The Dynamic Effect of Discounting on Sales: Empirical Analysis and Normative Pricing Implications

Praveen K. Kopalle • Carl F. Mela • Lawrence Marsh
Amos Tuck School of Business Administration, Dartmouth College, Hanover, New Hampshire 03755
Fugua School of Business, Duke University, Durham, North Carolina, 27708, mela@duke.edu
Department of Economics, University of Notre Dame, Notre Dame, Indiana 46556, lawrence.c.marsh.1@nd.edu

Abstract

Baseline sales measure what retail sales would be in the absence of a promotion (Abraham and Lodish 1993), and models that measure baseline sales are widely used by managers to assess the profitability of promotions (Bucklin and Gupta 1999–this issue). Estimates of baseline sales and promotional response are typically independent of past promotional activity, even though there is evidence to suggest that increased discounting reduces off-promotion sales and increases the percentage of purchases made on deal (e.g., Krishna 1994). As a result, models that do not consider dynamic promotional effects can mislead managers to overpromote. Given the widespread use of "static" models to evaluate the efficacy of promotions, it is particularly desirable to calibrate a dynamic brand sales model and use it to establish an optimal course of action.

Accordingly, we develop a descriptive dynamic brand sales model and use it to determine normative price promotion strategies. Our descriptive approach consists of estimating a varying-parameter sales response model. Letting model parameters vary with past discounting activity accommodates the possibility that market response changes with firms' discounting policies. In the normative model, we use the estimates obtained in the descriptive model to determine optimal retailer and manufacturer prices over time.

The results of the descriptive model indicate that promotions have positive contemporaneous effects on sales accompanied by negative future effects on baseline sales. The results of the normative model suggest that the higher-share brands in our data tend to overpromote while the lower-share brands do not promote frequently enough. We project that the use of our model could improve manufacturers' profits by as much as 7% to 31%.

More generally, the normative results indicate that i) if deals become more effective in the current period, i.e., if consumers are more price sensitive, promotions should be used more frequently; and ii) as the negative dynamic effect of discounts on sales increases, the optimal level of discounting should go down. Without our approach, it would be difficult to make this trade-off exact. Finally, we demonstrate that these dynamic effects provide another perspective to the marketing literature regarding the existence of promotions.
(*Price Promotions*; *Baseline Sales*; *Price Sensitivity*; *Scanner Data*; *Channel Dynamics*)

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1. Introduction

One of the most common tools managers use to evaluate the profitability of their promotions is the measure of baseline sales provided by Information Resources, Incorporated (IRI) and A.C. Nielsen (Bucklin and Gupta 1999—this issue). Baseline sales measure what a brand's retail sales would have been had it not been promoted (Abraham and Lodish 1993). Using this measure to calculate the incremental volume attributable to a deal (i.e., promotional response), retailers and manufacturers can assess the profitability and effectiveness of in-store promotions such as discounts. The importance of this issue (for example, some firms spend $3 billion annually on promotions) has inspired numerous studies of discount effectiveness and baseline sales (for a review, see Abraham and Lodish 1987, Abraham and Lodish 1993, and Tellis and Zufryden 1995).

Brand sales models can be extended along two dimensions. First, there is some evidence that estimates of baseline sales and discount effectiveness can be influenced by the history of promotions (Foekens et al. 1999, Krishna 1994, Zenor et al. 1998). We therefore develop and estimate a descriptive model of how promotions can impact baseline sales and promotional response over time.

Second, managers often wonder precisely what to do with baseline sales and price response information once they have it. Indeed, Bucklin and Gupta (1999–this issue) argue that it is a key research priority in marketing to "develop prescriptive models that will incorporate the key aspects of descriptive models as well as assess competitive reactions, impact on profits, and long-run health." Foekens et al. (1999, p. 266) also call for research ascertaining the optimal "timing and size of the discount at the store level."

Accordingly, we develop a dynamic, descriptive model of brand sales, and integrate it with a normative model of retailer and manufacturer pricing decisions. We formally analyze the trade-off between the effect of a promotion in the period it is offered (e.g., an immediate increase in sales) and the potentially negative effect it may have in subsequent periods (e.g., a reduction in future baseline sales). This analysis is especially helpful when both effects are large for a given brand. In this case, it is not evident whether the positive contemporaneous effect outweighs the adverse dynamic effects.[1]

1.1. Sources of Dynamics

Several sources of dynamics, not altogether unrelated, are commonly posited to affect brand sales. They include the effects of discounts on stockpiling, brand equity, repeat purchase rates, and reference prices. Although we do not explicitly disentangle these effects, each can induce dynamics in response.

Dynamics in Baseline Sales. Stockpiling is defined as the acceleration of a purchase in response to a price cut (Neslin et al. 1985). If consumers accelerate purchases, their inventories increase. This can decrease sales in subsequent weeks. However, the effect may be difficult to observe in store data (Neslin and Stone 1996).

Other mechanisms exist by which increases in discounting can reduce baseline sales. Blattberg and Neslin (1990) and Jedidi et al. (1999) argue that discounting can hurt brand equity, thus reducing regular price purchases. Similarly, increased discounting may reduce customer repeat purchase rates (Neslin and Shoemaker 1989), implying a likely decrease in off-deal purchases. Mela et al. (1998) argue that consumers may learn to lie in wait for deals, thus decreasing baseline sales. Finally, it is possible that an increase in discounts lowers reference prices. This would make regular prices appear less enticing by contrast. Sales would presumably be lower in such instances (Kalyanaram and Winer 1995). Consistent with all these theories, Foekens et al. (1999) and Zenor et al. (1998) find that increased discounting can lead to lower off-deal sales.

Dynamics in Price Sensitivity. The increased use of discounts may affect price sensitivity as well as baseline sales, although the likely effect is less clear. On the one hand, consumers might become more price-conscious with an increase in the frequency of discounts, thus increasing price sensitivity (Mela et al. 1997). On the other hand, an increase in discounting may reduce consumers' reference prices (Kalyanaram

[1]We use the term "dynamic" to denote enduring for more than one period. We use the term "contemporaneous" to denote instantaneous or immediate.

and Winer 1995), thereby leading to a lower level of utility for a fixed level of discount. This would imply that price reductions occurring immediately after discounts would yield a smaller increase in sales (suggesting a lower price sensitivity). Finally, changes in the baselines may make changes in price response difficult to predict because price elasticity is measured with respect to these changing baselines.

Evidence regarding the dynamic price sensitivity effect is mixed. Blattberg et al. (1995) suggest that increased promotions reduce the discount spike. Conversely, Zenor et al. (1998) find that increased promotions amplify the discount spike. Bolton (1989) finds no effect. Boulding et al. (1994) find the effect varies by brand. Narasimhan et al. (1996) indicate the effect may be category-specific.

Overall, we expect that discounting i) will lower baseline sales, and ii) may well affect price sensitivity. Finally, we expect higher levels of inventory to reduce baseline sales.

2. Methodology

To produce a normative model capable of trading off promotions' immediate and future effects, we first develop a dynamic model of brand sales. We then use the results of this model in our dynamic optimization.

