal effects (IRP) and contextual effects (ERP) play important roles in the impact of reference prices.

5.3 Managerial Implications

The reference price phenomenon is important for several reasons. First, it can serve as a strategic argument for the existence of price promotions. Greenleaf (1995) and Kopalle et al. (1996) pioneered this theme. Greenleaf takes the view of the retailer trying to maximize profits for a single brand, while Kopalle et al. take the view of a manufacturer and consider both monopoly and duopoly cases. Greenleaf's work is empirically based, while Kopalle et al.'s is analytical. Both papers rely on the same straightforward argument–if the gain in the promotion period due to the comparison of available price with reference price is sufficiently greater than the loss in the post-promotion period due to sticker shock, promotions increase profits.[3] Kopalle et al. find this even in the duopoly case, which is interesting. Both these papers suggest that the reference price phenomenon can raise profits. However, these papers do not distinguish between brand choice and purchase incidence effects. The monopolist case clearly relies on purchase incidence, but even in the duopolist case, Kopalle et al.'s work suggests that "market expansion" (p. 70) is crucial. These results are still important, but it is ironic that Greenleaf and Kopalle et al. both suggest that the value of reference price is derived from its ability to increase market size, whereas most of the empirical work on reference price has to do with brand choice.

Second, and at a more tactical level, the reference price effect influences the profitability of promotions, because (1) it increases the size of the promotion bump and (2) has a negative repeat-purchase effect after the promotion (Figure 5.1). In fact, the example shown in Figure 5.1 would probably yield unprofitable promotions. This is because in that example the net impact of the promotion is sales-neutral (calculated by summing the deviations between pre-promotion baseline sales and sales during and after the promotion). The promotion sales gain during the promotion, however, is at lower margin (assuming the manufacturer offered a trade deal during the promotion period) than the sales loss margins experienced after the promotion. So the impact of the promotion is to increase sales during a period of lower margin and decrease it during periods of higher margins. The net impact would be negative. Obviously, these specific results depend on the particular parameters employed, but the point is that one must account for reference price effects in calculating the short-term impact of a price promotion.

A third implication of the reference price phenomenon is that manufacturers should avoid promoting too frequently. Frequent promotions can render promotions less effective in the long-run (because reference price is lowered so a given discount doesn't seem very attractive) and

[3] "Sufficiency" depends on issues such as firm margins during the promotion and non-promotion periods. E.g., for manufacturers, margins will be lower during the promotion period if they have offered a trade deal to induce the retailer to decrease price. See Popescu and Wu (2007) and Fibrich et al. (2003) as well.

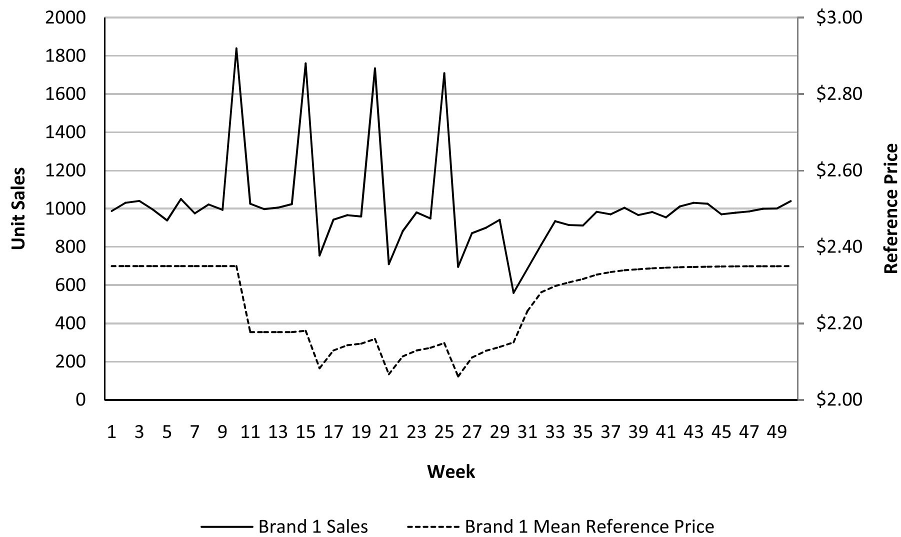

Fig. 5.2 Reference price effects when promotions are bunched together.

decrease baseline sales (due to sticker shock). Figure 5.2 shows the results of a simulation using the same parameters as in Figure 5.1. However, in this case, promotions are more tightly packed. Over time, the promotion bump becomes smaller and baseline sales erode. The key insight is that frequent, steep promotions are to be avoided. Notice this is due purely to consumer response to price and not to any degradation of the brand image *per se*.

5.4 Future Research

Reference prices have received considerable attention in the literature. However, several crucial issues are unresolved. First is the very existence and impact of internal reference prices. Most of the work on IRPs involves choice models that are subject to Chang et al.'s critique. One paper that addressed this found a reference price effect at the purchase incidence level but not at the choice model level. In general, much more work is needed to investigate category- versus brand-level impacts of reference prices. Second, we need dynamic structural models of reference price. Dynamic structural models include price expectations, so implicitly include reference price effects. However, we are not aware of work that places the (price − reference price) term directly in the utility function, so the issue of loss aversion cannot be investigated. Third, we need to resolve the issue of loss aversion, i.e., do indeed losses loom larger than gains? The evidence is frustratingly mixed. If loss aversion is real, this would severely limit the profitability of promotions, either strategically as part of a market equilibrium, or as short-term events.

Fourth, we need to extend the empirical work on IRPs to the domain of durables, services, and e-tailing. One would conjecture that reference IRPs would play a crucial role in durables — indeed, the term "sticker shock" refers to the consumer being shocked to find the price of a new car to be so high compared to the last time he or she purchased a car. Fifth, we need more work to clarify exactly the mechanism by which reference prices are formed. The Briesch et al. results suggest that consumers form brand-specific reference prices and pay attention to all previous prices. It is doubtful that this holds literally. On the other hand, this model predicts better than a sensible model that utilizes only one reference price. It appears that a better (compromise) representation of the IRP formation process should be possible.

6

Price Sensitivity

6.1 Illustration

Frequent exposure to sales promotions may affect consumer perceptions of promotional activity (Krishna et al., 1991) and change their response to promotion (Raju, 1992). Discounting policies are typically found to decrease price elasticities (make them more negative) by focusing consumers' attention to price-oriented cues (Boulding et al., 1994; Foekens et al., 1999; Mela et al., 1997; Papatla and Krishnamurthi, 1996; Pauwels et al., 2002).

