

## AN IMPLEMENTED SYSTEM FOR IMPROVING PROMOTION PRODUCTIVITY USING STORE SCANNER DATA

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"Single Source" databases based on scanner data offer new opportunities for evaluating promotions and improving their effectiveness. Decision support needs vary depending on the decision maker's organizational vantage point. Some managers require the evaluation of promotion results in the short term. Others should take a medium- to long-term focus. An implemented model and automated system for measuring short-term incremental volume due to promotions by developing baselines of store-level "normal" sales is presented using store-level scanner data. Empirical validation results and real life applications are presented and discussed, including the use of the baselines as measures of "brand health."

**(Promotion Evaluations; Scanner Data; Baselines)**

### 1. Introduction

Promotion productivity for marketers of consumer packaged goods is viewed from different vantage points depending on one's role as a stakeholder. Manufacturers of packaged goods, their marketing managers, brand managers, sales managers and sales people all have different concerns about promotion productivity because of their different roles in the organizations. Retail buyers, merchandising managers and store managers also have different objectives when they think of promotions.

In this paper we first describe the managerial promotion decision support needs both for manufacturers—including brand managers, senior marketing managers and salesforces—and for retailers. We differentiate decisions which depend on short-term versus longer-term promotion evaluation. This article describes only the systems for short-term promotion evaluation. We next describe the modeling needs that are required for supporting the different decisions which depend on short-term promotion evaluation and relate those to previous research. We then describe the syndicated data sources, our measurement and modeling methodologies, the automated system, PROMOTIONSCAN®, which brings them together, and we present empirical validation. We then show some actual system applications and how they are used by various stakeholders, show examples of the system's impact on a firm's decisions, and conclude with directions for further research.

### *Manufacturer Decision Support Needs*

Within a manufacturer of consumer packaged goods, different managerial roles require different decision support needs. *Brand managers* are concerned about how to use their promotion budget to maximize volume or market share during a planning horizon which is typically short-term. S/he is concerned about: (1) which promotion tactics are most efficient from a volume or profit standpoint?, (2) in which market areas should promotions be run?, (3) which sizes or flavors respond best to promotions?, (4) how often to promote?, and (5) how are competitors reacting to these promotions?

*Senior marketing managers*, on the other hand, should be more determined to evaluate incremental profit on their investment in promotion resources with a long-term perspective. Their concern is how to determine the level of a promotion budget for a brand or a portfolio of brands. Issues such as purchase acceleration of promotions (see Neslin et al. 1985) and cannibalization across brands are important or should be important. A brand manager will be concerned with the current quarter's performance, while the senior marketing manager should be concerned about borrowing sales for the current quarter from the following quarters and will be receptive to data that quantifies that phenomenon. These senior management long-term evaluations are not considered in depth in this article.

The *sales manager* and *sales people* in packaged goods companies have a different vantage point. They are local market oriented and their concern is to maximize short-term volume sold through to end users by their retailers and to create merchandising support to help increase their product's demand. They are concerned about: on which accounts or markets to spend their time, and, most importantly, what to ask the retailer to do to increase volume for a product. Should the retailer be featuring the product in newspaper ads? Should the retailer be displaying the product? Should the retailer be reducing the price, and at what level? The issue of qualitative promotion execution becomes very important to sales people. Do some accounts get more response from displays or featuring than other accounts? Why? How can this information be used in selling situations to help improve the company's performance? These *short-term* sales management issues are handled by the system.

The issue of translating the salesforce inducements to the trade into the trade's activity such as newspaper advertising, displays and price reductions (commonly described as "pass through") is also a very important problem. However, due to lack of data, this issue is not handled by our system.

The *sales manager* has other concerns as well. How well is the salesforce executing promotions? How is the salesforce doing compared to implementing similar promotions that have been run in the past? How are some areas in their salesforces doing compared to other areas in implementing a particular promotion program? How should short-term incremental sales objectives for the salesforce be set? The short-term models described below have been helpful to salespeople and managers for these issues.

### *Retailer Decision Support Needs*

Retailers are concerned about promotions from a very different vantage point. In particular, they are interested in increasing the sales in their stores of the product category to which a brand belongs, not just the brand alone. They are concerned with increasing store traffic using promotions, increasing store loyalty of shoppers and increasing total sales of all products per shopper once they are in the store. Furthermore, they are concerned with allocating across products such scarce resources as display space and feature lineage in their weekly newspaper advertisements. The issues of store traffic, shopper loyalty and total shopper sales are beyond the scope of the current system.

## 2. Modeling and Data Needs for Practical Uses: System Objectives

### Modeling Needs

Decision support needs of both manufacturers and retailers require a number of models and estimates of market responses. A basic building block, which will concern all stakeholders, is *incremental volume* from promotions: sales volume for the item on promotion that is attributable to the promotion which occurred because of the promotion and would not have occurred if the promotion had not been run.

However, the incremental volume can be either *short-term* or *long-term* and be evaluated differently from different vantage points. *Short-term* incremental volume is volume that is generated in the promotion week, in the promoting store, that is incrementally related to the promotion, and is incremental to "normal" sales in that store during that week that would have occurred if the promotion had not been run. However, some of the incremental sales during the short term may be accounted for by purchase acceleration of loyal users who purchased earlier or a larger quantity than they normally would have. This purchase acceleration phenomenon causes cannibalization of future sales of the brand in the same store or possibly in other stores and needs to be subtracted from short-term incremental sales to get *long-term* incremental volume. If the cannibalization is in other stores, the retailer is happy. The brand manager is not happy because s/he is just subsidizing someone who would have used the product anyway. Figure 1 summarizes how the different stakeholders' viewpoints is related to the modeling and measurement needs of those stakeholders.

Note that this article only documents the models, procedures and systems for short-term promotion evaluation. See Abraham and Lodish (1991) for the long-term evaluation models which use scanner panel data.

The issues of how often to promote and reactions to competitors can be helped by understanding the short-term incremental volume estimates described in Figure 1. If the number of promotions or the competitive environment has changed, then the system described below will estimate these changes on short-term incremental volume. However, this article does not describe the modeling of all of the phenomena which might be

S = Short-term incremental volume from promotions  
L = Long-term (including purchase acceleration and cannibalization)  
I.V. = Incremental volume from a promotion

STAKEHOLDERS					
Manufacturers				Retailers	
Sales People	Sales Mgrs	Senior Mktg Mgrs	Brand Mgrs		
*		S,L	S,L	S	I.V. by brand (including cross size, flavor cannibalization)
*	*		S,L	S	I.V. by size
*	*		S,L	S	I.V. by flavor
*	S	S,L	S,L		I.V. by area
S	S	S,L	S,L		I.V. by promotion type
S	S	S,L	S,L	S	I.V. by merchandising support
S	S			S	I.V. by account
S	S		S,L	S	I.V. by Promotion Event
*✓	*✓			S✓	Effect on Store Traffic/Switching
*✓	*✓			S✓	Incremental Shopping Trips

\* Salespeople are interested to aid in selling  
✓ are not implemented in the current Promotionscan system

All of the "S" Incremental Volume are discussed in this paper. The "L" Incremental Volume have been implemented but are not discussed in this paper.

FIGURE 1. Overlapping Estimation/Modeling Needs by Stakeholders.

considered in a comprehensive model for “optimal” promotion scheduling or competitive reactions.

### *Data Needs and Practical Uses*

As shown by Abraham and Lodish (1987), factory shipments to retailers are not precise enough to answer the questions posed by the modeling needs to measure short-term incremental volume, as described above in Figure 1. There are too many biases which relate to deal-to-deal buying by retailers and imprecision in understanding the effects of promotions to use just shipments. Recently, new data sources have become available which help understand, plan, control and evaluate promotion activity much more effectively.

This syndicated data includes weekly nationally and locally projectable sales and causal merchandising variable data from supermarkets equipped with scanners. The causal merchandising data includes newspaper features, displays and temporary price reductions. This low level of aggregation enables relatively easy estimation of short-term incremental store sales due to promotions. The PROMOTIONSCAN system uses the store-level scanner data to measure short-term promotion effects and relate them to merchandising activity.