2.1. The Sales Model

The Basic Model. Our model follows the SCAN*PRO model of store sales posited by Wittink et al. (1988), Foekens et al. (1999), and Christen et al. (1997). We choose this specification because it is widely used by industry and has been applied in over a thousand commercial applications (Foekens et al. 1999). As in Blattberg and Levin (1987), store sales are modeled as a function of price, competitive price, and market inventory of the category. We also include own and competitive features and displays as well (Christen et al. 1997). The sales of brand i in store k at time t, S_{ikt}, are therefore specified to be

$$S_{ikt} = e^{\beta_{0ikt}} \delta_{ikt}^{W_t} \left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right)^{\beta_{1ikt}} \beta_{2ik}^{F_{ikt}} \beta_{3ik}^{D_{ikt}} \beta_{4ik}^{\mathrm{inv}_{kt}} \cdot \prod_{\substack{m=1 \\ m \neq i}}^{M} \left(\left(\frac{p_{mkt}}{\tilde{p}_{mkt}}\right)^{\beta_{1mkt}} \beta_{2imk}^{F_{mkt}} \beta_{3imk}^{D_{mkt}}\right) e^{\mu_{ikt}}, \qquad (1)$$

where W_t are week of the year indicators ($W_t = W_{t+52}$) that control for seasonality; p is actual price; $\tilde{p}$ represents regular, nondiscounted price; F and D are indicator variables for feature and display, respectively; inv represents inventory; m indexes brands; μ is an error term; and the β and δ are response parameters to be estimated. The terms preceding the product operator are own-effects (e.g., the effect of a given brand's price on its sales) while those embedded within the product operator are cross-effects (e.g., the effect of other brands' prices). Cross-response parameters are indexed by two brand subscripts; β_{im} represents the cross-effect of brand m on brand i. When i) actual price equals regular price, ii) no features or displays are present, and iii) inventory is zero, then $\exp(\beta_0)$ represents nonpromoted or baseline sales.[2]

To eliminate possible overspecification issues arising from the inclusion of all possible cross-effects, we assume that larger competitors have higher cross-elasticities. This assumption conforms to the findings of Blattberg and Wisniewski (1989) and others.[3] This implies $\beta_{1imkt} = \beta_{1ijkt}{*}(s_m)$, where β_{ij} indicates the portion of the cross-effect that is common across brands, s represents share, $\beta_{2imk} = \beta_{2ijk}^{s_m}$, and $\beta_{3imk} = \beta_{3ijk}^{s_m}$. Incorporating these relationships into Equation (1) and taking the log of sales yields (proof available from the authors)

$$\log S_{ikt} = \beta_{0ikt} + (\ln(\delta_{ikt}))W_t + \beta_{1ikt} \ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right) + \beta_{1ijkt} \overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)} + (\ln(\beta_{2ik}))F_{ikt} + (\ln(\beta_{2ijk}))\overline{F_{jkt}} + (\ln(\beta_{3ik}))D_{ikt} + (\ln(\beta_{3ijk}))\overline{D_{jkt}} + (\ln(\beta_{4ik}))\mathrm{in}_{kt} + \mu_{ikt}, \qquad (2)$$

where a bar oer a regressor represents the olume- (or

[2]The model assumes negligible cross-store effects on sales (see Besanko et al. 1998 and Urbany et al. 1996).

[3]To test the validity of this assumption, we compare two models for each brand. The first model assumes cross-effect parameters vary with share, as proposed. The second assumes brand-specific, cross-effect parameters independent of share. In spite of the substantial increase in parameters, the "independent of share" model's fit is lower (the R^2 decreases from 0.798 to 0.793).

share-) weighted aerage, i.e., $\bar{x}_j = \Sigma_{m=1,m\neq i}^{M} (s_m x_m)$. We assume $\mu_{ikt} \sim N(0, \sigma_{0ik}^2)$.

Equation (2) depicts the economy of the cross-effects specification. The $M - 1$ cross-effects in Equation (1) can be replaced by a single olume-weighted aerage. For each brand's sales regression, this specification reduces the number of parameters to be estimated by $3(M - 1) - 3$.

Modeling Dynamic Effects. We hae suggested that stockpiling and other dynamic effects affect baseline sales. We model these effects as follows.

The Dynamic Effect of Discounts. Following Mela et al. (1997), we use a geometrically-weighted aerage of past discounting policy to assess the dynamic effects of discounts. In this formulation, the dynamic discounting history (LTDISC) at time t for brand i in store k can be captured by:

$$\text{LTDISC}_{ikt} = \lambda \text{LTDISC}_{ikt-1} + (1 - \lambda)\text{DISC}_{ikt-1}, \quad (3)$$

where $0 \leq \lambda < 1$ represents a distributed lag effect, and DISC is the discount level given by $\tilde{p} - p$. The parameter, λ, conveys information regarding the duration of a promotion's dynamic effect. If $\lambda = 0$, the effect in period t is equal to the discount in period $t - 1$. As λ increases, LTDISC becomes increasingly dependent on discounts that occurred more than one period ago.

The dynamic effect of discounting on baseline sales is then modeled as:

$$\beta_{0ikt} = \gamma_{00ik} + \gamma_{10ik} \text{ LTDISC}_{ikt} + \epsilon_{0ikt}. \quad (4)$$

As the discounting history can also affect price response, we specify the own- and cross-price parameters to be:

$$\beta_{1ikt} = \gamma_{01ik} + \gamma_{11ik} \text{ LTDISC}_{ikt} + \epsilon_{1ikt},$$

$$\beta_{1ijkt} = \gamma_{01ijk} + \gamma_{11ijk} \overline{\text{LTDISC}}_{jkt} + \epsilon_{1ijkt}, \quad (5)$$

where $\overline{\text{LTDISC}}$ is a share-weighted aerage. The errors in (4) and (5) are again assumed normal, $\epsilon_{0ikt} \sim N(0, \sigma_{ik}^2)$, $\epsilon_{1ikt} \sim N(0, \sigma_{1ik}^2)$, and $\epsilon_{1ijkt} \sim N(0, \sigma_{2ik}^2)$. Like Foekens et al. (1999), we assume the error terms of the different parameter process functions are uncorrelated.

Stockpiling. The effect of stockpiling is captured in Equation (1) through an inventory term, which is operationalized as

$$\text{inv}_{kt+1} = \text{inv}_{kt} + (S_{kt} - \bar{S}_k), \quad (6)$$

where $\bar{S}$ is the historical mean level of sales and inventory is initialized at zero. To prevent infeasible negative inventory levels, we add a sufficiently large constant to the inventory term in order to ensure that minimum inventory levels remain just above zero. Note that the inventory function presumes a constant consumption rate.