An increasing price sensitivity effect can be captured by a time-varying price coefficient (β_{1bt}) in the brand choice utility (Ataman et al., 2009):

$$Utility\_of\_Brand\_Choice^h_{bt} = \beta^h_{0b} + \beta^h_{1bt} Price_{bt}, \tag{6.1}$$

where

$$\beta^h_{1bt} = \delta_0 + \delta_1 \beta^h_{1bt-1} + \delta_2 Discount^h_{bt}, \tag{6.2}$$

where

$$\begin{aligned} Discount^h_{bt} = {} & Price_{btprev(h)} - Price_{btprev(h)-1} \\ & \text{if } Price_{btprev(h)} < Price_{btprev(h)-1}; \quad 0 \text{ else} \end{aligned}$$

Hence the discount variable reflects the difference in price in the week of the household's most recent purchase (*tprev(h)*) and the price in the week of the household's second-most recent purchase ($tprev(h) - 1$), at least if this difference is negative (the variable is zero otherwise). Equation (6.2) says that each period's price sensitivity is a function of an intercept (δ_0, expected to be negative due to the disutility of higher prices), an autoregressive term $\delta_1 \beta^h_{1bt-1}$ (where $\delta_1 \in (0,1)$ to capture a mean-reverting series), and a term $\delta_2 Discount_{bt}$ capturing the effect of past discounts with $\delta_2 > 0$. This implies that discounts make the price coefficient more negative. Hence over time, successive discounts makes a consumer increasingly price sensitive.

Figure 6.1 shows the simulations where the price sensitivity is made time-varying as in Equations (6.1) and (6.2). With every discount, the price sensitivity parameter becomes increasingly negative, after which it slowly crawls back to its original mean. Over time, baseline sales start to decline as the "normal price" gets an increasingly negative weight. Promotional peaks start to increase as the response to a price

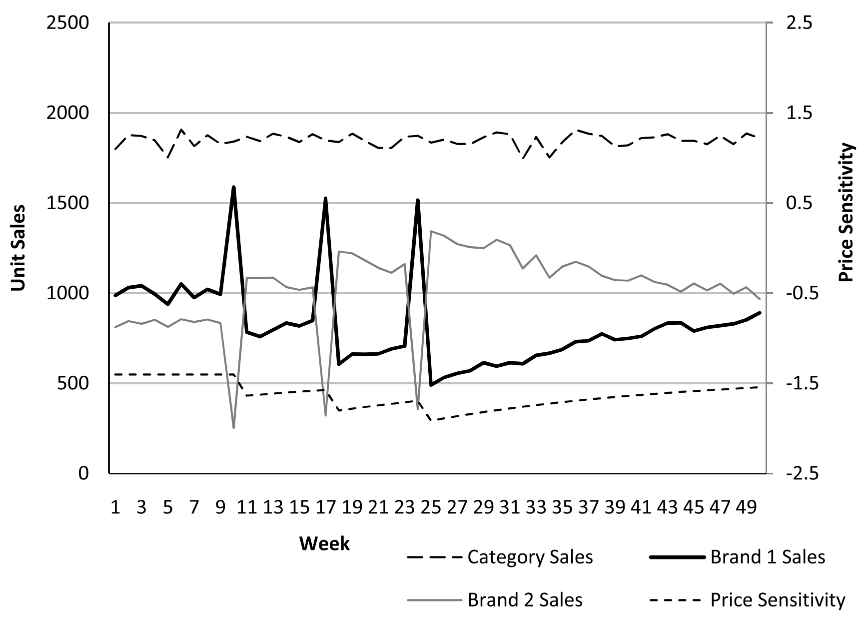

Fig. 6.1 Effect of increased price sensitivity due to promotions.

discount becomes increasingly strong. Category sales are flat, because the increased price sensitivity materializes only in the brand choice decision. Of course, on could also allow for increasing price sensitivity in the incidence and quantity decisions. Brand 2 sales are the mirror image to Brand 1 sales. Note that its demand does not become more price sensitive due to Brand 1 promotions (at least not in our model).

6.2 Empirical Findings

In behavioral-learning theory, the counterpoint of not reinforcing brand attitudes is that consumers learn to be price and promotion sensitive. Papatla and Krishnamurthi (1996) were among the first to find that price promotions increase price, display, and feature sensitivity, coupons increase price sensitivity, displays increase display sensitivity, and features increase feature sensitivity.

Boulding et al. (1994) examined quarterly data for 826 business units. They found that promotions were associated with higher price sensitivity for higher-priced firms and lower price sensitivity for lower-priced firms. The price sensitivity of firms offering products at average or slightly below average prices was not apparently affected by promotions. While the study covered a broad spectrum of firms, some aspects of the study called for refinements. For one, the relatively high temporal aggregation level of the quarterly data may have induced an aggregation bias (Clarke, 1976; Tellis and Hans Franses, 2006). And second, the partly cross-sectional nature of the analysis may raise questions about the causality of the findings.

To overcome these aspects, Mela et al. (1997) studied the long-term effects of promotion and advertising on consumers' brand choice behavior utilizing a natural experiment in which promotions increased and advertising decreased. Their results based on $8\frac{1}{4}$ years of panel data for a frequently packaged good suggest that consumers become more price and promotion sensitive over time because of reduced advertising and increased promotions. Non-price promotions (features, displays) decreased sensitivity to price among loyal consumers, and increased it among nonloyals. Jedidi et al. (1999) also find that price promotion was associated with increased sensitivity to price.

Mela et al. (1998) conclude that the increased long-term exposure of households to promotions has reduced their likelihood of making category purchases on subsequent shopping trips. However, when households do decide to buy, they tend to buy more of a good. Such behavior is indicative of an increasing tendency to "lie-in-wait" for especially good promotions, i.e., to decelerate.

While Mela et al. (1997, 1998) and Jedidi et al. (1999) studied only one product category, Ataman et al. (2009) studied 25 product categories and 70 brands across a five-year period. They consider the long-term effect on regular price sensitivity of the entire marketing mix (advertising, price promotion, product, and place). They conclude that regular price elasticities become more negative due to discounting and distribution, but they are increased (become less negative) through advertising and line length.

Bijmolt et al. (2005) provide a meta-analysis across 1,851 price elasticities reported in more than four decades (1956–1999) of academic research in marketing. Across this period, promotions have generally gained importance (Neslin, 2002). Without directly suggesting causality, a salient finding is that in the same period, the average (ceteris paribus) elasticity of sales to price went from -1.8 to -3.5. The relative elasticities (i.e., choice and market share) are stable (i.e., no significant change). Thus, the primary demand part of the sales elasticity is increasing over time, whereas the secondary demand part is stable. This finding is consistent with "lie-in-wait" behavior reported by Mela et al. (1998), but inconsistent with an increased sensitivity of the brand choice decision to price reported by Mela et al. (1997).