Though we have developed models and measurement procedures for all of the indicated needs in Figure 1, we have had more practical use for the short-term incremental volume (“S”) models and procedures described below than for the long-term (“L”) procedures, which use consumer scanner panel data. Senior managers are interested in looking at the long-term effects of promotion, typically on a one-shot basis. Once the assessment of long-term profitability is made in a strategic sense, the tactics are usually evaluated for the short term only. Also, because the scanner panel data is not as geographically projectable, the adjustments for purchase acceleration are not as precise as the short-term incremental volume estimates. The use of short-term incremental volume is an upward-biased estimate of the true incremental volume because of the long-term purchase acceleration phenomenon, which is a net subtraction from the short-term incremental volume. Managers would rather see a higher estimate (short-term) of the incremental sales and profits than a lower one (longer-term). This is just human nature.

### *System Objectives*

PROMOTIONSCAN is an attempt to bring to fruition Little’s forecast for Marketing Decision Support Systems (Little 1979). He foresaw a transition from *market status reporting* (what happened? when? where?) to *market response reporting* (why did it happen? how can we improve?). The specific system objectives include:

- (1) Timely evaluation of the short-term incremental consumer sales of promotions broken out by retailer, geographic area, size and brand for all brands in a category.
- (2) Preliminary diagnosis of the possible causes of short-term incremental consumer sales at the retail level, e.g., feature advertising in newspapers, display, price cuts or special packs.
- (3) Estimation of the efficiency of the possible retail promotion options. This information is useful to retailers as well as manufacturers.
- (4) Help to manufacturers’ sales forces in understanding which promotion devices they should attempt to induce retailers to use to increase the short-term incremental sales of their brand.
- (5) Early warning of successful competitive retail promotions so that counter-strategies can be developed by the marketer.

### *System Constraints*

PROMOTIONSCAN’s objectives dictate constraints on the models and associated system. The amount of data that is input into PROMOTIONSCAN is quite large. Approximately

2,700 stores are in the database. For each store, data are available by brand, size and flavor, for each week. The data include sales, prices and promotion variables occurring that week, including size of any feature ad in a newspaper, display (including its location within the store), coupon usage information and special package identifiers.

In order to efficiently process such data, analyst intervention must be kept to a minimum. It is impossible for an analyst to monitor every evaluation of every promotion in every store for each size, flavor, etc. Since the objectives include evaluation of competitive promotions, the system must also be able to be used without input from any of the companies whose brands are being analyzed. This means that retailer promotions have to be found from the data themselves as opposed to a promotion calendar which would be externally supplied by each firm whose brands are being analyzed.

A particularly difficult problem is adjusting the evaluation of promotions for extraneous factors in markets, unrelated to promotions, that can cause sales to change unrelated to promotions but which might be mistakenly related to a promotion. These factors could include our brand's advertising, competitive activity of a nonpromotional nature, such as advertising, consumer promotions for competitors, seasonal irregularities such as Easter or Thanksgiving, weather, category effects, etc.

### 3. Previous Research

For complete reviews of the literature on promotion evaluation, see Abraham and Lodish (1987) and Blattberg and Levin (1987). Since the store-level scanner data which our system uses is still relatively new, there have been few authors who have published models which use the data. Wittink et al. (1987) and Blattberg and Wisniewski (1988) develop an approach to promotion analysis using store scanner data. Their approach using econometric analyses to estimate the average display, feature and price elasticity coefficients for a market is very different from ours. We have found that there is tremendous variation in promotion execution by chain, by specific promotion event and by market. Thus, a coefficient which is an average estimate, while valuable as a merchandising planning tool, may not be as helpful to stakeholders, such as sales managers and brand managers, who are also interested in what the results were of a specific promotion event in a specific market.

Currim et al. (1988) and Guadagni and Little (1983) are examples of the use of micro level modeling to estimate display, feature and price response from scanner panel data. This approach works with individual-level choice data and would thus be different in its objective from our system for short-term promotion evaluation, which must work with the weekly store-level scanner data at the market and key account levels of aggregation.

This system also should be related to our previous promotion analysis system, PROMOTER (Abraham and Lodish 1987). PROMOTIONS SCAN is different from PROMOTER in its objectives, constraints, the underlying model and methods of operation. Specifically, PROMOTER focuses on measuring total incremental volume for a promotion event for only one brand, and does not relate that incremental volume to retailer merchandising variables such as features, display and price reductions. PROMOTIONS SCAN estimates the total short-term incremental volume, as well as the incremental volume by causal condition for all brands, including competitors. In addition, PROMOTIONS SCAN measures the incremental volume sensitivity to various levels of price reduction. While both systems use a "baseline" methodology for estimating incremental volume from time series sales data, the two methods are different in modeling seasonality, adjusting for outliers and out-of-stock, adjusting for a variety of market specific factors, and in the specific implementation recognition rules for promotion and post-promotion periods. In addition, the specific smoothing techniques used in estimating baselines are different reflecting, in part, the difference between shipment and scanner data. Finally, PROMOTIONS SCAN does not

suffer from the estimation biases related to deal-to-deal buying, as discussed in Abraham and Lodish (1987).

#### 4. The Model and Methodology

##### *System Overview*

The system has two parts that are covered in this section. The first part is the baseline procedure used to estimate the short-term within store incremental sales due to promotions run by retailers. The second part relates these short-term incremental sales to the causal factors—features, displays and price cuts.

##### *The Short-Term Baseline Model: Overview*

We next describe the methodology and underlying model that PROMOTIONS SCAN uses to evaluate the short-term, within-store incremental sales due to promotions run by retailers. Depending on how the raw store, item and week incremental sales are aggregated, these incremental sales estimates are used for all the “S” parts of Figure 1. The basic building block of the model is the *baseline* algorithm whose objective is to project what sales would have been during promotion-affected weeks had those promotions not been run.

The *baseline* is an estimate for each store week of what the sales of the item would have been had *only* the item’s promotion not been run. All other elements of the item’s and the competitor’s marketing mix are assumed *ceteris paribus*. The baseline is *not* a long-term estimate of what items’ sales would be without promotion. For example, many manufacturers believe that their trade promotions affect the distribution of their products. This medium-term effect is *not* considered by our short-term baseline estimation. This baseline is developed for *each brand-size-flavor combination* for *each store* in the data base. This baseline is developed by projecting forward from “normal” periods that were not affected by promotions. The periods that were not affected by promotion, however, have to be adjusted for market-specific factors that could cause sales to be different from “normal.” These factors include advertising by our brand and competitors, competitive promotions, weather, etc. The baseline calculation involves six steps:

*Step 1.* The store week data is adjusted for seasonality which is calculated at the market (local) level for each product category.

*Step 2.* Promotions are identified so that weeks affected by promotions can be isolated.

*Step 3.* Outliers are detected.

*Step 4.* Preliminary baselines are calculated by smoothing normal periods, reseasonalizing, and adding trend back in.

*Step 5.* Adjustment is made for out-of-stock situations for slow moving items.

*Step 6.* The baseline for a store week is adjusted for the market specific factors by projecting from stores that did not promote during that week.

Step 1 is done for each category on a yearly basis. Steps 2 through 6 are done on an ongoing, weekly basis for each item (brand-size-flavor combination), and the results reported every four weeks. We next describe each step in detail.

*Step 1—Seasonal adjustment.* Seasonal adjustment is done once per year at the market level for a product category. The algorithm can use up to three years of weekly data. The objectives of the seasonal adjustments are to isolate true seasonal factors of demand from category sales which may be compounded by seasonal promotions. The procedure we use is to first calculate a trend. Then detrended category sales are depromoted and then iteratively smoothed to isolate the affected trend and seasonality.

Specifically:

*Step 1.1.* Develop a 52-week centered moving average of category sales as an estimate of trend  $T(t)$ .

