*Modeling the Impact of Sales Promotion on Store Profits*

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# Modeling the Impact of Sales Promotion on Store Profits

Per-Göran Persson

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*To Mother and Father*

# PREFACE

This report is a result of a research project carried out at the Foundation for Distribution Research at the Economic Research Institute at the Stockholm School of Economics. It is part of a larger project concerning how the information potential in supermarket scanner data can be used in decision making.

This volume is submitted as a doctor's thesis at the Stockholm School of Economics. As usual at the Economic Research Institute, the author has been entirely free to conduct and present his research in his own ways as an expression of his own ideas.

The Institute is grateful for the financial support provided by the sponsors of the Foundation for Distribution Research.

The present volume would not have been possible without the cooperation with the owners and personnel of the ICA store where the data were collected. The Economic Research Institute wishes to warmly thank the store for their generosity and openness.

Stockholm, April 1995

*Claes-Robert Julander*
Professor,
Director of the Economic Research Institute at
the Stockholm School of Economics,

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Stockholm, April 1995

*Per-Göran Persson*

# TABLE OF CONTENTS

## 4. *PROMOTION PROFITS*



## 5. *MODEL DEVELOPMENT*

## 6. *SIMULATING PROMOTION PROFITS*



## 7. *EMPIRICAL DATA AND ESTIMATION METHOD*

## *8. EMPIRICAL ILLUSTRATION 1: COFFEE*



## *9. EMPIRICAL ILLUSTRATION 2: CEREALS*

# 1. INTRODUCTION

## 1.1. The Problem

Sales promotion is frequently used in grocery retailing. It takes up a large share of the resources grocery retailers spend on marketing. The heavy usage of sales promotion has recently become questioned by retailers and manufacturers. Despite the large sums yearly spent on sales promotion, the economics of sales promotion is poorly understood. Consequently, there is a great knowledge gap to fill, and this study is an attempt to contribute to this effort.

As will be seen later in this study, measurement of store profits of retailer promotion is difficult because retailers carry large assortments and sales of the individual items in these assortments are interdependent.

The aim of this study is to improve our knowledge of the impact of sales promotion on retailer profits. More specifically, the study develops a framework model for measuring the impact of sales promotion on store profits. The model is then used in a simulation study and in three studies using empirical data.

This chapter first defines and describes sales promotion in order to give the reader the necessary background to better understand the problem. Readers already familiar with the concept of sales promotion may skip sections 1.2. to 1.6. and continue directly with section 1.7. Section 1.7 states the research purpose and with the relevant delimitations. The chapter concludes with a description of the organization of the report.

## 1.2. What is Sales Promotion?

This section defines and describes sales promotion, starting with a formal and general definition of sales promotion. Then, a typology of sales promotion is presented along with examples of each type of sales promotion.

### 1.2.1. Defining Sales Promotion

The literature provides several definitions of sales promotion, some of which are presented by Blattberg and Neslin (1990). These are:

*Sales promotion consists of a diverse collection of incentive tools, mostly short-term, designed to stimulate quicker and/or greater purchase of a particular product by consumers or the trade (Kotler 1988, p.645).*[1]

*Sales promotion is the direct inducement or incentive to the sales force, the distributor, or the consumer, with the primary objective of creating an immediate sale (Schultz and Robinson 1982, p.8).*[2]

*Sales promotion, deals, and display can be defined under the general term of 'short-term inducements to customer buying action' (Webster 1971, p.556).*[3]

*Sales promotion represents those marketing efforts that are supplementary in nature, are conducted for a limited period of time, and seek to induce buying (Davis 1981, p.536).*[4]

Based on these definitions, Blattberg and Neslin (1990) develop their own definition of sales promotion. They choose to exclude *short-term* from the definition because of the dispute concerning the long-run effects of sales promotion. Their definition reads:

*Sales promotion is an action-focused marketing event whose purpose is to have a direct impact on the behavior of the firm's customers.*

We shall not consider another definition of sales promotion here. For the present study, any of the above definitions will suffice. The next section presents different types of sales promotion.

### 1.2.2. Types of Sales Promotion

Sales promotion can be classified in three types, depending on the initiator and the target of the promotion. *Retailer promotion* and *consumer promotion* are directed toward the consumers by retailers and manufacturers, respectively. The manufacturers direct *trade promotion* to the retailers. The three types of promotions are illustrated in Figure 1.1.

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[1]Kotler, Philip (1988), *Marketing Management: Analysis, Planning, Implementation, and Control,* 6th ed., Englewood Cliffs, NJ: Prentice-Hall.

[2]Schultz, Don E. and William A. Robinson (1982), *Sales Promotion Management,* Chicago: Crain Books.

[3]Webster, Frederick E. (1971), *Marketing Communication,* New York: Ronald Press.

[4]Davis, Kenneth R. (1981), *Marketing Management,* 4th ed., New York: John Wiley.

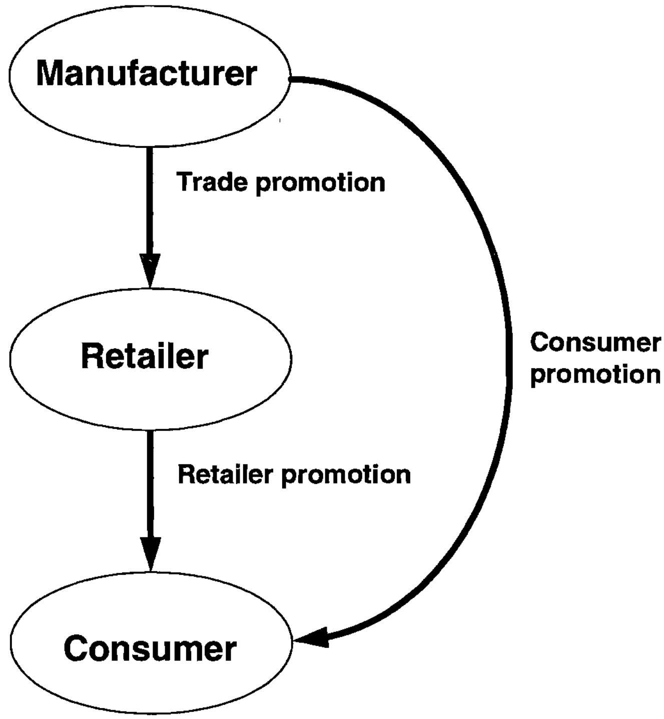


*Figure 1.1. Types of sales promotion.*

A large number of different promotional tools are used by retailers and manufacturers. Table 1.1 gives some examples of these tools.

| ***Retailer Promotions*** | ***Trade Promotions*** | ***Consumer Promotions*** |
|---|---|---|
| Price cuts | Case allowances | Couponing |
| Displays | Advertising allowances | Sampling |
| Feature advertising | Trade coupons | Price packs |
| Free goods | Spiffs | Value packs |
| Retailer coupons | Financing incentives | Refunds |
| Contests/premiums | Contests | Continuity programs |
| Double couponing | | Financing incentives |
| | | Bonus packs |
| | | Special events |
| | | Sweepstakes |
| | | Contests |
| | | Premiums |
| | | Tie-ins |

*Table 1.1. Examples of sales promotion tools. Source: Blattberg and Neslin (1990)*

The most important and most frequently used retailer promotions in grocery retailing are price cuts, special displays, newspaper feature advertising, and coupons. Very often, combinations of two or more promotional tools are used.

## 1.3. Why is there Sales Promotion?

In this section, we look at *why* sales promotion exists. First will come a review of some of the more precise objectives that marketing managers have when using sales promotion. Then, an overview of some previous research concerned with the economic rationale for the existence of sales promotion is presented.