In summary, there is ample evidence that an extended exposure to price promotions make consumers more price sensitive. This result is replicated in primary analyses of data at various aggregation levels and also in a secondary (meta)-analysis of published findings.

6.3 Managerial Implications

An ever-increasing price sensitivity means that price plays an increasingly important role in consumer choice processes. One strategy is to capitalize on this trend by offering sharper price discounts and engaging in more frequent price promotions. This strategy could backfire, however, as it will further enhance price sensitivity, which calls for an even more focused low-price strategy. This is exactly the price promotion spiral that many brands and retailers are trapped in.

To get out of this trap, one could start reducing the reliance on low prices and price promotions. However, this offers opportunities to competitors who can now attract the focal brand's customers. The findings of Ataman et al. (2009) offer alternative routes to make consumers less price sensitive. One is to increase line length (the number of products offered by a brand), as this renders consumers less price sensitive. More differentiated or customized alternatives decrease price sensitivity because strongly differentiated items can serve loyal niches. Another suggestion is to spend more money on advertising. Consistent with the market power theory that says that advertising increases product differentiation (Mitra and Lynch, 1995), Ataman et al. (2009) find that advertising reduces price sensitivity. Making product lines longer and higher advertising expenditures also bring the added benefit that these moves enhance base sales.

6.4 Future Research

Overall, there is fairly strong evidence that promotions affect price or promotion sensitivity. It should be noted, however, that this evidence is subject to the same methodological concerns as the feedback studies (inferring causality and separating dynamic from cross-sectional effects) and more work is needed to distinguish price promotions from non-price promotions and to distinguish choice from quantity and purchase-incidence effects.

In the illustration we assumed that promotions for one brand do not make consumers more sensitive to another brand's price. The rationale is that exposure to promotions for one brand provides incentives to consumers to respond more strongly to that brand's price, but these incentives are absent for another, non-promoting, brand. The question is whether this is a valid assumption, or whether a promotion for one brand increases the price sensitivity of another's brand demand. It would also be interesting to see whether there are asymmetries: is the effect of price promotions for brand A on the price sensitivity of brand B as strong as the reverse effect? Do these price-sensitivity-enhancing effects even play a role across categories?

When consumers have become very price sensitive, they may be only willing to buy from deal to deal. While the consumer experiments have demonstrated that consumers may engage in deal-to-deal purchasing (Krishna, 1994a,b), it is unclear what the magnitude of deal-to-deal purchasing is in the real world. What percentage of households does (often) engage in deal-to-deal purchasing? For what categories? It is also not clear how deal-to-deal purchasing is categorized in the decomposition of promotional bumps.

The literature has clearly demonstrated that the *increasing* use of price promotions leads to an *increasing* price sensitivity. A core question if the reverse also holds: does *decreasing* the use of price promotions lead to a *decreasing* price sensitivity? In other words, is it possible to un-train consumers to be hooked to price promotion? Does it take longer to un-train consumers than to train them? These are important questions for managers seeking a way out of the price promotion trap.

7

Permanent Effects

7.1 Illustration

One of the goals of promotions is to offer consumers an incentive to try a product at a reduced price. If consumers like the product, they may repurchase the product and become loyal customers (e.g., Lewis, 2006). Hence, a promotion may have a permanent effect on consumer loyalty and brand sales. We can capture this permanent effect by adding a term in the brand choice utility that captures the cumulative effect of successive price promotions:

$$Utility\_of\_Brand\_Choice_{bt}^{h} = \beta_{0b}^{h} + \beta_{1b}Price_{bt} + \beta_6 Npromo_{bt}^{h}, \qquad (7.1)$$

where $Npromo_{bt}^{h}$ is the cumulative number of price promotions for brand b seen by household h at time t. If each discount makes the brand choice utility larger we have $\beta_6 > 0$. The rationale for a positive permanent effect of promotions draws from the state dependence literature, which assumes a positive albeit short-term effect. A positive long-term effect could result from consumers learning something about the brand that sticks with them permanently, e.g., an enduring attribute such as quality. Obviously, one could also reason $\beta_6 < 0$ if promotions degrade the image of a brand.

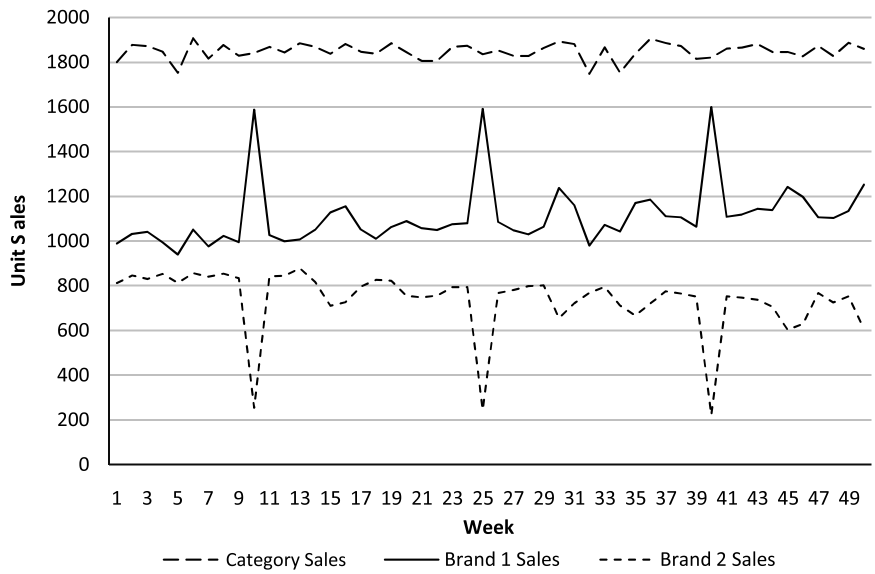

Fig. 7.1 Permanent effects of promotions.

Figure 7.1 shows what happens to simulated purchases if we add the permanent effects of promotions on brand choice utility with $\beta_6 > 0$. Over time, successive promotions slowly enhance the sales of the promoted Brand 1. The non-promoted Brand 2 suffers from a decline in sales while category sales are flat–note that the permanent effects materialize through the brand choice model.

7.2 Empirical findings

Recently, researchers have started to investigate the permanent effects of promotions. Permanent effects are defined as permanent changes in the mean level of criterion variables (e.g., sales) caused by sales promotions. There seems to be an important difference between the permanent effects of promotions for new and small brands versus mature and large brands. We discuss this difference next.

