Retailer Dynamic Pricing and Ordering Decisions: Category Management versus Brand-by-Brand Approaches

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Abstract

This paper provides a framework for retailer pricing and ordering decisions in a dynamic category management setting. In this regard, the key contributions of this paper are as follows. First, we develop a multi-brand ordering and pricing model that endogenizes retailer forward buying and maximizes profitability for the category. The model considers (i) manufacturer trade deals to retailers, (ii) ordering costs incurred by the retailer, (iii) retailer forward buying behavior, and (iv) both own- and cross-price effects of all the brands in the category. Second, we use this model to compare differences in ordering and pricing decisions, and in profits, resulting from using a category management versus a brand-by-brand management approach. Our approach allows us to derive implications in a dynamic setting about the impact of interdependence among the brands upon decisions on pass-through of trade deals and retailer order quantity. We show that category management results in noticeably higher profits versus brand-by-brand and cost-plus (markup) approaches. Further, our results suggest an interaction between a brand’s own-price effect and its cross-price effect emerges. If the cross-price effect for a brand is low – that is, the brand takes away relatively few sales from the other brands – the retail pass-through should increase with that brand’s own-price effect. On the other hand, when the cross-price effect is high, the retail pass-through decreases with the brand’s own-price effect.

Keywords: Retail pricing; Ordering decisions; Ordering costs; Trade deals; Category management; Dynamic programming; Pass-through

Introduction

The growth of Efficient Consumer Response (ECR) from the 1990s and the subsequent emphasis on category management encourages retailers to focus on the profitability of an entire product category rather than of individual brands (Chain Store Age 1995; Levy et al. 2004; Progressive Grocer 2001; Publishers Weekly 2001). This issue is particularly important in the consumer packaged goods industry where brands within a category have interrelated demands and their relative profitability changes over time with the occurrence of frequent trade deals (discounts from manufacturers to retailers) and forward buying by retailers (Blattberg and Neslin 1990). This necessitates a dynamic category-level model which incorporates changing brand profitability over time and the interdependence among brands.

Focusing on the scenario described above, we develop a dynamic model of category ordering and pricing decisions that endogenizes retailer forward buying and maximizes retailer profit for the category. The model considers (i) manufacturer trade deals to retailers over time, (ii) ordering costs incurred by the retailer, (iii) retailer forward buying behavior, and (ii) both own- and cross-price effects of the brands in a category. Ordering and pricing decisions are inherently intertwined as ordering decisions impact costs over time, which in turn affect retail prices. However, ordering costs have largely been ignored in previous category pricing models even though our interviews with retail managers at three large retail stores indicate that the cost of placing an order is non-trivial.

We use this model to compare the ordering and pricing decisions that result from an individual brand management model versus a category management model. The latter approach allows us to derive implications about the impact of interdependence among brands upon decisions on pass-through of trade
Tellis and Zufryden (1995) incorporate ordering decisions but assume that orders for all brands are placed simultaneously and with the same periodicity. Lal, Little, and Villas-Boas (1996) provide an analysis of manufacturer trade dealing where category demand is fixed and the retailer can forward buy utmost one unit. We build on this work by endogenizing retailer ordering and pricing decisions and allowing category expansion along with optimal forward buying quantities. Also, we develop the impact of own and cross-price effects on optimal pass-through policies in a dynamic setting. Thus, in this paper, we jointly optimize pricing and ordering decisions for multiple brands in a category in the presence of ordering costs and retailer forward buying, and evaluate retail pricing and pass-through decisions.

Retailer pricing and ordering problem

The retailer faces a multi-brand (category management), multi-period ordering and pricing problem. In each period \( t \), manufacturers of the \( m \) different brands within a product category offer their brand \( i \in [1, \ldots, m] \) to the retailer at a regular cost, \( c_{it} \), and may offer a trade deal to the retailer of value, \( Deal_{it} \). The retailer determines an order quantity, \( x_{it} \), for each brand in each period and also determines a price, \( p_{it} \), to charge consumers. The prices in each period determine the demands \( D_{it} \) in each period. The retailer incurs an ordering cost, \( K_{it} \), in period \( t \) which may be dependent on whether orders for multiple brands are being placed separately or together. In other words, if orders for two brands happen to occur at the same time, the cost of ordering the two brands from a wholesaler may very well be less than the sum of the ordering costs for the two brands separately. We show that ignoring ordering costs leads to sub-optimal pricing and ordering decisions. The cost of holding one unit of product \( i \) from period \( t \) to period \( t + 1 \) is given by \( h_{i} \). The objective is to maximize the retailer’s discounted profits over a finite time horizon.

We assume linear holding costs and zero lead times.\(^4\) We allow trade deals for different brands to be of different values and durations and they can arise at different times. Trade deals for a given brand may also differ in value and duration from one trade deal to another. The model permits any number of orders to be placed during the duration of a trade deal.

Table 1 shows typical data available to a retailer on future trade deals.\(^5\) These data are consistent with prior research which suggests that the retailer has knowledge of future trade deals for the time horizon under consideration and that manufacturers’ sales representatives often show their trade deal calendar to retailers to aid them in their planning (Ailawadi, Kopalle, and Neslin 2005; Silva-Risso, Bucklin, and Morrison 1999; Tellis and Zufryden 1995).