### 1.3.1. Sales Promotion Objectives

Given the definition above, the existence of sales promotion might not seem problematic; sales promotion simply exists "... to have a direct impact on the behavior of the firm's customers" (Blattberg and Neslin 1990). However, the definition is a very general statement of the *objective* of sales promotion, i.e., what it is supposed to do. To understand why manufacturers and retailers employ sales promotional tools, we need a somewhat more specific description of their objectives with sales promotion.

Manufacturers and retailers have different—and, to some extent, conflicting—objectives with their sales promotions. Concerning the manufacturers' objectives with trade promotion, Quelch (1983) states:

> *When manufacturers offer trade promotions, they expect that the financing costs associated with taking additional inventory will persuade retailers to provide special merchandising support to accelerate product movement. This might include passing the manufacturer's price reduction through to the consumer, featuring this price cut in store advertising, and displaying the product prominently.*

Blattberg and Neslin (1990) list the following objectives of *trade promotion*:

- Inducing retailer merchandising activities
- Retail sales force incentives
- Loading the retailer with merchandise
- Gaining or maintaining distribution
- Avoiding price reductions
- Competitive tool

The general objective of trade deals is to push merchandise through the channel while consumer promotions are used to pull merchandize through the channel. The manufacturers' specific objectives with *consumer promotions* according to Blattberg and Neslin (1990) are:

- to increase brand awareness
- to attract new customers
- to increase sales to present customers.

Blattberg and Neslin (1990) state that common retailer objectives with *retailer promotions* are:

- to generate store traffic
- to move excess inventory
- to enhance the store's image
- to create a price image.

Rossiter and Percy (1987) distinguish two types of promotion action objectives: trial and usage. From a retailer's point of view, the trial action objective refers to attracting new customers to the store. The usage action objective refers, according to Rossiter and Percy, to inducing the present customers to visit the store more often. More frequent store visits are in themselves unlikely to be the retailer's true objective; they might indeed not even be desirable if the customers only increase their shopping frequency while their total purchase amount in the store remains constant. The retailer's usage objective would rather be to induce the present customers to spend a larger share of their household budget in the store. This objective may be reached in two ways: (1) the customers may choose the store more often for their shopping trips; or (2) the customers may spend larger amounts on each visit to the store. The usage action objective is likely to be the more important action objective for an established grocery retailer while the trial objective may be more important for recently established stores.

### 1.3.2. Economic Rationale for Sales Promotion

The existence of sales promotion has been analyzed from a micro-economic point of view. The literature taking this approach is mainly theoretical, with only occasional empirical evidence presented as illustration.

Blattberg, Eppen, and Lieberman (1981) find the frequent dealing-behavior in grocery retailing problematic from a theoretical point of view. Why do retailers offer price deals, i.e., reduced prices? The common explanation of dealing as a means of increasing store traffic is not enough. It would lead to reduced profits, since the total consumption cannot be increased much by dealing. They argue that a prisoners' dilemma situation, where no retailer can stop dealing as long as the others continue, is not probable; price wars seldom last long.

That retailers would use price deals to take advantage of manufacturers' trade deals is countered with the argument above applied to the manufacturers. The explanation forwarded by Blattberg *et al.* is based on *differential inventory costs* of retailers and households. If some households have lower inventory costs than the retailer, then dealing is economically rational because deals shift inventory from the retailer to the households, reducing the retailer's average inventory of the product. The inventory holding cost that differs between the retailer and (at least some) households is the cost of storage space. While storage space is a scarce resource for the retailer, it is, within reasonable limits, an almost free resource for the household. Blattberg *et al.* do not claim that differential inventory costs are the only explanation for deals but they provide a rationale for the observed behavior.

Using theoretical mathematical models, Lal (1990a; 1990b) investigates why manufacturers prefer to offer substantial price discounts for a short period and then raise the price to its normal level. According to Lal (1990b), national firms use sales promotion to compete with local brands for the price-sensitive, brand-switching segment. If the switching segment is large enough, it will be optimal for the national brands as a group to price deal in such a way that there is always one and only one national brand on promotion.

Lal (1990a) shows that such a pattern of price promotions of national brands can represent long-run equilibrium strategies for those brands in their defense against the threat from local brands. Lal assumes that the local brands have no loyal customers and therefore constantly compete for the switching segment.

Wernerfelt (1991) builds a mathematical theoretical model. He defines two types of brand loyalty; inertial brand loyalty results from time lags in awareness while cost-based brand loyalty results from intertemporal utility effects. The effects of these types of loyalty are modeled at the market level. It is found that inertial loyalty leads to equilibrium with price dispersion. Cost-based loyalty can also lead to equilibrium with price dispersion but single price equilibria are possible.

Salop and Stiglitz (1977) explained the existence of price dispersion among stores by showing that differential search costs among consumers can lead to a two-price equilibrium, where some stores charge a high price and some stores charge a lower price. Consumers with high search costs will find it more economic to remain uninformed, while those with low search costs will be informed. The high-priced stores sell only to unlucky, uninformed consumers while the low-priced stores sell to informed consumers and lucky, uninformed consumers. Their model, which gives one explanation for the existence of price dispersion across stores, was used as point of departure by Varian (1980) who used differential search costs as the economic rationale for sales promotion. According to

Varian, firms use price deals to discriminate between informed and uninformed customers. This explains the observed temporal price dispersion

Salop and Stiglitz (1982) showed that price dispersion across stores or over time may result from the mere existence of search costs, even if all customers are identical with respect to search costs. If searching is expensive enough, so that consumers only search once per period, stores with high prices will sell less than stores charging the lower price. This is because consumers arriving at a low-price store will buy more than consumers arriving at a high-price store. The price difference between the two types of stores will offset the disadvantage of lower sales in the high price stores.

Narasimhan (1984) builds a model where coupons are shown to serve as a device for price discrimination. The more price-sensitive consumers can be given a lower price by coupons. Less price-sensitive consumers do not find the effort of using coupons worthwhile, and pay the full price.

Lazear's (1986) explanation for temporal price dispersion is that the existence of more than one time period gives the retailer a richer set of pricing strategies. Retailers will find it profitable to charge a high initial price and deal the product in later periods if the product did not sell. The economic rationale is that the retailer is uncertain about the consumers' reservation prices.

Mulhern and Leone (1991) note that the retailer's rationale for sales promotion is fairly different from that of the manufacturer. They state that price bundling, i.e., charging one price for the combination of two or more products, is the economic rationale for retailer promotions. The argument is that visiting retail stores is costly for the consumers. Consumers consequently buy a basket, or bundle, of items when visiting a store and prices of individual items are of less importance than the price of the bundle. Although the consumer may pick single items from different stores, the cost of visiting more stores induces the consumer to buy a bundle of items when visiting a store.

In summary, the theoretically oriented research has suggested that the ecomomic rationales for sales promotion are: (1) differential inventory holding costs, (2) price discrimination, (3) search costs, (4) uncertain demand, and (5) price bundling.

## 1.4. Planning Sales Promotion

This section describes the promotion-planning process and some tools used for planning sales promotions. The description starts with promotion planning as a part of the corporate planning and proceeds to the planning of promotional tactics and the choice of items to promote.

### 1.4.1. Sales Promotion Planning Process

The retailer's promotion-planning process should be based on the progression from corporate objectives through marketing strategy, promotion objectives, and promotion strategy, to promotion tactics (Blattberg and Neslin 1990). A corporate objective can, for example, be to capture 20 percent of the market in a certain area. A retailer's marketing strategy has several dimensions. The most important dimensions of retailer marketing strategy are: price level, promotional strategy (high/low or everyday low pricing), service level, variety, focus, and convenience (multiple locations, few locations). The dimensions combine into marketing strategies (Blattberg and Neslin 1990). The chosen marketing strategy determines the relevant promotion objectives. Important promotion objectives for retailers are to generate store traffic, to move excess inventory, to enhance the store's image, and to create a price image.