Estimation. To estimate the model, i) data are pooled across stores; ii) store-specific intercepts are added to control for average differences in stores' sales; and iii) parameters are constrained to be constant across stores.[4] Using these restrictions and substituting Equations (4)–(6) into Equation (2) yields the dynamic brand sales model

$$\begin{aligned} \log S_{ikt} &= \gamma_{00i} + (\ln(\delta_{it}))W_t + (\ln(\kappa_{ik}))K_k \\ &+ \gamma_{01i} \ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right) + \gamma_{01ij} \overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)} + (\ln(\beta_{2i}))F_{ikt} \\ &+ (\ln(\beta_{2ij}))\overline{F_{jkt}} + (\ln(\beta_{3i}))D_{ikt} \\ &+ (\ln(\beta_{3ij}))\overline{D_{jkt}} + (\ln(\beta_{4i}))\text{inv}_{kt} \\ &+ \gamma_{10i} \text{ LTDISC}_{ikt} + \gamma_{11i} \ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right) \text{LTDISC}_{ikt} \\ &+ \gamma_{11j} \overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)}\, \overline{\text{LTDISC}}_{jkt} + \zeta_{ikt}, \end{aligned} \quad (7)$$

where

$$\begin{aligned} \zeta_{ikt} &= \mu_{ikt} + \epsilon_{0ikt} + \epsilon_{1ikt} \ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right) + \epsilon_{1ijkt} \overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)} \\ &\equiv e_{ikt} + \epsilon_{1ikt} \ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right) + \epsilon_{1ijkt} \overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)}. \end{aligned} \quad (8)$$

K is a store indicator variable that assumes a value of 1 if the store $= k$ and is zero otherwise, and κ is a store multiplier parameter.

[4]Our attempt to estimate parameters at the store/brand level was frustrated by a high level of multicollinearity (the determinant of the correlation matrices ranges down to 1.0EE-8). Parameters are therefore highly unstable (for example, price sensitivity estimates at the brand-store level ranged from −53.7 to +18.9).

The error in (7) is heteroscedastic. Letting $\sigma_{0i}^2 + \sigma_i^2 = \sigma_{00i}^2$, the variance of the error term is then given by

$$\operatorname{var} \zeta_{ikt} = \left(1 + \frac{\sigma_{1i}^2}{\sigma_{00i}^2}\left(\ln\left(\frac{p_{ikt}}{\tilde{p}_{ikt}}\right)\right)^2 + \frac{\sigma_{2i}^2}{\sigma_{00i}^2}\left(\overline{\ln\left(\frac{p_{jkt}}{\tilde{p}_{jkt}}\right)}\right)^2\right)\sigma_{00i}^2 \equiv w_{ikt}\sigma_{00i}^2. \quad (9)$$

Thus, Equation (7) may be estimated by weighted least squares, with w representing the weights. As the weights are unknown, we employ an estimation approach similar to the two-step regression-based GLS estimation approach outlined in Greene (1990, pp. 407–410). We use ML rather than regression in the two-step approach to estimate the unknown variances. Equations (7) and (9) yield one intercept, 51 week multipliers, $K - 1$ store multipliers, ten response parameters, and three error parameters for each of the six brand level log sales regressions.

Price Reaction Functions. If changes in a brand's price affect other brands' prices, its optimal price policy may be affected (for example, a price war can affect profits). Jeuland and Shugan (1988) argue that manufacturers, aware of the influence of their action on other channel members, form conjectures regarding price reactions and use them in policy decisions. Thus, similar to approaches used in the industrial organization literature (Kadiyali et al. 1996), we use a price reaction function to capture manufacturer conjectures regarding competing brands' retail prices.

We specify M reaction functions (after Leeflang and Wittink 1992, 1996):

$$\ln\left(\frac{p_{mkt}}{p_{mkt-1}}\right) = \alpha_{0m} + \sum_{\substack{i=1\\ i\neq m}}^{M} \tilde{\alpha}_{im}\,\mathrm{RLP}_{ikt} + e_{mkt}, \quad (10)$$

where $\tilde{\alpha}_{im} = \alpha_{im}(1 - \lambda_r)$, and $\mathrm{RLP}_{ikt} = \lambda_r \mathrm{RLP}_{ikt-1} + (1 - \lambda_r)\ln(p_{ikt}/p_{ikt-1})$. The first term, α_{0m}, represents the trend in brand m's price, while α_{im} characterizes the influence of brand i's prices on brand m's prices. λ_r is a decay parameter, and $e_{mkt} \sim N(0, \sigma_m^2)$. The decay parameter, λ_r, for this model can be estimated via a grid search (we search for the decay parameter that maximizes the average R^2 for the brand regressions in Equation (10)).[5]

Equation (10) implies that brand m's ($m \neq i$) prices can change several periods or more after brand i changes its price. When λ_r is small, these reactions occur primarily within a few periods. In general, when reactions occur largely within four periods, they are thought to be retailer-dominated, while longer-duration responses are manufacturer-dominated (Leeflang and Wittink 1992). Leeflang and Wittink (1992) further categorize retailer-dominated price reaction into two types: i) retailer-dominated short-run (suggesting that retailers alternate promotional weeks—implying a negative relationship between brands' retail prices); and ii) retailer-dominated longer-run (suggesting that retailer pricing reflects the competitive nature of the promotional schedules that are preestablished by the manufacturers—implying a positive relationship between brands' retail prices).

Lee and Staelin (1997) offer an additional reason why the signs of the reaction functions may change. In some instances, it is optimal for a retailer to decrease its margins when manufacturers lower their margins (strategic complementarity). In other instances, retailers will seek to increase their margins (strategic substitutability). Accordingly, the actions of the retailer may lead to different signs for the price reaction functions.

2.2. The Optimization Approach

Current Practices. Our normative model builds upon several insights we obtained from interviews with a retailer and a manufacturer. Upon setting a budget, the manufacturer and retailer meet to allocate that budget across the planning period. The retailer typically sets retail prices to maximize its profits, given the manufacturer budget decision. A Stackelberg game in which the manufacturer moves first is a good approximation of this process.

We found that forward buying and diverting on the part of the retailer (as well as lack of compliance with

[5]Equation (10)'s use of a geometric decay parameter parsimoniously captures the finding of Leeflang and Wittink (1992) that reactions are likely to occur systematically more frequently, the shorter the lag.

the pricing schedule) is strongly discouraged by the manufacturer. To limit forward buying, manufacturers often i) withhold subsequent promotions when retailers forward buy; ii) limit shipments in promotional weeks to discourage forward buying; and/or iii) structure promotions to prohibit forward buying. This last option is becoming increasingly common, as evidenced by the use of "scan-back" or "bill-back" promotions (which Bell and Drèze 1998 show to be optimal for retailers as well as manufacturers). In fact, the number of off-invoice promotions used by manufacturers has declined from 90% of all promotions in 1981 (Lunde 1995) to 33% of all promotions in 1998 (Cannondale Associates 1998). According to one retailer, "everyone is getting rid of off-invoice and there is no way we can stop it, no matter how much we dislike the lost forward buy" (Cannondale Associates 1996).

The Dynamic Pricing Game. We assume the point of view of a manufacturer whose goal is to set prices for its brand. In our model, the manufacturer sells the product to the consumers through a retail channel. We model this channel interaction using a Stackelberg game (McGuire and Staelin 1983) in a dynamic feedback framework. In this game, the manufacturer maximizes its brand profits, while the retailer maximizes its category profits. Following normative models of price promotions in which parameters are fixed, we use prices over time as the control variables (Greenleaf 1995, Kopalle et al. 1996, Neslin et al. 1995, Tellis and Zufryden 1995). A critical point of departure between our analysis and many other dynamic pricing optimization models is that our approach includes i) both manufacturer and retailer objective functions, ii) the likely effect of changes in policy on competitive prices, and iii) promotional dynamics.[6]

Thus, the manufacturer's profit, Π, for brand i in period t at store k is given by

$$\Pi_{ikt} = (g_{ikt} - c_i)S_{ikt}\,(p_{ikt}, p_{mkt}, \mathrm{LTDISC}_{ikt}, \mathrm{LTDISC}_{mkt}, \mathrm{inv}_{kt}) - \mathrm{FC}_i, \tag{11}$$

where g_{ikt} is the manufacturer price to the retailer; c_i is unit variable cost; S represents retail sales ascertained via Equation (7); p_{ikt} is the retail price of brand i (the control variable in the retailer's objective function below); p_{mkt} represents the vector of competing brands' prices (indexed by $m = 1, \ldots, M, m \neq i$) obtained from Equation (10); LTDISC is defined in Equation (3); and FC is fixed cost.[7] Without loss of generality, we assume that the profit is rescaled so that the fixed cost is zero. Finally, we assume the features and displays for a given brand are set to their mean levels and that their cost is absorbed into the fixed costs.