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\(^4\) A non-zero lead time can easily be incorporated within this model framework since this simply shifts the time in which the retailer receives an order that was previously placed.

\(^5\) The authors thank the vice president of a supermarket chain for furnishing them with this data.
As seen in Table 1, retailers have knowledge of trade deals for these stock keeping units (SKUs) for an upcoming 90-day period. Conversations with retail managers and industry pricing experts indicate deterministic knowledge of trade deals over three to 6 months is the general rule, at least in the grocery trade.6

Retailers’ objective function

The retailer’s objective is to choose prices \( p_{it} \) and order quantities \( x_{it} \) for each brand \( i = 1, \ldots, m \) in each period \( t \), to maximize discounted profits over time \( T \), i.e.,

\[
\max_{p_{11}, p_{21}, \ldots, p_{mt}, x_{1t}, x_{2t}, \ldots, x_{mt}} \sum_{t=1}^{T} \left[ p_{it} D_{it}(p_{11}, \ldots, p_{mt}) - (c_{it} - \text{Deal}_{it})x_{it} - h_{i} \ln \text{Inv}_{it} - K_{it}(x_{i1}, x_{i2}, \ldots, x_{im}) \right]
\]

where \( \text{Inv}_{it} = \text{inventory} \) for brand \( i \) at time \( t = \text{Inv}_{i,t-1} + x_{i,t-1} - D_{i,t-1}(p_{1,t-1}, \ldots, p_{m,t-1}) \geq 0 \), \( h_{i} = \text{per unit holding cost of inventory} \), \( K_{it} = \text{ordering cost} \), \( \beta = \text{discount rate} \), \( c_{it} = \text{wholesale price of brand} \ i \ \text{in time} \ t \), \( \text{Deal}_{it} = \text{trade deal for brand} \ i \ \text{in time} \ t \), \( D_{it} = \text{consumer demand for brand} \ i \ \text{in time} \ t \), and \( x_{it} \geq 0 \), \( D_{it}(p_{1t}, \ldots, p_{mt}) \geq 0 \).

For brand \( i \), price times demand \( p_{it}D_{it} \) denotes the revenue in time \( t \). The term \( (c_{i} - \text{Deal}_{it})x_{it} \) represents the purchasing cost (\( c_{i} \)) for \( x_{it} \) units of brand \( i \) in period \( t \) less the trade deal, \( \text{Deal}_{it} \). The term \( h_{i}\text{Inv}_{it} \) represents the cost to hold \( \text{Inv}_{it} \) units of brand \( i \) from period \( t-1 \) to \( t \). Thus, \( [p_{it}D_{it}(p_{1t}, \ldots, p_{mt}) - (c_{i} - \text{Deal}_{it})x_{it} - h_{i}\text{Inv}_{it}] \) represents the retailer’s profit in period \( t \) for brand \( i \). This is summed across brands \( 1 \) through \( m \), the ordering cost \( K_{i} \) is subtracted, and the result is discounted appropriately. The demand for brand \( i \) in period \( t \) is given by \( D_{it}(p_{1t}, \ldots, p_{mt}) \). In general, demand, \( D_{it} \), will not equal order quantity \( x_{it} \) due to retailer forward buying and holding of inventory.

Dynamic programming formulation

We formulate our problem as a Markov decision process where the state space is an \( m \)-vector in which the \( i \)th element, \( s_{i} \), represents the period in which an order was last placed for brand \( i \). The decisions to be made in each period include the price for each brand and whether to place an order for each of the brands. Our solution procedure endogenously determines optimal order quantities and inventory levels. We designate the optimal value function by \( v_{t}(s_{1}, s_{2}, \ldots, s_{m}) \). This function represents the value of following the optimal policy starting in period \( t \) when orders were last placed in periods \( s_{1}, s_{2}, \ldots, s_{m} \) for products \( 1, 2, \ldots, m \), respectively. We use binary (0–1) variables, \( I_{it} \), to indicate whether an order for brand \( i \) was placed in period \( t \) (where \( I_{it} = 1 \) denotes placement of an order). Note that the order quantity is a function of both retailer costs and prices. Similarly, the prices charged depend on the cost of the item and when the item was ordered. Since ordering costs are jointly determined by number of brands being ordered, pricing and ordering decisions for all brands are interdependent; that is, the ordering and pricing decisions for brand \( i \) depend on the ordering and pricing decisions for all brands. The optimal order quantity for a brand is arrived at by adding up the demand over the periods between optimal

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6 We discussed with four independent consultants to supermarkets, one grocery store owner, one food broker, one vice president of a large supermarket chain, and two marketing managers. All nine people strongly suggested that retailers know exactly when trade deals for different brands will occur and generally know what the trade deal price will be in an upcoming 3- to 6-month period.
orders. The period of forward buying is given by the number of periods covered by the order.