*Step 1.2.* Use a regression model to deseasonalize and depromote category sales. The dependent variable is category sales divided by trend. The independent variables are 12 four-week indicator or dummy variables which are set equal to one for four-week periods and zero otherwise. Other independent variables are the percentage of volume sold of the category on a newspaper feature, the percentage of volume sold on display only, the percentage of volume sold both on feature and display, and the percentage of volume sold on manufacturers' coupon. The specific model is:

$$\log \left( \frac{S(t)}{T(t)} \right) = \alpha + \beta P(t) + \sum_{i=1}^m a_i X_i(t) + \sum_{j=1}^{12} r_j D_j(t) + \sum_{l=1}^L h_l H_l(t), \quad \text{where} \quad (1)$$

$S(t)$  = category sales at time (week)  $t$ ,

$T(t)$  = category trend at time  $t$ ,

$P(t)$  = average category price at time  $t$ ,

$X_i(t)$  = % of volume sold with deal type  $i$  (which is available directly from the store scanner data),

$D_j(t)$  = dummy variable  $D$  for a four week period  $j$ , e.g.,  $D_1(t) = 1$  for the first four weeks of the year, and 0 otherwise, and

$H_l(t)$  = dummy variable for holiday weeks such as Christmas, Easter, Thanksgiving, Labor Day, etc. These dummy variables have a value of 1 during the week of the holiday and 0 otherwise.

The normalized seasonal coefficient  $I_j$  for period  $j$  is

$$I_j = \frac{12e^{r_j}}{\sum_{k=1}^{12} e^{r_k}}. \quad (2)$$

*Step 1.3.* The effect of promotions is taken out of the data by subtracting the sales effect of all of the promotion coefficients in the above equations which have the correct signs. Incorrect signs which are significant are extremely rare.

*Step 1.4.* Because the initial trend had the effect of promotions in it, trend is recalculated based now on a 52-week moving average of the depromoted category sales and Steps 1.1–1.3 are repeated.

*Step 1.5.* The procedure above is done four times using four different starting weeks, each one week apart. The seasonal factor for a week is then the average of the four weeks immediately around that week. This estimate of seasonality is smoother than putting in 52 weekly dummy variables at once, reflecting our concern that, except for holiday weeks, seasonality should not jump around from week to week.

This model's fit of the data depends on how seasonal and how responsive to promotions the category is. Its mean  $R^2$  across markets is summarized for six categories in the table.

Category	Mean $R^2$
Barbecue sauce	0.98
Soup	0.95
Ice Cream	0.75
Stomach remedies	0.38
Mouthwash	0.37
Dentifrice	0.30

The seasonality coefficients were much stronger and more significant in the first three categories than in the second three.

A particular strength of the model is how it deals with highly seasonal categories where promotions typically follow the seasonality of demand. Even though promotional intensity rises during the high season, the variables  $X_i(t)$ —percent of volume by type of deal—vary significantly from week to week and season to season, and are never close to 100% of the market level. For instance, in the highest seasonal category examined above, none of the  $X_i(t)$  variables exceed 50% and none are constant from season to season. Given this variability in the intensity of promotions by type of merchandising, multicollinearity is not a practical concern.

Also, unique seasonal factors such as Easter or Thanksgiving—holidays which are different weeks each year and may affect items differently—are recovered by the procedure in Step 6 below. It is not clear that this initial step of seasonal adjustment is really needed, given the power of Step 6. We have not tested eliminating Step 1 extensively yet, because our predictive testing has shown that the system works quite well. See the validation section (§5).

*Step 2—Promotion identification and deseasonalization.* The next step in the baseline algorithm is to identify those store/weeks for each item that were affected by promotion and to remove them. Each weekly time series by store for all brands/sizes/flavors in the category is deseasonalized and detrended by dividing the series by the category trend and seasonality. Promotions are identified by weeks—one week before, during and one week after—when there was a feature in the newspaper, a display, a special pack, a temporary price reduction or any combination of these devices. The lead and lag of one week is to account for possible differences in the timing of the week when the promotion was recorded and the specific week in which the sales data is reported because the weeks may not begin or end on the same day.

All of the promotion types, except temporary price reductions, are obvious from the data. In order to detect a temporary price reduction, a simple pattern recognition algorithm is utilized. A heuristic procedure estimates everyday shelf price as the most recent shelf price not associated with a feature, a display, or a price reduction lasting less than  $N$  weeks.  $N$  is a parameter specified by category based on expert judgment. A price is determined to be a temporary price reduction when it is lowered by greater than five percent and then is raised by greater than three percent within less than eight weeks from the time the price was reduced. If, in the interval after the price reduction, there were weeks with features or displays, these weeks do not count in the calculation of the eight-week period. In some categories, the price level reduction of five percent, the subsequent three percent increases, and the eight-week parameters may change. However, given that retailers have developed patterns for implementing temporary price reductions, we have found a great deal of similarity between price reduction patterns over a number of categories.

The number of weeks that are removed by this step obviously varies with categories and specific brands and items. In practice we have found a maximum of 30 weeks per year and a minimum of 0 weeks per year which are removed. Though a brand may be on promotion a lot, the actual number of weeks in which a particular size/flavor/type is on promotion are typically few during a year. For items of actively promoted brands, the modal number of store weeks removed by this procedure is about ten per year.

*Step 3—Outliers detection.* Even with all the periods removed that might be affected by promotions, there are still situations where outliers may occur. In order to eliminate outliers, the “normal” periods are first smoothed using the variable window weighted moving average that was described in the PROMOTER article (Abraham and Lodish 1987). Outliers are found by developing a standard deviation of all the points higher than the smoothed baseline estimate (positive outliers) and a different standard deviation for those points below the smoothed baseline (negative outliers). The reason for the positive



and negative standard deviations is that different factors will cause sales to be lower than normal than sales that are higher than normal. Aside from random fluctuations, higher than normal sales might be caused by the brand's own consumer promotions or features or displays that might not have been recorded. Negative outliers may be caused by unusually strong competitive promotions or partial out-of-stocks. The decision criteria for determining outliers is that the probability, based upon a log normal distribution assumption of the deviations around the moving average, is greater than 95%. Note that observations with zero sales are automatically counted as outliers.

*Step 4—Data smoothing, reseasonalizing and retrending.* Once the outliers have been eliminated, the remaining observations are again smoothed using the variable window weighted moving average of PROMOTER (see Abraham and Lodish 1987). However, once the data has been initially smoothed this way, updates on an on-going basis are made with an exponential smoothing process. The baseline is then reseasonalized and trended by multiplying by the category trend and seasonal factors that were determined earlier. Note that there may be a difference in the item's seasonality and the category's seasonality. The adjustment in Step 6 for market specific factors will correct for any consistent seasonality differences.

It is important to note that the purpose for outlier detection is to add to the robustness of the baseline, rather than adjust for unusual store level events. If an item is not promoted during a given week, the point estimate in that week does not matter much because we only calculate incremental volume when there is a promotion. However, because of the exponential smoothing process, a highly unusual sales level during that week, will affect the baseline estimates in future weeks, long after the cause for the unusual blip is gone. By trimming outliers, we are in essence employing a resistant smoothing technique similar to the concepts used in PROMOTER (Abraham and Lodish 1987) and SABL (Cleveland et al., 1981).

Note also that in a case when the positive and negative outlier phenomena are simultaneously occurring and canceling each other out, this procedure will miss that. However, in the spirit of the above comment, if the case's residual from the baseline is small, it will not bias the baseline any more than a normal observation with a similar residual.

*Step 5—Adjustment for possible out-of-stock situations for slow-moving items.* Finally, for slow moving items, the baseline needs to be adjusted for those sales that would drop naturally to zero because of retailer out-of-stock situations as opposed to situations where no consumers bought the product even when it was on the shelf. Step 3 treats these observations as outliers, even though, in the latter case, they clearly are not.

