Practice Prize Report—Quantifying and Improving Promotion Effectiveness at CVS

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Practice Prize Report

Quantifying and Improving Promotion Effectiveness at CVS

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We quantified the net unit and profit impact of each promotion offered in 2003 by CVS, a leading U.S. drug retail chain, and analyzed the key drivers of variation in this net impact. We used this analysis to identify the least effective promotions and conducted a controlled field test to demonstrate the impact of eliminating them before chainwide implementation. Our key findings are as follows. First, approximately 45% of the gross lift from promotions is incremental for CVS. Further, for every unit of gross lift, 0.16 unit of some other product is purchased elsewhere in the store. Still, more than 50% of promotions are not profitable because the lower promotional margin is not sufficiently offset by incremental units. Second, there is substantial variation in net profit impact across categories. Our field test shows that eliminating promotions chainwide in 15 of the worst performing categories will decrease sales by about $7.8 million but will improve profit by approximately $52.6 million. This is very impressive given that CVS front store sales in 2003 were approximately $9 billion while the net profit impact of promotions was −$25.3 million.

Key words: promotion profitability; retail promotions; retail promotion impact
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1. The Managerial Problem

1.1. Company Background

CVS is a U.S. drugstore chain with over 4,000 retail stores in 35 states. It sells over 200 categories of health, beauty, edible grocery, and general merchandise products. "Front store" revenues (i.e., excluding prescriptions) were over $9 billion in 2003. In recent years, competition has intensified significantly in this industry, especially from mass merchants. It is telling, for instance, that in Texas $0.72 out of every consumer dollar spent on health and beauty products goes to mass merchants. These products are the mainstay of a drug chain.

CVS is a HILO (high-low) retailer, i.e., it offers price promotions on several products each week. Approximately 30% of its sales are made on promotion. The company's research showed that direct competition from every day low price mass retailers like Wal-Mart is lowering consumers' reference prices and hurting the price perception of CVS. Although the company's promotional prices are low, regular price points are in many cases so much higher than their every day low price competition as to not be sustainable. Further, effectiveness seems to vary widely among the tens of millions of promotions that CVS runs each year.

The company has no intention of abandoning its HILO positioning but it wants to ensure that its promotional pricing decisions are effective in competing with other retailers and in their net sales and profit impact for the company. To do so, it needs to (1) determine which promotions are effective, which ones are not, and why; (2) eliminate or modify ineffective promotions; and (3) reinvest the savings in more competitive prices and better merchandising.

1.2. Research Objective

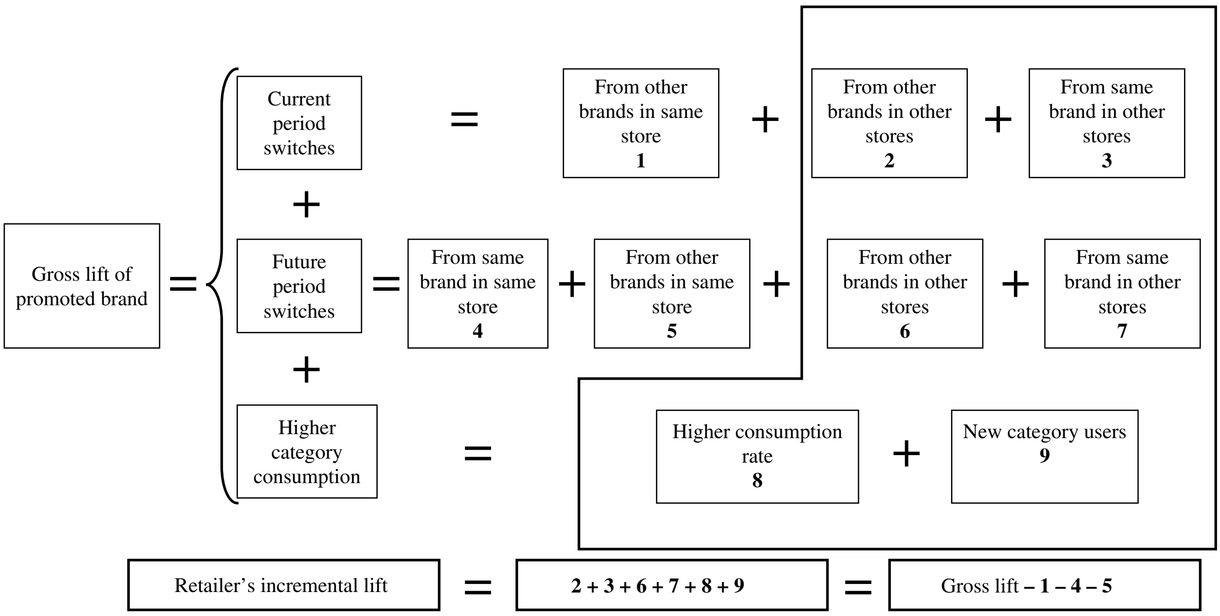
The overarching purpose of this project was to quantify and improve the net impact of CVS's promotions. We compiled data for each of the over 30 million promotions offered in any of its approximately 4,000 stores during 2003 and (a) estimated the immediate or gross lift of the promotion; (b) decomposed the gross lift into three components, i.e., current period switching from other brands in the store, stockpiling from future period category sales in the store, and incremental lift for the store; (c) estimated the "halo" effect of the promotion, i.e., the extent to which it increases sales of other product categories in the store; (d) accounted for differences in promotional and regular margins and the funding provided by the manufacturer; and (e) calculated the net unit and profit impact of the promotion. We then conducted a meta-analysis of how this net impact varies with characteristics of the promotion, brand, category, and market, and identified the most unprofitable promotions as candidates for elimination. This analysis not only helped the company determine which promotions were particularly ineffective and which ones were more effective but also provided a deeper understanding of why such variation exists, and how to implement more effective promotions.

