The Impact of Category Management on Retailer Prices and Performance: Theory and Evidence

Category management (CM) is a recent retail management initiative that aims at improving a retailer’s overall performance in a product category through more coordinated buying, merchandising, and pricing of the brands in the category than in the past. Despite tremendous retailer and manufacturer interest in the process of CM and its rapid adoption in the industry, much uncertainty exists about the consequences of CM for channel members. The present study focuses on how a shift to CM by a retailer affects its equilibrium prices, sales, and profitability in a competitive retail setting. On the basis of an analysis of a model of two competing national brand manufacturers that supply two competing common retailers, the authors find that one retailer’s adoption of CM increases its average unit price of the category and reduces its sales volume and revenues. However, this retailer can still enjoy an increase in its gross margin profits as competing manufacturers’ wholesale prices fall in the process. Also, the CM adopter’s profits are greater than those of a symmetric competing retailer that follows the traditional brand-centered management of a product category when the interbrand competition is high but interstore competition is low. Applying the intervention analysis methodology, the authors empirically test several of these analytical findings, employing a unique data set that contains information about a supermarket chain’s weekly average unit prices and sales of the laundry detergent category before and after this product category was moved to CM by the retailer. The propositions that adoption of CM will lead to higher retail prices and lower sales are upheld in this empirical study. The authors discuss the implications of these findings for practitioners and researchers, the limitations of the study, and directions for further research.

A fundamental change is taking place in the retail grocery and drug store industries as retailers and manufacturers begin to embrace a process called category management (CM). Traditionally, retailers assigned buyers to purchase brands of specific manufacturers, instead of making all purchases within a particular product category. Individual brand-oriented buyers sought to improve their economic performance by procuring large quantities of product on deals and then relying on retail pricing, promotions, and merchandising activities to deplete brand-level inventories as quickly as possible. In contrast, CM recognizes the interrelatedness of products in the category and focuses on improving the performance of whole product categories rather than the performance of individual brands. Under CM, traditional brand (vendor)-oriented buyers are replaced with category managers who are responsible for integrating procurement, pricing, and merchandising of all brands in a category and jointly developing and implementing category-based plans with manufacturers to enhance the outcomes of both parties (Pellet 1994; Progressive Grocer 1995a, b; Supermarket News 1997).

Retailer interest in CM is high. For example, according to one recent industry report, 83% of grocery retailers surveyed view CM as the most important issue facing them (Progressive Grocer 1996), and another study shows CM initiatives to be the most important reason that retailers are improving their information technology systems (Chain Drug Review 1997). Despite the interest in CM and its rapid adoption in the industry (ACNielsen 1998), however, much uncertainty exists about the consequences of CM for retailers, manufacturers, and consumers. For example, beyond anecdotal reports, few studies have rigorously investigated how a retailer shift from brand-centered management (BCM) to CM affects retail prices or retailer and manufacturer profits as its proponents maintain (Harris and McPartland 1993; Category Management Report 1995). The objective of the present research is to investigate the impact of a retailer’s shift from BCM to CM on retail and wholesale prices, sales, and profits in a competitive decentralized channel setting. Adoption of CM results in many changes in the retailer’s operations and management. We restrict our inquiry to pricing decisions and their outcomes, however, because one of the key benefits of CM is a more profitable pricing structure (ACNielsen 1998; Category Management Report 1995; McLaughlin and Hawkes 1994). Examining pricing under CM is important because changes in the retailer’s approach to pricing can directly affect manufactur-
ers, competing retailers, and consumers, who are believed to benefit from CM adoption.

For the purpose of this study, CM is defined as a situation in which a category manager jointly sets the prices of all brands in the category so as to maximize total category profits. Traditional BCM of a category is defined as a situation in which each brand’s retail price is set independently so as to maximize its own profit contribution and the prices of competing brands in the category are taken as given. These definitions are consistent with the basic notion that CM involves more coordinated management of brands in a category, including price setting, than in the past (Category Management Report 1995; Food Marketing Institute 1995). We recognize that in practice, some level of coordinated price setting takes place under BCM. Clearly, CM calls for a high level of price coordination, which is the phenomenon examined in the present research. In this study, we first lay out the strategic approach that surrounds the CM business process. On the basis of this discussion, we analyze how a retailer’s shift from BCM to CM alters equilibrium prices, sales, and profits within the context of a model of a two-level (competing national brand manufacturers/competing common retailers) channel system. More specifically, we derive and compare equilibrium retailer prices, sales, and profits as functions of demand function parameters in a category composed of two national brands sold by two competing common retailers. Comparisons of prices, sales, and profits are made under three commonly occurring scenarios: (1) Both retailers practice BCM, (2) one retailer practices CM and the other employs BCM, and (3) both retailers practice CM. The comparative analyses produce several propositions about how the adoption of CM by one retailer affects its prices, sales, and profitability compared with a competitor that stays with BCM or might also shift to CM. Several interesting implications of the retailer’s adoption of CM for the manufacturers and consumers in the channel also emerge from this investigation.

We test the implications of the key analytical propositions using store-level scanner data in the laundry detergent category obtained from Information Resources Inc. The database contains information on average prices, sales volumes, and revenues of brands in this category collected from 21 stores that are affiliated with a large supermarket chain over a three-year period, January 1993 to December 1995. These 21 stores are all located in one major Midwestern metropolitan market. The supermarket chain switched the laundry detergent category from BCM to CM in February 1994, allowing an examination of the category before and during CM. Information about the average prices and sales for competitors to the chain who did not switch to CM are also contained in the database, providing researchers and practitioners with a rare look at CM effects for the retailer and its suppliers, competitors, and patrons.

The Strategic Framework for CM and Theoretical Analysis

CM Framework

In 1995, the Category Management Subcommittee of the ECR Best Practices Operating Committee and the Partnering Group Inc. published an important study: Category Management Report: Enhancing Consumer Value in the Grocery Industry. This report is basically the how-to of CM and lays out eight critical steps that are necessary for a proper implementation of CM by a retailer. The basic steps in the CM process are outlined in Figure 1. It is important to understand the strategic structure and process surrounding CM to evaluate the outcomes of its implementation effectively.

Step 1: category definition. This is the first step in the category planning process. This step determines the products that constitute a category, subcategory, and major segmentation. The category definition should include all products that are either highly substitutable or closely related, subject to operational constraints.

Step 2: category role. This step assigns the category role (purpose) based on a cross-category analysis that considers the consumer, distributor, supplier, and marketplace. Designating a role also helps the retailer allocate resources among various categories.

Step 3: category assessment. This step involves gathering and analyzing historical data and relevant information and then developing insights for managing the category.

Step 4: category scorecard. In this step, performance measures are established to evaluate program execution,
including target gross margins, return on inventory goals, service levels, and so forth.

Step 5: category strategies. Typical category strategies include cash generating, excitement creating, profit generating, traffic building, and so forth. For example, a traffic-building strategy is focused on drawing consumer traffic to the store and into the aisle, and a profit-generating strategy seeks to increase category gross margin percentage and gross profit dollar.

Step 6: category tactics. This step involves the determination of optimal category pricing, promotion, assortment, and shelf management that are necessary to achieve the agreed-on role, scorecard, and strategies. “Pricing policies should be applied to the current prices to develop price changes and set overall price changes for the category. Promotional policies should be applied in the development of a promotional plan that includes frequency of promotions and recommended price points” (Category Management Report 1995, p. 45).

Step 7: plan implementation. An implementation plan generally includes what specific tasks are to be done, when each task should be completed, and who is to accomplish each task. The plan should also note the start date of each task.

Step 8: category review. This step involves the regular management of the intended results of the overall plan. Reviews should be scheduled at established intervals and listed in the implementation plan.