The promotion strategy follows from the marketing strategy and the promotional objectives. Examples of promotional strategies given by Blattberg and Neslin (1990) are to maintain the promotional to total sales ratio at a certain level, to maintain a certain margin on promoted products, and to promote items with a broad appeal. The promotion strategy is implemented by translation into promotional tactics. Promotion tactics relevant to the retailer are event planning, selection of items to promote, setting of the discount level, merchandising and feature advertising of the promoted items, and retailer's forward buying.

Event planning refers to the creation of a special event or a theme for the promotion. The events are typically tied to the seasons and holidays and make it easier for the retailer to communicate the promotion to the customers. The retailer must then select the item or items to include in the promotion. For a grocery retailer, the selection of items to promote, the discount level, and merchandising and feature advertising are influenced by manufacturers' trade promotion (Chevalier and Curhan 1976; Walters 1989). The retailer may also use the manufacturers' trade promotions to purchase products that will be sold after the promotion. This is referred to as forward buying.

Holmberg (1992) describes the promotional planning of the largest Swedish grocery retailer, ICA. The planning is done at different organizational levels. TV-advertising and sponsoring are planned nationally for the whole chain, whereas a weekly leaflet is planned at the regional level. The planning horizon is one year for dry products and six months for perishables. The dry products' plan is revised after six months. Negotiations with manufacturers are part of the planning of the leaflet. At the local level, the newspaper feature advertising is planned based on the regionally produced leaflet; products are added and deleted from the plan depending on local agreements with manufacturers. In Swedish grocery retailing, each department usually receives some space in the feature advertisement and in the leaflet. The leaflet and the feature advertisement thus reflect the organization of the retailer (Holmberg 1992).

### 1.4.2. Store Level Promotional Strategy

Blattberg and Neslin (1990) present a model for planning retailers' margins by focusing on markups and markdowns. The model is aimed at helping the retailer plan a promotional strategy. Blattberg and Neslin define the following variables:

| | | |
|---|---|---|
| $S$ | = | total retail sales over the planning period |
| $N$ | = | total retail sales for product sold at regular price |
| $D$ | = | total retail sales for product sold at reduced price |
| $X$ | = | total markup for product sold at regular price |
| $Y$ | = | total markup for product sold at reduced price |

They then define the average fraction total markup as:

$$M_t = \frac{X+Y}{S} = \frac{N}{S}\cdot\frac{X}{N} + \frac{D}{S}\cdot\frac{Y}{D} = (1-P)\cdot M_r + P\cdot M_p \qquad (1.1)$$

where $P$ is the fraction of total sales made at reduced price, $M_r$ is the average fraction markup on product sold at regular price, and $M_p$ is the average fraction markup on product sold at reduced price. The equation shows that the average fraction total markup is a weighted average of the fraction markup on products sold at regular and reduced price. Blattberg and Neslin suggest that the equation is useful for comparing store strategies, for example, high/low-pricing (Hi-Lo) versus everyday low-pricing (EDLP). They note that $P$ is dependent among other things on the markups and the frequency of deals. This can be written:

$$N = f(M_r, M_p, F, E) \qquad (1.2)$$

$$D = f(M_r, M_p, F, E) \qquad (1.3)$$

where $F$ is the frequency of deals and $E$ is the percentage of the merchandise that is offered at reduced price. The retailer's problem is to maximize the store's profits:

$$\max \pi = S\cdot M_t = N\cdot M_r + D\cdot M_p \qquad (1.4)$$

If the response functions for $N$ and $D$ would be known, the profit-maximizing strategy could be determined. However very few attempts to specify and estimate the response functions have been reported, according to Blattberg and Neslin (1990). The model is used in practice to compare store strategies. Table 1.2 shows an example provided by Blattberg and Neslin of a comparison of two hypothetical supermarkets.

| | ***Standard Retailer*** | ***Everyday-Low-Price Retailer*** |
|---|---|---|
| Percentage of sales sold at reduced price (P) | 20% | 10% |
| Average regular price markup (Mr) | 25% | 20% |
| Average reduced price markup (Mp) | -10% | 0% |
| **Total average markup (Mt= (1-P)Mr+ PMp)** | 18% | 18% |

*Table 1.2. Pricing and promotion strategies for two supermarkets*

Lodish (1982) uses a model with a similar structure in a marketing decision support system for retailers. The model was developed for a multi-store retailer to support yearly planning and resource allocation on a high level. The unit of analysis is an entity, which might be a store or a product category within a store. Managerial judgment was used to parameterize the model.

Lodish divided sales of an entity into three parts: (1) regular sales $R$, (2) price-event sales $E$, and (3) markdown sales $D$. Markdown sales is modeled as a fraction of regular sales and price event sales. This fraction is modeled as a function of inventory level, merchandise character, and the markup. Regular sales and price-event sales are thought to be equally affected by national advertising, inventory levels, and selling space. Competition and a growth trend are also thought to affect regular sales and price-event sales equally. Price-event sales are particularly affected by the average price-off percentage, the number of price events, the merchandise character, price event local advertising, and the average retail markup. Regular sales are particularly affected by the average retail markup, regular-price local advertising, and the merchandise character.

The model assumes reference levels for the sales variables as well as for the controllable and uncontrollable marketing variables. Deviations in any of the independent variables from their reference level are translated into an effect index by use of a response function. At its reference level, the effect index of a marketing variable is 1.0. For example, if regular-price local advertising is expanded 10 percent, the response function may produce an effect index number of 1.08, meaning that regular sales would be up eight percent. The effect indices for all independent variables are then multiplied together to give the effect index for the relevant sales variable. The sales forecast is given as the reference sales level times the effect index. The multiplicative structure makes the model modular and enhances the adaptivity of the model. New marketing phenomena can easily be included in the model by creation of a new effect index.

The model produces sales forecasts conditional on the managers' inputs. Cost relationships are applied to the conditional sales forecasts to provide projected profit and loss forecasts for marketing plans and scenarios. The projected outcomes of different plans under various scenarios can then be compared.

Lodish reports that although the system was originally implemented using managerial judgment, it was complemented with a sales and marketing database. The database was used to improve the knowledge of sales response to the marketing variables and to track the effectiveness of past decisions.

Hoch *et al.* (1994) recently investigated the profit impact of the EDLP strategy versus the Hi-Lo strategy. They found that the EDLP strategy implied lower retailer profits than the Hi-Lo strategy mainly because the incremental regular sales volume was insufficient to overcome the negative effect on regular profit margin. However, it should be noted that their study tested the implementation of the EDLP concept in some product categories, rather than the whole store.

Mulhern and Leone (1990) used intervention analysis to investigate the effect a change in promotional strategy had on store sales and store traffic. The strategy change was from a promotional strategy with many small price cuts to one with fewer but deeper price cuts. Intervention analysis is a type of time-series analysis where a dummy variable is used to indicate the intervention. The intervention, in this case, is the shift in promotional strategy. They found that the new strategy increased store sales but had no impact on store traffic.

In summary, these models provide retail management with useful tools for evaluating the overall promotional strategy for a store or a chain. The models are less useful for planning specific promotional activities.

### 1.4.3. Selecting Items to Promote

Blattberg and Neslin (1990) discuss empirical findings reported by Curhan and Kopp (1986)[5] concerning retailers' selection of products to promote. The seven factors reported by the retailers as being important when deciding on which items to promote were:

- Item importance
- Promotion elasticity
- Manufacturer's brand support
- Promotion wear-out

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[5] Curhan, Ronald C. and Robert J. Kopp (1986), "Factors Influencing Grocery Retailers' Support of Trade Promotions," Report No. 86-104, Cambridge, MA: Marketing Science Institute.

- Sales velocity
- Item profitability
- Incentive amount

Blattberg and Neslin note that cannibalization[6] and effects on store traffic are not included in the list. If retailers do not consider these effects when deciding which items to promote, they may produce less than optimal results.