Promotion impact is certainly not a new subject for academics or practitioners, with the studies based on scanner data dating back to the eighties (e.g., McAlister 1986, Gupta 1988). Packaged goods manufacturers spend over 50% of their total marketing budgets on promotions (Cannondale Associates 2000) and market research companies generate significant revenue from the reports they provide to manufacturers quantifying the gross lift that manufacturers' brands get from promotion. Further, academics have spent considerable effort in understanding why the gross lift varies across categories and brands as well as in decomposing that lift into brand switching, consumer stockpiling, and primary demand components, at least for a few categories.

Why then did we need to conduct our own study of promotion effectiveness? The reason is that most work on promotion impact takes the perspective of manufacturers (see Cooper et al. 1999, Srinivasan et al. 2004 for two exceptions). Further, lack of publicly available cost data has prevented analyses of the profit impact of promotion. Retailers make decisions about promotions that are offered to consumers, they experience the direct financial impact of those decisions, and effectiveness for a retailer is quite different from effectiveness for a manufacturer. Any promotion-induced increase in category consumption benefits both manufacturers and retailers, but aside from that manufacturers benefit by switching consumers from competing brands whereas retailers benefit by switching consumers from competing stores.

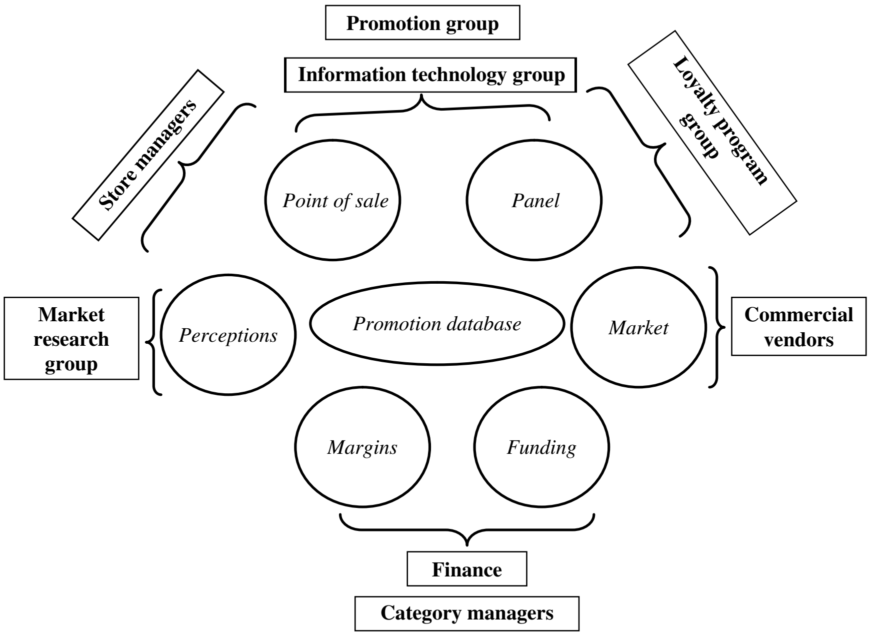
Figure 1 depicts all the components of the gross lift for a promoted brand in a given store in a given period and highlights the components that comprise incremental lift for the retailer. Along with this incremental lift within the category, the retailer must consider any "halo" effect that the promotion may have

Figure 1 **Components of Gross Lift**



Retailer's Incremental Lift + Halo Effect = Retailer's Net Unit Impact

Figure 2 Promotional Database: Key Elements and Sources



on sales of other categories in the store to determine the net unit impact of the promotion in the store. Further, the retailer must account for regular and promotional margins, including manufacturer funding, to determine the net profit impact of the promotion in the store. Even after accounting for manufacturer funding, CVS' promotional margin is often lower than regular margin.

Although there is a significant gross lift when a promotion is offered, substantial variation seems to exist in the net impact of different promotions. How much of the gross lift is incremental and how much is simply switched from other brands in the store or pulled forward from consumers' later purchases at CVS? Are promotions on some products particularly effective in increasing sales elsewhere in the store? Does a net increase in units after accounting for these components imply a net increase in profit? In which categories are promotions most and least effective and why? CVS needs answers to these questions, especially in its core health and beauty categories that are rarely studied by academics with access to grocery product data.

1.3. Key Challenges

Conducting a study of this scale and magnitude for the first time posed significant data, organizational, and methodological challenges even though it had the full and enthusiastic support of senior management. We realized very quickly that real data in a company with such widespread operations are not readily available in the well-organized, clean, ready-to-use form that academics working with a few categories from one or more markets are used to.