There are two components to the retailer's category profits: the profits it earns selling the manufacturer's brand, i, and the profits it earns from the other $M - 1$ brands in the category. We consider first the retailer's profit for the manufacturer's brand, i, in period t:

$$\pi_{ikt} = (p_{ikt} - g_{ikt})S_{ikt}(p_{ikt}, p_{mkt}, \mathrm{LTDISC}_{ikt}, \mathrm{LTDISC}_{mkt}, \mathrm{inv}_{kt}), \tag{12}$$

where g_{ikt} is provided by Equation (11), and S_{ikt} is provided by Equation (7). As noted above, the vector of prices, p_{mkt} $(m \neq i)$, is determined via the price reaction function in Equation (10). Note that retailer pass-through may be calculated as $(\tilde{p}_{ikt} - p_{ikt})/(\tilde{g}_{ikt} - g_{ikt})$ where $\tilde{g}_{ikt}$ denotes the "regular" price (the price the manufacturer typically charges the retailer in nondeal periods).

Next, we consider the retailer profits for the other $M - 1$ brands in the category (i.e., for brands $q = 1, \ldots, M$, $q \neq i$). The form of the profit function is identical to (12):

$$\pi_{qkt} = (p_{qkt} - g_{qkt})S_{qkt}\,(p_{qkt}, p_{nkt}, \mathrm{LTDISC}_{qkt}, \mathrm{LTDISC}_{nkt}, \mathrm{inv}_{kt}), \tag{13}$$

where p_{nkt} is an $M - 1$ vector of brand prices that excludes the price of brand q. This price vector includes i) the price of brand i (the control variable in the retailer's objective function), and ii) the prices (cf. Equation (10)) for all brands other than i and q (p_{qkt} is also determined by Equation (10)). S_{qkt} may be calculated

[6]As our model is a reduced form, our analysis is subject to the Lucas critique (see Keane 1997 for a detailed discussion). Our objective in incorporating dynamics is simply to help managers obtain a better understanding of incremental sales.

[7]The expected value of $\exp(\mu_{ikt})$ in Equation (1) is not zero. Thus, sales predicted using $\exp[\ln(S_{ikt})]$ must be multiplied by $\exp(-\sigma^2/2)$.

using the parameter estimates for the qth brand's sales regression in Equation (7). Although the manufacturer of brand i has knowledge of its own prices to the retailer, it does not know the prices that competing manufacturers charge the retailer, g_{qkt}. Accordingly, we use a retailer margin of 25% to determine g_{qkt} (similar to Dhar and Hoch 1996, Silva-Risso et al. 1999–this issue, and Tellis and Zufryden 1995). Once again, we assume features and displays are set to their mean levels.

The total retailer category profit across brands is then the sum of the profit for manufacturer i's brand as well as the other brands and is given by

$$\pi_{kt} = \pi_{ikt} + \sum_{\substack{q=1 \\ q \neq i}}^{M} \pi_{qkt}. \tag{14}$$

Dynamic Optimization. The retailer's and the manufacturer's goals are to maximize their respective sum of discounted profits over time. We solve their dynamic problem as follows:

$$\max_{\{u_t\}_{t=1}^{T}} \sum_{t=1}^{T} \theta^t r(x_t, u_t) \tag{15}$$

subject to:

$$x_{t+1} = f(x_t, u_t), \tag{16}$$

where θ is the discount factor; r is the profit function; the x are the state variables; and the u are the control variables. The control variable in the retailer model is the retail price of brand i, and the control variable in the manufacturer model is the manufacturer's price for brand i. The state variables in the model are inventory, the M lagged prices, the M LTDISC variables, and RLP_{ikt} (defined in Equation (10)).

The number of the state variables is therefore considerable; with M brands, the number of state variables is $2M + 2$. Using a first-order Taylor series expansion, it can be shown that the state space can be reduced to four state variables (regardless of M) by using the pricing history of the brand optimizing its prices (i.e., brand i) to determine the other brands' prices and LTDISC terms (proof available from the authors).

Using Bellman's (1957) principle of optimality, we can solve the problem indicated by Equations (15) and (16). To determine the manufacturer's and the retailer's optimal pricing strategies over time, we use a Stackelberg framework with a dynamic feedback algorithm implemented via dynamic programming. Finally, we repeat the normative analysis for each manufacturer (by setting i = brand 1, then setting i = brand 2, etc. until i = brand M).

Endogeneity. Should the retailer or manufacturer's decision to offer (rescind) a discount be related to an expected reduction (increase) in demand in a given week, descriptive results could be biased, and normative results could be suboptimal (Besanko et al. 1998).

Our model differs from Besanko et al.'s specification in some key respects, however.[8] In particular, we model the effect of discounting rather than changes in regular price. As demand effects are likely to be manifested over longer periods and occur at the category level, they are more likely to be reflected in the regular price than in the discount price. Changes in demand may arise from changes in tastes or preferences, which probably evolve over weeks and months rather than change from week to week. While discounts vary weekly, regular price changes occur over longer periods. As a result, they more plausibly reflect this source of endogeneity.

Endogeneity in discount prices, in contrast, may arise when the retailer chooses to promote stronger brands during critical periods (such as the holiday weeks). However, our inclusion of weekly dummies can control for these seasonal demand effects. Omitted seasonal marketing activity (e.g., coupons or advertising) that might induce a correlation between discounting policy and model error could be captured by these dummies (because they would be correlated with seasonal marketing activity).[9]

3. Data

To estimate our model, we use 124 weeks of A. C. Nielsen store-level data for liquid dishwashing detergent. The category is ideal because there is sufficient

[8]We thank the Area Editor for providing these insights.

[9]To test for endogeneity, we conduct Hausman's (1978) specification test. We specify changes in quantity to be a linear function of changes in price, changes in feature, and changes in display. Using lag changes in price as an instrument for changes in price, we find that the null hypothesis of no endogeneity for price cannot be rejected (i.e., price is not correlated with the error), $\chi^2(1) = 0.042$, $p < 0.84$.

discounting to calibrate the model, and the product is stockpilable. On the presumption that reductions in baseline sales are more difficult to detect when baseline sales are small to begin with, we focus on the six largest brands. These brands have a combined market share of 88% (none of the remaining brands have a share in excess of 2%). Regular price is determined as in Abraham and Lodish (1987, 1993).