An inspection of the CM framework reveals that once the category definition (Step 1) and the category role (Step 2) are chosen, the bulk of the action lies in determining the category strategy (Step 5) and then executing the specific category tactics (Step 6). Although different strategies may be appropriate for different categories, retailers predominantly practice CM to increase profits and sales. As ACNielsen (1998, p. 5) notes in its Eighth Annual Survey of Trade Promotion Practices, “Retailers practice category management with several ends in mind, but increasing profitability, increasing revenue and optimizing item mix are … the most important motivators.” For example, 97% of retailers surveyed indicated that the top priority for practicing CM is increased profitability. Similarly, the retailer examined in this study employed a variety of strategies, including a profit-generating strategy, consistent with CM. For modeling purposes, we assume that the retailer sought to build profits by CM.

We use the components of the strategic framework of CM to develop and analyze a model of a decentralized distribution channel that consists of two competing retailers, Retailers A and C, each carrying two differentiated national brands that are produced by competing manufacturers M1 and M2, as shown in Figure 2.

Theoretical Analysis

Note that most trading areas are more complex than the one shown in Figure 2 and are composed of multiple retailers (e.g., Winn-Dixie, Kroger, Safeway, Albertson’s) that sell multiple brands in a product category, which are produced by multiple manufacturers. However, replacing the $2 \times 1 \times 2$ structure (2 manufacturers, each produces 1 brand, 2 retailers) with a more complex structure (e.g., a $2 \times 3 \times 2$ structure) would not change the substantive nature of the results from the present modeling framework. Because the benefits of greater realism in the form of more manufacturers and brands are outweighed by the costs of a more analytically complex model that does not alter our predictions about the effects of retailer adoption of CM, we opted for a simpler structure. The study focuses on the demand-side implications of a retailer’s shift from BCM to CM. In keeping with this thrust, we assume that the manufacturers are symmetric with respect to their costs of production and that the manufacturers’ marginal costs of production are constant; for ease of exposition, manufacturers’ marginal costs of production are set equal to zero. We also assume that the manufacturers sell their brands to the retailers at a constant per-unit charge (i.e., the wholesale price) and the retailers incur no other costs of acquisition. Last, we assume that each manufacturer sells its brand at the same wholesale price to each retailer. This is in keeping with legal restrictions against discriminatory price discounts by manufacturers that exist in practice (see, e.g., Ingene and Parry 1995; Kotler and Armstrong 1996, p. 88).

Our investigation employs the traditional game-theoretic approach to analyzing problems of channel price coordination and competition (e.g., Choi 1991; Coughlan and Wernerfelt 1989; Ingene and Parry 1995; Jeuland and Shugan 1983; McGuire and Staelin 1983; Raju, Sethuraman, and Dhar 1995; Trivedi 1998; Zenor 1994). As do many previous researchers who model decentralized channels in this stream of literature, we assume, first, that each manufacturer determines the wholesale prices to maximize its profits. Given these wholesale prices, managers at the two retailers decide on the retail prices to maximize their respective objective functions. The manufacturers know each retailer’s pricing decision rule and take these into account when setting their wholesale prices. That is, we assume that the interaction between the firms is such that each manufacturer acts as a Stackelberg leader in setting its wholesale price, and the retailers follow with their retail price decisions. Adopting a manufacturer–Stackelberg rather than retailer–Stackelberg perspective is reasonable, because no store brands are
involved in our analysis. Second, we assume that the retailers face symmetric brand-level demand functions that are linear in the brands’ prices. More specifically, we denote the quantities of manufacturer’s brand, \( k (k = 1, 2) \), demanded at retailers \( j (j = A, C) \) by \( q_k \), respectively. Then we specify the corresponding demand functions as follows:

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\begin{align*}
(1) & \quad q_{A1} = \frac{1}{4} \left[ 1 - p_{A1} + \eta(p_{A2} - p_{A1}) + \gamma(p_{C1} - p_{A1}) \right], \\
(2) & \quad q_{A2} = \frac{1}{4} \left[ 1 - p_{A2} + \eta(p_{A1} - p_{A2}) + \gamma(p_{C2} - p_{A2}) \right], \\
(3) & \quad q_{C1} = \frac{1}{4} \left[ 1 - p_{C1} + \eta(p_{C2} - p_{C1}) + \gamma(p_{A1} - p_{C1}) \right], \text{ and} \\
(4) & \quad q_{C2} = \frac{1}{4} \left[ 1 - p_{C2} + \eta(p_{C1} - p_{C2}) + \gamma(p_{A2} - p_{C2}) \right],
\end{align*}
\]

where the demand function parameters \( \eta \in [0,1) \) and \( \gamma \in [0,1) \), respectively, denote the interbrand cross-price sensitivity (degree of product differentiation) and the interstore cross-price sensitivity (degree of store differentiation), and \( p_k \) is the price of brand \( k (k = 1, 2) \) at retailer \( j (j = A, C) \). Thus, the quantities of brand \( k \) demanded at retailer/store \( j \) are directly affected by the brand’s own price at store \( j \), the difference between the two competing brands’ prices at store \( j \), and the difference between the brand’s price at store \( j \) and its price at the competing store. A value of \( \eta \) close to zero implies that the two national brands are highly differentiated, whereas \( \eta \to 1 \) implies that the brands are highly substitutable. Similarly, as \( \gamma \) increases from zero to one, demand for a brand at one retailer is increasingly influenced by its price at the other retailer; that is, store competition for consumers is more intense. Last, note that aggregate demand in the product category at zero prices for the brands is scaled to 1.

Previous models of decentralized channel price competition involving a common retailer (i.e., an independent retailer carrying brands of different manufacturers) that faces a linear demand function structure include those of Choi (1991, 1996), Zenor (1994), Raju, Sethuraman, and Dhar (1995), and Trivedi (1998). Among these authors, only Choi (1996) and Trivedi (1998) analyze a duopoly common retailer model similar to ours. However, the focus of these authors is to compare the effects of varying channel power relationships on profits and prices, assuming that both retailers are natural category managers. In contrast, our focus is the competitive effects of a retailer’s move from BCM to CM, and we derive and compare equilibrium prices, sales, and profits for the following three retail competitive scenarios:

1. The BCM–BCM scenario, in which both retailers practice BCM; (2) the CM–BCM scenario, in which one retailer (Retailer A) shifts to CM and the other (Retailer C) stays with BCM; and (3) the CM–CM scenario, in which both retailers adopt CM. None of these scenarios in a two-level duopoly channel structure has been previously analyzed in the literature. Indeed, only Zenor (1994) has focused on CM issues. However, Zenor concentrates on the pricing and profit benefits of CM by competing multibrand manufacturers marketing to a monopolistic retailer. In contrast, our analysis focuses on the effects of the adoption of CM by a retailer in a competitive retail setting. We now describe the three scenarios that will generate the propositions that we subsequently subject to empirical testing.