7.2.1 New and Small Brands

Slotegraaf and Pauwels (2008) argue that prior research has too often focused on just the top selling brands in a category, ignoring the smaller brands. For example, Fok et al. (2006) consider the top four brands across 25 categories and find that there are no permanent effects of price promotions since all 100 sales series are stationary. Slotegraaf and Pauwels (2008) wonder whether these results also hold for smaller brands. They use data for seven years across seven product categories from 100 brands with market shares varying from tiny to huge. Slotegraaf and Pauwels (2008) employ a two-stage approach in which long-term promotional effectiveness is first estimated with persistence modeling and then these effectiveness estimates are related to brand factors. By examining a broad range of brands in each category, the authors find that positive sales evolution from promotional efforts is only common for small brands. In particular, no brand over 3.1% market share showed positive sales evolution (unit root) over the full period whereas more than 25% of the small brands with between 0 and 3% share did. This implies that promotions can only have permanent effects for these smaller brands.

Ataman et al. (2008) look at new brands only. Their aim is to decompose the success of a new brand into its ultimate market potential and the rate at which it achieves this potential. To achieve this aim they formulate a Bayesian dynamic linear model (DLM) of repeat-purchase diffusion wherein growth and market potential are directly linked to the new brand's long-term advertising, promotion, distribution, and product strategy. Ataman et al. (2008) perform the analysis on 225 new-brand introductions across 22 repeat-purchase product categories over five years to develop generalized findings about the correlates of new-brand success. While access to distribution breadth plays the overall greatest role in the success of a new brand, discounting plays the second most important role in accelerating brand growth in the initial stages. The non-price promotions feature and display have the second-largest effect (after distribution) on market potential, which implies that their short-term effect on weekly sales is supplemented by their ability to build long-run demand for new brands. Discounts have an insignificant effect on long-term market potential.

Overall, these findings across several hundreds of new and small brands suggest that promotions play an important role in accelerating the upward trajectory of brand sales. Once the growth of a brand has leveled off, there seems to be less scope for a permanent effect of price promotions.

7.2.2 Mature and Large Brands

The question is whether promotions can have permanent effects for mature and large brands. Nijs et al. (2001) study the effects of consumer price promotions on *category sales* of mature brands across 460 consumer product categories over a four-year period. The data describe national sales in Dutch supermarkets and cover virtually the entire marketing mix. The key results are displayed in Table 7.1. Note that in 98% of the cases, there is no permanent effect of promotions on category sales.

Steenkamp et al. (2005) use a time series model to study the permanent effects of promotions and advertising on *brand sales* based on scanner data for the top three brands from 442 frequently purchased consumer product categories in the Netherlands. Their major results are displayed in Table 7.2. A key conclusion is that in the far majority of the cases, there are no permanent effects of sales promotions and advertising on own-brand sales. In the short term, these effects do exist, and they are more prevalent and much stronger for promotions than for advertising.[1] Interestingly, Pauwels et al. (2002) show, based on mature brands in the canned soup and yogurt categories, that permanent promotion effects are virtually absent for brand choice, category incidence, and purchase quantity.

Table 7.1. Category-Demand Effects of Price Promotions across 460 Categories.

	Short-term effects (%)	Permanent effects (%)
Positive	58	2
Negative	5	0
Zero	37	98

This table is based on Nijs et al. (2001).

[1] We note that the final version of this paper (Steenkamp et al., 2005) does not contain these results for anymore, since the journal requested the authors to focus on competitive reactions.

Table 7.2. Own-Brand Sales Effects Across 442 Categories.

	Non-significant (%)	Positive own-sales elasticity (%)	Negative own-sales elasticity (%)	Mean own-sales elasticity
Short-term effects				
Price promotions	30.96	63.54	5.50	3.989
Advertising	67.00	20.45	12.55	0.014
Permanent Effects				
Price promotions	94.99	4.15	0.86	0.046
Advertising	98.23	1.28	0.49	0.000

This table is based on Steenkamp et al. (2005). Please note that price promotion elasticities are in the positive domain, because they are defined as the percentage sales change due to a 1% temporary price discount.

Ataman et al. (2009) argue that few studies consider the relative role of the integrated marketing mix (advertising, price promotion, product, and place) on the long-term performance of mature brands — instead emphasizing advertising and price promotion. Hence, little guidance is available to firms regarding the relative efficacy of their various marketing expenditures over the long run. To investigate this question, Ataman et al. (2009) apply a dynamic linear function model to five years of advertising and scanner data for 25 product categories and 70 brands in France.

To calculate the sales elasticities of the four marketing variables, over the short- and long-term, they set each variable at its mean, and then increase each marketing variable, in turn, by 1% in week t. The effect on ln(sales) in week t is the short-term elasticity. This shock in marketing also carries forward to future periods via the model's long-term effects, inertia, and performance feedback effect. The cumulative implication of this shock for ln(sales) over a time window of 52 weeks (weeks $t+1, \ldots, t+52$), represents the long-term elasticity. This way of calculating the elasticity ensures that the short- and long-term elasticity can be compared as they are both measuring the effect on mean weekly sales.

Table 7.3 indicates that the long-term sales elasticity for product is 1.29 and for distribution it is 0.61. In sharp contrast, the total elasticities for advertising and discounting are only 0.12 and −0.02, respectively. The interpretation of the long-term elasticity of −0.02 is that mean weekly sales would decrease by 0.02% if the average promotion depth is increased by 1%. The discount elasticity is very modest for two reasons. First, the discount elasticity captures the effect of a 1% increase in the average discount depth (e.g., from a 20% discount to a 20.2% discount), which typically represents a much lower monetary discount than a 1% decrease in price. Two, the discount elasticity captures the effect of a general increase in the average discount depth while controlling for the short-run effects of price promotions and the other elements of the marketing mix. The short-run promotional price elasticity is −3.35, which is quite a strong elasticity, but it is consistent with the average promotional price elasticity of −3.63 reported in the meta-analysis of Bijmolt et al. (2005).

Table 7.3 also indicates that the long-term effects of discount depth are one third the magnitude of the short-term effects. The ratio is reversed from other aspects of the mix (where long-term effects exceed four times the short-term effects), underscoring the strategic role these tools play in brand sales.

Bawa and Shoemaker (2004) present a model of *free sample* effects and evidence from two field experiments on free samples for extant products. The model incorporates three potential effects of free samples on sales: (1) an acceleration effect, whereby consumers begin repeat purchasing of the sampled brand earlier than they otherwise would; (2) a cannibalization effect, which reduces the number of paid trial purchases of the brand; and (3) an expansion effect, which induces purchasing by consumers who would not consider buying the brand without a free sample. The empirical findings suggest that, unlike other consumer promotions such as coupons, free samples can produce measurable

Table 7.3. Sales Impact of 1% Temporary Increase in Marketing Support (%).