The first ten weeks of data are used to initialize the LTDISC variable. There are 59 grocery stores in the data set, although not all stores sell all six brands every week. This results in a total of 36,772 observations to be used across the 6 brand sales models.

The means of the variables for each brand are reported in Table 1. Although the model is estimated using ounces, to facilitate the exposition we convert ounces to bottles by using a conversion rate of 28 ounces per bottle.

The brand-level variables are created from sku-level variables. The aggregation from sku- to brand-level may lead to differences between sku- and brand-level parameter estimates, especially when there is heterogeneity in promotional practices across items (Christen et al. 1997). In our data, the average correlation between brands' store-level sku prices is 0.57 indicating some modest heterogeneity in pricing. However, the parameter estimates we report in §4.1 are consistent with those of prior studies (Wittink et al. 1988) thus alleviating, to some degree, the likelihood of substantial aggregation bias. Although our brand level model may result in some aggregation bias, there are also some trade-offs to using a sku-level specification (e.g., collinearity, large state space).

Some strategy differences are evident across brands. Palmolive, Sunlight, and Dawn pursue a high-price position with relatively frequent discounting. Ivory also pursues a premium price, but it rarely discounts. Crystal White Octagon employs an everyday low-price strategy. Dove also offers a low price, but promotes more frequently.

4. Results

4.1. Consumer Model Results

Table 2 portrays the key results. The first column of data in Table 2 presents the mean parameter estimates across the six brand-level regressions. The remaining columns report the estimated parameters for the six brand-level regressions. To calculate the variance of these mean parameter estimates, we assume that the parameter estimates are independent across regressions, and set the variance for a particular mean parameter estimate (e.g., price sensitivity) to $1/M^2 \sum_{m=1}^{M} \text{var}_m$ where $m = (1, \ldots, \text{M})$ indexes the parameter variance estimates for the M brands.

Contemporaneous Effects. The parameter estimates in Table 2 are consistent with both our expectations and results in the prior literature. The average price elasticity (γ_{01i}) estimate is -1.63 ($t = -26.3$, $p <$

Table 1 Variable Means (Standard Deviations in Parentheses)[a]

Variable (Units)	Crystal White Octagon	Dove	Dawn	Ivory	Palmolive	Sunlight
Price ($/bottle)	1.03 (0.21)	1.38 (0.23)	2.07 (0.42)	2.06 (0.28)	2.02 (0.60)	1.77 (0.42)
Regular Price ($/bottle)	1.05 (0.21)[b]	1.46 (0.26)	2.13 (0.40)	2.06 (0.27)	2.17 (0.54)	1.88 (0.40)
LTDISC ($/bottle)	0.02 (0.02)	0.08 (0.07)	0.06 (0.05)	0.01 (0.02)	0.14 (0.11)	0.10 (0.07)
Sales (bottles)	25.3 (25.3)	24.9 (31.8)	97.9 (92.4)	36.8 (23.9)	55.2 (58.6)	53.7 (99.8)
Inventory (bottles)[c]			540 (892)			

[a]Units are converted from ounces to bottles using the mean of 28 ozs. per bottle. This facilitates the presentation but does not affect the analysis. For example, the regular price of Sunlight is ($2.06/bottle)/(28 ozs./bottle) = $0.073/0z.

[b]Note that the regular price variance includes price variance across stores. The median of the within-store regular price variance across brands is 0.604, while the median within-store price variance is 0.954 (we report the median rather than the mean because the distribution of the regular price variance is skewed). The smaller regular price variance indicates regular price changes are more infrequent than price changes.

[c]Inventory is adjusted so that the minimum inventory level is just above zero.

Table 2 Demand Model Parameter Estimates[a]

Parameter	Mean Across Brands	Crystal White Octagon	Dove	Dawn	Ivory	Palmolive	Sunlight
Model Fit (R^2)	0.80	0.79	0.66	0.90	0.85	0.84	0.76
Price (γ_{01i})	**−1.63**	**−1.72**	**−1.83**	**−1.49**	**−2.18**	**−1.53**	**−1.02**
Competitive Price (γ_{01ij})	**0.61**	−0.25	**1.45**	**0.27**	−0.21	**1.68**	**0.69**
Feature Multiplier (β_{2i})[b]	**1.65**	**1.44**	**1.87**	**1.31**	**1.26**	**1.64**	**2.78**
Competitive Feature Effect (β_{2ij})	**0.88**	0.96	**0.74**	0.96	**0.93**	**1.10**	**0.65**
Display Multiplier (β_{3i})	**1.69**	**1.51**	**2.58**	**1.53**	**1.35**	**1.59**	**1.84**
Competitive Display Effect (β_{3ij})	**0.88**	0.97	**0.82**	**0.92**	**0.94**	**0.82**	**0.79**
Inventory Multiplier (β_{4i})	0.9999998	1.000000	**1.000001**	**0.999999**	1.000000	**0.999997**	1.000000
The Effect of LTDISC on							
Baseline Sales (γ_{10i})	**−24.1**	−5.5	**−70.6**	7.3	**−49.6**	**−19.6**	−6.5
Price Sensitivity (γ_{11i})	−52.7	**−172.9**	−2.7	**100.3**	−200.6	**−25.1**	−15.1
The Effect of Competitive LTDISC							
on Competitive Price Sensitivity (γ_{11ij})	**−60.5**	**246.3**	72.9	**−56.6**	**128.0**	**−523.1**	**−230.7**
Error Variance							
Model (σ^2_{00i})	**0.42**	**0.43**	0.58	0.29	0.29	0.38	0.55
Price Parameter (σ^2_{1i})	0.22	**0.86**	0.12	0.25	0.00	0.09	0.00
Competitive Price Parameter (σ^2_{2i})	**0.27**	**0.53**	**0.62**	0.00	0.20	0.29	0.00

[a]**Bold** indicates significant at $p < 0.01$ via a two-tailed test.

[b]Note that the regression in Equation (7) estimates the log of the multiplier and inventory parameters (ln β_2 through ln β_4). In this table we convert the log parameters to the original multiplier parameters in Equation (1) by taking their anti-log. A multiplier value greater (less) than one indicates that an increase in the regressor increases (decreases) sales. To ascertain significance values for these anti-log parameters [note, var(exp(x)) ≠ var(x)], we use the delta rule. Note that the appropriate statistical test is whether these multiplier parameters differ from 1 (as a value of 1 implies no effect—-see Equation (1)).

0.001). This elasticity is close to the lowest (least negative) estimated by Wittink et al. (1988), who find elasticities as low as −1.42. Thus, the elasticity for this category is relatively low. Cross-price effects (γ_{01ij}) are positive, as expected, averaging 0.61 ($t = 6.71$, $p < 0.001$).[10]

The own-price elasticity and the cross-price effect imply a category expansion effect greater than 50%. A number of studies suggest that primary demand effects should be lower, although our finding is consistent with i) extant results from store data models (Blattberg and Wisniewski 1987, Foekens et al. 1999), and ii) the finding by Bell et al. (1999) that primary demand effects can be as high as 51.2% in some categories. In general, it may be that increased consumption (Ailawadi and Neslin 1998) and store switching (Urbany et al. 1996), which are beyond the scope of our model, can manifest themselves as category expansion. Purchase acceleration effects that are not captured in our model can also lead to higher estimated price elasticities. To the extent that store data models such as ours overstate primary demand effects, the corresponding optimal promotion levels could be overstated.