First, we had to identify the sources within the company that could help compile different portions of the data. This required bringing together people from different organizational units and locations, getting them to buy into the project, and convincing them to share their knowledge and data even if this revealed limitations in their existing decision processes. Figure 2 summarizes the different organizational units involved in building the complete promotion database. Information on consumer perceptions of CVS prices and value came from the marketing research team, the point-of-sale data that form the backbone of our analysis and are routinely collected by CVS were provided by store managers in each market and the corporate IT team, the loyalty program (called "Extra Care" by CVS) panel data for analysis of stockpiling were provided by the Extra Care loyalty program team, data on promotion characteristics required input from the promotions group and some manual compilation from weekly flyers in each market, and data on margins and vendor funding were provided by category managers and the finance group.

Second, we faced a significant political challenge within the organization. CVS is a HILO retailer and its promotional pricing strategy is a cornerstone of its marketing position. Many people viewed this project with skepticism and were concerned that it was aimed at cutting their key sales lever—promotions. It was therefore very important to (1) ensure and publicize strong support from the top, especially the executive vice president of marketing and merchandising and the vice presidents of marketing and merchandising; (2) highlight "improvement in ROI from promotion spending" as a critical goal for all relevant groups in the company's annual process of setting and monitoring goals and priorities; (3) make the data, methods, and analysis completely transparent; (4) implement the project in stages; and (5) get active participation particularly from the promotions and merchandising groups at each stage.

The first and most critical phase of the project was to quantify promotion impact. We ensured that all affected groups were aware of and had the opportunity to provide feedback on the data, assumptions, methodology, and analysis in this phase. Only then did we enter the next stage of analyzing variations in promotion impact, identifying the least and most effective promotions and recommending changes. To further build confidence in (and of course to test) the validity of the recommendations, we designed a controlled field experiment in which the impact of the recommended changes was tested and quantified before chainwide rollout. And the expected revenue impact of the implemented changes was explicitly taken into consideration in revising targets and budgets for each group. In this way, all affected parties saw that changes were being made based not on the whims of top management or gut feel but on scientific measurement and tests that they were involved in themselves.

A third challenge was that of database preparation. The nature of the data offered a key advantage that eased this task. These are all objective, archival data so we did not have to deal with the complexity and potential biases involved in using more subjective, perceptual data. Further, the data warehouse capabilities at CVS are quite impressive. The company's product line is organized in a hierarchy of departments, categories, subcategories, and individual items or SKUs. Each SKU has a unique code that identifies its category, subcategory, manufacturer, brand, specific flavor, size, etc. The same code is used throughout CVS and by its vendors so it was easy to merge data from different sources by the SKU code. However, some modifications were needed to group items into what constitutes a product category from the consumer's viewpoint. In most cases, subcategories (e.g., manual toothbrushes, power toothbrushes, toothpaste, dental floss, etc. within the oral hygiene category) appropriately define product categories from the viewpoint of the consumer. However, in some cases, subcategories are too narrow to reflect the reality of how consumers switch between individual items. For instance, naproxyn, acetaminophen, ibuprofen, and aspirin are separate subcategories within pain relievers but consumers view them as substitutable. The research team worked with category managers to combine subcategories where necessary, examining switching patterns in sales data in the very few cases where the appropriate level of aggregation was not obvious.

There were other issues in database preparation and storage that took a few months to tackle. These include (a) manually correcting the point of sale data for prices and discount depths of BOGO ("buy one, get one free") promotions; (b) allocating total vendor funding to individual brands and items and also to promotional versus nonpromotional sales (since not all vendor funding is tied to promotions); and (c) buying and setting up a new server and other computing resources devoted to the large-scale data storage, retrieval, and analysis required for this project.

The fourth challenge was identifying a suitable methodology. We needed a methodology that (a) provides robust estimates of the gross lift and net impact; (b) is practical for CVS to implement on an ongoing basis for the evaluation of millions of promotions offered in its stores each year; (c) can be used with only one year of point of sale data and/or two years of panel data because that is the most CVS can store at any given time. The company wanted to obtain reasonable estimates of the net sales and profit impact of each promotion but, perhaps more importantly, it wanted to be able to compare different promotional events using the same method in order to distinguish between poor and good performers, understand the correlates of variation in effectiveness, and use that understanding in future promotion decisions.

As van Heerde et al. (2004) note, estimating how many units of the gross lift come from other products, other periods, and higher consumption is crucial for determining the net unit impact of promotions. However, we did not use their methodology because we need the gross lift and net impact of individual promotions rather than an average effect for a brand. Also, we found that their methodology could not quantify stockpiling in a drugstore chain with only 52 weeks of aggregate data. Consumers shop at drugstores less than once in two weeks (versus at least once a week at a grocery store), and the average purchase frequency for most products at CVS is less than twice a year. As a result, stockpiling effects are spread over a much longer period than the 6–8 weeks for grocery stores (van Heerde et al. 2004, Macé and Neslin 2004). We therefore use two years of panel data to estimate stockpiling but follow the spirit of van Heerde et al.'s (2004) approach in estimating switching and halo rates.