	Short-term (same week t)	Long-term (cumulative effect across weeks $t+1 \ldots t+52$)	Total (short-term plus long-term)
Discount Depth	0.06	−0.02	0.04
Advertising	0.01	0.12	0.13
Distribution	0.13	0.61	0.74
Line length	0.08	1.29	1.37

Source: Ataman et al. (2009).

long-term effects on sales that can be observed as much as 12 months after the promotion.

With the exception of a few studies (e.g., Bawa and Shoemaker, 2004), the bulk of the marketing literature seems to suggest that there are no permanent effects of temporary promotions for mature and large brands. Promotion dynamics for these brands only occur within a relatively small time window around the promotion (weeks or months rather than quarters or years).

7.3 Managerial Implications

The picture that emerges from the literature review is that there is quite a strong difference in the permanent effect of promotions for new and small brands versus mature and large brands. For new and small brands, promotions generate trial and can lead to a long-term increase in sales. Such brands have typically relatively few users, and a price discount may expand the base of users. Hence in the initial stages of a brand's life, promotions are recommended to achieve fast growth.

For mature and large brands, promotions tend to have no or very small permanent effects on sales. Their customer base is established and there is little scope to attract new users. Hence for these brands, discounting plays a largely tactical role by generating strong bumps in the short run, but it has no or little value as a strategic long-term marketing instrument.

7.4 Future Research

Almost all research on the permanent effects of promotions has used aggregate data. These data bring the benefit that the dependent variable (sales, market share) is metric and that therefore time series methods can be applied. These methods are uniquely suited to measure permanent effects using the unit root testing framework (e.g., Slotegraaf and Pauwels, 2008). However, there is a dearth of research on permanent promotion effects at the individual household level. Key questions include: To what extent do aggregate data mask permanent effects due to the cancellation of opposite effects for different households? What household characteristics moderate the magnitude of permanent promotion effects? Is one type of promotion (e.g., free samples) better in achieving permanent effects than other types (e.g., price discounts)?

Measuring permanent promotion effects at the individual level has probably been hampered by a lack of household-level models with time series aspects such as unit roots. In that light, a particularly interesting development are Bayesian state space models for nonmetric-dependent variables (e.g., Lachaab et al., 2006). These models allow for the study of short- and long-run marketing effects on choices and other limited-dependent variables at the individual customer level, which is valuable for firms yet has not been captured by traditional methods (Leeflang et al., 2009).

8

Competition

8.1 Illustration

Brands may use price promotions to attract customers from competitor brands. Since a price promotion is relatively easy to implement, retaliation is likely. Hence a price promotion by one brand may be swiftly followed by a price promotion by another brand. To capture competition in a reduced-form fashion, we can specify a reaction function that explains a brand's wholesale price (cf. Nijs et al., 2007):

$$\begin{aligned} &\mathit{WholesalePrice}_{bt} \\ &= \psi_{0bt} + \sum_{b'=1}^{B} \psi_{1bb'} I[\mathit{WholesalePrice}_{b',t-k} - \mathit{WholesalePrice}_{b',t-k-1} < 0] \\ &\quad \times (\mathit{WholesalePrice}_{b',t-k} - \mathit{WholesalePrice}_{b',t-k-1}) \end{aligned} \tag{8.1}$$

$$\mathit{Price}_{bt} = \sum_{b'=1}^{B} \theta_{bb'} \, \mathit{WholesalePrice}_{b't} \tag{8.2}$$

where $\mathit{WholesalePrice}_{b't}$ is the wholesale price charged by brand b' at week t, and $I[X] = 1$ if X is true; 0 if X is false. Equation (8.1) shows the price setting mechanism for the wholesale price. The wholesale

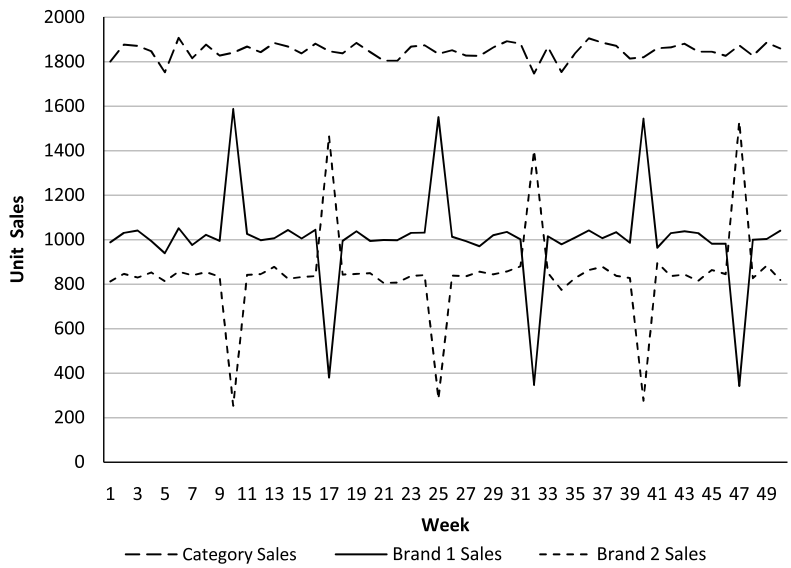

Fig. 8.1 Effects of competitive reactions.

price of brand b in week t is governed by the past wholesale prices of all brands in the category. Specifically, if there was a wholesale price discount k periods ago for brand b', brand b responds through $\psi_{1bb'} > 0$. Equation (8.2) says that the retail price for brand b at week t is set as a function of the wholesale prices in the category.

Figure 8.1 shows the impact of competitive reactions on sales for a $k = 7$ lag period. We assume that Brand 1's marketing plan called for three promotions. However, each of these promotions induces Brand 2 to follow in kind. The result is that the gains for Brand 1 due to promotion are ephemeral. They are wiped away by competitive response. A time series like Figure 8.1 could also be generated assuming that Brand 1 exogenously specified only the first promotion, but the brands react to each other in "tit-for-tat" fashion afterward. The point is that competitive response clearly can diminish the short-term gains of promotions.

8.2 Empirical Findings

Since promotions affect cross-brand sales and market shares, and they are relatively easy to replicate, competitive reactions are likely.

Competitors may either retaliate or accommodate a promotion initiated by a rival brand. Moreover, they may respond in-kind with the same instrument (e.g., price cut followed by price cut) or with another instrument (e.g., price cut followed by volume-plus promotion).