As an illustration, suppose the weekly sales series during nonpromoted weeks was: 1, 0, 2, 0, 1, 2. The mean of the series including zeros is 1, whereas the mean excluding zeroes is 1.5. If weeks with few sales were caused by out-of-stock, then 1.5 is the legitimate baseline. On the other hand, if zero sales were normal occurrences caused by the stochastic sales process, 1 would be the correct baseline. Without costly shelf audits by UPC and stores, we can never be sure whether a week with zero sales was a normal occurrence or caused by out-of-stock. One way around this dilemma is to estimate the mean of the process using the mean conditioned on positive sales. Using conditional means:

$$E(S(t)) = P(S(t) > 0)E(S(t)/S(t) > 0) + P(S(t) = 0)E(S(t)/S(t) = 0).$$

However,  $E(S(t)/S(t) = 0) = 0$ . Therefore,

$$E(S(t)) = P(S(t) > 0)E(S(t)/S(t) > 0).$$

The baseline estimated in Step 4 is  $E(S(t)/S(t) > 0)$ . The probability  $P(S(t) > 0)$  is derived from the probability distribution of the sales process. Appendix A, which is

available from the authors, shows the derivation of  $P(S(t) > 0)$  as a function of the mean and variance of nonzero sales.

*Step 6—Adjusting the baseline for market-specific factors.* The baseline for each item for each store in each week needs to be adjusted for extraneous factors in the store's market that can cause sales to be different than projecting normal sales would indicate. Such factors are competitive activity, consumer promotions, category effects, holidays, weather-related seasonal irregularities, differences between item and category seasonality, etc. The baseline needs to be adjusted for the effect of these factors. Sales in those stores during the same week that are not promoting are used to develop a baseline adjustment. The adjustment is made by comparing the total of actual sales to their baseline estimate for all the stores that did not have any promotion during the same week. The baseline for the store we are estimating is adjusted by the ratio of actual sales to baseline sales for all the other nonpromoting stores in the market. For example, if all other stores that did not promote during a week had item sales averaging 25% higher than their baseline, we would add 25% to the baseline sales to all stores in the market. If this adjustment were not made, then a store's baseline would be 25% too low for that week. This would cause a promotion during that week to be evaluated in error as too high because of some market-specific phenomena. The specific adjustment works as follows.

Let

$b_i(t)$  = deseasonalized baseline estimates in step 4 for store  $i$  at time  $t$ ,

$I(t)$  = seasonal index at time  $t$ ,

$S_i(t)$  = actual sales in store  $i$  and time  $t$ ,

$N$  = set of stores not promoting at time  $t$ ,

$A(t)$  = adjustment factor to be calculated and

$B_i(t)$  = final baseline for store  $i$  and time  $t$ .

The adjustment requires predicted baseline sales to be equal to actual sales for the stores in set  $N$ :

$$\sum_{i \in N} B_i(t) = \sum_{i \in N} S_i(t).$$

By definition,  $B_i(t) = A(t)I(t)b_i(t)$ . Hence,

$$A(t) = \frac{\sum_{i \in N} S_i(t)}{\sum_{i \in N} I(t)b_i(t)}.$$

Once the baselines have been estimated, adjusted and reseasonalized, it is relatively straightforward to calculate incremental volume for promotions which have been identified.

#### *Calculating Short-Term Incremental Volume*

Incremental volume (short-term) is calculated for stores that may have any promotion activity during a week and for stores where a positive outlier was observed and where a promotion occurred in a prior or following week. This procedure is designed to capture the effect of merchandising that affected only a fraction of a week. Incremental volume for an item (brand-size-flavor) for a store during a week is its sales minus its baseline. The incremental volume over a group of stores (either for a geographical area or a key account) is calculated as the sum of the incremental volume for each store. Figures 2A and 2B show baselines, "normal" periods, and incremental sales as well as promotion conditions for a store and the total U.S. for Trix 12 oz. cereal, a heavily promoted item.

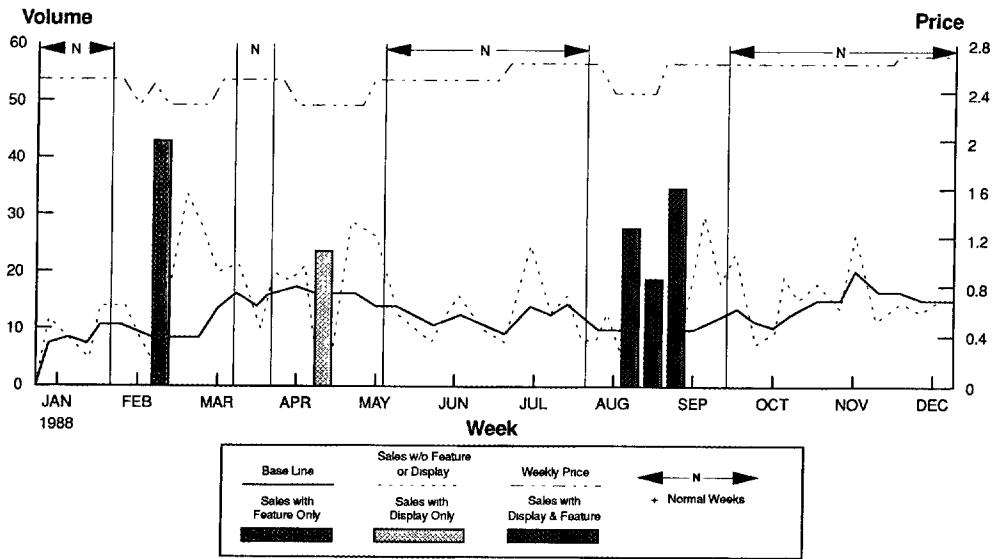


FIGURE 2A. A Store-Level Baseline, TRIX 12 oz., Store E.

*Estimating Sales Response to Retail Merchandising*

The production version of PROMOTIONSCAN does a simple cross-tabulation to summarize incremental sales associated with various retail merchandising activities. See the last columns of Figure 3 entitled, "Incremental Share Points," for example. For each merchandising condition (Price Reduction Only, Feature Only, Display Only, Feature and Display), all of the store weeks with that condition are isolated. An ACV-weighted (All Commodity Volume) sum of incremental sales is divided by an ACV-weighted sum

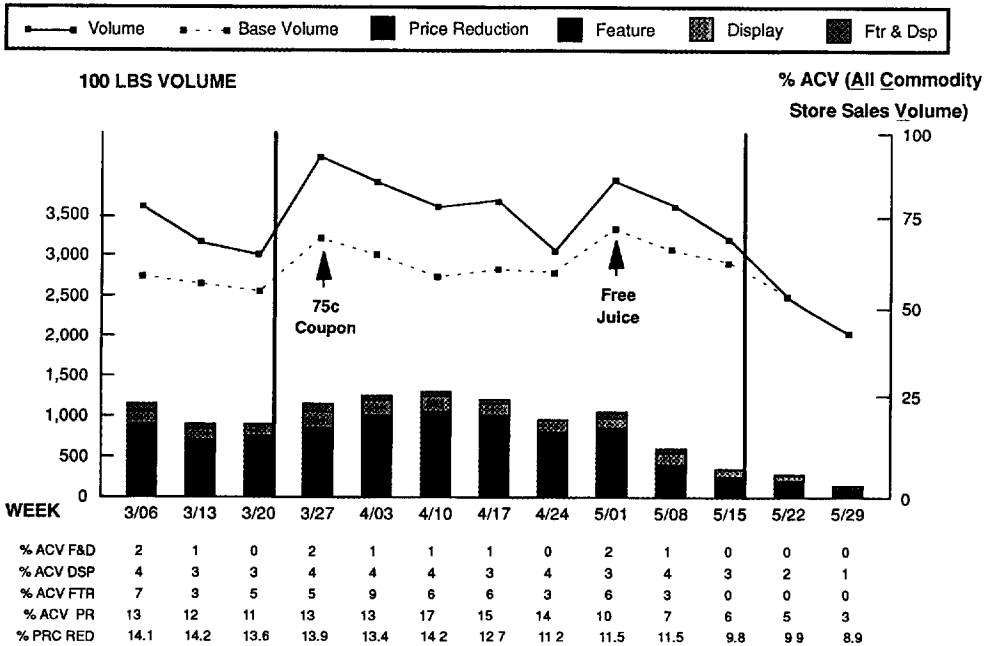


FIGURE 2B. PromotionScan Summary, TRIX 12 oz., Total United States.

of the store weeks to get an average incremental share point per store week of that merchandising condition.