For our problem (given by Eq. (1)), Lemmas A.1 and A.2 (presented in the appendix section) show that (i) it is optimal for the retailer to place an order for an item only when existing stock is exhausted, and (ii) orders will cover total demand over some number of sequential future periods. Lemmas A.1 and A.2 allow us to restate the retailer’s problem in Eq. (1) as an optimal control problem in discrete time (Stokey and Lucas 1989). The optimality equation in period t is given by:

\[
\begin{align*}
    v_t(s_1, s_2, \ldots, s_m) &= \max_{I_{1t}, I_{2t}, \ldots, I_{mt}} \left\{ \sum_{j=1}^{m} \left( p_{jt}D_{jt} - (c_{jt} - \text{Deal}_{jt})D_{jt}I_{jt} \right) \right. \\
    & \left. - \left( c_{js_j} - \text{Deal}_{js_j} + \sum_{i=1}^{t-1} h_j \right) D_{jt}(1 - I_{jt}) \right. \\
    & \left. - K_t(I_{1t}, I_{2t}, \ldots, I_{mt}) + \beta I_{t+1}(s_1 + I_t(t - s_1), s_2 + I_t(t - s_2), \ldots, s_m + I_{mt}(t - s_m)) \right\}
\end{align*}
\]

This formulation tracks the periods in which the brands were last ordered and uniquely determines order sizes and costs, including any holding costs. We use dynamic programming to solve Eq. (2) (Bertsekas 1987) and begin with initial conditions where inventory levels are zero. The solution approach and the algorithm are presented in the appendix section Dynamic programming solution approach and algorithm for optimal pricing and ordering policy.

Although the above formulation allows general demand functions that allow for interdependence in demand between the various brands in a product category, linear demand functions are common both in practice and existing literature (Basu and Majumdar 1995; Choi 1991; Kim and Staelin 1999; Kopalle, Mela, and Marsh 1999; Lee and Staelin 1997). While this choice is generally made for reasons of tractability, in this paper, we also examine two non-linear demand functions. Thus, incorporating feature and display as covariates, we have,

\[
\begin{align*}
    D_{it}(p_{it}, p_{2t}, \ldots, p_{mt}) &= a_i - b_i p_{it} + \sum_{j=1}^{m} \left( b_{ij} p_{jt} + \gamma_{1i} \text{Feature}_{it} + \gamma_{2i} \text{Display}_{it} \right) \\
    & \quad \text{for } j \neq i
\end{align*}
\]

We refer to the coefficient \( b_i \) as “own-price effect” of brand \( i \) and \( b_{ij} \) as “cross-price effect” of brand \( j \), i.e., the effect of the price of brand \( j \) on the demand for brand \( i \). In Eq. (3), prices (and hence demand) are dynamic since retail costs are dynamic due to ordering and inventory holding costs and trade deals over time. The coefficients \( \gamma_{1i} \) and \( \gamma_{2i} \) capture the impact of feature and display of brand \( i \) on its sales. Finally, we estimate Eq. (3) using regression analysis. The sufficient conditions for the concavity of Eq. (2) are given in the appendix section Concavity of the value function in prices.

An application of the model and results

Here, we empirically estimate the demand functions and then use these demand functions to solve the pricing and ordering problem for the retailer. We then develop optimal pricing and ordering decisions for the retailer for a 24-week time horizon; we run the model for 36 weeks and ignore the last 12 weeks to remove any end-game effects. These policies are derived using the model presented in the preceding section. We provide a measure of the gains that result from a category management approach to pricing and ordering and derive the impact of own- and cross-price effects on dynamic pricing.

Data description, estimation, and parameter values

Data description

In order to estimate demand functions, we obtained 48 weeks of store-level data for children’s cold cereal from a major grocery store chain. We replicated our results in another category, refrigerated orange juice, where we consider 52 weeks of data for the top three selling brands: Tropicana, Minute Maid and Tree Fresh. For brevity, here we only report the results from the children’s cold cereal category; the data cover two stores in a metropolitan area and provide weekly data on unit sales, regular prices, regular costs, trade deals, discounts to consumers, feature, and display activity. Here, we focus on the popular 14–17 oz size and consider the top three brands, Captain Crunch, Post Pebbles, and Kellogg’s Frosted Flakes, which together account for about 46.4 percent of unit share in the size category we consider at the grocery chain; the average prices for the three brands were $3.12, $3.39, and $2.88, respectively. Since multiple SKUs are offered within the same brand, we first examined the correlations in prices across the SKUs within a brand. The three Captain Crunch SKUs and the two Post Pebbles SKUs have highly correlated pricing policies (\( r > .80, p < .01 \)). Given these high correlations among prices, we combined the correlated SKUs into a single brand and averaged the corresponding prices and sales.

Demand function estimation

We first estimate the demand functions for the top three brands in the children’s cold cereal category. We obtained similar results for the two stores and hence pooled the data across the two stores.\(^7\) The unit sales were deseasonalized at the category level following Abraham and Lodish (1993), and Blattberg and Briesch (1995).\(^8\) The estimation results are given in Table 2. We obtained similar results using two-stage least squares where we

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\(^7\)The results of the pooling test (Johnston 1984, p. 219) show that the corresponding f-stats are not significant (\( p > .05 \)).

\(^8\)We first generate an index for each month so that expectation across months equals one. We then generate an index for the weeks within each month so that expectation across weeks equals one. We multiplied the two indices to get the final seasonal index for each week.
used lagged prices, feature, and display activity as instruments. Note that we followed prior research which argues that it is not necessary to estimate the supply side model to control for endogeneity in the demand side (Ailawadi, Kopalle, and Neslin 2005, p. 18).9

Parameter values for dynamic programming algorithm

We used the parameter values obtained in the demand estimation stage (Table 2) to determine the optimal pricing and ordering decisions for a retailer in both the category management and brand-by-brand case. Using a discount rate of .998 per week (which translates to about 10 percent per year, a reasonable interest rate), we apply the dynamic programming algorithm discussed in the section Dynamic programming formulation. We used normal manufacturer prices to the retailer (i.e., in the absence of trade deals) of $1.95, $2.85, and $1.90 in the cereal category. The trade deal pattern we considered is given in Fig. 1, where the deals offered on the three brands in both categories are $1.00, $1.40, and $1.20 per unit, respectively.