Analysis of the BCM–BCM scenario. In this scenario, we assume that each retailer has separate managers for procuring and pricing the two manufacturers’ brands. Considering the known wholesale prices, \( w_i \), \( i = 1, 2 \), of each brand, each of these managers sets price so as to maximize own-brand profits, taking the price of the other brand at the same store as well as the two brands’ prices at the competing retailer as fixed. Thus, the objective functions of the two buyers at Retailer A are, respectively, \( \max_{p_{A1}} (p_{A1} - w_{1BCM})q_{A1} \) w.r.t. \( p_{A1} \) and \( \max_{p_{A2}} (p_{A2} - w_{2BCM})q_{A2} \) w.r.t. \( p_{A2} \). Similarly, the objective functions of the two buyers at Retailer C are \( \max_{p_{C1}} (p_{C1} - w_{1BCM})q_{C1} \) w.r.t. \( p_{C1} \) and \( \max_{p_{C2}} (p_{C2} - w_{2BCM})q_{C2} \) w.r.t. \( p_{C2} \). Substituting the corresponding demand functions in Equations 1–4 into these objective functions and simultaneously solving the four buyers’ first-order conditions for profit maximization gives us the (Nash) equilibrium retail prices, \( p_{A1} \) and \( p_{A2} \), \( p_{C1} \) and \( p_{C2} \), and \( p_{1BCM} \) and \( p_{2BCM} \) as functions of the given wholesale prices, \( w_{1BCM} \) and \( w_{2BCM} \), and parameters \( \eta \) and \( \gamma \). Substituting these retail pricing decision rules into the demand equations, Equations 1–4, we obtain the corresponding demands \( q_{A1} \), \( q_{A2} \), \( q_{C1} \), \( q_{C2} \), and \( q_{1BCM} \) and \( q_{2BCM} \) as functions of the wholesale prices \( w_{1BCM} \) and \( w_{2BCM} \) and the demand parameters. Then, considering the retailers’ conditional pricing decision rules, Manufacturer i’s (\( i = 1, 2 \)) problem is to determine the wholesale price, \( w_{iBCM} \), that maximizes its profit. We assume that Manufacturer i does so taking the other manufacturer’s wholesale price as fixed; that is, the manufacturers are themselves engaged in Nash competition. Thus Manufacturer i solves \( \max_{w_{iBCM}} \{ q_{A1}(w_{iBCM}, w_{jBCM}) + q_{A2}(w_{iBCM}, w_{jBCM}) \} \) w.r.t. \( w_{jBCM} \), \( i = 1, 2 \), and \( i \neq j \). Simultaneously solving the manufacturers’ first-order conditions gives the Nash equilibrium wholesale prices, \( w_{1BCM} \) and \( w_{2BCM} \). With these solutions in hand, it is straightforward to derive the expressions for the equilibrium retail and wholesale prices, retail demands, each retailer’s total category profits, and the manufacturers’ brand profits as functions of the demand parameters. The analytical results for this scenario, the CM–BCM scenario, and the CM–CM scenario may be obtained from the authors.

Analysis of the CM–BCM scenario. In a fairly common situation, one retailer adopts CM and a competitor in the same trading area remains with BCM (e.g., Supermarket News 1997b). More specifically, assume that Retailer A replaces its two separate national brand buyers with one category manager who jointly sets the two brands’ prices so as to maximize total category profit, taking into account the announced wholesale prices and treating Retailer C’s brand prices as fixed. This category manager’s objective function is then \( \max_{p_{1BCM}} \{ (p_{1BCM} - w_{1BCM})q_{A1} + (p_{2BCM} - w_{2BCM})q_{A2} \} \) w.r.t. \( p_{1BCM} \) and \( p_{2BCM} \). In contrast, the objective functions of the two buyers of Retailer C are the same as in the previous scenario; that is, \( \max_{p_{C1}} (p_{C1} - w_{1BCM})q_{C1} \) w.r.t. \( p_{C1} \) and \( \max_{p_{C2}} (p_{C2} - w_{2BCM})q_{C2} \) w.r.t. \( p_{C2} \).
everywhere. This difference in prices increases as the value specified range. We see that the price difference is positive BCM–BCM scenarios at various values of objective function is then Max{(pA1 \text{CMCM} - w_1 \text{CMCM}) + (\text{pC1CMCM} - \text{w1CMCM}) \text{w}.r.t. \text{pA1CMCM} and \text{pC1CMCM}}, and Retailer C's category manager's objective function is Max{(pC1 \text{CMCM} - w_1 \text{CMCM}) + (\text{pC2CMCM} - \text{w2CMCM}) \text{w}.r.t. \text{pC1CMCM} and \text{pC2CMCM}}, Following the same game solution approach as already described, the expressions for the equilibrium retail and wholesale prices, demands, and the retailers’ and manufacturers’ profits are derived.

Analysis of the CM–CM scenario. In this scenario, we assume that each retailer has a category manager who jointly sets the prices of the brands in the category so as to maximize total category profit, taking into account the announced wholesale prices and treating the competing retailer’s prices as fixed. Retailer A’s category manager’s objective function is then Max{(pA1 \text{CMCM} - w_1 \text{CMCM}) + (\text{pA2CMCM} - \text{w2CMCM}) \text{w}.r.t. \text{pA1CMCM} and \text{pA2CMCM}}, and Retailer C’s category manager’s objective function is Max{(pC1 \text{CMCM} - w_1 \text{CMCM}) + (\text{pC2CMCM} - \text{w2CMCM}) \text{w}.r.t. \text{pC1CMCM} and \text{pC2CMCM}}, Following the same game solution approach as already described, the expressions for the equilibrium retail and wholesale prices, demands, and the retailers’ and manufacturers’ profits are derived.

Comparative Analyses
To gain insight into the results obtained in the previous scenarios, we numerically evaluate the behavior of the retailers’ equilibrium prices, sales, and profits in these scenarios and the differences between them as the values of the demand function parameters \( \eta \) (measuring intracategory brand competition) and \( \gamma \) (measuring interstore brand competition) are each varied over the range \([0,1]\). Next, we summarize our findings in the form of propositions with accompanying explanations.

Impact of CM on Category Prices
The initial set of issues examined involves the CM retailer’s pricing decisions. A comparative analysis between various scenarios suggested by our model leads us to the following proposition, which deals with pricing changes within a retailer:

\( P_1: \) All else being equal, the retail price of competing brands in a product category will increase when a retailer (Retailer A) moves the category from BCM to CM. This is true irrespective of whether the competing retailer (Retailer C) remains with BCM (i.e., the CM–BCM scenario) or shifts to CM (i.e., CM–CM scenario).

Figure 3 displays the computed difference between Retailer A’s equilibrium prices in the CM–BCM and BCM–BCM scenarios at various values of \( \eta \) and \( \gamma \) in the specified range. We see that the price difference is positive everywhere. This difference in prices increases as the value of \( \eta \) increases and that of \( \gamma \) decreases. However, the retailer’s prices in the two scenarios are the same when \( \eta = 0 \), whatever the value of \( \gamma \) is. The rationale for the results is that in the CM regime, Retailer A engages in coordinated or cooperative pricing of brands in the category to maximize total category profits as opposed to the competitive pricing of brands that occurs under BCM. Coordinated pricing results in higher prices. There is no difference between coordinated and competitive pricing outcomes when the brands are perfectly differentiated, that is, when their demands are independent of each other’s prices (\( \eta = 0 \)). However, when the brands are substitutable (\( \eta > 0 \)), coordinated management has the effect of dampening this natural price competition that exists between the brands, which results in higher prices. This dampening effect becomes more significant as the brands become more substitutable, leading to larger differences between coordinated and competitive pricing outcomes as \( \eta \to 1 \). However, the price increase effect of within-store pricing coordination is tempered by the need to be competitive with the lower prices of the other retailer, which stays with BCM. This competitive effect becomes more pronounced as shoppers’ propensity to engage in cross-store shopping increases. Thus, as interstore cross-price sensitivity \( \gamma \) increases, the difference between Retailer A’s prices in the two scenarios diminishes. The analysis of a retailer move from BCM–BCM to CM–CM is analogous.

The following proposition relates to pricing changes and comparisons across retailers:

\( P_2: \) All else being equal, the increase in the retail price of brands in a product category moved to CM by a retailer (Retailer A) will be higher than the increase in retail price of that category at the competing retailer (Retailer C) that continues with BCM (i.e., CM–BCM scenario).