1.4. Preview of Key Findings

Before providing details of our analysis and the insights it provided for CVS, we preview our key findings. First, approximately 45% of the gross lift is due to switching within the store and 10% is due to stockpiling future purchases in the store, leaving a substantial 45% as incremental lift for CVS. Second, there is a significant halo effect of promotion—for every unit of gross lift, 0.16 units of some other product is purchased elsewhere in the store. Third, despite the sizeable magnitude of the net unit impact, more than 50% of CVS's promotions are not profitable because the company's promotional margin is often less than its regular margin. Fourth, there is substantial variation across brands and categories but, overall, promotions have the worst net impact for health products and the highest net impact for beauty products. Finally, a field test shows that eliminating promotions chainwide in approximately 15 of the worst performing categories decreases sales by about \$7.8 million but improves profit by approximately \$52.6 million. This is extremely impressive given that 2003 front store sales were approximately \$9 billion while the net profit impact of promotions was −\$25.3 million.

2. Methodology for Quantifying Promotion Impact

Complete details of the methodology that has been tested and put in place at CVS are available in Ailawadi et al. (2006) but we provide an overview below. We estimate the gross lift of each promotion, the percentage that represents in-store switching from other items in the category (Figure 1, box 1), the percentage that is stockpiled and pulled forward from future category sales in the store (Figure 1, boxes 4 and 5), and the halo effect on sales of other categories in the store. As shown in the figure, subtracting the in-store switching and stockpiling components from the gross lift provides the incremental lift of the promotion, and adding in the halo effect provides the net unit impact of the promotion in the store.

2.1. Gross Lift

The gross lift for a promoted item in a given store in a given week is equal to the unit sales of that item during the promotional week minus its baseline unit sales in that week. Like Abraham and Lodish (1993), we estimate the baseline as a moving average of the item's unit sales in neighboring nonpromotional weeks. Initial analysis showed that baselines computed using a fixed number of lagging weeks were not robust for highly seasonal and relatively slowmoving items. We therefore use a combination of lagging and leading weeks. A long lag is used for very slow-moving items with little seasonality since more weeks are necessary to get a good estimate of sales and the representativeness of earlier weeks is not compromised because the item is not seasonal. In contrast, shorter periods are used for seasonal and relatively fast-moving items. For highly seasonal items, we use both lags and leads instead of just lags so that the weeks remain representative of the season for which baseline sales are being estimated.

2.2. Switching

If, for every unit increase in the gross lift of all promoted items in category c in store s in week t, there is a corresponding unit increase in total category units in the store that week, then the promotion is not switching any sales from nonpromoted items in the category. On the other hand, if the gross lift is purely due to switching from other items in the category, there should be no increase in total category units in the store. To illustrate, consider a category with five items, of which two are promoted in a given week. If the gross lift for the promoted items is ten units and six units, respectively, and total units sold of the category increase by sixteen, then the switching percentage is zero. If, on the other hand, total category units increase by only ten units, then six units are switched from the nonpromoted items in the category, making the switching percentage 37.5% of the total gross lift. The following regression of weekly category unit sales on weekly category gross lift allows us to estimate this switching percentage:

$$\text{Category Units}_{cst} = \beta_{0c} + \beta_{1cs}\,\text{Category Gross Lift}_{cst} + \varepsilon_{cst},$$

where

$$\text{Category Gross Lift}_{cst} = \sum_{i\in c} \text{Gross Lift}_{icst}; \qquad (1)$$
$$\beta_{1cs} = \beta_{1c} + \beta^*_{1cs}; \qquad \beta^*_{1cs} \sim \mathrm{N}(0, \sigma_c^2).$$

We estimate this random coefficients model for each category using deseasonalized and first-differenced data from all stores. β_{0c} and β_{1c} are category fixed effects and β^*_{1cs} is a random effect for each store. The switching percentage for category c in store s is given by $1-(\beta_{1c}+\beta^*_{1cs})$. Note that the independent variable is the gross lift summed across all promoted items in category c in store s in week t. Thus, we account for all promoted items in the category though we assume that they have the same switching percentage.

2.3. Stockpiling

The stockpiling component of the gross lift is the percentage that is taken from future category sales in the store. As noted earlier, this stockpiling effect is spread over a fairly long period of time. We use two years of CVS loyalty program panel data to estimate the reduction in future category purchases when consumers buy on promotion by comparing subsequent purchases of promotional buyers with subsequent purchases of nonpromotional buyers.[1] We order

[1] We do this because the time series of each panelist does not contain enough purchases to reliably estimate his or her own future decrease in category purchase after a promotional purchase.

buyers into annual spending deciles and compare promotional and nonpromotional buyers within each decile. Thus, promotional buyers are compared with nonpromotional buyers whose annual spending in the category is similar to their own. For each purchase in each group in each decile, we calculate the time until the next purchase of the category at CVS and compute the difference in average time between promotional and nonpromotional purchases in that decile. We weight this difference by each decile's average number of category units per purchase occasion to obtain an overall average reduction in category units. This reduction divided by the gross lift in the category observed in the panel is the stockpiling percentage.