Feature and display were set at the respective averages. Simulations performed with other (i) parameter values, (ii) levels of trade deals, and (iii) ordering and holding costs yielded qualitatively similar results. We determined appropriate per-period holding and fixed ordering costs based on interviews with retail managers at three large retail stores in a town in the northeastern United States. Retailer’s per unit inventory holding cost was estimated to be about 5 percent of retailer cost per month (Ailawadi, Kopalle, and Neslin 2005), and on average it translates to about $0.15/month. The average cost for placing an order across various brands was estimated to be about 1-hr salary for a store clerk under a fully burdened labor rate of $50 per hour. Below, we discuss the results of our analysis.

Impact of ordering costs on pricing and ordering decisions

Here, we discuss how a retailer’s optimal ordering and pricing policies are affected by ordering costs. For both the category management and brand-by-brand approaches, we use the demand function estimates in Table 2. We implemented the dynamic programming algorithm (discussed in the section Dynamic programming formulation) twice—once with order-

![Fig. 1. Timing and amount of trade deals.](image-url)
Table 3
Retailers’ optimal order timing and order quantity decisions: impact of ordering costs.

<table>
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<tr>
<th>Week</th>
<th>Captain Crunch</th>
<th>Post Pebbles</th>
<th>Kellogg’s Frosted</th>
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<td>With order costs</td>
<td>Without order costs</td>
<td>With order costs</td>
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ing cost and once without. The latter corresponds to a situation where costs of ordering are ignored by retailers in the pricing and ordering decisions even though the costs are (obviously) incurred by them. Via backward induction, we then determine the optimal order timing and quantity decisions for each brand in each week for the category management case. The results are given in Table 3 where we see, for example, that for the Post Pebbles brand, using the model with ordering costs the retailer orders 43 units in week 1 (which covers demand during weeks 1–4) and does not order any units in weeks 2–4. On the other hand, when ordering costs are ignored, the retailer orders 16, 17, 20, and 21 units, respectively, in weeks 2–4. Thus, when ordering costs are ignored, the model would recommend (incorrectly) that retailers place orders in multiple weeks even when there is no trade deal offer. When ordering costs are considered, the retailer needs to balance the costs of ordering against the cost of holding inventory for an additional, say, 2 or 3 weeks. If the additional cost of inventory holding is higher than the ordering cost, the retailer will place additional “fill-in” orders.

Further, we find that the optimal prices under ordering costs are noticeably higher relative to without ordering costs. Most dynamic pricing analyses in the marketing literature have ignored fixed costs of ordering, which, at the outset, seems reasonable since fixed costs do not appear in the first order conditions for the optimal price and therefore such “fixed” costs should not affect prices. However, as seen above, higher ordering costs also result in higher variable costs, via the inventory holding cost. Therefore, incorporating ordering costs generally leads to less frequent ordering, higher average inventory levels, and thus greater holding costs, which increases variable costs. Our results suggest that some of this increase in variable costs should (optimally) be passed on to the consumer via higher prices.

Differences in pricing and ordering decisions in a category management versus a brand-by-brand approach

In this section, we compare optimal pricing and ordering policies under a category management setting versus a brand-by-brand approach. Both models incorporate ordering costs. In the brand-by-brand approach, profit for each brand is maximized separately over the time horizon considered. On the other hand, in the category management approach, the sum of profits across all the brands in each category is maximized over the same time horizon. The same demand function estimates (Table 2) are used for the two approaches. We find three consistent results across all brands. First, while the order timing (when to place orders for each brand) is the same in the brand-by-brand and category management approaches, the order quantities are much higher in the case of a brand-by-brand approach relative to a category management approach (see Fig. 2). Second, given the higher order quantities in a brand-by-brand approach (relative to category management), the prices never hit the sweet spot—they are either too low to clear existing inventory or too high, which does not clear the inventory. This is because in a brand-by-brand approach, the demand interdependence across the three brands in each category is ignored wherein only the average impact of the other brands is captured.

Finally, we find that the optimal pass-through of a trade deal is higher (i.e., a larger fraction of the trade deal is passed through
Fig. 2. Optimal order quantity and order timing decision under category management versus brand-by-brand approaches.

Profit comparison of category management and brand-by-brand approaches

Here, we compare the overall profitability over time for the two approaches over the 24-week time horizon. As a benchmark, we also evaluate the profitability of a cost-plus markup rule where the order quantity is decided after setting the prices. We varied the markup from 25 to 75 percent in steps of 10 percent. At a markup of 25 percent, the reduction in profit relative to a category management approach was about 60 percent—the cost-plus approach performs worse due to sub-optimal pricing, more frequent ordering, and larger inventory. The least reduction in profit under the cost-plus rule relative to a category management approach was obtained with a markup of 45 percent and the loss was about 50 percent.