Figure 4 shows differences between the retailers’ equilibrium prices within the CM–BCM scenario when values of
η and γ are varied. The intuition is similar to that for P1. The retailer that sets prices so as to maximize total category profits will have a higher price level than a symmetric retailer that sets each competing brand’s price so as to maximize its own profit contribution. However, although the basic economic explanation for P1 and P2 is fairly straightforward, the practical implications of these results are significant. Specifically, a higher average retail price in a category as a result of CM is hard to reconcile with the efficient consumer response (ECR) objective of providing higher consumer value to attract and keep customers. We return to this issue subsequently.

**Impact of CM on Category Sales Volume and Revenues**

Industry CM experts argue that adoption of CM should improve overall category sales for a retailer. For example, a leading trade journal (*Progressive Grocer* 1995, p. S4) states that “Category management’s ultimate objective ought to be to increase total store sales.” Similarly, another report (*Category Management Report* 1995, p. xvii) maintains that “Category Management represents a significant and results-proven opportunity to achieve substantial business improvements.” However, as stated in the following proposition, the present analysis suggests a decline in category sales when a retailer adopts CM.

P3: All else being equal, the total unit sales in a product category will decrease when a retailer (Retailer A) moves the category from BCM to CM, irrespective of whether the competing retailer (Retailer C) remains with BCM (i.e., a CM–BCM scenario) or shifts to CM (i.e., a CM–CM scenario).

Figure 5 shows the decrease in Retailer A’s unit sales upon moving from BCM to CM as values of η and γ are varied. These outcomes are not surprising given the earlier observation that prices increase under CM. Note that the decline in sales is greatest when η is high and γ is low, that is, in the conditions under which Retailer A’s price increase is greatest. Furthermore, a higher interstore cross-price sensitivity will temper Retailer A’s price increase somewhat but not enough to prevent a loss in sales to lower-priced BCM retailers such as Retailer C in a CM–BCM scenario. Therefore, we give the next proposition, which is illustrated in Figure 6. The analysis of a retailer move from BCM–BCM to CM–CM is analogous.

P4: All else being equal, the total unit sales of a product category moved to CM by a retailer (Retailer A) will be lower than the total unit sales of that category at a symmetric competing retailer (Retailer C) that continues with BCM (i.e., a CM–BCM scenario).

These analytical results are consistent with the finding of a recent survey conducted in several large U.S. cities that significant numbers of shoppers have switched away from stores practicing CM (Cottrell 1995).

Next, turning to sales revenues, the analytical results lead to the following proposition (see Figure 7):

P5: All else being equal, the sales revenues of the category will decrease when a retailer (Retailer A) moves the category from BCM to CM, irrespective of whether the competing retailer (Retailer C) continues with BCM (i.e., a CM–BCM scenario) or shifts to CM (i.e., a CM–CM scenario).

Revenues decline because the price increase under CM by Retailer A does not compensate for the resulting reduction in consumer demand at this retailer. Next, we turn to category profits.
CM and Category Profits

So far in our analysis, the move to CM appears to offer little benefit to Retailer A. However, this conclusion changes when we examine this retailer’s category profits (average gross margin times sales in dollars) after CM adoption. From its inception, CM has been touted as a mechanism for retailers (and manufacturers) to build overall category profits (see, e.g., Category Management Report 1995; Food Marketing Institute 1995). Our findings, summarized in the following proposition, support this contention and are consistent with the retailer’s strategies in the category.

P6: All else being equal, the profits of a product category will increase when a retailer (Retailer A) moves the category from BCM to CM, irrespective of whether Retailer C remains with BCM (i.e., a CM–BCM scenario) or shifts to CM (i.e., a CM–CM scenario).

Figure 8 displays the positive difference between Retailer A’s equilibrium profits in the CM–BCM and BCM–BCM scenarios at various values of $\eta$ and $\gamma$. The realization of higher profits despite a decline in Retailer A’s unit sales as well as revenues implies a significant increase in this retailer’s unit gross margin. A contribution to this increase in unit gross margin comes from a decline in the brands’ equilibrium wholesale prices. As illustrated in Figure 9, our analytical results indicate that equilibrium wholesale prices in the CM–BCM scenario are lower than the corresponding levels in the BCM–BCM scenario.

The equilibrium wholesale price is lower in the CM–BCM scenario because of the reduction in the overall demand for the manufacturers’ products caused by Retailer A’s price increase. More precisely, in the face of lowered total market demand, the competing manufacturers maximize their individual profits at a lower wholesale price. Effectively, therefore, the move to CM helps Retailer A gain profits at the expense of the suppliers.

The lower wholesale price induced by Retailer A’s move to CM also benefits the competing Retailer C that stays with BCM. Figure 10 displays Retailer C’s increase in profits when Retailer A moves from BCM to CM. Thus, within the context of our model, both retailers gain profits at the expense of the manufacturers, even though only one retailer adopts CM. The analysis of a retailer move from BCM–BCM to CM–CM is analogous.

Adoption of CM will always increase Retailer A’s profit, as stated in P6. However, because A’s action also enhances Retailer C’s profitability, it would be interesting to compare the relative profits. An evaluation and comparison of the equilibrium profits of Retailers A and C in the CM–BCM scenario (Figure 11) shows that Retailer A’s equilibrium profits are greater than those of Retailer C only under certain circumstances. Retailer A’s profits are higher if the interbrand cross-price sensitivity is high (i.e., $\eta$ close to unity) and if the interstore cross-price sensitivity, $\gamma$, is close to zero. Conversely, Retailer C’s equilibrium profits can dominate those of Retailer A when $\eta$ is large and $\gamma$ is small. That is, although Retailer A’s profits under CM are higher than its own profits under BCM, relative to Retailer C, Retailer A can enjoy higher profits if few consumers visit the competing retailer, which has lower prices. But if cross-store shopping is significant, Retailer A’s improved margin under CM does not adequately compensate for its loss in demand to Retailer C. This leads us to the following proposition:
P7: Retailer A’s category profits are greater than those of Retailer C when interbrand cross-price sensitivity, $\eta$, is high and interstore cross-price sensitivity, $\gamma$, is low, and Retailer A’s category profits are lower than Retailer C’s profits when $\eta$ is low and $\gamma$ is high.

P7 echoes some conclusions of Cottrell’s (1995) study: “It is still not clear that those [retailers] who don’t practice [CM] find themselves at any competitive disadvantage. In fact, the study found many [retailers] to be performing better than those competitors who were practicing it” (Progressive Grocer 1995, p. S8).

Empirical Tests of the Propositions

Data

Empirical tests of the propositions require time series data from a trading area where a retailer is known to have moved to CM. More precisely, time series data covering pre-CM and CM regimes for a retailer and its competitors are needed to test the propositions. However, such data on the effects of CM are difficult to obtain because CM is a fairly recent phenomenon, which limits the number of retailers that have databases comprehensive enough to capture category performance before and during CM. Fortunately, the data set used in this study overcomes this hurdle, providing researchers and practitioners with a rare opportunity to measure CM effects.

Aggregate store-level weekly scanner data from 21 stores of a national supermarket retail chain, hereafter called Retailer A, that had moved its laundry detergent category to CM were obtained from Information Resources Inc. (IRI). The stores are all located in one defined Midwestern U.S. urban market and together account for 35% share of laundry detergent sales in this market. The data set also contains aggregated information from the major competitors of Retailer A, hereafter labeled Retailer C. The data include the weekly average (weighted by stockkeeping unit sales) unit retail prices as well as the weekly unit sales in the laundry detergent category for Retailers A and C for 156 weeks: from January 1, 1993, through December 31, 1995. In general, implementation of CM in a product category by a retailer occurs over a period of time rather than during a particular week. The intervention analysis methodology employed here requires a specific date for the switchover to CM, however. The managers of the supermarket chain indicated to the authors that CM began in earnest around the 57th week of the data. Therefore, for analytical purposes we have assigned this week as a switchover date, acknowledging fully that CM implementation was spread over a period of time around that date. None of the competing retailers in Retailer C adopted CM during this three-year period; all stayed with traditional management approaches (BCM) throughout. Thus, the data set covers 56 weeks of the pre-CM regime (i.e., BCM) and 100 weeks of the CM regime for Retailer A and 156 weeks of only BCM regime for Retailer C. Unfortunately, the data set does not include information on wholesale prices or the retailers’ margins. Therefore, we are not in a position to rigorously test our analytical propositions pertaining to retailers’ profits.