2.4. Halo

If, for every unit increase in the gross lift from promoted items in a given store in a given week, there is a change in total store units (after adjusting for the nonswitched portion of the gross lift), then the promotion has a halo effect on other categories sold in the store. Thus, we estimate the effect of gross lift on store (adjusted) unit sales:

$$\text{Adjusted Store Units}_{st} = \beta_0 + \sum_{d=1}^{4} \beta_{ds} \text{ Total Gross Lift}_{dst} + \varepsilon_{st},$$

where

$$\text{Total Gross Lift}_{dst} = \sum_{i \in d} \text{Gross Lift}_{idst}; \qquad \beta_{ds} = \beta_d + \beta^*_{ds}; \qquad \beta^*_{ds} \sim \text{N}(0, \sigma_d^2). \tag{2}$$

There are four independent variables in this model—the total gross lift from all promoted items in department d in store s in week t—where d goes from 1 to 4 for the health, beauty, edible products, and general merchandise departments, respectively. Thus, we estimate separate halo effects for each department. As with switching, data are deseasonalized and first-differenced before estimation. We estimate fixed effects β_0 and β_d and random effects β^*_{ds} for each store, and $(\beta_d + \beta^*_{ds})$ is the halo effect of promotions in department d in store s.

2.5. Net Unit and Profit Impact

The net unit impact of the promotion in the store is:

$$\begin{aligned}\text{Store Net Unit Impact} \\ &= \text{Gross Lift} \times (1 - \%\ \text{Switching} \\ &\qquad - \%\ \text{Stockpiling} + \%\ \text{Halo}).\end{aligned} \tag{3}$$

Accounting for CVS's regular and promotional margin of the promoted item inclusive of manufacturer funding, activity-based costs (ABC), the regular and average margin of other items in the category (for switching and stockpiling, respectively), and the average margin of all items in the store (for halo) provides the net profit impact of the promotion in the store:

$$\begin{aligned}&\text{Store Net Profit Impact}\\ &= \text{Promo Units} \times (\text{Promo Price} - \text{Manuf. Price}\\ &\qquad - \text{ABC} + \text{Nonpromo Funding} + \text{Promo Funding})\\ &\quad - \text{Base Units} \times (\text{Regular Price} - \text{Manuf. Price}\\ &\qquad - \text{ABC} + \text{Nonpromo Funding})\\ &\quad - (\%\ \text{Switching} \times \text{Gross Lift} \times \text{Regular Category}\\ &\qquad \text{Price} \times \text{Regular Category}\ \%\ \text{Margin})\\ &\quad - (\%\ \text{Stockpiling} \times \text{Gross Lift} \times \text{Average Category}\\ &\qquad \text{Price} \times \text{Average Category}\ \%\ \text{Margin})\\ &\quad + (\%\ \text{Halo} \times \text{Gross Lift} \times \text{Average Store Price}\\ &\qquad \times \text{Average Store}\ \%\ \text{Margin}).\end{aligned} \tag{4}$$

Note that the (regular) manufacturer price is unambiguous because that is clearly recorded for every item. Further, CVS has a well-established system for estimating its activity-based costs. However, manufacturer funding has to be allocated—some of this funding is linked to promotions and is therefore applied only to promotional margin while some of it is linked simply to sales and is therefore applied to both promotional and regular margin.

3. Empirical Analysis: Promotion Impact

3.1. Overview of Promotion Impact

Table 1 provides the starting point of our findings regarding CVS promotion effectiveness. It summarizes the size of the gross lift as a percentage of baseline sales and the switching, stockpiling, and halo rates. There are several important insights here. First, neither the typical discount depth nor the size of the lift is much different from grocery stores (Blattberg and Neslin 1990, p. 351; Narasimhan et al. 1996). At CVS, the median gross lift due to promotion is 310% of baseline sales. Second, the median percentage of the gross lift that is attributed to switching from other items in the category within the same store is about 46%. This is much closer to the 35% or so recently reported by van Heerde et al. (2003) than the 75%–80% reported by Gupta (1988), Bell et al. (1999), etc. in their elasticity decompositions.

Third, the percentage of the gross lift that is pulled forward from future CVS sales due to consumer stockpiling is fairly small, at about 10%. Note, however, that some part of consumer stockpiling, which is

Table 1 Overview of Promotion Impact

Variable	Median	Standard deviation
Baseline units (per item per week per store)	0.86	6.0
Baseline profit (per item per week per store) ($)	1.29	5.1
Promotional discount (as a percent of regular price) (%)	30.0	14.5
Gross lift % (as a percent of baseline units) (%)	310	581
Switching rate (portion of every unit of gross lift for a promoted item that is switched from other items in the category within the store in the same week)	0.46	0.16
Stockpiling rate (portion of every unit of gross lift for a promoted item that is pulled forward from future category sales within the store due to consumer stockpiling)	0.10	0.10
Halo rate (number of units of some other product sold elsewhere within the store in the same week for every unit of gross lift for a promoted item)	0.16	0.17
Net unit impact (per item per week per store, computed using Equation 3)	1.05	12.7
Net profit impact (per item per week per store, computed using Equation 4) ($)	−0.62	13.5

taken from future sales in competing stores, is incremental lift for CVS. Also note that the mix of product categories for CVS is quite different from a grocery chain. CVS carries a much higher percentage of health and beauty products than food products, and the former are more need based. Even though they can be stored, consumers do not stockpile them unless they foresee a need for them. Fourth, promotions at CVS have a significant halo effect that varies substantially across departments. For every unit of gross lift, an extra 0.16 unit of some other product is sold in the store.