Impact of own- and cross-price effects and interactions on dynamic pricing

We use the category management approach to better understand the effects of own- and cross-price interactions for pricing decisions over time. We use numerical simulation to develop the results for a three-brand case. The parallel analytic results for a two-brand scenario are provided in the appendix section Deriving analytical results for a two-brand model. To arrive at the numerical simulations, we varied own- and cross-price effects, wholesale prices, and trade deal amounts. The variation was ±25 percent in steps of 5 percent centered around the base values reported in Table 2 and the wholesale prices and trade deal amounts discussed in the section Parameter values for dynamic programming algorithm.

Result 1 extends Moorthy’s (2005) category management results to more than two brands and demonstrates convergent validity with prior research. Results 2 and 3 are novel, particularly to a context of retail dynamic pricing and ordering decisions.

Result 1. Ceteris paribus, the dollar amount of pass-through for brand \( i \) increases with the (i) trade deal amount and (ii) own-price effect of brand \( i \). Further, (iii) the brand whose cross-price effect on competing brands is greatest exhibits the largest pass-through.

We find that as the retailer cost decreases due to a trade deal, the price, \( p_{it} \), is lower. This mirrors the brand-by-brand result that larger trade deals result in greater pass-through. The higher the trade deal amount on brand \( i \), the more profit the retailer makes by switching consumers from brand \( j \) to brand \( i \) (for \( j \neq i \)) and, to the consumer) in the brand-by-brand model relative to a corresponding trade deal in a category management setting. This occurs because the brand-by-brand approach ignores the impact of brand switching. Since brand switching dilutes the benefits of price reductions at the category level, the increase in profit resulting from the pass-through is overestimated in the brand-by-brand case.

Category management versus a cost-plus approach

We also compared the profitability from the category management approach with that of a cost-plus markup rule where the order quantity is decided after setting the prices. We varied the markup from 25 to 75 percent in steps of 10 percent. At a markup of 25 percent, the reduction in profit relative to a category management approach was about 60 percent—the cost-plus approach performs worse due to sub-optimal pricing, more frequent ordering, and larger inventory. The least reduction in profit under the cost-plus rule relative to a category management approach was obtained with a markup of 45 percent and the loss was about 50 percent.
therefore, the higher the dollar amount the retailer should pass-
through. This finding is also consistent with the observations
of Chevalier and Curhan (1976), Hardy (1986), Walters (1989),
and Tellis and Zufryden (1995) that larger trade deals result in
greater amount of pass-through. Further, as own-price sensitivity
increases, so does the incentive to increase the amount of pass-
through.

Result 1 (iii) focuses on the impact of cross-price effect on
trade deal pass-through. Note that the cross-price effect \( b_{ij} \)
is brand \( j \)'s effect on sales of other brand when it changes its price.
Per Result 1 (iii), pass-through should be greatest for the brand
whose demand exhibits the strongest cross-price effect—that is,
if \( b_{ij} > b_{ji} \), a greater fraction of the trade deal should be passed
through for brand \( j \). This is because trade deals on a brand imply
higher margin on that brand thereby making it optimal to covert
consumers to that brand. However, in deciding on the amount
of trade deal to pass-through, the retailer needs to balance the
increase in revenue from these converted consumers with the
decrease in price given to old consumers of the brand. With
greater ease of converting consumers, i.e., greater cross-price
effect, a larger number of consumers are converted from another
brand when there is more pass-through of a trade deal. Thus, the
increase in total margin (due to the trade deal and pass-through
of the trade deal) is higher. As such, the retailer finds it optimal
to give a higher pass-through.

Blattberg and Wisniewski (1989) and Blattberg and Neslin
(1990) suggest that there is asymmetric competition across price
tiers so that higher price tier brands have greater cross-price
effects. Combining their result with our Result 1 (iii), we would
suggest that higher price tier brands should get larger pass-
through of trade deals. As an example, in the cola category,
Coke should get larger pass-through than Royal Crown Cola.

We believe the next set of results are unique and not as obvious
a priori.

Result 2. The pass-through (absolute amount as well as relative
to base cost) increases with a brand’s own-price effect when the
cross-price effects of that brand with the other brands are low. On
the other hand, when the brand’s cross-price effects are large, the
amount of pass-through decreases with that brand’s own-price
effect.

Result 2 indicates that there is an interaction of own- and
cross-price effects on trade deal pass-through, i.e., increased
own-price effect does not always correlate with greater pass-
through; rather, it results in greater pass-through only if the brand
exhibits a relatively low cross-price effect. That is, for the brand
that steals fewer sales from the competing brand when its price is
lowered (e.g., brand \( i \) when \( b_{ij} < b_{ji} \)), pass-through increases
with its own-price effect—this occurs since the price decreases
due to a lower own-price effect do not have a big impact on
the other brands due to the lower cross-price effect; rather such
decreases result in expanding category sales. On the other hand,
if the cross-price effect of the target brand is high, pass-through
decreases with its own-price effect since the price decreases that
happen due to higher own-price effects have a stronger effect,
i.e., steal more share from the other brands rather than expanding
category sales. In other words, when brand \( i \)’s cross-price effects
\( (b_{ij}) \) are small, changes in the price of brand \( i \) have relatively little
negative impact on the demand for the other brands. Thus, pass-
through of a trade deal on brand \( i \) would result in a relatively large
increase in net demand and not just a redistribution of existing
demand within the category.