This simple methodology is intuitive to managers, quite robust and can be performed on an automated basis. More detailed measures describing incremental volume response by various levels of promotion and price have been developed. In addition, we have developed models relating consumer response to various levels of in-store merchandising run on store-level PROMOTIONSCAN observations with minimal levels of analyst intervention. For more details see Abraham and Lodish (1990). We have also initially investigated explicit computer models for explaining base and incremental shares. See the further research section (§7).

## 5. Validation

In this section we report system validation on two levels. We first describe predictive validation of the short term baseline models, and then we discuss the validity of the assumptions behind the market specific adjustment factors for the baselines.

### *Predictive Validation of Short-term Incremental Sales*

Given that a number of heuristics are used to obtain the estimates of short-term incremental volume, it is important to verify that the methodology is unbiased in predicting what would have happened to sales had there been no promotion. In order to address this bias issue, using a holdout validation technique (Efron 1982), we took a random sample of 200 store weeks for each of five different items in five different categories where there was no promotion for the store-weeks for that item. This is the equivalent of the number of observations involved in estimating a baseline over a normal reporting period of four weeks in a typical market with sample size of 50 stores. The typical PROMOTIONSCAN report is provided at the market level every four weeks. Therefore, the standard errors in estimation reported below could be viewed as standard errors in an “average” market of 50 stores. Standard errors for markets with a different sample size  $n$ , involve a sample size adjustment of  $\sqrt{50/n}$ .

We then developed PROMOTIONSCAN baselines and incremental value estimates using all the other available data, but leaving out the sample store weeks. If the procedure is unbiased, it should reproduce exact volume without a systematic bias. For 200 store weeks for five different items ( $n = 1000$ ), the average difference between actual and baselines sales was  $-0.14\%$  of actual sales. Table A summarizes the results for the five products along with a standard error of market level baselines during a four-week period. None of the results is significantly different from zero. Thus, the system seems to be unbiased in predicting what happens in store weeks when there is no promotion for a brand, item or category.

TABLE A  
*Average % Difference in Actual Versus Baseline  
Volume Across 200 Store Weeks*

Product	Average % Difference	Standard Error of % Difference
A	0.22%	1.76%
B	-1.96%	1.95%
C	-0.49%	1.48%
D	1.07%	1.82%
E	-0.46%	1.84%
Average	-0.14%	

### *Validity of the Market Adjustment Factor*

One assumption underlying the market factor adjustment is that sales of nonpromoting stores are not affected by the promotion activity in promoting stores. However, a promoting store may theoretically capture its sales at the expense of nonpromoting stores. This would depress sales in the nonpromoting stores and cause the adjustment factor  $A(t)$  to be lower, hence introducing a downward bias on  $A(t)$  and the baselines  $B(t)$ . This assumption is common to other research modeling in-store promotions such as Blattberg and Wisniewski (1988), and Wittink et al. (1987), which do not allow for cross-store cannibalization. Kumar and Leone (1988) dealt directly with the subject and found no evidence of cross-store cannibalization except for disposable diapers.

Fortunately, in our case, there is a simple way to test this assumption empirically and assess beforehand whether the market adjustment will be biased. Let us think of the market as a closed system composed of a set  $P$  of stores promoting and a set  $N$  of stores not promoting. We want to assess to what degree the sales in set  $N$ ,  $S_N(t)$  are affected by the promotion activity in set  $P$ . It is important to note that the stores in sets  $N$  and  $P$  vary from week to week. In one week stores in set  $P$  may represent 10% of the market all commodity volume (ACV). In another week, stores in set  $P$  may represent 30% of the ACV. It is reasonable to expect that the larger set  $P$  becomes, the more cross-store cannibalization affects stores in set  $N$  and the larger the percentage decline in  $S_N(t)$ . It is also reasonable to assume that if promotions are more successful in set  $P$ , they will hurt  $S_N(t)$  and  $A(t)$  proportionally more. Hence, if we used a measure of incremental volume in set  $P$ ,  $I_P(t)$ , as a surrogate for both the size and success of promotions in set  $P$ , the decline in  $A(t)$  will be positively correlated with  $I_P(t)$ . The higher the absolute value of the negative correlation, the higher the cross-store cannibalization. If there is no correlation, we can safely assume that  $S_N(t)$  is not affected by the promotions in set  $P$  and their incremental volume  $I_P(t)$ . The above logic provides a simple empirical test of the extent of cross-store cannibalization.  $I_P(t)$  is calculated in stores  $P$  as:

$$I_P(t) = \sum_{i \in P} s_i(t) - I(t)b_i(t).$$

In other words,  $I_P(t)$  is not affected by the final adjustment  $A(t)$ . A simple correlation test between  $I_P(t)$  and  $A(t)$  will assess the degree of cross-store cannibalization if any. This procedure has been performed across 30 markets, 150 brands, and 5 product categories with no evidence of significant negative correlations ( $p < 0.05$ ). In fact, correlations tend to be slightly positive. From 20 to 40% of the products in each category had significant positive correlations ( $p < 0.05$ ) over all 30 markets and a 52-week period. This confirms the fact that  $A(t)$  is representing market level factors that affect  $I_P(t)$  and  $S_N(t)$  in the same direction.

Note that if the adjustment factor  $A(t)$  had a very large effect on sales compared to the incremental sales effect, then, even if there were some cross-store cannibalization, it could be swamped by the market specific factors. However, as the mean absolute deviation of  $1 - A(t)$  has been below 10% in practice, but the incremental sales due to promotion at stores can be as much as 300 to 500%, this is not a practical problem for this test. Note also that these tests as used can only detect cross-store cannibalization during the same weeks. It would make more sense to use household-level scanner panel data to test for these effects over time.

The lack of cross-store cannibalization evidenced by these tests is consistent with Kumar and Leone's results. The correlation test we just discussed allows us to empirically check for any given category, whether it is an important phenomenon. If it is, the market adjustment step is omitted to avoid introducing estimation biases. To our knowledge this has never been a practical concern. However, we have developed methodologies to adjust for this bias which are beyond the scope of this paper.

The above empirical analysis shows that there is little cross-store cannibalization due to retail promotions for an individual item. However, retailers generally promote a number of items simultaneously. The impact of all of the items together may cause consumers to switch stores. The evaluation of this multi-item impact is beyond the scope of the present PROMOTIONSCAN system.

In practice the mean absolute deviation of  $A(t) - 1$  is below ten percent. Sanity checks on its magnitude during coupon drops on special seasonal peaks and holidays, indicate that  $A(t)$  plays a useful role in capturing systematic deviations from history due to known market level factors. See Figure 2B for example. The impact of the 74¢ coupon and “Free Juice” consumer promotion are apparent in the baseline.

## 6. Sample Applications and Accomplishments

In this section we describe some typical real applications of the short-term system and how the various stakeholders have used them, including baseline trends as indicators of “brand health.” We also show a sample integration of short-term and long-term evaluation models. We then discuss the results obtained from other applications.

### *Short-Term Applications*

One of the basic building blocks of most applications is the category and brand top-line report as shown in Figure 3. Using the cross-tabulation methodology described above, this report summarizes the results of promotions of all brands (broken out by item) in a category for a given area and time period. Depending on the level of aggregation, all of the short-term incremental volume estimates denoted in Figure 1 can be reported in a report like Figure 3. The first group of volume measures breaks down the total volume share for a product into its base share (not influenced by promotion) and its incremental share (associated with promotions) and shows the percentage of base business that was incremental. Note for example that the Crest brand had a 41.3% share, of which only 5.2 share points were incremental. Its major competitor, Colgate, had a lower total share of 33.0%, but a higher level, 6.8 share points, of incremental business. The base and incremental shares come from the procedure in Steps 1 through 6.