Methodology

To test the propositions related to CM’s effects on average prices and sales, a simple t-test might be used to compare the means of the dependent measures (average prices, sales, revenues) before and after adoption of CM by Retailer A. However, the use of a t-test to determine whether a significant difference exists between the means of the two regimes is not appropriate when the dependent measures come from the same time series. This is because a t-test assumes that data for each group are independently generated from samples with normal distributions and constant variances. The time series data used in the study does not meet these assumptions because of the presence of autocorrelation. Therefore, we employ intervention or interrupted time series analysis (e.g., Box and Tiao 1975; McDowall et al. 1980) to study the impact of Retailer A’s adoption of CM on prices, sales, and revenues. Although applications of intervention analysis in the marketing literature are few (e.g., Krishnamurthi, Narayan, and Raj 1986; Mulhern and Leone 1990; Wichern and Jones 1977), the technique is widely used in other social sciences. Figure 12 (see McCain and McCleary 1979) summarizes the details of the four stages—autoregressive integrated moving-average method (ARIMA) identification, estimation, diagnosis, and intervention hypothesis testing—of the intervention analysis procedure.

Empirical Analyses

We now investigate P1 through P6, which are derived from our analytical model, using the intervention analysis approach. However, to begin with, we perform a rough test of whether the laundry detergent category at Retailer A is characterized by conditions favoring CM—a high interbrand cross-price sensitivity at Retailer A and demand that is relatively insensitive to other retailers’ prices. Following Raju, Sethuraman, and Dhar (1995), we use the category own-price sensitivity as a surrogate for national brand cross-price sensitivity. This approach is reasonable given the one-to-one relationship between own-price sensitivity $\eta'$ and cross-
price sensitivity $\eta$, namely, $\eta' = (1 + \eta)$, in our specification of the demand functions (Equations 1–4). Consistent with the linear form of the demand functions assumed in the analytical model, we estimate the following equation:

$$Q^i_A = \alpha + \eta'P^i_A + \gamma P^i_C + e_A, \quad i = 1, 2, \ldots, 56.$$

where $Q^i_A$ = Retailer A’s weekly unit sales of laundry detergent, $P^i_A$ = Retailer A’s average weekly unit price, $\eta'$ = intrastore own-price sensitivity, $P^i_C$ = Retailer C’s average weekly unit price, $\gamma$ = interstore cross-price sensitivity, $\alpha$ = intercept, and $e_A$ = the error term. The regression results are reported in Table 1.

The results indicate that the own-price price sensitivity of the average item in the category, $\eta'$, is negative and significant for Retailer A. The nonsignificant but positive estimate of the interstore cross-price sensitivity ($\gamma$) suggests that little price-based cross-store shopping takes place for brands in the category. Overall, the results suggest that the laundry detergent category possesses the competitive characteristics that support Retailer A’s move to CM for this category.

Testing Implications of Propositions on CM and Retail Price

A testable implication of $P_1$ is that Retailer A’s average unit retail price of laundry detergents in the CM regime will be higher than the average unit retail price level in the pre-CM regime. A testable implication of $P_2$ is that the increase in the average unit retail price of Retailer A as it moves from pre-CM to CM will be higher than the increase, if any, of the average unit retail price of Retailer C. Summary descriptive statistics with respect to the mean of the laundry detergent category’s weekly average unit price series of Retailers A and C before and after Retailer A’s move to CM are shown in Table 2. It appears that Retailer A’s mean weekly average unit price rose by approximately $0.33 after the move to CM. Furthermore, Retailer A’s mean weekly average unit price was $0.16 lower than that of Retailer C in the pre-CM regime but higher by approximately $0.06 in the CM regime.

The time series plots of Retailer A’s weekly average unit prices and the difference between Retailer A’s and Retailer C’s weekly average unit price series are displayed in Figures 13 and 14, respectively. Figure 13 indicates that there is a gradual upward shift in A’s prices from the pre-CM period to the CM period, and Figure 14 shows that Retailer A’s prices rose more and were higher on average than those of Retailer C in the CM period.

Intervention analysis tests of $P_1$ and $P_2$. The results of the ARIMA model identification and estimation stages with respect to the time series data shown in Figures 13 and 14 are reported in Table 3. Diagnosis checks of the autocorrelation functions (ACFs) and the partial autocorrelation functions (PACFs) of the residuals of each of the estimated models in Table 3 revealed that they were white noise; that is, the models were found to be adequate.

Figures 13 and 14 show that the series in each case underwent a gradual and permanent change after the adop-
### TABLE 2
Descriptive Statistics of Key Variables

<table>
<thead>
<tr>
<th>Relevant Proposition</th>
<th>Variable</th>
<th>Pre-CM Regime</th>
<th></th>
<th></th>
<th>CM Regime</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Minimum</td>
<td>Maximum</td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>P1</td>
<td>Weekly average unit price of A</td>
<td>3.77</td>
<td>.21</td>
<td>3.21</td>
<td>4.13</td>
<td>4.11</td>
<td>.29</td>
</tr>
<tr>
<td>P2</td>
<td>Weekly average price difference between A and C</td>
<td>-.16</td>
<td>.23</td>
<td>-.74</td>
<td>.54</td>
<td>.06</td>
<td>.26</td>
</tr>
<tr>
<td>P3</td>
<td>Weekly average unit sales of A</td>
<td>38,257</td>
<td>5198</td>
<td>30,007</td>
<td>55,917</td>
<td>32,990</td>
<td>3975</td>
</tr>
<tr>
<td>P4</td>
<td>Weekly average market share of A</td>
<td>.344</td>
<td>.028</td>
<td>.280</td>
<td>.420</td>
<td>.346</td>
<td>.025</td>
</tr>
<tr>
<td>P5</td>
<td>Weekly average revenues of A</td>
<td>143,589</td>
<td>16,471</td>
<td>115,100</td>
<td>206,893</td>
<td>135,295</td>
<td>15,567</td>
</tr>
<tr>
<td>P6</td>
<td>Computed weekly average profit of A</td>
<td>22,313</td>
<td>7331</td>
<td>1731</td>
<td>35,438</td>
<td>30,716</td>
<td>9586</td>
</tr>
</tbody>
</table>
tion of CM by Retailer A. Therefore, the following models for the intervention hypothesis testing stage of the analysis were specified:

\[ p_{A_t} = \delta p_{A_{t-1}} + \omega I_t + a_t - \theta a_{t-1}; \]

\[ 0 < \delta < 1 \text{ and } I_t = \begin{cases} 0 & \text{for } t < 57 \text{ and } \\
1 & \text{for } t \geq 57 \end{cases} \]

\[ 0 < \delta < 1 \text{ and } I_t = \begin{cases} 0 & \text{for } t < 57 \text{ and } \\
1 & \text{for } t \geq 57 \end{cases} \]

Note that in these equations, \( \delta p + \omega I \) (elsewhere, simply \( \omega I \)) is the intervention component, or what is commonly referred to as the “transfer function.” Furthermore, all the series that we consider in this article have been differenced once to make them stationary. The maximum likelihood estimates of the parameters of these models are reported in Table 3.