Returning to our example of Coke and Royal Crown Cola,
if Coke customers become more price sensitive, pass-through
on Coke should decrease, but if Royal Crown Cola customers
become more price sensitive, pass-through on Royal Crown
should increase. Thus, the amount of pass-through for a brand
is not only dependent on the own-price effect for that brand but
exhibits an interaction between its own-price and cross-price
effects, i.e., the amount of pass-through increases with the own-
price effect but the magnitude of this response decreases as the
cross-price effect increases.

Result 3. If two brands offer trade deals at different times rather
than at the same time, retailer profit increases; that is, the retailer
earns a greater profit when the trade deals are not coincident.

Result 3 is obtained through a set of simulations in the cate-
gory management setting where deals were either coincidental
or not. The demand functions for the three brands, holding costs,
and trade deal amounts are as given in Fig. 1, except that trade
deals for brand 1 were eliminated. In the non-coincident deal sce-
ario, trade deals for brands 2 and 3 occurred alternately every
4 weeks. In the coincident deal scenario, trade deals for these
two brands occurred simultaneously every 8 weeks. In the latter
case, unit sales and retailer profits for each brand were lower
during the 8-week cycle, thus reducing profits for the retailer.

Result 3 follows from the fact that reducing both retail prices
together provides less benefit than the combined benefit of
reducing each alone. The intuition for this result is as follows:
retailers benefit from non-coincident trade deals because they
get enhanced overall demand within the category and less brand
switching within the category, thus leading to greater profits.
The above argument complements the suggestion that manufac-
turers offer alternating trade deals in order to limit competitive
encroachment (Lal 1990).

Conclusion and future research

While there is a trend in the retail industry to move toward a
category management approach, it is not clear whether retail-
ers have really adopted it with respect to both pricing and
ordering decisions. Here, we model retailers’ dynamic pricing
and ordering decisions in a category management setting
with time varying unit costs, ordering costs, and retailer for-
ward buying. The contributions of this paper are: (1) our model
provides a framework to examine how interactions between
trade deals, own-price demand effects, and cross-price demand
effects should affect retailers’ optimal ordering and pricing deci-
sions. We incorporate retailer ordering costs and show their
impact on retailer pricing policies over time. (2) We empiri-
cally estimate the demand functions, develop optimal pricing
and ordering decisions over time under both brand-by-brand
and category management approaches, and show the profitabil-
ity gains obtained via the category management approach. (3)
We derive insights (Results 1–3) concerning the effect of own- and cross-price effects and their interaction on retailer pricing strategy.

We find an interesting interaction between a brand’s own-price effect and its cross-price effect. If the cross-price effect for a brand is low – i.e., the brand does not take away sales from the other brands – the retail pass-through should increase with that brand’s own-price effect. On the other hand, when the cross-price effect is high, the retail pass-through decreases with the own-price effect. Our results also suggest that the greater the category growth caused by a price cut on a brand (i.e., the greater the own-price effect and the lower the cross-price effect of that brand) the higher should be the pass-through for that brand.

However, it appears that despite the advocacy of the category management approach in trade and research publications alike, the implementation of such an approach, at least at the retailer pricing level, is not widespread. Our in-depth interviews with pricing managers at retail stores further provide convergent validity to our empirical results. The focus during the interviews was on understanding how managers handle categories, such as refrigerated orange juice and children’s cold cereal, with respect to pricing and ordering decisions. That is, do they manage each brand separately, do they consider interactive price effects of multiple brands, or do they simply use a cost-plus pricing for each brand? The following quote from a pricing and merchandizing manager of one such chain, aptly summarizes our discussion:

“Yes, we have been talking about category management for a while now. But the fact of the matter is that many times we simply don’t have the data to figure out the complex interactions among the brands, and when we do have the data, we either don’t have the time to analyze it fully or we don’t have the expertise to conduct an in-depth analysis. It is far easier for us to go with a markup rule or look at each brand to see how much of a lift we get if we reduce the price by a certain amount.”

This is consistent with McAlister’s (2005) analysis as well as with reports such as the one by AMR Research, Inc. (2000) which suggest that (i) category management based pricing is a complex task and retailers do not have good tools for making pricing decisions, (ii) retailers need new tools to drive innovation in revenue management, (iii) common pricing and markdown practices fall short, (iv) item-level pricing-decision mechanisms are not integrated within categories, and (v) there is a lack of focus on cross-price elasticities.

Future research must consider how our results would change if some of our assumptions are relaxed. In this paper, we follow a deterministic demand approach that is widely used in marketing (Besanko, Dubé, and Gupta 2005; Kim and Staelin 1999; Kopalle, Mela, and Marsh 1999; Moorthy 2005; Tellis and Zufryden 1995; Tyagi 1999). Also, this may be quite tenable in mature product categories, such as staple grocery items, where demand may be predicted relatively easily upon accounting for the effect of seasonality, prices, etc. Further, a normal error term in the demand response function, with mean 0 and standard deviation σ, may be an appropriate way to capture uncertainty in demand. We expect our deterministic model to provide good results if the standard deviation of demand is small relative to the mean demand, our deterministic model will do a good job of tracking “average” system performance. Incorporating uncertainty may imply a newsvendor model, where the costs of running out (lost margin) would need to be balanced against the costs of holding too much (holding costs). One option is to explicitly incorporate demand shocks and examine the corresponding impact on out of stock and over-stock situations and profitability would be quite interesting. Also, it would be interesting to evaluate how the basic implications of this paper would change with consumer stockpiling.