Table 1 also provides an overview of the net unit and net profit impact of promotion. These numbers are in units and dollars, respectively, and the unit of analysis is a week-long promotion on an individual item or UPC. To put them in context, we also report the baseline units and profit per item per store per week. Thus, the average item's baseline weekly sales in a CVS store are 0.86 units and its baseline weekly profit is $1.29. A week-long promotion on an average item in a CVS store creates a net increase of 1.46 units and decreases profit by $0.33.

The first take-away from this analysis for CVS is that although the net unit impact of a promotion is positive on average, the net profit impact is negative. The substantial switching and stockpiling components are one part of the reason but can not be the only reason, because the net unit impact is positive. We find that after accounting for all manufacturer funding and allocating it to promotional and nonpromotional sales, CVS margin on promotional sales is often significantly less than its regular margin. And of course all units sold during the promotion earn the lower margin, not just the truly incremental units. This can make net profit impact negative even if net unit impact is positive.

These results about the magnitude and composition of promotional effects were very insightful for CVS. They provided a rigorous analysis-based estimate of the incremental portion of the gross lift rather than one based on anecdotal evidence or vendor supplied information.

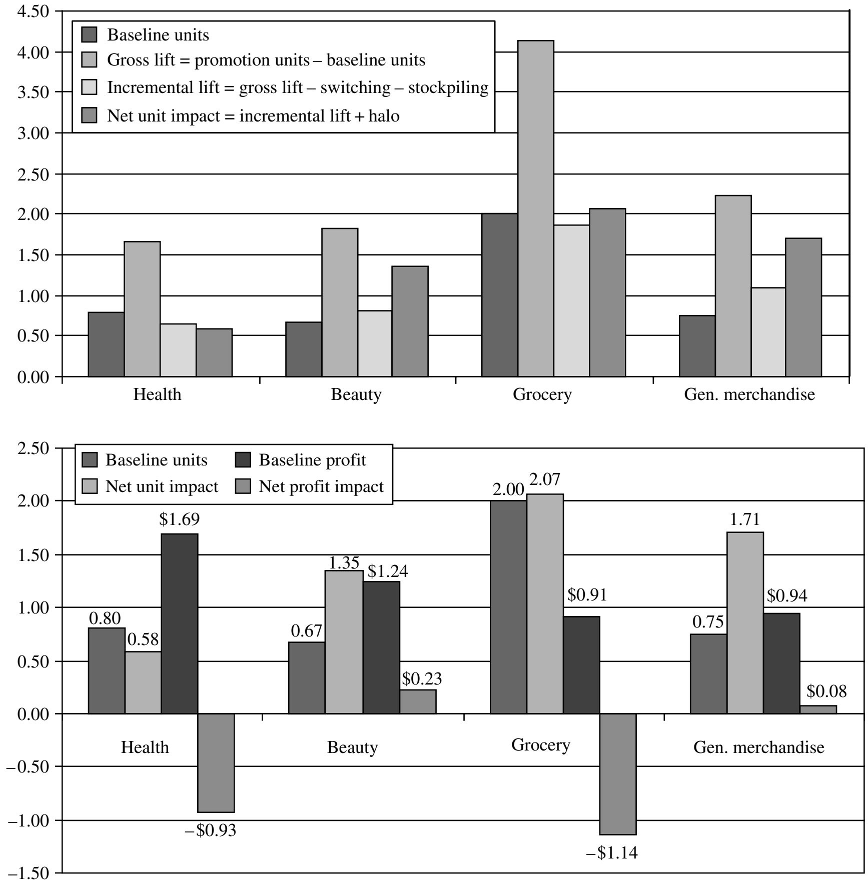
3.2. Variation in Promotion Impact Across Departments

Figure 3 shows how the impact of promotion varies across the four main product departments at CVS—health, beauty, edible grocery, and general merchandise products. The top chart depicts the median values of baseline units, gross lift, incremental lift, and net unit impact for each department. As before, the unit of analysis here is a week-long promotion on a given item in a given store. As the chart shows, health products have the smallest gross and incremental lift in absolute terms as well as relative to baseline units. Further, the halo rate is slightly negative (−0.04), making the net unit impact smaller than the incremental lift. In contrast, beauty products show a much higher gross and incremental lift relative to baseline units. And their net unit impact is substantially higher than the incremental lift because of a high halo rate. Indeed, the 0.30 halo rate for beauty products is higher than that for any of the other departments. The gross and incremental lift for grocery products is high in absolute units but not relative to baseline units, and with a small halo rate of 0.05 net unit impact is only slightly bigger than incremental lift.

Figure 3 shows not just the net unit impact but also the net profit impact of promotions in each department. Promotions have a substantial negative net profit impact for health and grocery products. In both of these departments, the net unit impact is not high enough to offset the smaller margin that CVS makes on promotion. In contrast, beauty product promotions have the highest net profit impact, with general merchandise promotions just breaking even.

These differences in promotion impact across departments are important for CVS, as they want to flag the most ineffective promotions for possible change. Among the bottom 15% of promotions in terms of net profit impact, 51% are health products and only 10% are beauty products. In contrast, among the top 15% of promotions, 44% are beauty products and 26% are health products. Of course, there is plenty of variation in net impact even within departments. In order to provide CVS with a deeper understanding of this variation, we estimated a model of how promotion, brand, category, and market characteristics are associated with the net impact of promotions. Detailed

Figure 3 **Variation in Promotion Impact by Department**



results of this analysis are available in Ailawadi et al. (2006).