According to Blattberg and Neslin (1990) most retailers use some type of heuristic for selecting items to promote. Such a heuristic may start with a classification of the items as high (H), moderate (M), and low (L) volume items. The retailer then decides on the number of times a year that the categories should be promoted. H items are promoted frequently, but are rotated so that given items are not promoted too frequently. The M items are promoted when the manufacturer offers an attractive deal. M items may also be promoted to complement a promotion event. The L items are used to fill out the advertisement.

McCann, Tadlaoui, and Gallagher (1990) described a knowledge-based system for advertising design in retailing. The system decides which items to include in a retailer's leaflet. The layout of the items within the leaflet is also decided by the system. The system uses rules of thumb and scanner-collected data to design the retailer's leaflet.

Blattberg and Neslin (1990) summarize the state-of-the-art in the item selection as follows:

> *"...item selection is an art form. It is based on the merchandiser's intuition. A planning model, using decision calculus combined with statistical models, can be created to simplify the process. Currently, though, very few retailers use a scientific approach to item selection" (Blattberg and Neslin 1990, p.450).*

In summary, when deciding which items to promote, the retail manager currently does not utilize formalized marketing models to a significant extent.

### 1.4.4. Deciding the Promotion Frequency

Achabal, McIntyre, and Smith (1990) developed a model for determining the optimal promotion frequency by maximizing profits from periodic department store promotions.

Their sales-response model for a merchandizing program has a multiplicative structure. Achabal, McIntyre, and Smith note that the model can be interpreted as base sales level and four effect indices or lifts. The effects modeled are the price reduction effect, the timing effect, the inventory effect, and the seasonal effect:

[6] I.e., substitution within a product line, or, when defined for the retailer, within an assortment.

$$S = S_0 \cdot (p/p_0)^{-\gamma} \cdot (p/p_0)^{-\beta \cdot (1-1/t)} \cdot (I/I_0)^{-\sigma} \cdot d(k) \tag{1.5}$$

where

| | | |
|---|---|---|
| $S$ | = | sales for a merchandise program during one week |
| $S_0$ | = | sales during a normal week for a merchandise program |
| $p_0$ | = | regular price per item for the merchandise program |
| $p$ | = | price per item for the program this week |
| $t$ | = | number of weeks since the last promotion of this program |
| $I_0$ | = | fixture fill (i.e., nominal) inventory level for the program |
| $I$ | = | actual (beginning of week) inventory level for the item |
| $d(k)$ | = | seasonal scale factor for this week and program |
| $\gamma, \beta, \sigma$ | = | model parameters (elasticities) |

This model is interesting and unique because it explicitly includes the effect of the time between sales promotions. The timing effect is of course important when the optimal promotional frequency is determined. They assume that sales in weeks adjacent to the promotion are not depressed by the promotion.

The gross margin for a department during a week is given by two equations. During normal weeks, i.e., weeks without a promotion, the gross margin for a department is:

$$G_1(I_1) = (p_0 - c) \cdot S(p_0, p_0, I_1, t) - h \cdot I_1 \tag{1.6}$$

During the promotional weeks, the gross margin is:

$$G_2(p, f, I_2) = (p - c) \cdot S(p, p_0, I_2, t) - h \cdot I_2 - V_0 \tag{1.7}$$

where

$c$ = retailer's marginal cost per unit
$h$ = inventory holding cost per week per unit
$I_1$ = inventory level for normal weeks
$I_2$ = inventory level for promotional weeks
$f$ = 1-1/$t$ = fraction of weeks that promotions are not held
$V_0$ = fixed cost of holding a promotion

The average gross margin per week can be calculated as:

$$G(p, I_1, I_2, f) = f \cdot G_1(I_1) + (1 - f) \cdot G_2(p, f, I_2) \tag{1.8}$$

The sales response equation is inserted in the gross margin equation. Achabal, McIntyre, and Smith (1990) then solve for the set of decision variables that maximizes the average weekly gross margin.

## 1.5. Importance and Growth of Sales Promotion

Sales promotion has become institutionalized in Swedish grocery retailing. According to Holmberg (1992), the largest Swedish grocery retailer, ICA, distributes 217 million leaflets a year to the 4.5 million Swedish households. A normal-sized ICA-store temporarily reduces prices of somewhere between 500 and 700 items every week and builds special displays for around 200 of these items (Holmberg 1992).

The extensive use of sales promotion means that deal-sales represent a large share of the total sales; in many product categories, deal sales represent half of category sales, while in some categories, deal sales account for as much as 80 percent of total sales (Holmberg 1992). Deal sales as a share of sales are especially high in product categories used by the retailers as traffic builders or loss leaders, i.e., to attract customers into their stores.

Sales promotion has large short-run effects on brand sales in a store. Previous studies show that weekly brand sales increase ten to fifteen times the weeks when the brand is promoted. The large-short run effects imply that retailer support for promotions is essential for the brand's sales. This has led to fierce competition among brand managers to obtain retail support for their promotions.

Sales promotion takes a large and growing share of the marketing budget. Spending on sales promotion now exceeds image advertising expenditures, according to Blattberg and Neslin (1990). The rapid growth of sales promotion has recently lead to a counter reaction, with a growing skepticism concerning the benefits of the system. Manufacturers find that the system is too expensive, that it hands over the control of the marketing budget to the retailers, and they fear that sales promotion erodes brand loyalty. They are also concerned that much of their promotional efforts are absorbed by the retailers and not passed through to the consumers. Procter & Gamble recently reduced their reliance on sales promotion drastically (*The Economist* 1992).

Retailers are also starting to question their use of sales promotion. New retail formats have entered the market with less reliance on special offers. The everyday-low-pricing (EDLP) strategy is an example of such a counter strategy. Stores adopting EDLP set regular prices somewhere between the inflated regular prices and the low-deal prices in Hi-Lo-pricing stores. While the Hi-Lo-pricing stores switch between high and low prices, the pure EDLP pricing stores never offer price deals.

This counter-trend should be seen from the perspective that the use of sales promotion has reached a very high level. There is no evidence that manufacturers and retailers would actually stop using sales promotion. As Hoch *et al.* (1994) note, even the stores that have implemented the EDLP-concept use sales promotion rather frequently. Sales promotion as a topic, thus, continues to be of great importance in retailing.

## 1.6. Complex Planning Problem

This section proposes that the effects of sales promotion are not fully known and that methods for measuring the profits of retail promotions are missing. It is also argued that although the problem is theoretically simple to solve, the large assortments of grocery retailers make the solution far from trivial in practice.

### 1.6.1. Unknown Profit Impact

One would assume that the effects of such a widely-used tool as sales promotion would be well understood. That is however not the case, and there are important knowledge gaps to fill. Two areas that have been especially neglected are the profit impact of sales promotion and the retailer perspective. This is problematic because an understanding of the profit impact of sales promotion is the key to effective planning and use of sales promotion (Hoofnagle 1965).

The lack of research taking the retailer perspective is disturbing because the retailers and manufacturers have different objectives. As Rossiter and Percy (1987) put it, while the manufacturer wants the consumer to buy his brand in any store, the retailer is satisfied if the consumer buys any brand in his store.

Not only do retailers and manufacturers have different objectives with sales promotion, the effects of sales promotion also differ between the two groups. The retailer perspective makes cross-elasticities important, because when cross-elasticities are high, the effects on store performance are very different from the effects on brand performance. Previous research has found cross-elasticties to be large in grocery retailing. Bultez *et al.* (1989) state:

> *A retail business is continuously confronted with a need to monitor the interdependencies generated within its multiproduct assortments. The word "cannibalism" denotes retailers' concern for multiple forms that substitution effects may take within their departments: between brands, either within or across variety-types, and vice versa, between variety-types, either within or across brand lines. (Bultez, Gijsbrechts, Naert, and Vanden Abeele 1989)*

The neglect of the retailer perspective may be a reflection of the traditional power balance between manufacturers and retailers. Most models of sales promotion encountered in the research literature assume a brand manager perspective.