We also do not consider cross-category effects (Chen et al. 1999; Tyagi 1999) and multiple markets (Bolton and Shankar 2003; Shankar and Krishnamurthi 2005), which can be considered in future research. If a product attracts more consumers to a store, the additional profit from the sale of items in other categories could lead to a larger pass-through of trade deals. Future research would extend our analysis either by capturing the essence of retail competition (Dickson and Urbany 1994; Kumar and Leone 1988; Shankar and Bolton 2004) by allowing customers to have different valuations for the product at the focal store and for outside retailers or by explicitly considering two retailers in the model (Moorthy 2005; Kumar, Rajiv, and Jeuland 2001). Yet another future research opportunities includes modeling both manufacturer and retailer behaviors.

The category-level approach that we adopt is important today given that multiple brands with interdependent demand exist in virtually every product category. In order to get a sense for the complexity of our optimization approach, we extended our model and algorithm to a five-brand context. It turns out that while the three-brand algorithm takes about 1.5 hr to converge, the five-brand model takes about 24 hr to converge. Note that the computing time may be reduced by one or more of the following: (1) identifying sub-categories within a category, (2) linearizing the value function, (3) conducting a non-exhaustive search, and (4) using a coarse grid for optimal price search. Our hope is that our paper along with other such papers will result in more retailers adopting a category management approach for pricing and ordering decisions and foster further research in this area.

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Appendix A.

Zero-ordering and period-covering properties

Lemma A.1 (Zero-ordering property). There exists an optimal policy such that orders are placed only when inventory of an item is exhausted, i.e., $I_{it} \times \delta_{it} = 0$.

Lemma A.2 (Period-covering property). There exists an optimal policy such that $x_{it} = 0$ or $x_{it} = \sum_{j=1}^{K} D_{ij}$ for some $t \leq k \leq T$.

Proofs of Lemmas A.1 and A.2 are available from the authors.

Dynamic programming solution approach and algorithm for optimal pricing and ordering policy

Solution approach

Our backwards recursion solution approach follows two stages in each period. In the first stage, optimal prices are determined as a function of the ordering decisions and the state. In the second stage, optimal ordering decisions are determined as a function of the state. We first consider the last period, $T$, where $v_{T+1} = 0$. Given a state vector and a vector of potential ordering decisions (which together determine the relevant variable cost of the $m$ products), we solve for the optimal prices for each of the $m$ products in period $T$.

Next, for each combination of the ordering decisions (note that there are $2^m$ combinations of possible ordering decisions for the $m$ products in any period), the corresponding optimal prices are substituted into the left-hand side of (2). Thus, for the maximum of these candidate values. We let $v_{s_1, s_2, \ldots, s_m, t_i}$ denote the optimal (maximizing) ordering decisions that correspond to $v_{T}(s_1, s_2, \ldots, s_m)$ is defined as the maximum of these candidate values. We let $I_{1T}^*, I_{2T}^*, \ldots, I_{MT}^*$, denote the optimal (maximizing) ordering decisions that correspond to $v_{T}(s_1, s_2, \ldots, s_m)$.

Algorithm

For $t = T$ to 1 (where $t$ is a time index for the period)

For each possible value of the state vector $(s_1, s_2, \ldots, s_m)$ (where $s_i$ is the period of last purchase for product $i$)

For each of the $2^m$ possible values of $(I_{1t}, I_{2t}, \ldots, I_{mt})$ (where $I_{it} = 1$ if we purchase product $i$ in period $t$ and $I_{it} = 0$ in we carry forward from last purchase)

The values $(I_{1t}, I_{2t}, \ldots, I_{mt})$ determine the cost of the products in the current period, $z_{it}$

Solve simultaneous equations to determine optimal prices $p_{it}^*$ for $i = 1, \ldots, m$

Compute $\Pi_t = \sum_{i=1}^{m} (p_{it}^* - z_{it}) D_{it} (p_{it}^* - p_{2t}^* \ldots, p_{mt}^*)$

Compute $u_i(s_1, \ldots, s_m, I_{1t}, \ldots, I_{mt}) = \Pi_t + v_{T+1}(s_1 + I_{1t}(t - s_1), \ldots, s_m + I_{mt}(t - s_m))$

Increment to next value of $(I_{1t}, I_{2t}, \ldots, I_{mt})$

Compute $v_i(s_1, s_2, \ldots, s_m) = \max_{t_{i1}, \ldots, t_{im}} \{u_i(s_1, \ldots, s_m, I_{1t}, \ldots, I_{mt})\}$

Increment to next value of $(s_1, s_2, \ldots, s_m)$

Decrement to next value of $t$

Concavity of the value function in prices

Proposition A.1. Given Eq. (3), the Hessian matrix $H$ has the form:

$$H = \begin{bmatrix}
-2b_1 & b_{12} + b_{21} & \ldots & b_{1m} + b_{m1} \\
 b_{12} + b_{21} & -2b_2 & \ldots & b_{2m} + b_{m2} \\
 \vdots & \vdots & \ddots & \vdots \\
b_{1m} + b_{m1} & b_{2m} + b_{m2} & \ldots & -2b_m
\end{bmatrix}$$

and a sufficient condition for strict concavity of the Hessian is:

$$b_i > \sum_{k=1}^{m} b_{ik} \quad \text{and} \quad b_i > \sum_{k=1}^{m} b_{ki}$$

for all $i$ and $k$.