Leeflang and Wittink (1992, 1996) specify reaction functions similar to Equation (8.1) that allow for the measurement of the degree and nature of competitive reactions. For the grocery category under study, Leeflang and Wittink (1992) find that competitor reactions occur quite frequently, especially using the same marketing instrument as the initiator. In a follow-up study, Horváth et al. (2005) add cross-brand feedback effects (via lagged cross-brand sales) to reaction functions. They find that the role of cross-brand feedback effects is greater than the role of traditional competitive reaction effects.

By studying competitive reactions based on over 400 consumer product categories over a four-year time span, Steenkamp et al. (2005) test the empirical generalizability of Leeflang and Wittink (1992, 1996). Table 8.1 shows that the predominant reaction to a price promotion attack is no reaction at all. Indeed, for 54% of the brands under price promotion attack, the average short-term promotion reaction is not significantly different from zero. Furthermore, the significant short-term promotion reactions are twice more as likely to be retaliatory than accommodating (30% versus 16%). Table 8.1 also shows that long-term reactions are very rare. In over 90% of the instances, price promotion attacks do not elicit a persistent or long-term price promotion on the part of the defending brand. Nijs et al. (2007) reach a similar conclusion: competitive retailer prices account for less than 10% of the over-time variation in retail prices.

Steenkamp et al. (2005) find that absence of reaction corresponds primarily to the absence of harmful cross-sales effects. Only 118 out of 954 brands miss an opportunity in that they could have defended

Table 8.1. Competitive Reactions to Price Promotions.

Reaction with price promotion	Short-term effect (%)	Long-term effect (%)
No reaction	54	92
Competitive reaction	30	5
Cooperative reaction	16	3

This table is based on Steenkamp et al. (2005).

their position, but they chose not to. When managers do opt to retaliate, effective retaliation is prevalent (63%). In 56% of these cases the response neutralizes the competitive attack, whereas in 36% of these cases the net effect is positive for the defending brand.

An interesting perspective is provided by Pauwels (2007). He finds that competitive response to promotions plays a relatively minor role in post-promotion effects. The major factor in post-promotion effects is the company's own "inertia" to continue promoting in subsequent weeks. That is, companies tend to follow up promotions in period t with more promotions in period $t + 1$, etc. This is a very interesting finding in that it says companies are highly myopic when it comes to formulating promotion policy, basing the frequency of future promotions on the frequency of past promotions, rather than considering the competitive implications.

Overall, empirical evidence regarding competitive reactions to sales promotions is mixed. While in the short term there are some indications for competitive reactions in a minority of the cases, in the long term the percentage of cases hardly exceed the percentage one would expect to find by chance when testing at an alpha of 5%.

8.3 Managerial Implications

Competition lies at the heart of capitalistic economies, so it comes as no surprise that competitive reactions are a fact of life in the sales promotion realm. Price is the logical weapon of choice: it is easy to change fast (Kalra et al., 1998), unlike many other instruments of the marketing mix. Despite these facilitating properties, competitive reactions are not as prevalent as one may assume. Internal calculi are stronger determinants of promotion timing decisions (Nijs et al., 2007).

Nevertheless, when a firm is contemplating a price promotion, it pays off to anticipate how the competition will respond. Reaction functions such as the ones developed by Leeflang and Wittink (1992) can help to predict competitor response. Also when a firm evaluates the sales effect of promotions, it can be important to include competitive reactions in the evaluation (Leeflang and Wittink, 1996). That is, the direct (positive) effect of a promotion may be largely mitigated by the indirect (negative) effect due to competitor reactions. As a case in point, compare Figure 2.1 showing the sales response to promotions in the absence of competitive reactions, to Figure 8.1 showing what happens in the presence of competitive reactions. In Figure 8.1, the gains during own-brand promotions are completely nullified by the losses during cross-brand promotions.

From one brand's perspective, in an ideal world there are no competitive reactions and the brand can extract monopolistic profits. Of course, this ideal world is a utopia, but are there ways to mitigate competitive reactions? One example of how do the opposite and provoke competitive reactions was shown in the Dutch grocery retailing industry (Van Heerde et al., 2008). The leading supermarket chain Albert Heijn decided to try and stop its market share from sliding and announced it wanted to cut prices across the board "to become less expensive than the market average". This ignited very strong competitive reactions: within days, all major chains decreased their prices, undercutting Albert Heijn's lowered prices. Over the next quarters an unprecedented price war developed. We cannot ascertain to what extent such strong responses were fueled by the competition-focused announcement "to become less expensive than the market average," but it probably did more harm than good. Hence to mitigate competitive responses a consumer-focused announcement (e.g., "savings for you") seems better than a competition-focused one.

8.4 Future Research

While significant headway has been made documenting competitive reactions, it is not entirely clear under what circumstances these reactions are stronger or weaker. A meta-analysis of published reaction coefficients would allow us to understand what brand-, market-, consumer-, and country-characteristics moderate the strength of the response of one firm to the other. For example, are responses stronger if the initiator has a high or a low market share? Are some countries–due to fewer economic regulations–more amenable to competitive reactions?

Competitive reactions, and their anticipation, lie at the heart of the so-called prisoner's dilemma that many firms face. The dilemma claims that firms A and B would both be better off without sales promotions, but since there is an incentive for both of them to start offering sales promotions (see Figure 2.1), they both end up offering sales promotions (see Figure 3.1). While this explanation sounds plausible, an alternative explanation is that it is actually more profitable for both firms to offer sales promotions. That is, perhaps there is no prisoner's dilemma. To investigate this conundrum, we need more empirical studies comparing actual profits in the absence or presence of sales promotions.

Research that documents the actual transition into a prisoner's dilemma is also scarce. Such research could determine the factors that facilitate this transition. Understanding of these factors will help governments on how to strengthen competition to enhance consumer welfare, and help firms to reduce competition to increase firm profits. The reverse transition out of a prisoner's dilemma has been documented by a landmark study by Ailawadi et al. (2001). This study looks at what happens after Procter and Gamble's move away from sales promotions to everyday value pricing. Ailawadi et al. (2001) conclude that competitors' reactions to a sustained change in advertising and promotion policy by a market leader vary with the degree to which their market share is affected. Reactions also vary by structural factors, such as the market share position of the competitor and the number of markets in which it competes with the initiator of the policy change. The study finds that the net impact for Procter and Gamble is a decrease in market share, though it is plausible that its profits increased. We need additional studies that look at more cases of fundamental changes in promotion policy to understand their antecedents and consequences.

9

Summary

This article has given an overview of several dynamic effects associated with sales promotions. Illustrating each dynamic effect in turn, the graphs in the beginning of each section clarify the aggregate (sales) implications of each effect. Of course, in the marketplace, these dynamic effects do not occur in isolation, but they happen simultaneously instead. Figure 9.1 shows what happens if we combine the dynamic effects discussed in this article: purchase acceleration, increased quantity, increased consumption, deceleration, state dependence, reference price effects, price sensitivity effects, permanent effects, and competitive reactions.