It is believed that the rapid development of information technology will shift the power balance towards the retailers. However, the retailers need knowledge to harness the power of the information potential in their scanner systems. Once retailers have this knowledge, manufacturers will also find that understanding retailers' profits from sales promotion is important. With such knowledge, the brand manager may craft deals that are profitable for the retailers and the manufacturer. Without that knowledge, he may find sales go to competitors with a better understanding of retailers' needs.

### 1.6.2. Easy in Principle

Kotler (1991) describes the theory of effective marketing resource allocation, an application of standard micro-economic theory to the brand manager's decision problem. The theory development starts with the definition of the profit equation, where the profits are the product's revenues minus its costs. The next step is to specify the unit sales volume as a function of variables under control by the firm and variables not under the firm's control. Assume that the sales equation is known, i.e., we know the relevant variables, their functional relation to unit sales volume, and the numerical values of the parameters in the equation. Then the unit sales volume can be estimated for any combination of the controllable variables. The result can be inserted into the profit equation to estimate the profit of the combination of the firm's controllable variables. We then have a marketing-plan simulator (Kotler 1991).

A marketing plan simulator allows the marketing manager to simulate the outcomes of a large number of possible marketing plans without actually having to execute the plans. The manager then chooses the plan with the most appealing outcome. The marketing-plan simulator can also be used to find the plan that maximizes profits.

Interesting results can be obtained from the model even if the unit sales volume equation is not known. A general result is that the marketing budget should always be allocated in such a way that the marginal profit of a marginal dollar spent on a marketing tool is equal for all marketing tools. Profit maximization implies that the marginal profit for each tool equals zero.

These results generalize to the case when the firm sells more than one product. If the unit sales volumes of the firm's products are independent of each others' sales (with the exception of budget interdependencies), then the marketing budget should be allocated over the products and marketing tools so that the marginal profits are equal for all tools and products. On the other hand, if unit sales volumes of the firm's products are interdependent, e.g., if they are substitutes or complements, then the problem is more complex and is treated in models of product-line pricing (see e.g., Rao 1984; Reibstein and Gatignon 1984).

The retailer's problem is considerably more difficult than the brand manager's. As noted by Doyle and Saunders (1990):

> *For the single brand, the optimum level of advertising depends upon its margin and the advertising elasticity of demand. But for a retailer's product three additional factors are important: (1) the advertising support offered by the manufacturer, (2) the cross effects of the advertised products on other items in the retailer's assortment, and (3) the impact on overall store traffic (Doyle and Saunders 1990).*

The retailer who wants to maximize store profits from sales promotion needs to find the promotion portfolio that maximizes gross profits. The gross profit from a promotion portfolio is calculated in three steps. First, conditional unit sales estimates for all items are needed. Second, each unit sales estimate is multiplied by the gross profit of that item. Third, the sum is computed, and the profit-maximizing portfolio is chosen. Easy in principle, impossible in practice, as we will see.

### 1.6.3. Impossible in Practice

The conditional sales forecasts are computed from a matrix of direct- and cross-elasticities and the promotion portfolio. Some calculations will show the enormous size of that matrix. We assume that the retailer carries 10,000 items, which is the approximate number of items carried by the average Swedish supermarket. Our retailer uses only one type of sales promotion (to reduce the number of cross-elasticities). Assuming that we know the correct model specification, we only have to estimate the cross-elasticity matrix. For each item in the assortment, we need to estimate 10,000 cross-elasticities. Taken times the number of items, we have 100,000,000 (100 million) elasticities to estimate. If the retailer calculates one elasticity per second the job would take a little more than 3 years. A computer calculating, say, one thousand elasticities per second would need a little more than a day.

The advent of new advanced computer technology brings many promises and hopes. Computers are becoming faster and faster and their storage capacity larger and larger. But fast computers with almost unlimited storage capacity are not enough.

The problem is that we only get 10,000 observations per time period. If we have weekly observations it would take 197 years of data collection to accumulate the 100 million observations which would be the absolute minimum. Using daily observations would speed up the data collection considerably, but it would still take more than 27 years to accumulate enough data for estimation. We could just hope that the elasticities would remain constant over that time. This example shows that the problem is lack of data more than lack of computing power. Not even the fastest computer can do anything about that.

We have two alternatives: the first is to get more observations per time period, the second is to reduce the number of elasticities we need to estimate.

More observations per time unit can be obtained in two ways. We could shorten the time period of the observations, e.g., use hourly observations instead of daily observations. With hourly data, we would get ten or twelve times as many observations per year. The data collection would still take more than two years, but that might be acceptable. Multicollinearity would, however, be a problem if the promotion schedule is not accelerated.

More observations per time unit can also be obtained by pooling data from different stores. A chain with 100 stores collects 100 million observations in 100 days. Pooling gives more observations per time period but assumes that the elasticities are constant across stores. In other words, we constrain the elasticities.

Our second alternative is to reduce the number of elasticities we need to estimate. The number of elasticities to estimate can be reduced by assuming that the cross-elasticity matrix follow a certain pattern or model. There are theoretical reasons to believe that such patterns exist. For example, it has been found that the more similar two products are, the closer substitutes they are and the higher cross-elastisities they have. The problem is to find the "right" pattern, i.e., a theoretically sound explanation for the pattern that corresponds to the facts. To find the right pattern might not be so easy either, as Lodish (1982) points out:

> *"...some managers thought that if Entity A would have sales greater than reference, then Entity B's sales should also go up because of increased store traffic. Other managers thought just the opposite because of cannibalization between the two entities. ... Without consideration of these synergistic effects, many of the marketing activities would not be profitable" (Lodish 1982).*

Difficult or not, the combination of theory-based models and empirical data is powerful and is used in most fields of study to advance scientific knowledge. There is no reason why studies of promotion profits in retailing should not benefit from that combination.

## 1.7. Purpose and Delimitations

Sales promotion has now been described and the knowledge gap concerning the profit impact of retailer promotion has been identified. This section defines the research purpose, makes the necessary delimitations, and outlines the steps that will be taken in order to fulfill the purpose.

### 1.7.1. Research Purpose

The overall purpose of this study is to investigate the mechanisms by which retailer sales promotion influences store profits. In more specific terms, the purpose is to develop a model for measurement of the profits of retailer promotions. Along with the academic interest in structuring the thinking about the profits of retailer sales promotions, it is hoped that the present research shall help retailers to make sales promotion more profitable. The model is supposed to be useful as tool for the retail managers for planning and control of sales promotion.

A further specific purpose of this work is to use the promotion profit model developed to:

- Examine how retailer profits from sales promotions and depend on factors such as the deal size, gross margins, sales response and cannibalization, and the trade deal.

- Define how to maximize promotion profits, identify important determinants of the optimal deal size as well as to show how the profit-maximizing deal and the maximum profits depend on these factors.

- Demonstrate the difference between retailer-oriented promotion profit measurement and item-oriented promotion profit measurement, and how the measurement level affects promotion profits, optimal deal, and profits from optimal deal.

To clarify, it should be noted that the present research is not an attempt to evaluate whether sales promotion is used in a profitable way in retailing. The emphasis is on the development of a model for measuring promotion profits to understand how promotion profits are affected by a number of factors. The model developed here may then be used in future research to evaluate whether current usage of sales promotion is profitable or not.

Further, the study assumes a retailer perspective. This means that the interest here is the promotion profits for the retailer. Manufacturers' profits are thus not a topic of the present study. However, it will however be argued that efforts to maximize manufacturers' profits from sales promotion must be based on an understanding of the retailers' promotion profits.

### 1.7.2. Delimitations

The following four delimitations were made to make the study feasible: First, although the model developed may be useful also for other types of retailers, the emphasis is on the grocery retailer. Grocery retailing differs from many other types of retailing in that consumers make frequent purchases of baskets of relatively low priced products.