Proof. Proposition A.3 follows from diagonal dominance of the Hessian matrix (Horn and Johnson, 1985). The condition $b_i > \sum_{k=1}^{m} b_{ik}$ suggests that the own-price effect dominates the sum of the cross-price effects of all other brands on the target brand. \square

Deriving analytical results for a two-brand model

Below, we focus on a two-brand category to obtain analytical results where intuition is not obscured by complexity. Here we focus on the role of the variable costs for product $i$ in period $t$, $z_{it}$. Clearly, a trade deal will lower $z_{it}$, all else held constant. Also, our intuition tells us that larger ordering costs $K_i$ will result in fewer orders placed less frequently, resulting in greater total holding costs, thus increasing total variable cost, $z_{it}$. Note that one measure of retail pass-through is provided by $\partial p_{it}^*/\partial z_{it}$, which measures the pass-through of a $1$ trade deal under the optimal pricing decision. We use subscripts $i$ and $j$ (with $i \neq j$) to refer to the two products.
Solution characteristics under linear demand

Let $z_{it}$ denote the variable cost of product $i$ held for sale in period $t$, i.e., $z_{it}$ includes purchase cost with trade deals, variable ordering costs, and holding costs, if any. The value $z_{it}$ clearly depends on the ordering decisions because of wholesale price, trade deals, inventory costs, etc. While the optimal prices have no direct dependence on the fixed ordering costs $K_i$, these prices do depend on the fixed ordering costs to the extent that these fixed ordering costs affect the ordering decisions. As seen in Eq. (2), the optimal value function in period $t+1$, $v_{t+1}$, is dependent only on when the orders were last placed for each brand, as tracked by the state vector, but not on the optimal prices $p_{jt}^*$, $i=1,\ldots,m$ in period $t$. Therefore, the search for the vector of optimal prices in Eq. (2) for period $t$ can be reduced to:

$$
\max_{p_{1t}, p_{2t}, \ldots, p_{mt}} \left\{ \sum_{j=1}^{m} (p_{jt} - z_{jt})D_j(p_{1t}, p_{2t}, \ldots, p_{mt}) \right\} \quad \text{(A4.1)}
$$

Brand-by-brand solution. In the case of a brand-by-brand optimization, i.e.,

$$
\max \{ (p_{1t} - z_{1t})(a_1 - b_1 p_{1t}) \} \quad \text{p}_{1t}
$$

the optimal price is given by\textsuperscript{11}:

$$
p_{1t}^* = \frac{a_1}{2b_1} + \frac{z_{1t}}{2}
$$

and so the change in price due to a change in own-price effect, $b_1$, and variable cost, $z_{1t}$, is:

$$
dp_{1t}^* = -\frac{a_1}{2b_1}db_1 + \frac{dz_{1t}}{2}
$$

Category management solution. Proposition A.2 (Prices and pass-through relationships). The optimal prices for the two-brand case are:

$$
p_{jt}^* = \frac{2b_j(a_j + z_{jt}b_i - z_{jt}b_j)}{4b_ib_j - (b_{ij} + b_{ji})^2},
$$

$$
i, j = 1, 2, i \neq j
$$

Upon differentiation with respect to $z_{jt}$, and due to $b_i > \sum_{k=1}^{m} b_{ik}$ and $b_i > \sum_{k=1}^{m} b_{ki}$ for all $i$ we get:

$$
dp_{jt}^* = \frac{2b_jb_i - b_{ij}(b_{ij} + b_{ji})}{4b_ib_j - (b_{ij} + b_{ji})^2} > 0
$$

and

$$
dp_{jt}^* = \frac{b_j(b_{ij} - b_{ji})}{4b_jb_i - (b_{ij} + b_{ji})^2}
$$

If $b_{ij} > b_{ji}$,

$$
\frac{\partial p_{jt}^*}{\partial z_{jt}} < \frac{1}{2}, \quad \frac{\partial p_{jt}^*}{\partial z_{jt}} > \frac{1}{2}
$$

Proposition A.3 (Pass-through sensitivity). If $b_{ij} > b_{ji}$,

$$
\frac{\partial (dp_{jt}^*/\partial z_{jt})}{\partial b_j} > 0 \quad \text{and if} \quad b_{ji} > b_{ij}, \quad \frac{\partial (dp_{jt}^*/\partial z_{jt})}{\partial b_j} < 0
$$

Proof. Differentiation of the pass-through results in Proposition 1 and using the chain-rule, we obtain the above result.\textsuperscript{□}

Proposition A.4 (Trade deal timing). Retailers are better off under non-concurrent trade deals by brands $i$ and $j$.

Proof. Proposition A.4 follows from the fact that $\partial^2 \Pi^*/\partial z_{1t} \partial z_{2t}$ is negative, where $\Pi^*$ is the optimal profit for the retailer in Eq. (A4.1). Thus, reducing both prices together provides less benefit than the combined benefit of reducing each individually.\textsuperscript{□}

References


\textsuperscript{11} Note that the intercept, $a_1$, captures the case where a retailer includes cross-price effects (non-myopic) in the single-product demand function but does not jointly optimize the two products (single brand focused).