The feature multiplier, β_2, averages 1.65 and is significantly greater than one ($t = 19.2$, $p < 0.001$) while the display multiplier, β_3, averages 1.69 ($t = 26.2$, $p < 0.001$).[11] The estimates for these parameters are within the range estimated by Wittink et al. (1988). The competitive feature effect, 0.88 ($t = -9.21$, $p < 0.001$), and

[10]It is possible to obtain the cross-price elasticity for a specific competitor by multiplying γ_{01ij} by the competing brand's share (see §2.1). Thus, the cross-price elasticity for Dawn would be about 0.61*0.33 = 0.2. Analogously, the cross-feature multiplier for Dawn would be $(0.88)^{0.33} = 0.96$.

[11]The t-values reported for the multiplier parameters are based on a null hypothesis that the multiplier value is one (indicating no effect).

competitive display effect, 0.88 ($t = -10.6$, $p < 0.001$), are significantly less than one—indicating that a brand's sales will decrease when competitors feature or display their brands.

Finally, we note that the brands with the highest level of sales (Palmolive, Sunlight, and Dawn) tend to have the lowest price sensitivity. Conversely, the lower-selling brands (Octagon, Ivory, and Dove) have higher price sensitivities, suggesting that these brands may need to promote more in order to maximize their profits.

Dynamic Effects. The dynamic model leads to a significantly better fit than a model with no dynamic terms. As the static model is nested within the dynamic model, we conduct F-tests to assess the improvement in fit provided by our model. The F-statistics range from 3.43 to 79.5, averaging 27.3. All are highly significant ($p < 0.01$). The estimated lag, λ, is 0.94 (see Fader et al. 1992 for estimation details). Small deviations in the lag specification do not affect model fit or parameter estimates significantly.[12]

Baseline sales appear to be dynamic; discounting reduces baseline sales ($t = -8.67$, $p < 0.001$). Thus, the positive, contemporaneous effect of promotions is offset to some degree by a subsequent negative effect of promotions on baseline sales in future periods. This finding is consistent with Foekens et al. (1999) and Zenor et al. (1998).

The inventory multiplier is slightly less than one, as expected, although the effect is negligible ($t = -1.27$, $p > 0.10$), perhaps owing to an inability to measure inventory directly, or because detergent is easy to stockpile for a very long time (thus spreading the inventory effect over many weeks).

As noted in the theory section, the likely effect of discounting on own-price (discount) sensitivity is unclear. Although the overall effect is negative and marginally significant ($t = -1.69$, $p < 0.10$), the effect varies across brands. The effect of competitive brands' discounting on cross-price effect also varies. On average, though, the effect is negative and significant ($t = -3.14$, $p < 0.01$), indicating that an increase in the use of discounting by a brand's competitors decreases the efficacy of those competitors' discounts (i.e., diminishes the competitors' ability to "steal" customers with a promotion). This result may be due to a perceived reduction in the brand equity or value brought about by the increase in discounting of those competing brands. Also, the reduced reference values for those competing brands may mitigate the attractiveness of their current period discounts.

Taken together, the results suggest that an increased use of promotions by a brand i) reduces its baseline, ii) increases price sensitivity thereby making it more difficult to maintain margins, and iii) diminishes its ability to use deals to take share from competing brands. Thus, an increase in the use of discounting produces a sort of "triple jeopardy."

Table 2 further indicates an interesting cross-brand difference with respect to the relative magnitude of contemporaneous and dynamic effects. Brands with higher contemporaneous effects also exhibit i) a greater dynamic effect of discounting on baseline sales (the correlation between γ_{01i} and γ_{10i} is 0.63), and ii) a greater dynamic effect of discounting on price sensitivity (the correlation between γ_{01i} and γ_{11i} is 0.59). Similarly, greater cross-price elasticities correlate with greater (more negative) dynamic effects of competitive brand discounting (the correlation between γ_{01ij} and γ_{11ij} is -0.71).

One explanation for these correlations is that a greater contemporaneous discount effect is indicative of greater salience for price (for example, discounts carry greater weight in brand purchase behavior). When this price information is more salient in the current period, it is likely to be better attended and thus have a greater dynamic effect as well.

To obtain a better sense of the dynamic effect sizes, we decompose β_{0ikt} and β_{1ikt} (see Equations (4) and (5)) into i) the portion influenced by LTDISC, and ii) the portion independent of LTDISC. The portion of the intercept independent of LTDISC averages 6.63 across stores, weeks, and brands. We then computed the range by which LTDISC causes the intercept for each brand to vary. This range averages 0.65 across the six brands, indicating the dynamic effect can decrease the log intercept's value by 10%. The nonvarying portion

[12] As small changes in the lags across brands have little effect on the regression results but complicate estimation and analysis greatly, we opted for the common lag specification across brands. We select the lag that leads to the highest average fit across the regressions.

of price sensitivity is -1.63. The range averages 0.67 across brands, indicating that past discounting activity can affect price elasticity by as much as 41%.

Price Reaction Functions. The results of the price reaction functions are presented in Table 3. The lag is relatively modest, $\lambda_r = 0.37$, indicating retailer-dominated pricing reactions (0–4 weeks). Three of the 15 brand pairs exhibit negative price reactions, suggesting short-run retailer price reactions; i.e., the retailer tends to alternate deals from week to week (Leeflang and Wittink 1992). For four of the 15 brand pairs, the price reactions are positive, suggesting retailer reactions that indirectly capture some of the competitive manufacturer pricing activity (Leeflang and Wittink 1992).[13] The trend effects are all insignificant, mitigating the likelihood of discount endogeneity (as trends could be indicative of demand shocks).

4.2. Normative Model Results

Several specification decisions are necessary to proceed with the normative model. First, to derive the optimal price path, we use a time horizon of 36 weeks. To remove end-game effects, we report only the first 26 weeks (two quarters) in this paper.[14] Second, given the short time horizon considered, we set the discount factor, θ, at 1.0. Third, as the effect of inventory is insignificant, and its corresponding parameter estimate is extremely small, we find it has little effect on our results, so we treat it as a constant in our subsequent analysis. Fourth, we obtained manufacturer costs for one of the brands by interviewing a liquid dishwashing detergent category manager at an anonymous consumer packaged goods firm. We assume similar costs for other leading brands, but also assume that costs are proportionately lower for the lower-priced brands, Octagon and Dove.[15] Finally, we average the store and week multiplier parameters in our normative analysis. Our normative results may thus be interpreted as an "average store in an average week." This last simplification has little effect on the insights arising from the analysis.

Dawn, Palmolive, and Sunlight. The results for Dawn, Palmolive, and Sunlight (the highest share brands) are presented in Figures 1 through 3. The graphs suggest that, in steady state, the manufacturer and retailer should curtail promotion of these brands. As the contemporaneous price effects are the lowest for these brands, the insufficient incremental volume

[13]The estimated price reactions in our data are smaller than those found in Leeflang and Wittink (1992). To the extent these reactions are understated, the profitability of promotions for the manufacturer would likely be overstated.

[14]To facilitate exposition further, we reduce the lag slightly in our analyses to 0.9. Longer lags, by virtue of their greater memory, result in longer start- and end-game effects.