Second, the model is meant to be used to evaluate the promotion profits from individual promotions. This means that the model is limited to the measurement of the effect of rather small changes in the store's promotional mix. There are two reasons for this delimitation, one related to the intended use of the model and one more pragmatic or technically determined. The model is intended to measure the profitability of individual promotions, rather than of the entire promotion portfolio. This is the everyday problem faced by retailers and forms the basis for a systematic approach to deal design. Design of individual promotions is supposed to be done within the frame of the store's promotional strategy. On the pragmatic and technical side, the small changes are more frequent than changes in the promotional strategy, implying that models evaluating small changes would be more relevant as a tool in the daily operations. The low frequency of strategy changes also limits the usefulness of statistical models in the design of promotional strategy, though, statistical models can be used *ex post* to evaluate the effect of a change in promotional strategy.

Third, the model considers short-term effects. This excludes long-term and dynamic effects of promotion. The reason is that long-term effects can be assumed to be small for the type of promotions studied. If long-term effects are negative, as when future sales are cannibalized, the focus on short-term effects will give a positively biased view of promotion profits. It will later be argued that this effect should in general be small for the retailer. The negative bias that could occur as a consequence of positive long-term effects is also likely to be small since future store traffic hardly would be expected to be influenced.

Fourth, the model developed here is positioned as a research model. It is also aimed to be a basis for a decision support system for the retailer, while it is not a ready-to-use version of such a system. That would make implementation and information system aspects too dominant in this report. Although the model is not supposed to be an implemented system, it should be implementable. This means that it should use data available to the retailer, i.e., scanner data. While the level of detail must be possible to handle, it should not be too abstract. Another facilitator for implementation is that the model is easy to understand, ideally intuitively appealing.

### 1.7.3. Steps to Achieve the Purpose

Four steps lead to the fulfillment of the purposes described above. The first step is a review of previous research about sales promotion presented in the literature. The literature review serves as a platform for the second step, the model development, in that it presents the existing knowledge about sales promotion as well as identifies the missing pieces. The second step is the development of a model for measurement of promotion profits in retailing. The model consists of two parts: a sales response model and an income and cost accounting model. The third step is to use the model of promotion profits in a simulation study to illustrate the profit impact of sales promotion for hypothetical model parameters. The fourth and last step is to apply the model to empirical data from three product categories in a store.

In short, the steps can be described as:

- literature review
- analytical and theoretical work
- simulation
- empirical illustrations

## 1.8. Organization and Overview of the Report

This report is divided into eleven chapters and a list of references. Although the reader should proceed in a linear path through the chapters from chapter one to chapter eleven, it may be useful to note that there are groups of chapters with similar function. This structure is illustrated by Figure 1.2.

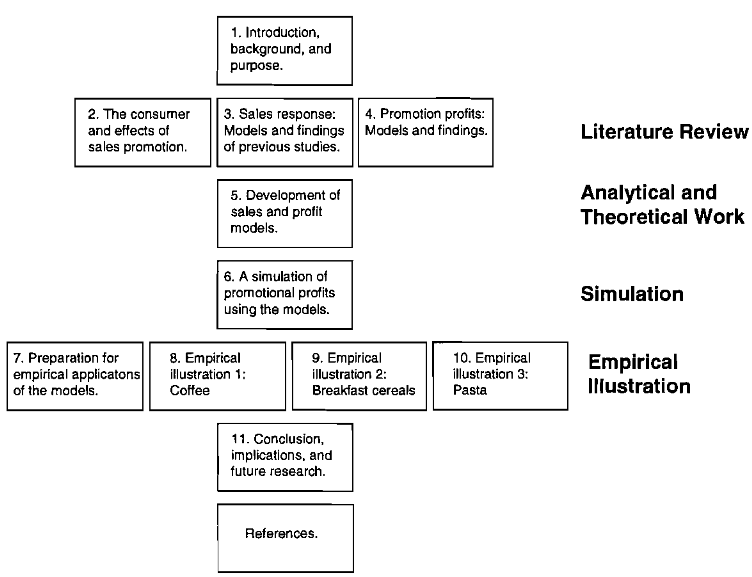


*Figure 1.2. Structure of the report.*

Chapter 1 identified the problem, defined and described sales promotion, and specified the purpose of the research as well as its delimitations.

The following three chapters present models and empirical results of previous research, mainly concerning sales promotions. Chapter 2 discusses the decisions the consumer makes when shopping as well as the effect sales promotion has on these decisions. The purpose of chapter two is to see the consumer behind the aggregate sales-response to sales promotion.

In Chapter 3 and Chapter 4, the retailer's perspective is assumed; Chapter 3 is devoted to promotional sales response models while Chapter 4 concerns sales promotions and profits. Promotion profits are defined, and methods for measuring and evaluating past promotions are reviewed. Then some models for planning future sales promotions are presented. It should be noted that some overlapping between these three chapters could not be avoided.

The overlaps between Chapter 2 and Chapter 3 are natural because these chapters examinine the same phenomenon from different perspectives. The parallels beteen the consumer's decisions and the retailer's sales are intended to contribute to our understanding of the promotional effects. The overlaps between Chapter 3 and Chapter 4 are different; they occur because all profit models contain sales response models.

Chapter 5 develops the model for planning and evaluating sales promotions. First, a sales response framework model is developed. Then, it is used in the development of a promotion profit model.

Chapter 6 illustrates the use of the promotion profit model using simulated model parameters. This chapter can be seen as a blueprint for analyzing the profits of sales promotions. Important in this chapter is the decomposition of promotion profits and the three levels at which the retailer can measure promotion profits.

The empirical part of this research starts with Chapter 7, which describes the empirical data used and discusses some methodological aspects of scanner data as well as some statistical considerations of great importance in the empirical work. Detailed descriptions of the procedures used in the empirical studies are given in connection with the presentation of the empirical results.

Chapter 8, 9, and 10 serve as illustrations of the methods as well as tests of the hypotheses and models.

Chapter 8 applies the model to the coffee category, probably the most analyzed product category. Chapter 9 and Chapter 10 are applications of the model to data from the breakfast cereals and the pasta categories. In these chapters, the method description is cut back to a minimum.

Chapter 11 summarizes the conclusions, discusses what can be generalized and what cannot, and identifies limitations of the research. Suggestions for further research are given as well as some managerial implications of the present work.

# 2. SALES PROMOTION AND THE CONSUMER

## 2.1. Introduction

This chapter provides a framework describing the decisions implicit in the consumers' shopping behavior. This framework of implicit decisions links consumer behavior and retailer's sales as will be seen in the next chapter. First there will be a brief discussion of the decisions consumers have to make when shopping. Then, the empirical evidence of the effect of sales promotions on the consumers' decisions is discussed.

Meal production is an important task in most households. The well-being or utility of the household is influenced by the organization of the meal production process. Meals must meet taste as well as nutritional requirements. To meet such requirements the meals not only have to be of good quality but also must ensure sufficient variation over time to avoid boredom. Differences in taste preferences among the household members and changing preferences complicate the planning of meals. The complex task of meal production takes place in an environment where time and money are often scarce resources.

The household uses groceries as inputs in the meal production process. Most occidental households purchase groceries in supermarkets as packaged and branded products. A meal usually consists of a number of products all of which have to be available at the consumption occasion. Logistics and inventory management considerations imply that the household purchases a bundle of products when shopping.

The prices of the individual products in the bundle that the household plans to purchase may vary across stores. The sum of the prices of the bundle of products may be minimized by purchasing each product in the store charging the lowest price. However, visiting a store costs time. The cost in terms of shopping time for obtaining the lowest prices for all products in the bundle can be considerable, especially when prices change over time. A household therefore visits few stores at each shopping trip and buys bundles of products in the stores visited. The purchases can be made faster when the shopper is familiar with the store and the brands in the store.