Diagnosis checks applied to the residuals of each of the estimated models showed the residuals to be white noise, indicating that the models fit the data well. As shown in Table 3, the \( \omega \) coefficient in Equation 6a is positive and statistically significant, which indicates that Retailer A’s adoption of CM resulted in increased prices. For example, the first postintervention observation is \( Y_{57} = .206 \), which implies that the level of the series rose by approximately \$.21 in the first postintervention period. Similarly, in each subsequent week \( t \), the increment in the level of the price is \( \delta \), where \( \delta = .223 \). The asymptotic level of the series is \( .27 \) (or \( .206/[1 - .223] \)), which implies that adoption of CM by Retailer A gradually and permanently increased average unit prices in the category by approximately \$.27. Prices under CM are approximately 7% higher than prices under BCM for Retailer A. Overall, the results support P1 and lead to the conclusion that adoption of CM by Retailer A resulted in a significant increase in the average unit retail price in the product category from its pre-CM level.

For P2, the results in Table 3 show that the \( \omega \) coefficient is positive and significant. Because we are working with the price difference series, the positive coefficient indicates that the difference between the changes in the price of Retailer A and the changes in the price of Retailer C was positive. The significant \( \delta \) coefficient means that the difference between their price changes was gradual and permanent. Thus, P2 is supported by the data.

**Testing Implications of Propositions on CM and Sales**

A testable implication of P3 is that Retailer A’s shift to CM will lower this retailer’s category sales. Summary descriptive statistics with respect to the means of the weekly category unit sales of Retailer A in the pre-CM and CM regimes are shown in Table 2, and the graph of the weekly unit sales series is displayed in Figure 15. From Table 2, it is clear that the weekly unit sales declined from the pre-CM period to the CM period. The average weekly decline was approximately 5267 units. Therefore, Figure 15 and Table 2 suggest that there was indeed a significant decline in Retailer A’s weekly unit sales after adoption of CM.

**Intervention analysis for P3.** Retailer A’s weekly category unit sales (\( S_{A_t} \)) data were log-transformed and then identified as an ARIMA (0, 1, 1) process. The results of the identification and estimation stages are reported in Table 3. Figure 15 shows that the category unit sales for Retailer A underwent an abrupt, permanent decline with the adoption of CM. Therefore, the intervention hypothesis test model was specified as

\[ S_{A_t} = \omega I_t + a_t - \theta a_{t-1} \text{ where } I_t = \begin{cases} 0 & \text{for } t < 57 \\ 1 & \text{for } t \geq 57 \end{cases} \]

Table 3 reports the maximum likelihood estimates of the parameters of Equation 7. As shown in Table 3, the \( \omega \) coefficient in Equation 7 was found to be negative and statistically significant, which indicates that Retailer A’s adoption of CM had a significant, negative effect on category sales. More specifically, because the estimate of the \( \omega \) coefficient is stated in natural logarithms, the effect of \( \omega \) is actually \( e^{\omega} \).
<table>
<thead>
<tr>
<th>Relevant Proposition</th>
<th>Series</th>
<th>Identification of Series</th>
<th>Estimation of Series</th>
<th>Maximum Likelihood Estimates of Parameters for Intervention Hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \theta_1 = .72^{***} )</td>
<td>( \theta_1 = .92^{<em><strong>} ) N/A ( \theta_2 = .21^{</strong>} ) ( \omega = .206^{<strong>} ) ( \delta = .223^{</strong></em>} ) N/A</td>
</tr>
<tr>
<td>P1 Weekly average unit price of A</td>
<td>Weekly average unit price of A $p_A = a_t - \theta_1 a_{t-1}$</td>
<td>( \theta_1 = .92^{***} )</td>
<td>( \theta_2 = .21^{**} )</td>
<td></td>
</tr>
<tr>
<td>P2 Weekly average price difference between A and C</td>
<td>Weekly average price difference between A and C $p_A - C_t = a_t - \theta_1 a_{t-1}$</td>
<td>( \theta_1 = .85^{***} )</td>
<td>( \theta_2 = .21^{<strong>} ) ( \omega = .168^{</strong>} ) ( \delta = .138^{**} ) N/A</td>
<td></td>
</tr>
<tr>
<td>P3 Weekly average unit sales of A</td>
<td>Weekly average unit sales of A $S_t = a_t - \theta_1 a_{t-1}$</td>
<td>( \theta_1 = .89^{***} )</td>
<td>( \theta_2 = .24^{***} )</td>
<td></td>
</tr>
<tr>
<td>P4 Weekly average market share of A</td>
<td>Weekly average market share of A $m_s_A = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$</td>
<td>( \theta_1 = .69^{***} )</td>
<td>( \theta_2 = .24^{<em><strong>} ) ( \omega = .645^{</strong></em>} ) ( \delta = -.002 \text{n.s.} ) ( \phi_1 = -.485^{***} ) N/A</td>
<td></td>
</tr>
<tr>
<td>P5 Weekly average revenues of A</td>
<td>Weekly average revenues of A $R_A = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2}$</td>
<td>( \theta_1 = .73^{***} )</td>
<td>( \theta_2 = .18^{<em><strong>} ) ( \omega = .181^{</strong></em>} ) ( \delta = -.092^{**} ) N/A</td>
<td></td>
</tr>
<tr>
<td>P6 Computed weekly average profit of A</td>
<td>Computed weekly average profit of A $\pi_A = a_t - \theta_1 a_{t-1}$</td>
<td>( \theta_1 = .38^{***} )</td>
<td>( \theta_2 = .24^{<em><strong>} ) ( \omega = .403^{</strong></em>} ) ( \delta = .229^{*} ) N/A</td>
<td></td>
</tr>
</tbody>
</table>

*Significant at the \( p < .10 \) level.
**Significant at the \( p < .05 \) level.
***Significant at the \( p < .01 \) level.
Notes: n.s. = not significant, N/A = not applicable. The vertical line at the 57th week depicts the time of adoption of CM in the category by Retailer A. The horizontal line indicates zero price difference.
Because $e^{1.21} = 1.21$, it can be concluded that the ratio of the pre-CM series to the CM series is 1.21, or a value that represents a 17% reduction in the average category unit sales from the pre-CM period. Given that the mean pre-CM category sales level was 38,257 units each week (Table 2), the results indicate that the intervention of CM was associated with an abrupt and permanent drop in the category unit sales by approximately 6503 units a week. Thus, the empirical results strongly support P3.

A testable implication of P4 is that Retailer A’s shift to CM will lower the retailer’s category sales in comparison with Retailer C’s sales. Thus, this proposition aims at a relative comparison of sales between the two retailers. Given that Retailer A controls approximately 35% of the market, comparison of sales between the retailers in absolute terms is meaningless. Therefore, we resort to market share. This measure will provide a suitable relative comparison for the purposes of this proposition. Summary descriptive statistics with respect to the means of the weekly market shares of Retailer A in the pre-CM and CM regimes are shown in Table 2, and the graph of the weekly market share series is displayed in Figure 16.

Intervention analysis for P4. The results of the ARIMA model identification and estimation stages are reported in Table 3. Figure 16 shows no detectable change in the market share with the adoption of CM. However, to test the proposition, we conjecture a gradual decline in the market share. Therefore, the intervention hypothesis test model was specified as follows:

$$ms_{A_t} = \delta ms_{A_{t-1}} + \omega I_t + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2},$$

where $I_t = \begin{cases} 0 & \text{for } t < 57 \\ 1 & \text{for } t \geq 57 \end{cases}$.

Table 3 reports the maximum likelihood estimates of the parameters of Equation 8. As shown in Table 3, the $\omega$ coefficient is found to be negative, but it is not significant. Therefore, P4 cannot be supported from the data.

Testing Implications of Propositions on CM and Revenues

A testable implication of P5 is that Retailer A’s revenues (weekly average unit price times unit sales volume) will decline after adoption of CM. Table 2 presents the summary descriptive statistics on the means of Retailer A’s weekly revenues in the pre-CM and CM regimes, and Figure 17 displays the graph of the revenue series. The data suggest that weekly average revenue declined for Retailer A.