Figure 9.1 shows very strong promotion bumps for both brands, which are not unrepresentative for actual aggregate data. While Figure 9.1 does clearly show competitive reactions (via promotions for Brand 2), some post-promotion dips and some permanent effects, other effects (e.g., deceleration, repeat purchasing) are harder to ascertain.

Figure 9.1 begs the question to what extent we can estimate all these dynamic effects in one empirical model. To the best of our knowledge, there has not been a single empirical study trying to do the Herculean task to uncover each of these dynamic effects in one model. The best

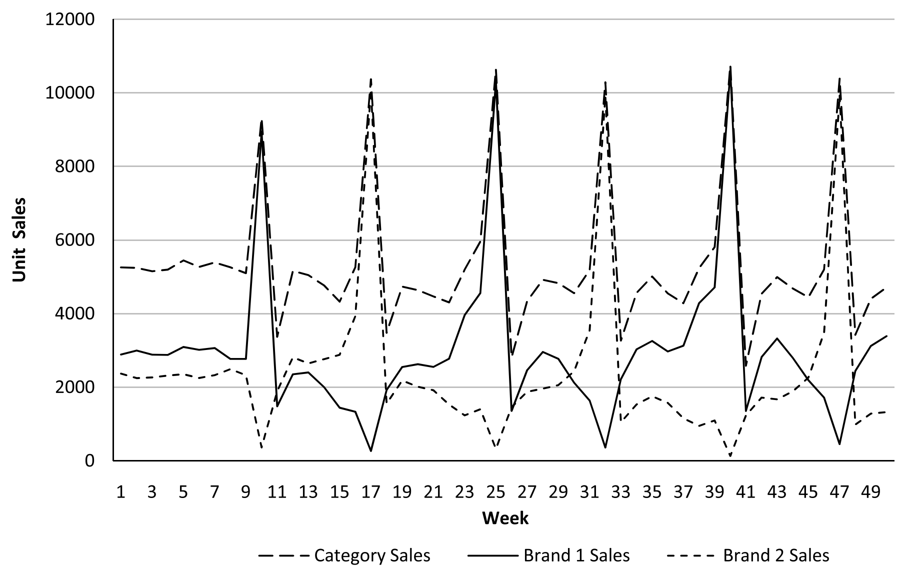

Fig. 9.1 Combination of all dynamic effects discussed in this article.

shot at it would be to use household-level data as these dynamic promotion effects lead to certain (subtle) household-level purchase behavior that should allow for estimating the parameters associated with each effect. However, even with household-level data, some effects are empirically so similar that it is an real question whether they are separately identified. For example, both reference price effects and the price sensitivity effect imply lower baseline purchases and stronger responses to price deals. The question is whether the model would pick this up via the reference price process or via the price sensitivity process.

These identification issues are likely to be amplified when one would use aggregate data to try to identify various dynamic effects. Just imagine trying to uncover all dynamic effects based on the aggregate data from Figure 9.1 alone! Therefore, it appears that aggregate data can only provide an aggregate estimate of the joint contribution of multiple dynamic effects. Notwithstanding this limitation, aggregate data do offer some benefits over disaggregate data: they represent a census of all store sales, their metric nature allow for time series techniques, they are more readily available across longer time periods, and they are often less expensive. Perhaps the biggest challenge for future research would be to disentangle the nine dynamic promotion effects we have reviewed in this article using just aggregate time series data.

In sum, this article we try to summarize the very large field of dynamic promotion effects in one coherent framework. We hope this summary is useful to students and practitioners–especially the illustrations and managerial implications–, and also useful to academic researchers–especially the empirical results and the directions for future research.

A

Details on the Promotion Dynamics Simulation[1]

General Simulation Parameters

Burn-in	=	100 weeks
Initialization	=	100 weeks
Promotion Simulation Period	=	40 weeks
Number Households	=	10,000

Key Outputs

- Total category sales each week = Number households times incidence for week t.
- Sales for each brand each week = Number of households incidence times choice times quantity for week t.
- Inventory = Average inventory level across households in each week.
- Consumption = Average consumption level across households in each week.

[1] The parameter values not in parentheses are for the baseline case illustrated in Figure 2.1. The values in parentheses show the parameter values when we simulate various dynamic effects.

- Price = Price of each brand in each week.
- ReferencePrice = RefPrice for each brand in each week.
- β_{1bt} = Price sensitivity for each brand in each week.

Incidence Model

$$P(I_t^h = 1) = \frac{1}{1 + e^{-Utility\_of\_Incidence_t^h}} = P(\text{household } h \text{ makes purchase in period } t) \quad \text{(A.1)}$$

Captures purchase acceleration

$$Utility\_of\_Incidence_t^h = \gamma_0 + \gamma_1 InclValue_t^h + \gamma_2 \overline{CONS}^h$$

Captures deceleration

$$+ \gamma_3 INV_t^h + \gamma_4 TimeSinceLastPromo_t^h \quad \text{(A.2)}$$

$$InclValue_t^h = \ln\left(\sum_{b'=1}^{B} e^{Utility\_of\_Brand\_Choice_{bt}^h}\right) \text{(see Equation (3.1) in text)} \quad \text{(A.3)}$$

$$INV_t^h = INV_{t-1}^h + \Omega PurQty_{t-1}^h - CONS_{t-1}^h \quad \text{(A.4)}$$

$$TimeSinceLastPromo_t^h = \sum_{b=1}^{B} w_{hb} TimeSinceLastPromo_{bt} \quad \text{(A.5)}$$

$$CONS_t^h = \left\{ \begin{array}{ll} \min\left(Inv_t^h, \overline{CONS}^h\right) & \text{if } c = 1 \\ Inv_t^h \left[\frac{\overline{CONS}^h}{\overline{CONS}^h + (Inv_t^h)^f}\right] & \text{if } c = 0 \end{array} \right\} \quad \text{(A.6)}$$

Captures increased consumption

Variables:

$\overline{CONS}^h \sim N(\mu_c, \sigma_c^2)$
$INV_0^h \sim N(\mu_I, \sigma_I^2)$

TimeSinceLastPromo is "time since last promotion".

$INV_t^h =$ Inventory household h has at the beginning of week t.

$PurQty_t^h =$ Purchase quantity (in units) bought during period t (Ω is ounces/unit).

$CONS_t^h =$ Amount consumed by household h during week t.

$c = 1$ if using the "min" consumption model;
0 if using the flexible consumption Inv% model.