The next four columns show the average number of weeks stores had some type of promotion effort. The average is weighted by the total all commodity volume (ACV) for each store in the calculation. Promotional effort is broken out by price reduction only during a week, newspaper feature only during a week, display only and features and display combined during the same week. Note that Crest had less than half the number of weeks with price reductions (10.0) as Colgate (21.1).

The next four columns show the estimated average incremental share response (using the cross-tabulation approach described above) during the week in which any of the promotional devices are used for each product. Note that the promotional price response for Colgate and Crest is almost identical (6.3 versus 6.5). Note also that the combination of features with displays is synergistic, typically having higher response than the sum of the response of features alone or displays alone. The last column portrays the average price reduction when the product was temporarily reduced on promotion. This average price reduction is volume-weighted by the volume sold under the various price/promotion conditions. More detailed reports can detail the average price reduction for each type of promotion condition and relate it to incremental sales.

The example in Figure 3 is a summary of promotional performance nationally. The brand manager and sales manager use it to measure progress on promotionally-induced sales and execution by the salesforce of various promotion devices, and to diagnose if the promotion devices are getting the response they have been expecting and if they are getting as good a response as the competition. The same performance information is also

FIGURE 3. TOPLINE REPORT, PromotionScan, Category and Brand Topline Report.

Company: Category: Dentrifice Market Area: Total US		Time Period: 2/2/87-9/27/87 IRI Weeks: 388-421									
		Volume Measures					ACV Weighted Weeks				
		Vol Share	Base Share	Inc Share	% Incr Total Share	Red Only	Feat Only	Displ Only	Ftr & Dsp	Price Red Only	Incremental Share Pts.
Product											
CREST		41.3	36.1	5.2	14.3	10.0	4.6	9.3	2.0	6.5	
All Other Crest		2.1	2.1	0.0	1.4	1.2	0.1	1.1	0.0	0.2	27.2
CREST TUBE		31.7	27.5	4.3	15.5	6.6	4.0	7.1	1.8	5.8	1.0
Reg. 4.6		4.3	3.9	0.4	9.1	1.6	1.0	1.2	0.2	1.4	26.2
Reg. 6.4		8.4	6.9	1.5	21.0	2.6	1.7	3.5	0.9	2.7	10.5
Reg. 8.2		3.1	2.6	0.4	16.5	1.1	0.6	1.0	0.2	1.2	16.9
TC 4.6		4.8	4.4	0.4	9.0	2.2	1.6	3.4	0.6	1.1	8.2
TC 6.4		7.7	6.5	1.3	19.9	2.6	1.6	2.8	0.7	2.5	1.4
TC 8.2		3.4	3.0	0.4	15.1	1.3	0.6	0.7	0.2	1.5	4.7
CREST PUMP		7.4	6.6	0.9	13.2	4.3	1.8	5.1	0.8	1.8	18.1
Reg. 4.6		1.5	1.2	0.3	21.5	2.4	1.1	3.7	0.6	0.5	11.3
Reg. 6.4		1.3	1.2	0.1	10.0	1.1	0.5	1.1	0.2	0.4	7.9
TC 4.6		2.6	2.2	0.3	15.1	2.5	0.9	3.2	0.4	0.8	1.0
TC 6.4		2.1	1.9	0.1	7.4	1.4	0.6	0.8	0.1	0.5	1.6
COLGATE		33.0	26.1	6.8	26.2	21.1	5.1	7.1	1.6	6.3	1.3
All Other Colgate		1.7	1.6	0.1	3.4	2.4	0.1	1.4	0.0	0.2	4.0
COLGATE TUBE		26.4	20.6	5.7	27.8	18.2	4.8	4.4	1.2	5.3	23.9
Reg. 4.6		4.2	3.4	0.9	26.0	6.1	1.3	0.9	0.3	0.9	0.7
Reg. 6.4		6.9	5.3	1.5	28.4	6.0	1.6	1.9	0.5	1.9	8.5
Reg. 8.2		3.4	2.8	0.6	22.2	4.1	0.5	0.6	0.1	1.5	24.7
TC 4.6		3.3	2.4	0.9	36.6	4.3	1.6	1.3	0.3	0.9	14.3
TC 6.4		4.2	3.2	1.1	33.9	6.0	1.5	1.6	0.3	1.1	14.2
TC 8.2		4.3	3.6	0.7	18.6	7.6	1.4	0.9	0.2	0.5	15.2
COLGATE PUMP		4.9	3.9	1.0	25.4	8.0	1.4	2.9	0.4	1.2	14.9
Reg. 4.6		3.1	2.5	0.6	25.3	5.8	1.2	2.4	0.4	1.0	8.7
TC 4.6		1.8	1.5	0.4	25.1	4.8	1.1	1.7	0.3	0.4	2.1
AQUA FRESH		10.8	8.4	2.4	28.9	19.6	4.0	7.8	0.8	2.7	3.2
All Other Aqua Fresh		0.8	0.7	0.1	20.3	3.2	0.1	3.6	0.0	0.2	1.2
AQUA FRESH TUBE		6.0	4.6	1.4	30.5	14.5	2.7	2.8	0.4	1.8	3.8
Tube 4.6		1.9	1.4	0.5	35.7	7.0	1.2	1.3	0.2	0.4	0.7
Tube 6.4		2.9	2.2	0.7	32.4	7.8	1.2	1.4	0.2	0.4	3.4
Tube 8.2		1.3	1.1	0.2	16.0	5.2	0.4	0.2	0.0	0.5	2.0
AQUA FRESH PUMP		4.0	3.2	0.8	26.1	10.0	2.0	3.2	0.4	1.0	2.8
											7.7
											16.3

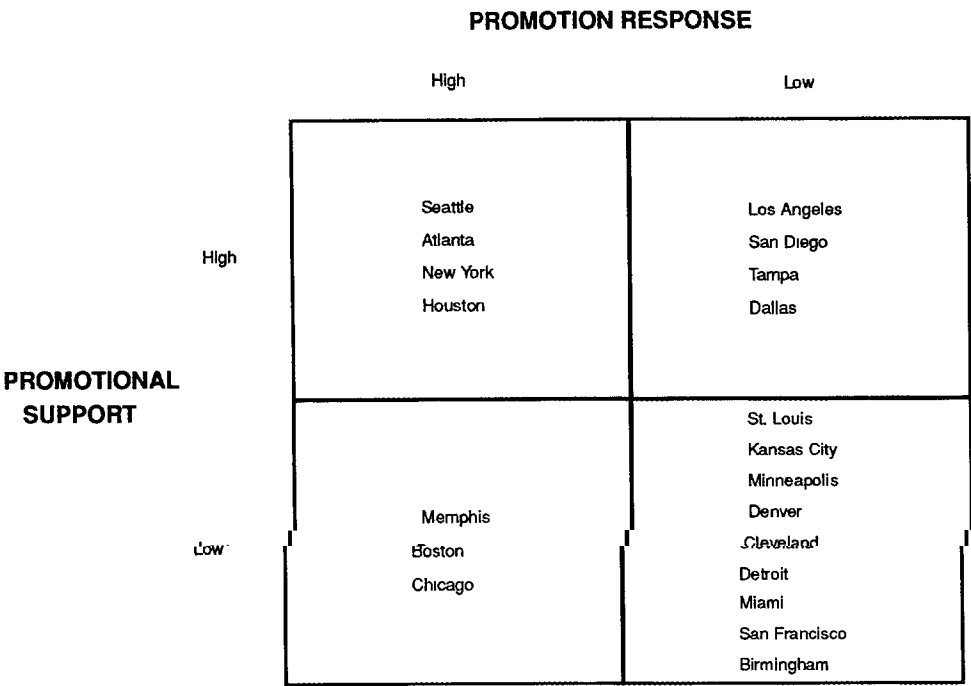


FIGURE 4. Market Opportunity Matrix.

available by *market* or *key account*. This is very useful for regional or district management and to aid the brand manager in developing different promotion programs for local markets.