Intervention analysis for P5. Retailer A’s weekly average revenues ($R_{At}$) data were log-transformed and then identified as an ARIMA (0, 1, 2) process. The results of the identification and estimation stages are reported in Table 3. Figure 17 shows that the revenues for Retailer A underwent an abrupt, permanent decline with the adoption of CM in a manner sim-
ilar to the category unit sales series. Therefore, the intervention hypothesis test model was specified as follows:

\[(9) \quad R_{A_t} = \omega I_t + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2},\]

where \(I_t = \begin{cases} 0 & \text{for } t < 57 \\ 1 & \text{for } t \geq 57 \end{cases} .\)

Table 3 reports the maximum likelihood estimates of the parameters of Equation 9. As shown in Table 3, the \(\omega\) coefficient in Equation 9 was found to be negative and statistically significant, which indicates that Retailer A’s adoption of CM had a significant, negative effect on the revenues. Because the estimate of the \(\omega\) coefficient is stated in natural logarithms, the actual effect of \(\omega\) is \(e^{\omega}\). Because \(e^{0.9} = 1.10\), it can be concluded that the ratio of the pre-CM series to the CM series is 1.10, or a value that represents a 9% reduction in the weekly revenue stream from the pre-CM period. Given that the mean pre-CM weekly revenue was $143,589 (Table 2), the results indicate that the intervention of CM was associated with an abrupt and permanent drop in the revenues by approximately $14,358 a week. Thus, \(P_5\) is strongly supported by the data. Next, we turn to the profits.

**Sensitivity Analyses with Respect to Profits**

\(P_6\) implies that Retailer A’s profits will increase after adoption of CM. We cannot directly test this proposition because the database does not contain direct profit information. Therefore, we perform a simulation analysis to determine if \(P_6\) can be supported by the available data, despite the fall in unit sales as well as revenues. To calculate profits, we must estimate the margins. Different trade publications indicate that supermarket margins in the laundry detergent category vary between 12% and 20%. We performed several intervention analyses assuming different profit margins—12%, 20%, and 16% (the average of these two). The results were all similar. Therefore, we report the result for a 16% margin. We took the average category unit price in the pre-CM period, $3.77 (see Table 2), and subtracted 16% of it to come up with the approximate average unit wholesale price, $3.17, for Retailer A in the pre-CM period. Then we calculated each week’s margin by subtracting this number from the corresponding weekly average unit price. For the CM period, we assumed further that the wholesale prices did not rise, and therefore we used the same wholesale prices for the CM period as well. Thus, we multiplied each week’s average unit margin (in dollars) by the corresponding unit sales to get to the profits. The last row of Table 2 displays the summary descriptive statistics for the computed weekly average profits of Retailer A, and Figure 18 shows the time series. The data suggest that weekly average profit increased for Retailer A. This took place despite declining unit sales and declining weekly revenues.

**Intervention analysis for \(P_6\)** Retailer A’s weekly average profits \((\pi_{A_t})\) data were log-transformed and then identified as an ARIMA \((0, 1, 1)\) process. The results of the identification and estimation stages are reported in Table 3. Figure 18 shows that the revenues for Retailer A underwent an abrupt, permanent increase with the adoption of CM. Therefore, the intervention hypothesis test model was specified as follows:

\[(10) \quad \pi_{A_t} = \omega I_t + a_t - \theta_1 a_{t-1}, \text{ where } I_t = \begin{cases} 0 & \text{for } t < 57 \\ 1 & \text{for } t \geq 57 \end{cases} .\]

Table 3 reports the maximum likelihood estimates of the parameters of Equation 10. As shown in Table 3, the \(\omega\) coefficient in Equation 10 was found to be positive and statistically significant, which indicates that Retailer A’s adoption of CM had a significant, positive effect on the category profits. Because the estimate of the \(\omega\) coefficient is stated in natural logarithms, the effect of \(\omega\) is actually \(e^{\omega}\). Because \(e^{0.22} = 1.25\), it can be concluded that the ratio of the CM series to the pre-CM series is 1.25, or a value that represents a 25% increase in the weekly average profits from the pre-CM period. Given that the mean pre-CM weekly average profits was $22,313 (see Table 2), the results indicate that the intervention of CM was associated with an abrupt and permanent increase in the weekly profits of Retailer A in the laundry detergent category by approximately $5578.

Basically, the sensitivity analysis suggests that if wholesale prices had stayed the same, profits would have been significantly higher for Retailer A. Because this analysis was based on the assumption of constant wholesale prices, the analysis would still be true if the wholesale prices declined as predicted by our theory.

**Disaggregate Analysis**

In addition to the aggregated analysis, we also conducted a disaggregated analysis of the data. Retailer A in the market area under scrutiny faced two major competitors—one is a typical hi/lo retailer and operates 14 stores in the trading area, and the second is a discount chain with 5 stores in the trading area. The combined market share of the three chains is 85%. (The remaining competitors are small operators that would not affect Retailer A substantively.) In most neighborhoods or locales within the trade area, Retailer A battles only one of these two competitors.

An identical intervention analysis approach was conducted on the disaggregated data pertaining to retail prices.
of the three chains before and during Retailer A’s adoption of CM. The price series were identified as ARIMA (0, 1, 1), similar to that in the aggregate analysis. The results of the disaggregate analysis were identical to the substantive results of the aggregate analysis. Therefore, the data have captured the nature of the effects of CM in the particular product category.

Discussion of the Results and Implications for Managers and Researchers

Category management is a widely heralded process designed to help the retailer achieve overall category performance objectives by coordinating buying, merchandising, and pricing decisions for products in the category. Although adoption of CM by retailers is rapidly increasing (ACNielsen 1998), little research on the effects of CM adoption on retailer prices and performance has been performed. In the present study, we attempt to measure how CM affects retailer prices, sales, revenues, and profits under different competitive conditions.

Several interesting propositions emerged from the analytical portion of the study that were subsequently confirmed by empirical analysis. For example, the data indeed show that a gradual and permanent increase in prices of laundry detergent brands occurred after CM was implemented. Prices in the laundry detergent category at the retailer were significantly greater than prices in the same category among competing retailers that did not move to CM. The results are consistent with previous work on manufacturer adoption of CM in a packaged goods category, which showed that interbrand price coordination produced higher prices for the brands in the manufacturer’s product line (Zenor 1994).

Our model in this article offers one rationale for price increase under CM—coordinated pricing. However, the price increases produced by CM in Retailer A could be an outcome of several strategies employed by the retailer, including a profit-generating strategy, which is expressly discussed in the CM literature and applied by many retailers in practice (e.g., Category Management Report 1995; McLaughlin and Hawkes 1994; Progressive Grocer 1995). For example, retailer deletion of low-margin items (Broniarczyk, Hoyer, and McAlister 1998) and a reduced emphasis on price promotions in the category may have contributed to the price increase. One downside associated with each of these strategies is the potential for retail prices to increase and thereby negatively affect retailer performance if a substantial segment of the category’s customers are price sensitive. The present study appears to capture this phenomenon, as is shown by the drop in consumer demand for Retailer A during the CM period.

Despite the higher prices under CM, the retailer’s move to CM from a traditional BCM approach built the category profitability. Profits rise under CM over the traditional management approaches (i.e., BCM) because a decrease in consumer demand causes manufacturers to lower their wholesale prices, which, in combination with higher retail prices, produces higher gross margins for the retailer. Therefore, the present study supports the claims of CM consultants, experts, and practitioners that CM produces enhanced business results (Category Management Report 1995).