[15]In general, we find that high costs lead to an optimal solution of no promotions; low costs lead to a solution of a deal in every period (implying regular price should be lowered); and moderate costs lead to a solution with promotions. Although our approximate cost specifications were made in conjunction with a manufacturer, we would ideally like to see more precise cost information for each brand. Manufacturers, however, are understandably reluctant to provide it.

Table 3 **Price Reaction Functions**[a]

Effect On	Trend	Dawn	Palmolive	Effect of Sunlight	Ivory	C.W. Octagon	Dove
Dawn	−0.00		**−0.07**	0.00	**0.50**	−0.07	**0.08**
Palmolive	−0.00	**−0.22**		**−0.13**	−0.05	**−0.16**	**−0.26**
Sunlight	−0.00	0.01	**−0.10**		−0.02	**0.15**	**0.25**
Ivory	−0.00	**0.18**	−0.02	0.01		0.01	−0.01
C.W. Octagon	−0.00	0.01	−0.02	**0.05**	0.04		−0.08
Dove	−0.00	**0.13**	**−0.12**	**0.06**	−0.03	**−0.05**	

Bold indicates significant at $p < 0.01$ via two-tailed test.

[a]Lag = 0.37.

Figure 1 Dawn

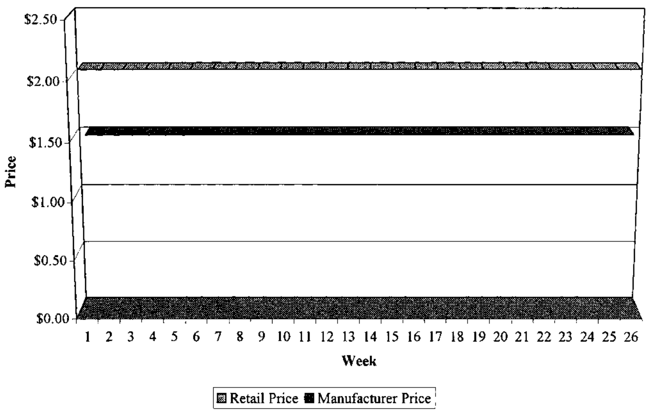


Figure 2 Palmolive

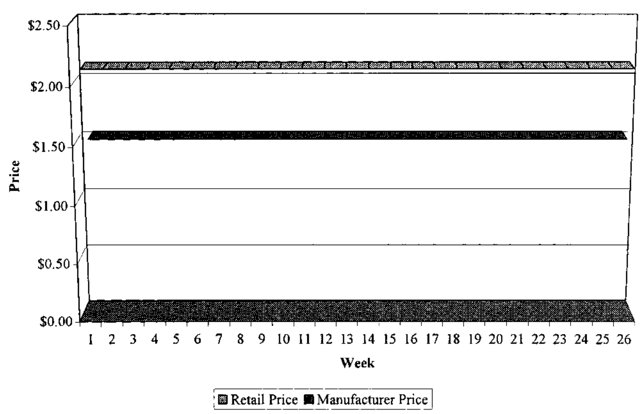
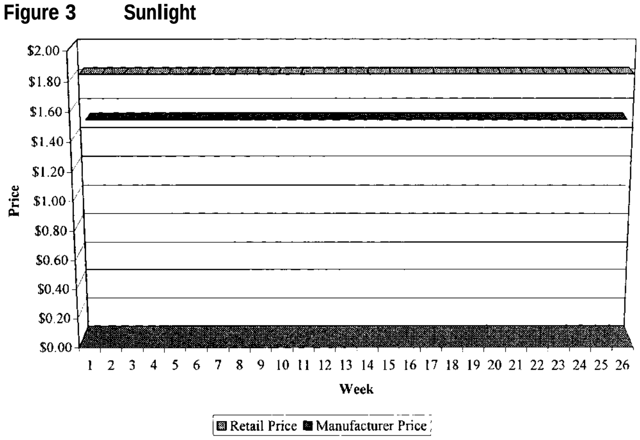


Figure 3 Sunlight



arising from a deal does not appear to justify the lower margins that the deal creates.

The model predicts that the manufacturer's profits in a given store over the 26-week period will be $1,338 for Dawn, $796 for Palmolive, and $565 for Sunlight. The predicted potential improvement in profit over that obtained with actual prices is 20.1% for Dawn, 21.2% for Palmolive, and 31% for Sunlight.[16]

We acknowledge that this normative policy should be tempered by factors beyond the scope of the model; there remain other reasons for offering discounts (e.g., cultivating retailer relationships, facilitating access to the retailer for the field sales force, the use of detergents as a loss leader, and/or inducing trial). Thus, discounts should be diminished for these brands, but perhaps not eliminated entirely. It is nonetheless instructive to learn that the largest (and presumably most powerful) brands in this market are overpromoting.[17]

Ivory and Crystal White Octagon. As both Ivory and Octagon have relatively high values for γ_{01i}, their contemporaneous price effect is fairly high. In contrast, the brands' negative dynamic effects are modest to small. One might then expect promotions to be optimal for both brands.

However, the large, negative dynamic effect of promotions on price sensitivity for these brands may moderate the optimal price path for these brands. Increased price sensitivity can lead to lower margins. Accordingly, these manufacturers should be careful that their promotions do not increase price sensitivity to the point where margins are eroded and profits reduced.

Figures 4 and 5 depict the optimal price paths for Ivory and Octagon. The graphs indicate that the brands benefit from promoting, and that Ivory should promote more frequently than Octagon. The optimal price path for Ivory suggests discounts in 50% of the

[16]To assess the potential increase in profits, we randomly select a string of actual prices from the store data and predict profits using these data. These profits are compared to the profits predicted by the optimal price path.

[17]The use of these brands as loss leaders may factor in their overpromotion. However, liquid dishwashing detergents, unlike carbonated beverages, are low-priced and infrequently purchased. Accordingly, it is unclear whether brands in this category are effective loss leaders.

periods, with an average depth at retail of 29%. Octagon discounts about 19% of the time at an average depth of 15%. These promotional schedules would lead to predicted manufacturer profits of $1,029 for Ivory and $103 for Octagon. The optimal price path leads to a predicted improvement in profits of 9.9% and 25.5% for Ivory and Octagon respectively.

Dove. Even though Dove's price sensitivity is reasonably high, the negative dynamic effect of promotions on baselines is greatest for this brand. The question of whether it should promote is thus difficult to answer without the normative analysis. The optimal price for Dove is shown in Figure 6. The graph indicates that Dove's promotions should be negligible. The profits for Dove are projected to be $126, a predicted increase of 7.4%.

4.3 Comparison to a Static Solution

To ascertain the improvement in profits that arises from using a dynamic model, we compute the profits a brand would have obtained had it estimated a model with no dynamic effects. Using a static Stackelberg game (McGuire and Staelin 1983), it is straightforward to show that the manufacturer's profit-maximizing price for a model that omits price reaction and dynamic effects (omit inventory and all the LTDISC terms from Equation (1)) is given by $g_i^* = \beta_{1i}c_i/(1 + \beta_{1i})$, where $\beta_{1i} < -1$ is the price sensitivity of brand i in a model estimated with no dynamic effects, and c_i is the manufacturer's cost. The corresponding profit-maximizing price for the retailer is given by $\beta_{1i}g_i/(1 + \beta_{1i})$.