This performance information by area makes possible a market response approach to resource allocation to markets. Figure 4 shows how the individual market analyses can be summarized. The market opportunity matrix divides markets by their combinations of level of promotion response and promotional support. Figure 5 is an example of how the market response performance by market was summarized for management in an action-oriented manner. Each market is indexed to the national averages for the number of weeks (weighted by all commodity volume, ACV) that the brand is on some type of promotion, and promotion response—the average response of the featuring and display activity in the market. Also indexed to the national average are weeks that the brand was only on price reduction and not supported by feature and display (“unsupported price reductions”), and the percentage the brand price was reduced when on promotion. The last column shows the indicated management action based upon the market response comparisons among the markets. The rules used to determine the appropriate actions are simple, but seem to cause management to then focus on the detailed data for each market with a rationale for improving promotion performance. Those markets which have more than average unsupported price reductions are indicated for attempts at more retailer featuring and display support. Similarly, those markets whose average promotion response is below average are indicated for improvements in quality. Perhaps some of the markets have not been getting the appropriate size of newspaper features or good display locations within the store. Most managers have found it helpful to show the market salespeople how they differ from the national average. It takes away some of the subjectivity of management control.

This market response approach should be contrasted with the traditional way that many marketers allocate promotional resources. Typically, markets are grouped by their



		% of Total Volume	ACV Weighted Weeks	Promotion Response	Unsupported Price Reductions	% Price Reduction	Indicated Action
S U S T A I N I N G	High Support/ High Response						
	Seattle	1.0	106	117	156	97	Support price reductions
	Atlanta	1.1	140	101	114	111	Support price reductions
	New York	7.2	111	133	90	105	--
	Houston	1.6	120	115	85	112	--
H I G H  Y I E L D	High Support/ Low Response						
	Los Angeles	7.8	125	74	98	77	Improve quality, support price reductions
	San Diego	1.0	120	64	111	78	Improve quality, support price reductions
	Tampa	0.9	116	60	89	89	Improve quality
	Dallas	1.7	107	99	120	102	Support price reductions
	Low Support/ High Response						
	Mempis	0.3	88	106	98	97	Increase level
	Boston	2.5	82	115	102	145	Increase level
	Chicago	3.0	99	170	112	103	Support price reductions
	Philadelphia	2.6	99	156	132	106	Support price reductions
D E V E L O P I N G	Low Support/ Low Response						
	St. Louis	0.8	68	88	71	118	Increase level
	Kansas City	0.4	79	72	72	90	Increase level, improve quality
	Minneapolis	1.0	74	90	99	103	Increase level
	Denver	1.5	77	39	92	85	Increase level, improve quality
	Cleveland	0.7	75	77	83	88	Increase level, improve quality
	Detroit	1.8	62	71	54	90	Increase level, improve quality
	Miami	1.6	89	59	74	103	Improve quality
	San Francisco	2.6	86	99	98	96	Increase level
	Birmingham	0.3	79	67	135	82	Increase level, improve quality, support price reductions

FIGURE 5. Promotion Strategies by Market, Indexed to Total U.S.

category development indices (CDI) and brand development indices (BDI). These indices portray whether a market is above or below average in category sales per household (CDI) or brand sales per household (BDI). Depending on the corporate culture, different rules arise for allocation. Examples include allocating more to markets with high CDI and low BDI (such markets are supposed to have higher potential) or allocating more to areas with high BDI (follow your strengths). The market response approach directly relates promotional activity with the *incremental* response that has occurred. It suggests allocating resources where they will get more marginal revenue per promotional dollar.

Another set of data provides information for each separate promotional event. As the content of each event and its execution by the salesforce may have very different impact on the market, management finds response summaries by event very helpful. These summaries are also available nationally, by market, and by key account within each market. For example, Figure 6 shows all the key accounts in Los Angeles ordered by their short-term incremental response to a specific event. Each account's support of the event is summarized as to the percent of its stores (weighted by ACV) which participated in each method of support and the number of average weeks per store which participated. At the bottom of the report is a summary of how Los Angeles compares to the rest of the U.S. It is easy in this case to see that the two lowest ranking accounts, Hughes and Boys, did not lower the price at all, did no featuring, and only displayed the brand in some of their stores for one week. Lucky's, the highest performing account, had broad participation in all elements of promotion support.

Reports like Figure 6 are used by regional sales managers to monitor the short-term performance of the salespeople in getting their accounts to execute promotional events productively. The salesperson responsible for Lucky's would be commended, while the persons in charge of Hughes or Boys would be highlighted for possible remedial action. A report similar to Figure 6 can summarize the event response by salesperson and rank them. Other reports and analyses can also relate the success of an event to competitive retailer promotions. However, it is typically the competitive offerings to the retailers

FIGURE 6. PromotionScan, Event Market Performance.

Company:		Time Period: 1/5/87-9/21/87										
Category:												
EVENT: KIDS OVERLAY												
START WEEK: 1/19/87												
Product:												
Market/Key Account (ordered by % increase in incremental sales)	Avg % Price Cut	Price Cut			Feature			Display			Ftr & Dsp	
		% ACV Participating	Weeks Per Store	% ACV Participating	% ACV Participating	Weeks Per Store	% ACV Participating	% ACV Participating	Weeks Per Store	% ACV Participating	Weeks Per Store	
Lucky, L.A.	9.7	100.0	3.8	100.0	100.0	1.0	89.8	82.4	7.0	82.4	1.0	
Safeway, Los Angeles	10.2	100.0	1.0	100.0	100.0	1.0	20.4	9.7	4.5	9.7	1.0	
VON'S, L.A.	7.7	100.0	1.0	100.0	100.0	1.0	46.9	36.2	4.2	36.2	1.0	
Other, L.A.	16.8	54.0	2.0	54.0	54.0	1.0	0.0	0.0	0.0	0.0	0.0	
Ralph's, L.A.	7.4	100.0	1.1	81.9	81.9	1.0	48.1	23.1	1.3	23.1	1.0	
Other Cert. Groc., L.A.	21.4	31.3	2.0	17.8	17.8	1.0	17.8	0.0	1.0	0.0	0.0	
Alpha Beta, L.A.	9.1	38.6	1.0	0.0	0.0	0.0	11.3	0.0	1.0	0.0	0.0	
Albertson's, L.A.	13.5	86.6	1.0	86.6	86.6	1.0	0.0	0.0	0.0	0.0	0.0	
Hughes, L.A.	0.0	0.0	0.0	0.0	0.0	0.0	24.9	0.0	1.0	0.0	0.0	
Boys, L.A.	0.0	0.0	0.0	0.0	0.0	0.0	41.9	0.0	1.0	0.0	0.0	
Market Performance Relative to Total US Time Period: 1/5/87 to 9/21/87												
Market	% Incr Share	ACV Weighted Weeks			% Inc. in Weekly Volume						Avg %	
		Price Red Only	Feat Only	Displ Only	Price Red Only	Feat Only	Displ Only	Ftr & Dsp	Ftr & Dsp	Displ Only	Price Red	
Los Angeles, CA	16.0	1.9	1.5	2.8	39	87	95	0.4	172	80	9.9	
Total US	15.1	1.2	0.7	1.1	43	141	80	0.2	304		13.1	

which cause the retailers to promote. Such data is not usually available and would be a big help to competitive promotion planning.

The same event response data can be aggregated by area and nationally for the brand manager and senior management to evaluate which areas are more or less responsive short-term to a particular promotional event. National and geographical summaries of each event can also be compared by brand managers to evaluate the performance of alternative events. When the PROMOTIONSCAN data is integrated with corporate promotion costs and profit margins, it is straightforward to calculate the short-term incremental profitability of specific promotion events and the cost per incremental case sold on promotion. This information is very useful for senior-level total budget and brand allocation decisions.

Many managers are using the trends in their brand's baselines as indicators of the brand's "health." They theorize that if a brand's baseline of what short term sales would have been if the brand's sizes were not promoted is decreasing, then its brand franchise due to consumer perceptions, product performance, advertising effectiveness, or other nonpromotion activities is decreasing. These are seen as fundamental problems that promotion typically cannot cure. Figure 7 shows a beer brand whose total sales are stable (until the last few months), but its base business is declining even in the face of recent massive promotion. The firm sees this as a very important sign of fundamental trouble with the brand. Note that in January 1990, total brand sales began to decline confirming the base sales trend.