The findings also show that a retailer enjoys higher profits under CM than do competing non-CM retailers, but only under certain conditions. For example, CM adoption produces the greatest economic benefits for the retailer when interbrand competition is high and consumer store switching is low. Few economic benefits exist for the CM retailer when little brand competition and much interstore competition are present. These findings suggest that categories characterized by much interbrand competition and little cross-store shopping should be the focus of the retailer’s CM efforts.

Implications for Managers

The present research holds several interesting implications for practitioners. First, the increase in retail prices under CM calls into question the consumer benefits of CM. The practitioner literature argues that CM adoption will enhance consumer welfare, as is captured in the definition of CM: “A distributor/supplier process of managing categories as strategic business units, producing enhanced business results by focusing on delivering consumer value” (Category Management Report 1995, p. vii). The price increases fostered by CM represent a diminution rather than an improvement in consumer value. These findings are not the first “red flags” that question the magnitude of consumer benefits from CM adoption. Research shows that retailer implementation of CM led some consumers to switch to non-CM stores, noting that “There is a certain naiveté on the part of retailers and wholesalers who believe [the benefit of] Category Management is transparent to the consumer” (Progressive Grocer 1995, p. S9). The selection of a profit-generating strategy for the category may have contributed to the price increases in the category, which suggests that other strategies might produce different, more consumer-beneficial results. Retailers should explore how CM adoption will benefit the consumer before implementing CM in the category.

A second major implication of the research is that the economic outcomes of CM are category specific. Retailers should implement CM in product categories in which (1) cross-price sensitivities among brands are high or much brand switching exists and (2) cross-store price sensitivities are low or little price-based cross-store shopping takes place for brands in the category. This implication is consistent with research showing that manufacturer adoption of CM has its greatest impact on manufacturer profitability when cross-price sensitivities among products in the manufacturer’s product line are high (Zenor 1994). The results suggest that the common practice of grocery retailers—applying CM to categories with high sales volumes (McLaughlin and Hawkes 1994)—is too simplistic. Empirical research shows that many high-volume categories (e.g., cookies, crackers), which appear to be ideal candidates for CM, actually possess low elasticities (e.g., Hoch et al. 1995) and probably low cross-price elasticities. Therefore, using high category sales volume as a major criterion for selecting product categories for CM may provide low returns for the retailer.

A third implication of the study is that retailer adoption of CM appears to offer manufacturers fewer economic ben-
effits than it offers retailers, contradicting the popular notion that CM benefits retailers and manufacturers (e.g., Food Marketing Institute 1995; Category Management Report 1995). This implication is based on the results that show manufacturer prices and margins declining, likely producing a drop in manufacturer profits. The findings of the present study are consistent with reports of concern among manufacturers that retailer migration to CM will produce a win–lose situation in the channel (The Economist 1997; McLaughlin and Hawkes 1994; Reda 1995). One approach that might alleviate such a scenario is for retailers and manufacturers to codevelop category plans, strategies, and tactics and jointly implement them to achieve mutually satisfactory goals. Experts in CM have long advocated a high level of cooperation between manufacturers and retailers in implementing CM, though such a relationship is difficult to implement in practice (see Category Management Report 1995, pp. 107–12).

Finally, CM can support the retailer’s ECR efforts. In the mid-1990s, ECR was a major thrust in the grocery industry: “ECR is a grocery industry strategy in which distributors and suppliers are working closely together to bring better value to the grocery consumer” (Efficient Consumer Response 1993, p. 1). The key strategies for ECR involve efficient product assortments, replenishment, promotion, and product introductions, and CM is directly linked to ECR primarily through category assortments and promotions. For example, CM can optimize the item mix by delisting slow-moving SKUs, an action consistent with the objectives of ECR. Ironically, the combination of fewer products and greater price coordination supports the retailer’s ECR initiatives while violating a basic tenet of CM to enhance consumer value because retailer prices are higher. Also, ECR calls for a lowering of the intensity of consumer and trade promotions (see Efficient Consumer Response 1993, pp. 79–85), an activity consistent with some CM strategies that are available to retailers for their categories. Therefore, retail managers can employ CM to support some components of their ECR efforts.

**Implications for Researchers**

The study offers marketing researchers several interesting implications as well. First, the current study presents researchers with fresh insights on relationships among retailer and manufacturer pricing, retailer unit sales, and category profitability under CM. For example, increases in average category prices and decreases in overall category sales resulting from CM implementation are two relationships that were not predicted in the previous empirical work on CM (e.g., McLaughlin and Hawkes 1994; Zenor 1994) or in the practitioner literature. As research findings and empirical generalizations on CM grow, more sophisticated perspectives on CM effects will develop, leading to better models of the process.

A second, related implication of the study is that the drop in manufacturer prices and margins resulting from CM adoption can significantly affect the nature of the relationship between manufacturers and retailers. Experts and researchers in CM need to expand constructions of CM effects to include scenarios in which opportunism exists in channel relationships under a CM approach and offer remedies for the problems that result. For example, integrating work showing high relational exchange (i.e., role integrity, preservation of the relationship, and harmonization of relationship conflict among channel members) to limit opportunism in channels (Brown, Dev, and Lee 2000) should be undertaken to enhance the efficacy of CM for all channel members.

A third implication for researchers is that the effects of CM are complex, containing significant indirect influences. For example, retailer adoption of CM resulted in higher prices, which caused retail sales and manufacturer prices to decline. This set of effects resulted in higher retailer margins and category profits. The complexity of these effects should stimulate researchers to develop more robust models, perhaps using structural equations approaches (i.e., systems of equations) to gain information on the indirect effects of the phenomenon. Researchers also should consider multiple measures of performance when assessing CM effects, because single-measure models based on sales volume provide only a partial view of CM.

Finally, game theory in combination with intervention analysis represents a novel approach to the study of the impact of CM on retailer and manufacturer performance. Game theory generated interesting and practical propositions about CM effects, and intervention analysis was employed to test these propositions with longitudinal data. The present methodology complements the survey approaches employed by other researchers who describe retail practices and outcomes. Certainly, research using a variety of methodologies is warranted to tackle problems of interest to researchers and practitioners.

**Limitations and Directions for Further Research**

The limitations of the present research also represent opportunities for interesting further research in the area. One limitation is the informational assumptions of our analytical model. For example, manufacturers and retailers typically do not possess perfect information about one another’s demand functions and costs as assumed in the model. Although rich data are available on manufacturer and retailer activities, in reality managers make decisions with imperfect knowledge about demand functions and costs. Further research might investigate how imperfect information among key decision makers influences CM outcomes. The model also assumes that the retailer seeks to maximize category profits. Retailers are often interested in maximizing other objectives, such as category sales or store traffic. Under a different category strategy—say, traffic building—the conclusions from the model might have been different. A future study might explore CM effects under a sales-maximization approach or a traffic-building approach and compare the results to add greater insights into the implications of a retailer move to CM. Also, our study assumes constant costs on the supply side and no quantity discounts offered by manufacturers. These assumptions could be relaxed in further research, especially given that lowering supply chain costs is an important aspect of the overall ECR initiative. Another limitation of the study is that the model does not account for competing explanations for why category prices increased, as described previously. Future model builders in
the CM area could incorporate factors such as product deletion and reduction of price discounts in their models to explain such phenomena.

Last, only one dimension of retailer CM, price coordination, was examined in the study. Category management is a much more complex process, involving coordinated buying, pricing, promotion, and merchandising of brands in the category. Future studies should examine how a more complete set of CM activities affects retailer and manufacturer performance. Furthermore, the present study focused on how retailer adoption of CM influenced retailer performance. Additional research is needed on how manufacturers are affected by retailer implementation of CM. The research could follow two tracks: focusing on how the relationship between the retailer and the manufacturer is influenced by retailer adoption of CM and how retailer adoption of CM affects manufacturer sales and profit performance. Much interesting work remains to be done on the complex process of CM.

REFERENCES