4. Impact on Practice

4.1. Benefits for CVS

The primary purpose of this project was to quantify the impact of CVS promotions, understand how and why it varies, and use that understanding to improve promotion profitability. Our analysis identified which promotions were the most and least effective and why. Based on this analysis, we identified 15 categories where promotions consistently had negative profit impact and at best a small positive net sales impact. We recommended that promotions of these categories be significantly cut back or eliminated. Before any chainwide changes were made, however, CVS wanted to validate our analysis. We therefore designed and implemented a controlled field test to assess the impact of eliminating promotions in these categories.

Approximately 400 CVS stores in 5 markets were selected as experimental stores in this field test for 1 quarter, i.e., 13 weeks. The experimental stores were chosen in consultation with category, merchandising, and store managers to be as representative as possible of the entire population of CVS stores. Criteria for experimental store selection included coverage of each major CVS region, average market size, store size and age, no major changes in the store or market area (e.g., store expansion or renovation), major competitive entry or exit, etc. Control stores were matched on market demographics, store sales, margin, growth rate, etc.

Promotions of the 15 categories were discontinued in the experimental stores whereas they were promoted as originally planned in a matched set of stores in other markets within the same region, which served as a control group. For the experimental markets, the blocks of space in the weekly promotion flyer used to feature promotions for these categories were replaced by nonprice messages and advertising about the same categories. Focus groups showed that consumers did not perceive differences between the two sets of flyers.

Our analysis predicted a small decrease in the sales of the 15 categories in the experimental stores relative to control stores, but no loss of sales of other categories and a significant increase in total profit. During the period of the field test, we tracked the number of transactions per day, item level sales, and profit in these experimental categories as well as in other categories in the stores. In addition, we tracked consumers' value ratings of sales and specials offered by CVS and purchase patterns of the panel of consumers in the CVS loyalty program.

The field test showed that in all but one of the categories the experimental stores indeed had higher profit even though category sales were lower. Further, there was no significant reduction in store traffic or sales of other categories in the store. The panel data supported these aggregate results—while there was a small decrease in penetration of the categories among program members, their store visits and their purchases of other products at CVS were unaffected. Finally, there was no significant difference between experimental and control stores in consumers' value ratings.

A projection of the results from the 13-week test in the experimental stores to a 52-week period chainwide showed a net sales loss of \$7.8 million but a net profit gain of \$52.6 million. Compared with total sales revenue of approximately \$9 billion, the sales loss is not of concern to CVS. In contrast, given that the net profit impact of promotions in 2003 was −\$25 million, a savings of \$52.6 million in profit is highly significant. In the words of a senior CVS executive, "\$52 million dollars in profit savings is the equivalent of \$250 million dollars of new business for the company!" In 2005, CVS implemented these changes chainwide and is investing the profit savings in lower regular prices and other merchandising support. Early analysis shows that actual changes in CVS unit and dollar shares in these categories, as tracked by Information Resources Inc. reports, are in line with those that were expected based on our analysis. The company continues to carefully track not only aggregate share and profit data but also customer level perceptions and purchase behavior.

While this project has delivered on its major goal, i.e., the improved profitability of promotions, it is also showing significant impact along some other dimensions. First, it served as a stimulus for CVS to put together a comprehensive picture of how much of total vendor funding comes unencumbered with any requirements, how much is tied to promotions, and how much is tied only to sales volume. CVS obtains vendor funding in several forms throughout the year. This includes but is not limited to lump-sum payments, promotional allowances for features and other merchandising, scan backs, and off-invoice discounts. Most of the funding is negotiated between the category manager and the vendor well before the beginning of the year, although funds come in and are spent during the year. CVS category managers regularly compile all vendor funding for their category, so the total amounts were available for this project. However, since only a small percentage (less than 15%) of total vendor funding is directly linked to individual promotions, the rest had to be allocated to promotional and nonpromotional sales and to individual promotions. This allocation process is not perfect, but going through it has proved to be extremely valuable in guiding promotion decisions and in vendor interactions.

Second, the fact base provided by this project is allowing CVS category managers to be better prepared for their interactions with vendors. Instead of simply considering gross lift of the promoted item or brand, they can now look at incremental lift in the category and net impact in the store as they negotiate manufacturer funding and decide on their quarterly promotional calendars. A third operational benefit, which is just beginning to surface, is an improvement in inventory management. The crests and troughs of demand are flattening out in the categories where promotions have been cut, making it easier to forecast sales and manage inventory.

It would be an exaggeration to claim that we have overcome all the challenges, particularly the politically charged ones around "promotion cuts," and that information availability, flow, and utilization is now optimal. However, we can honestly say that significant progress has been made on all these dimensions. The reason for this progress is that the project and the subsequent field test have demonstrated a real, quantifiable, and significant impact on the company's bottom line. The company's successful implementation of the tested promotion changes chainwide and its ongoing use of our promotion analysis methodology attests as nothing else can, to this impact.

4.2. Benefits for Industry

Promotion spending in the United States exceeds \$200 billion per year (Promotion Marketing Association 2003), so it is critical that businesses that are funding promotions and implementing them understand how effective they are both for the manufacturer whose brands are being promoted and the retailer who actually sells those brands to consumers. The importance of this activity is underscored by the fact that promotion strategy sessions are attended not just by promotion managers and promotion agency executives, but also by brand managers, directors of marketing and promotion, and in the majority of cases by CEOs and presidents (Promotion Marketing Association 2003).