Parameter values:

$\mu_c = 16$ oz.
$\sigma_c^2 = 16$
$\mu_I = \Pi\Omega(\Pi = 1 =$ initial number of units purchased per occasion.)
$\sigma_I^2 = 100$
$\gamma_0 = 0.3$
$\gamma_1 = 0$ ($= 0.75$ when simulating purchase acceleration)
$\gamma_2 = 0.05$
$\gamma_3 = -0.6$
$\gamma_4 = 0$ ($= -0.1$ when simulating deceleration)
$f = 0.15$
$c = 1$ ($= 0$ when simulating flexible consumption)
$B = 2$ (2 brands)
$\Omega = 64$ oz. = number of ounces contained in one unit.

Choice Model

Note: We use *tprev(h)* to signify the week in which the last purchase occasion occurred for household h. As a result, $(Price_{btprev(h)} - Price_{btprev(h)-1}) < 0$ signifies that there was a promotion in week *tprev(h)*. "Ifneg(X)" = X if X < 0, else $= 0$. So, $(ifneg)(Price_{btprev(h)} - Price_{btprev(h)-1})$ equals $(Price_{btprev(h)} - Price_{btprev(h)-1})$ if there was a promotion, else 0.

$$P(C_t^h = b | I_t^h = 1) = \frac{e^{Utility\_of\_Brand\_Choice_{bt}^h}}{\sum_{b'=1}^{B} e^{Utility\_of\_Brand\_Choice_{b't}^h}}$$
$$= P(\text{household } h \text{ chooses brand } b \text{ in week } t, \text{ given purchase}) \tag{A.7}$$

Captures reference price effects

$$Utility\_of\_Brand\_Choice_{bt}^h = \beta_{0b}^h + \beta_{1bt}^h Price_{bt} + \beta_{2b}^h (Price_{bt} - RefPrice_{bt}^h)$$
$$+ \beta_3 Last_{bt}^h + \beta_4 LastPromo_{bt}^h$$

Captures state dependence

$$+ \beta_5 Npromo_{bt}^h \tag{A.8}$$

Captures permanent effects

Reference price formation

$$RefPrice_{btprev}^h = \alpha RefPrice_{btprev(h)}^h + (1-\alpha) Price_{btprev(h)} \tag{A.9}$$

Price sensitivity parameter process function

$$\beta_{1bt}^h = \delta_0 + \delta_1 \beta_{1btprev(h)}^h + \delta_2 (ifneg)(Price_{btprev(h)} - Price_{btprev(h)-1}) \tag{A.10}$$

$$Last_{bt}^h = 1 \text{ if HH } h \text{ bought brand } b \text{ on the last purchase occasion; } 0 \text{ otherwise.} \tag{A.11}$$

$$LastPromo_{bt}^{h} = 1 \text{ if HH } h \text{ bought brand } b \text{ at the last purchase occasion } \textit{and} \text{ brand was on promotion (i.e., } (Price_{btprev(h)} - Price_{btprev(h)-1}) < 0) \quad \text{(A.12)}$$

$$Price_{bt} = \sum_{b'=1}^{B} \theta_{bb'}\, WholesalePrice_{b't} \quad \text{(A.13a)}$$

Captures competitive reactions

$$WholesalePrice_{bt} = \psi_{0bt} + \sum_{b'=1}^{B} \psi_{1bb'}(ifneg)[WholesalePrice_{b',t-k} - WholesalePrice_{b',t-k-1}] \quad \text{(A.13b)}$$

Variables

Last starts off at zero for each customer.
LastPromo starts off at zero for each customer.
V_{t-1} starts off at 0 for each customer.
$Npromo_{bt}$ = the cumulative # of times consumer bought brand b when it was on promotion, as of time t.
Starts accumulating the week after a promo.

Parameters

$\beta_{01}^{h} \sim N(\mu_1, \sigma_1^2)$ (Brand 1 baseline utility varies across households)
$\mu_{b1} = 0.2$
$\sigma_{b1}^2 = 0.25$
$\beta_{02}^{h} = 0$ (Brand 2 baseline utility is 0 for all households, relative to baseline for Brand 1)
$\beta_3 = 0$ ($= 0.9$ when simulating state dependence)
$\beta_4 = 0$ ($= -0.3$ when simulating impact of promotion on state dependence)
$\beta_5 = 0$ ($= 1$ when simulating permanent impact of promotion on utility)

$\alpha = 1$ (= 1 when reference price is constant, used when no reference price effect; = 0.1 when simulating reference price effect, i.e., assumes little memory of previous prices beyond last purchase)

$\delta_0 = -1.4$ (= −0.07 when simulating impact of promotion on price sensitivity)

$\delta_1 = 0$ (= 0.95 when simulating impact of promotion on price sensitivity)

$\delta_2 = 0$ (= 0.20 when simulating impact of promotion on price sensitivity)

$\omega_0 = 0$ (= −4.0 when simulating reference price effect)

$\omega_1 = 0$

$\omega_2 = 0$

$\psi_{01t} =$ \$1.88 for all t. (multiplied by 0.5 when Brand 1 is on promotion, i.e., Brand 1 decreases its wholesale price by 50% when it runs a promotion).

$\psi_{02t} =$ \$1.88 for all t

$\psi_{111} = 0$

$\psi_{121} = 0$ (= 1 when simulating competitive effects, i.e., Brand 2 plays tit-for-tat)

$\psi_{112} = 0$ (Brand 1 does not react to Brand 2 promotions)

$\psi_{122} = 0$

$\theta_{11} = 1.25$ (Retail price is 25% markup over wholesale price)

$\theta_{12} = 0$

$\theta_{21} = 0$

$\theta_{22} = 1.25$ (Retail price is 25% markup over wholesale price)

$k = 7$ (how many weeks it takes the brand or competition to react)

Quantity Model

$$\begin{aligned} P(\mathit{PurchQty}_t^h = k \mid I_t^h = 1, \mathit{BrandBought} = b) &\sim \mathit{Truncated\ Poisson}(\lambda_{bt}^h) \\ &= P(\text{Household } h \text{ buys } k \text{ units of Brand } b \text{ in week } t\text{, given the} \\ &\qquad \text{HH makes a purchase and the purchase is of Brand } b.\ k = 1\ldots. \end{aligned} \tag{A.14}$$

Captures quantity stockpiling effect of promotion

$$\lambda_t = \phi_1 + \phi_2 Price_{bt} \tag{A.15}$$

Parameters

$\phi_1 = 0.25$ ($= 2.6$ when simulating quantity stockpiling effect of promotion)

$\phi_2 = 0$ ($= -1$ when simulating quantity stockpiling effect of promotion)

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