### *Long Term Applications*

By using consumer scanner panel data and either micro models—such as Gupta (1988) or Currim et al. (1988)—or a course approximation based on switching patterns (see Abraham and Lodish 1991), an estimate can be made of the long-term impact of a promotion. This long-term estimate can be compared as a ratio  $r$  to the short-term

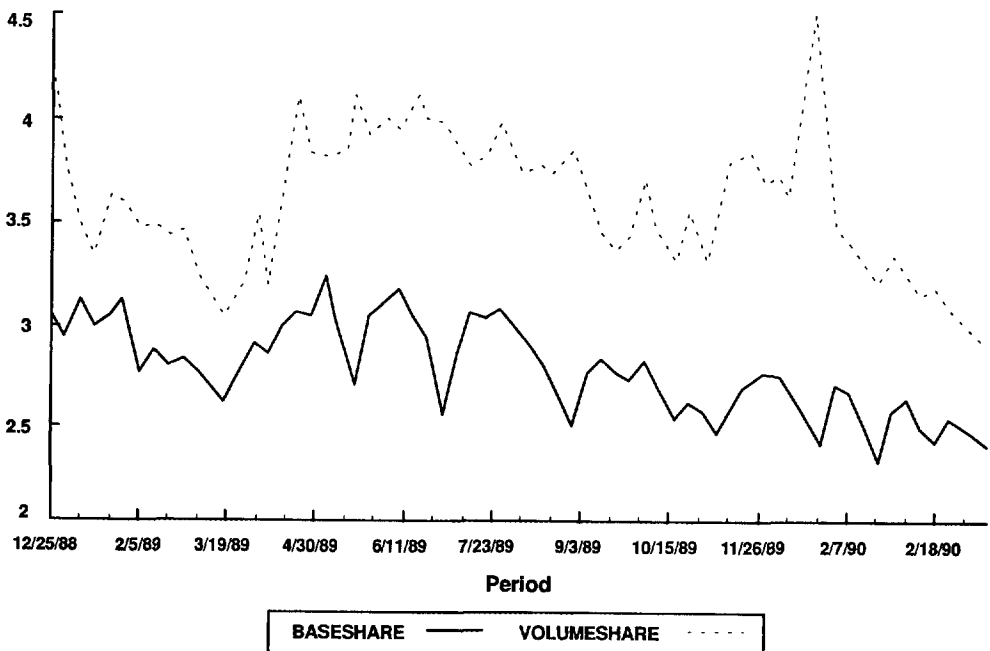


FIGURE 7. Base and Total Share, Total United States: Beer A.

incremental sales of the promotion. This procedure was applied to a health and beauty aid with three sizes with results as follows:

	Long Term Conversion Ratio			
	Price Reduction Only	Feature Only	Display Only	Feature & Display
Small size	0.98	0.93	0.92	0.93
Medium size	0.93	0.79	0.85	0.72
Large size	0.81	0.77	0.70	0.57

The interpretation of the conversion ratios is interesting. The lower the ratio, the higher the purchase acceleration and the more inflated short-term volume is relative to long-term incremental volume. An examination of the table reveals two interesting patterns:

(1) The purchase acceleration is higher as the package size grows. This may mean the users of smaller sizes tend to be convenience-oriented and are less likely to stockpile due to promotions.

(2) The purchase accelerations on price reduction only is lower than that for feature and display merchandising. This may indicate that in-store merchandising draws the attention of loyal buyers, buyers who would have bought the brand anyway, and cause them to accelerate their purchases proportionately more than temporary shelf price reductions.

#### *Sample Accomplishment with PROMOTIONSCAN*

The reader should note that each of the figures of sample data of the system are real data (sometimes disguised) that a manager used. Approximately half of all major packaged goods marketers are presently buying and using PROMOTIONSCAN information. In this section we briefly review a typical accomplishment with the system.

Conagra Corporation used PROMOTIONSCAN to evaluate the performance of its promotions during the "March Frozen Food Month" event that they ran in 1988. The evaluation was used to convince the trade to support its activity even more in March 1989 by using ads in trade publications and a presentation to retailers which summarized their reasoning. The presentation first showed that even though the pot pies and regular dinner subcategory was less than half the total volume of the largest subcategory—premium entrees—the pot pies subcategory generated 15% more *incremental* sales than premium entrees. They also showed that the total category sales increased 17% during frozen food month. The presentation also used the PROMOTIONSCAN data to show that Conagra brands had the largest share of incremental sales for the month and thus contributed to a higher percent of the category expansion.

The logic of the presentation and associated advertising contributed to a 13% *increase in incremental volume for Conagra brands during the next year*, even though their base volume was not keeping pace and their trade promotion budget was not increased.

### **7. Limitations and Directions for Further Research**

PROMOTIONSCAN is continuing to evolve as more retailers and manufacturers become more sophisticated and comfortable with the market response measurements. Obviously all of the components of the system can be improved by performing more complex analyses. However, until our knowledge of the idiosyncracies of the complex analyses can be encapsulated into expert systems, it will be difficult to incorporate them into

PROMOTIONSCAN. A big advantage of PROMOTIONSCAN is that the system output is available almost instantaneously with the raw scanner data.

*Areas of possible improvement include:*

(1) The method of store-level baseline calculation. If there is a negative correlation between a certain brand/size promotion and our sales, and if that brand/size is promoted when ours is not, then our baseline will be biased downward because those other brand/size promotions in other "nonpromoting" stores will lower it. This is not a major practical problem as our predictive validation has shown. It is only a problem in theory at this point.

(2) The adjustment for long-term effects such as purchase acceleration and category expansion. The system would be more precise if it could parameterize individual-level choice models on scanner panel data. See Guadagni and Little (1983) or Currim et al. (1988) for a choice model and Gupta (1988) for a model that combines brand choice, purchase frequency and purchased amount. However, given the state of the art in computer power, and the complexity of setting up and interpreting such models, their integration into our system is well in the future because of our design constraints.

(3) The presentation of the system output to the various stakeholders. There currently is a P.C.-based system for managers to use to access the PROMOTIONSCAN output. However, there is much improvement needed to encapsulate "analytical insight" so that the system can cause the manager to focus on the most potentially productive information. The geographical analysis in Figures 4 and 5 is an example of an insightful routine.

(4) Understanding the relationship between baselines and other measures of brand franchise and brand health. Base lines may be very current ongoing indicators of brand health which have significant long-term implications.

(5) Separating total sales into base and incremental sales enables the development of diagnostic models for understanding each component. Base sales are affected by distribution, the brand's regular price, consumer promotion and advertising. Incremental sales are affected by the trade's activity—temporary price reduction, distribution, features and displays. We have had initial success using macro Logit competitive models such as those developed by Cooper and Nakanishi (1988) to explain share of base sales and share of incremental sales by week by market using the appropriate competitive marketing variables as input. There are separate models for base and incremental sales for each market. There is a need for much empirical work to develop the best diagnostic competitive models.

## 8. Conclusion

PROMOTIONSCAN is currently being used by many firms as an aid toward furthering their promotion productivity. It is a step in moving from market status reporting toward market response reporting. Literally thousands of promotional events are being routinely evaluated on a weekly basis with little analyst intervention. Much remains to be done to improve the system, but a productive start has been made.<sup>1</sup>

**Acknowledgements.** The authors acknowledge helpful comments and assistance from Bari Harlam, Arvind Rangaswamy, John Little, Doug Honnold, Abba Krieger, Linda Boland, Brenda Hambleton, Eric Prosnitz, Phil Johnson, Cindy Haskins, Chitrabhanu Bhattacharya, Tim Butler and Greg Goff. They also acknowledge valuable suggestions from the referees and area editor.

<sup>1</sup> This paper was received March 3, 1989, and has been with the authors 20 months for 3 revisions. Processed by John R. Hauser.

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