## 2.2. Implicit Decisions in Grocery Shopping

To explore the household's shopping behavior we use the following fictitious example. It is ten minutes past seven on a Wednesday evening and Sven Svensson has just paid for his purchases at the grocery store *ICA Baronen* in Stockholm. He bought two liters of low-fat milk from *Arla*, three cans of *Pripps Blå* beer, 0.358 kilograms of cured meat, one bottle of *Heinz* tomato ketchup, 500 grams of bread, a *Mars* candy bar, and the evening newspaper *Expressen*. What are the decisions implicit in this description? As we shall see, an ordinary shopping trip as the one described here implies a long list of implicit decisions made by the shopper. Our shopper has decided on: the timing of the shopping trip; the store where the purchases are made; to purchase beer on this shopping trip, specifically *Pripps Blå* in cans, and in total three cans. Similarly, he decided to buy candy—*Mars*, one bar—in this particular store on this shopping trip. The store choice, category choice, brand and variety choice, quantity choice, and timing decision are all implicit for all the products in Sven's shopping basket.

Did he really make all these decisions for each product? Probably not explicitly. As Sven is only a fictitious character we can follow his thoughts and actions in detail. This morning, as Sven had breakfast, he ran out of bread to toast. He also recognized that only a little milk was left in the last carton in the fridge and that he needed something for dinner. Thus, he decided to shop on the way home from work. Sometimes he does some shopping during the lunch break, but he does not like to have the things in the office the whole afternoon. Walking home through the city, he passed a couple of supermarkets, but he preferred to shop in one of the stores closer to his home. Then, he did not have to carry his purchase so far. He chose *ICA Baronen* over the *Konsum* one block away despite its higher price image mainly because he was on that side of the street. Also, he did not intend to buy very much.

Sven took a shopping basket and went into the store. He placed two liters of low-fat milk from *Arla* in the basket. He always buys low-fat milk, and *Arla* is the monopolist. He bought two liters because one liter is too little and three liters is too much both because it is too heavy and he might not consume all before it becomes sour. He found the bread and chose one with sesame; not that you taste much of the sesame, but he just liked it better. He bought one loaf because that usually is enough and there were no price deals this week in this store. Looking for something to have for dinner, he found that the cured meat was on sale. Why not make some spaghetti bolognese, Sven thought, and took a pack containing 0.358 kilograms. He knew that he had enough pasta at home so he did not buy any. However, he did not remember how much tomato ketchup he had left so he decided to buy some, just in case, and put a bottle of *Heinz* in his basket. Two bottles would obviously have been too much. He could need some beer, also. He put three cans of *Pripps Blå* into the basket without much reflection.

Sven would have bought coffee had there been a deal on *Classic* or *Gevalia*, because the *Classic* package he bought three weeks ago was only half full last time he made coffee. This week *Luxus* coffee was on sale in *ICA Baronen* but Sven did not buy it.

Sven buys the evening newspaper three or four days a week on average. When waiting in the check-out line, he was looking at the headlines and decided to buy the paper. As usual, he bought *Expressen*. There was a special display for *Mars* next to the check-out. Sven felt some hunger and could not resist buying some candy, because the pasta would take some time to prepare. He put one bar of *Mars* in his basket, paid, and went home. On the way home, eating the candy bar, he passed the tobacconist's where he often buys the evening paper. However, today he had already bought the paper in the supermarket.

This example illustrates how a consumer may behave and the decisions implicit in everyday behavior. Marketing scholars have built formal models of the store choice, the category choice, the purchase timing, the purchase incidence, the brand choice, and the purchase quantity. Some models focus on one of the decisions, while other models include more than one of the consumers' decisions. Relations between the decisions have also been modeled. The next section describes some of the models and findings about the consumer's decisions. The models and findings mostly concern sales promotion's impact on the consumer's implicit purchase decisions. The decisions are discussed in what may seem a hierarchical order beginning from the top. This order is chosen only to provide some structure for the discussion. However, it is not assumed that this is a hierarchy or that the decisions are made in any particular order or that the decisions are sequential.

## 2.3. Sales Promotion and the Store Choice

The store choice decision discussed here is that of where the household or consumer buys a basket of products, i.e., the choice of destination for a shopping trip. The consumer's decision where to buy a specific product is not treated here (see e.g., Grover and Srinivasan 1992, Kumar and Leone 1988 and Bucklin and Lattin 1992). That decision is covered in Section 2.4 about category choice and in the discussion about indirect competition among stores (Section 3.2.3).

The store choice decision or the consumer's store patronage decision translates into store traffic for the retailer. The consumer's store choice has a long-term and a short-term component. We shall discuss the long-term component first.

Ahn and Ghosh (1989) review store choice models and find that the consumers' retail patronage decision has been modeled in two similar ways. The first is a form of attraction model called spatial interaction model. This tradition dated back to 1962 when Huff published his seminal work.[7] In this type of model, the number of customers visiting a store is proportional to the store's attraction relative to the total attraction of all stores. The second type of model is the multinomial logit model. This type of model predicts the that probability that a consumer will choose a store is proportional to the individual's utility of this store relative to the individual's utility of all stores. Mathematically these models are very similar. The difference between the models is mainly conceptual. The attraction type models are calibrated on aggregate data on the number of shopping trips while the logit models are calibrated on individual choice data. (See also Craig, Ghosh, and McLafferty (1984) for an excellent review of these models.)

Ahn and Ghosh (1989) extend the store choice models to overcome the independence of irrelevant alternatives (IIA) assumption of the attraction and logit models. They propose that the store choice is a hierarchical decision process where the consumer first makes a choice of shopping center and then, within this shopping center, makes the store choice. The nested logit model is used to model the sequential hierarchical decision. They found that the nested logit model performed slightly better than the multinomial model on data from a choice experiment on MBA students where the setting was clothes shopping.

Fotheringham (1988) also argues that store choice is a hierarchical process since the consumer cannot evaluate all information simultaneously. If choice is hierarchical, multinomial logit models are biased.

According to Engel, Blackwell, and Miniard (1986), location is the most important factor associated with store choice. They point out that the determinants of the store choice decision may vary by product class but list the following ten attributes that are usually salient.

- location
- nature and quality of assortment
- price
- advertising and promotion
- sales personnel
- services offered
- physical store attributes
- nature of store clientele
- store atmosphere
- post-transaction service and satisfaction

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[7]Huff, D.L. (1962), "Determination of Intra-urban Retail Trade Area," Real Estate Research Program, University of California, Los Angeles.

Kahn and Lehman (1991) study how the assortment enters the consumer's store choice decision. They find that the consumer's most preferred item is important when evaluating assortments. However, consumers also want flexibility for future choice. The larger the number of unique and acceptable items the assortment offers, the better the assortment. An assortment consisting of a large number of similar or unacceptable items, on the other hand, makes the consumer's choice unnecessarily time-consuming.

Price is also an important factor in the store choice. Mowen, Wiener, and Young (1990) used a conjoint experiment to investigate the importance of sales tax differences for store choice. Not surprisingly, they found that stores that did not have to charge a sales tax had an advantage over stores that had to charge the tax.

Malhotra (1986) found the following eight characteristics important for store choice:

- quality of merchandise
- variety and assortment of merchandise
- returns and adjustment policy
- service of store personnel
- fair prices
- convenience of location
- store layout
- credit and billing policies

Although the store choice decision occasionally can be a high involvement decision, Engel, Blackwell and Miniard (1986) state that "*the consumer usually has well-formed evaluative criteria and shops at the most convenient store as long as the store continues to satisfy those criteria*" (p.492). The well-formed evaluative criteria are often referred to as store image.

According to Steenkamp and Wedel (1991), store image has in previous research been found to be related to store patronage, store loyalty, and the share of the household budget spent in the store.