If price sensitivity is low, manufacturers and retailers will never promote. If price sensitivity is high, they will always promote (because, in a static model, there are no adverse dynamic effects to promoting). Thus, brands will either always or never promote.

Comparing the static and dynamic model solutions, we note that use of a dynamic model would lead to a predicted increase in profits of 15.5% for Ivory and 10.7% for Octagon. As the pricing recommendations for the remaining brands are the same, their profits will also be the same. When deals are optimal, the use of a static model to make pricing decisions could reduce profits by as much as 16%.

Figure 4 Ivory

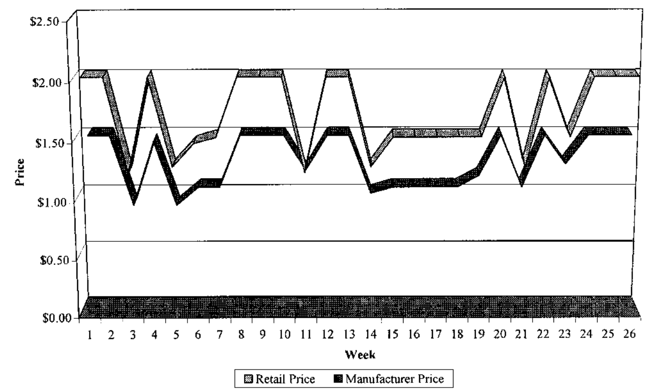


Figure 5 Crystal White Octagon

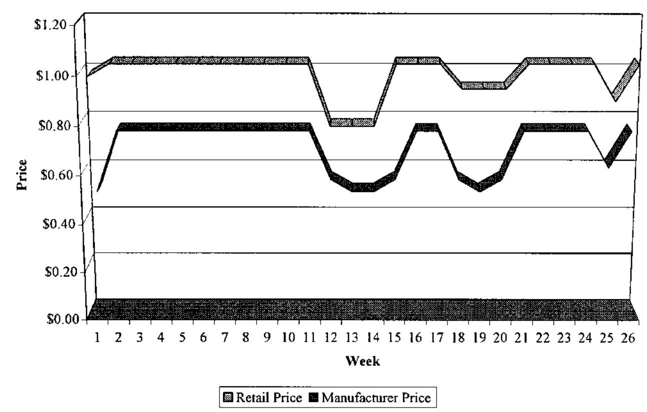
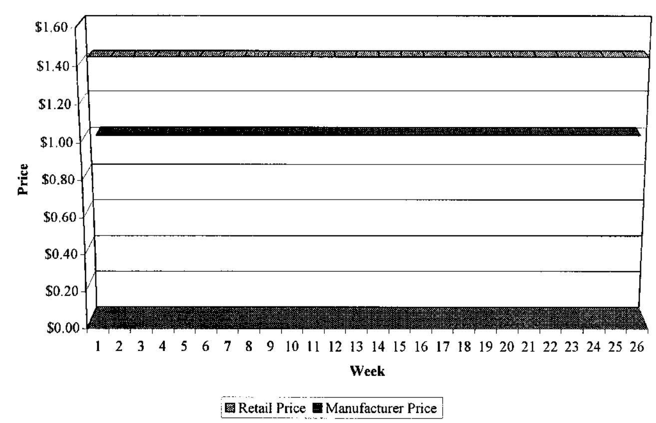


Figure 6 Dove



5. Conclusions

The most pervasive marketing models that major, packaged goods firms use to assess promotional profitability are baseline sales models (Bucklin and Gupta 1998). However, such models typically assume that promotions do not affect the behavior of markets into which they are introduced. This assumption has not been found to hold empirically in prior studies nor have we found the assumption to be tenable. Second, prior models offer little guidance regarding how managers should act on baseline information. We address both of these limitations.

To do this, we develop a varying-parameter sales model predicated on the dynamic SCAN*PRO based model developed by Foekens et al. (1999). Then, we develop a normative model of retailer and manufacturer pricing based on the descriptive consumer model.

Our results suggest that managers can increase profits by as much as 7% to 31% over their current practices. These findings indicate that it is important to balance the trade-off between i) increasing sales arising in the *current period* from a given discount, and ii) the corresponding effect of reducing (baseline) sales in *future periods*. To our knowledge, our analysis is the first to balance such effects to develop optimal price promotion strategies.

Second, we provide a theoretical explanation for promotions that may be new to the literature. Previously, i) Farris and Quelch (1987) have suggested that promotions result from skimming the demand curve; ii) Blattberg et al. (1981) noted that inventory cost shifting from the retailer to the consumer can cause promotions; iii) Lal (1990) and Rao (1991) found that competition between national and store brands can induce national brands to promote; and iv) Kopalle et al. (1996) argued that promotions can be caused by asymmetry in price response about a reference price. We show that another explanation for dynamic pricing exists: the trade-off between a promotion's contemporaneous and dynamic effects.

Third, we uncover a number of novel empirical findings. Our empirical analysis suggests that promotions can lead to a "triple jeopardy." First, as discounts become more endemic, baseline sales decrease. Second, temporary price reductions can increase price sensitivity, thus making it more difficult to command higher margins. Third, the frequent use of deals makes them a less effective tool for "stealing" sales from competing brands. This latter finding suggests that national brands' asymmetric pricing advantage (as outlined in Blattberg and Wisniewski 1989) could be compromised by excessive discounting.

Fourth, we find that brands with higher contemporaneous price effects also realize larger dynamic price effects. The increased salience of discounts in the short term may imply that discounts are better attended, thus implying a greater dynamic effect as well.

Finally, our model also makes a number of methodological contributions. Our dynamic normative model is among the first to include the dynamic effects of promotions on response parameters. We show that these effects have major implications for brands' optimal pricing paths. The normative approach is among the first in marketing to include both the retailer and manufacturer objective functions as well as price reactions in a dynamic Stackelberg game. Last, our integration of econometric and normative approaches is relatively novel and suggests that there are gains to be made by applying this integration in other contexts.

There are a number of potential extensions of this analysis. First, the model allows no retailer forward buying; such a modification would be a useful extension. Second, the model uses retailer price reaction functions to empirically capture the effect of the retailer and competing brands optimizing their respective prices. An explicit treatment of brands and retailers optimizing over all the brands' prices would be beneficial. In the case of manufacturers that own more than one brand (e.g., Proctor & Gamble (Ivory and Dawn) and Unilever (Sunlight and Dove)), this analysis might be particularly beneficial. Third, we use a Stackelberg game with the manufacturer as the leader. Other games could lead to different solutions. Fourth, as dynamics in baseline sales may be endogenous, the development of a complete structural model in a dynamic optimization setting may be warranted. Finally, a field test of our procedure could better demonstrate its ramifications for brand profitability.

By analyzing a topic of great managerial relevance, we have sought to fulfill the broader objectives of this special issue. We "analyze available data to better understand (and take action on) some phenomenon and . . . postulate a normative model for action . . . [and] show the parameters of the model can be estimated so that a decision can be made (Staelin 1997, p. iv)." We find that normative and dynamic treatments improve brand sales models and contribute to better managerial decisions. Accordingly, we hope that our work will encourage additional research in this area.[24]

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