As one of the first attempts to assess promotion impact (especially profit impact) from the viewpoint of the retailer, our work has some important lessons for managers. The first is the set of empirical findings we have revealed about how promotions work for a retailer. For instance, almost 50% of the gross lift is switched from other brands in the store but promotion-induced consumer stockpiling pulls forward only 10% of future sales from the store, and the halo effect of a promotion on sales of other products can be significant, as retailers have always hoped but not necessarily demonstrated. Perhaps most importantly, our finding that more than 50% of CVS promotions have negative profit impact gives pause to the conventional wisdom that promotions are bad for manufacturers but good for retailers. Managers must understand the real impact of promotions for manufacturers and retailers before they can take the next step of trying to create "win-win" promotion strategies that make both parties better off.

The differences we observe across product categories are also important for managers. Health and beauty products are core to a drug chain but are also strongly associated with mass merchandisers who continue to grow their clout and share in the market. The contrast between these two departments is both interesting and surprising—promotions are least profitable for health products and most profitable for beauty products. Both manufacturers and retailers must take note of this contrast and try to understand it better.

Of course, our analysis is based on a single retailer even though it spans an unprecedented number of promotions, brands, categories, and stores, and Shankar and Bolton (2004) have shown that there are significant differences in pricing and promotion strategy across chains. Therefore, the opportunity for others to apply our models in their own businesses is perhaps even more important than the lessons learned from our empirical analysis. Most of the data used in our analysis are available within a company. Since scanners are now ubiquitous in all but the smallest "mom and pop" stores, retailers routinely collect point-of-sale (POS) store data which form the backbone of our analysis. Companies that have a loyalty program can utilize it to quantify stockpiling. Others can either try to estimate it from a longer span of POS data or use our estimates and conduct a sensitivity analysis to assess worst- and best-case scenarios. Compiling data on costs, margins, etc. and allocating vendor funding requires significant effort, but our experience at CVS is that the effort is well worth the insights that such data provide. The econometric models we have developed are summarized here and fully described in Ailawadi et al. (2006). They provide an easily transferable methodology to conduct such analyses that is both practical to implement and has been demonstrated to be robust. Indeed, the retail/value engineering unit at Mercer Management Consulting has had many years of success using these types of models to drive financial improvement at many retail businesses, including several large grocers and drugstores in the United States and in Europe.

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References

Abraham, M. M., L. M. Lodish. 1993. An implemented system for improving promotion productivity using store scanner data. *Marketing Sci.* **12**(3) 248–269.

Ailawadi, K. L., B. Harlam, J. Cesar, D. Trounce. 2006. Retailer promotion profitability: The role of promotion, brand, category, and market characteristics. *J. Marketing Res.* XLIII (November) 518–535.

Bell, D. R., J. Chiang, V. Padmanabhan. 1999. The decomposition of promotional response: An empirical generalization. *Marketing Sci.* **18**(4) 504–526.

Blattberg, R., S. A. Neslin. 1990. *Sales Promotion: Concepts, Methods, and Strategies*. Prentice-Hall Publishers, Englewood Cliffs, NJ.

Cannondale Associates. 2000. *Trade Promotion Spending and Merchandising Industry Study*. Cannondale Associates, Wilton, CT.

Cooper, L. G., P. Baron, W. Levy, M. Swisher, P. Gogos. 1999. PromoCast: A new forecasting method for promotion planning. *Marketing Sci.* **18**(3) 301–316.

Gupta, S. 1988. Impact of sales promotions on when, what, and how much to buy. *J. Marketing Res.* **25**(November) 342–355.

McAlister, L. 1986. The impact of price promotions on a brand's market share, sales pattern, and profitability. Working Paper 1622-85, Sloan School of Management, MIT, Cambridge, MA.

Narasimhan, C., S. A. Neslin, S. Sen. 1996. Promotional elasticities and category characteristics. *J. Marketing* **60**(April) 17–30.

Promotion Marketing Association. 2003. Promotion trends report. http://www.pmalink.org.

Macé, S., S. Neslin. 2004. The determinants of pre- and postpromotion dips in sales of frequently purchased goods. *J. Marketing Res.* XLI(August) 339–350.

Shankar, V., R. Bolton. 2004. An empirical analysis of determinants of retailer pricing strategy. *Marketing Sci.* **23**(1) 28–49.

Srinivasan, S., K. Pauwels, D. Hanssens, M. Dekimpe. 2004. Do promotions benefit manufacturers, retailers or both? *Management Sci.* **50**(5) 617–629.

Sun, B. 2005. Promotion effect on endogenous consumption. *Marketing Sci.* **24**(3) 430–443.

van Heerde, H. J., S. Gupta, D. Wittink. 2003. Is 75% of the sales promotion bump due to brand switching? No, only 33% is. *J. Marketing Res.* **XL**(November) 481–491.

van Heerde, H. J., P. S. H. Leeflang, D. R. Wittink. 2004. Decomposing the sales promotion bump with store data. *Marketing Sci.* **23**(3) 317–334.