Mazursky and Jacoby (1986) define store image as:

> *1. a cognition and/or affect (or set of cognition and/or affects)*
>
> *2. which is (are) inferred*
>
> *3. either from a set of ongoing perceptions and/or memory inputs attaching to a phenomenon (i.e., either an object or event such as a store, a product, a "sale", etc.)*
>
> *4. and which represent(s) what that phenomenon signifies to an individual.*

How is the store image formed? Louviere and Gaeth (1987) propose a hierarchical model of consumers' evaluation of retail facilities. The overall judgment of the retail facility is modeled as a weighted mean of the judgments of four intermediary macromeasures (1) price, (2) selection, (3) convenience, and (4) quality. Each of these macromeasures is in turn a composite of a number of specific store attributes.

Price image is an important part of the overall image of the store. Cox and Cox (1990) state that consumers often use perceptions of the store's price level. They say that although little is known about how such perceptions are formed, the managerial retailing literature suggests that supermarket managers identify some key products on which they must be price competitive to project a low price image for the store. Cox and Cox find that the presentation of prices in advertisements influences consumers' price image of the store. Consumers perceive the store's overall price level to be lower when advertised prices are presented as reductions from a higher previous price. Thus, sales promotion may be important for the store's price image.

In a theoretical study, Feichtinger *et al.* (1988) modeled the price image formation process as a function of observed prices. In their model, the consumer's store choice is dependent on the store's price image. The purchase amount, however, depends on the actual prices encountered when visiting the store.

Now we have mainly considered the long term component of store choice and seen that sales promotion may be involved in the creation of store image. What determines the store choice in the short-term and does sales promotion affect the short-term store choice? That is what the next paragraphs will deal with.

In a Swedish study on grocery shoppers' store choice, Hernant (1992) found that 37 percent of the customers had chosen to visit that specific store because it was located close to the customer. Almost one out of five respondents said that they had chosen that store out of habit. Nine percent had chosen the store because they happened to pass by. Only three percent answered that they had chosen the store to take advantage of a price deal, while four percent had chosen the store because they wanted to buy a special product. Five percent had made the store choice dependent on the assortment.

Hernant's findings indicate that sales promotion may not be very important for the consumer's store choice.

Bucklin and Lattin (1992) studied competition among stores using scanner panel data for liquid detergents. They found no significant store traffic effects of retailers' marketing activities for detergents. In other words, the consumers' store choices were not influenced by the sales promotion.

Blattberg and Neslin (1990) argue that the effect on store traffic of promotions for single products is likely to be very small since hundreds of products are on sale every week.

Walters and Rinne (1986) found that store traffic was generally unaffected by portfolios of loss leaders (i.e., products are sold at negative gross margins). The store traffic effect of double couponing was also insignificant in all stores. Walters (1988) studied promotional effects on store traffic in six product categories. Promotions in four of the categories were found to have significant positive effects on store traffic. Walters and MacKenzie (1988) found that most loss leader promotions did not affect store traffic. They also found that neither double couponing nor in-store price specials had any effect on store traffic.

Julander (1984) states that the failure of promotional activities to affect store traffic does not imply that they are without effects on store traffic. Their effects might be overshadowed by competitors' actions. Also, when using historical data, failures to find effects of sales promotion on store choice may result from insufficient variation as well as lack of effects.

In summary, the consumer's store choice seems to consist of both long-term and short-term components. The long-term component gives the consumer's choice set, where store location, perceived price level, and assortment are the most important factors. Store location is also the most important factor for the short-term component of store choice. Sales promotion has been found to have limited effect on the consumer's store choice.

## 2.4. Sales Promotion and the Category Choice

One of the basic tasks the consumer has is how to allocate his resources. In other words, the consumer has to decide which products to consume. In micro-economics, this is modeled as an allocation problem where the consumer maximizes his utility subject to a budget constraint (e.g., Varian 1984). The consumer may then use promotions to come to a higher utility level. In reality, finding the optimal allocation and optimizing the usage of promotions are very difficult decision problems (see Meyer and Assuncao 1990). However, the consumer's allocation of resources gives his purchase rate of the product. The purchase rate enters marketing models of the timing of the consumer's purchases.

The consumer's product category purchase decision has, in marketing research literature, been modeled in two ways: (1) as a decision of *when* to buy the category, or (2) as a decision of *whether or not* to buy the category during a specified time period. The models of *when* to buy are referred to as *purchase timing* models while the the models of *whether or not* to buy are referred to as *purchase incidence* models.

Examples of models of purchase incidence are the Poisson distribution, the gamma distribution, and the NBD model (negative binomial distribution). Recent work has used the Erlang-2 distribution, where the probability of purchase incidence is dependent on the time since the last purchase (Blattberg and Neslin 1990). (See also Uncles and Ehrenberg

1990, for an application of the Dirichlet model on coffee purchases at *Safeway*.) Dalal *et al.* (1984) developed a purchase incidence model that can handle arbitrary heterogeneity among consumers' purchase rates.

Wheat and Morrison (1990) showed in a recent study that purchase incidence models are preferable to purchase timing models. The reason is econometrical; in a purchase timing model, individuals with long interpurchase intervals are usually excluded from the sample for two reasons. First, the number of observations for an individual is smaller the longer the average interpurchase time, and the number of observations may be too small to allow estimation. Second, the length of the last, interrupted, interpurchase period is unknown. This makes estimates of the interpurchase time biased. Including the people with very low purchase rates in the sample makes assessment of the reliability and goodness of fit difficult. Still another reason is that the purchase timing for most products is dependent on the timing of the shopping trip.

Another problem with interpurchase time models is the difficulty in including marketing variables. However, Gupta (1991) developed a model of households' interpurchase times that includes marketing variables in a parsimonious way. He found that feature advertising and display both significantly increased the purchase rate, and thereby shortened the interpurchase time. More remarkable is that he found that price cuts had no significant effect on the consumers' interpurchase time. Gupta forwards the explanation that unless the price cut is advertised or featured, only those who intended to buy the product are likely to recognize the deal. In the coffee data set Gupta used, he found that large household inventories lead to longer interpurchase time.

The positive relation between household inventory and interpurchase time was also observed by Neslin, Henderson, and Quelch (1985). Using an interpurchase time model, they found that sales promotion does not have much impact on the interpurchase time. Gupta (1988) also modeled interpurchase time as a function of sales promotion. Gupta found that 14 percent of the brand sales increase due to promotion comes from purchase acceleration. Chiang (1991) modeled purchase incidence as a function of sales promotion, and found that 13 percent of the brand sales increase as a result of promotion is due to increased purchase incidence. All three studies used scanner panel data for coffee.

Helsen and Schmittlein (1993) used hazard rate models to estimate the effect of sales promotion on interpurchase time for saltine crackers. They found that sales promotion decreased the time between purchases.

Vilcassim and Jain (1991) showed the importance of unobserved heterogeneity among consumers when modeling interpurchase time. They found that price, display, and family size variables explained 14 percent of the variance in repeat purchase rate for saltine crackers. The remaining 86 percent variation was attributed to unobserved heterogeneity among the consumers. Also using salt cracker data supplied by IRI (Information Resources Inc., a Chicago based subsidiary of Brad and Dunstreet), Bucklin and Lattin (1991) found promotional activities to have an impact on purchase incidence. Promotional activities had the most impact on the purchase incidence of consumers in the opportunistic state, i.e., consumers who had not planned to buy the product category before entering the store. They also found household consumption rates and inventories important determinants of purchase incidence.

Consumers make their grocery purchases when they visit grocery stores. When visiting a supermarket, the consumer usually buys a bundle of products. The implication of this is that the exact purchase timing for most products is dependent on the timing of the shopping trip, rather than the other way around. This was also pointed out by Wheat and Morrison (1990) as a reason why models predicting whether or not a consumer makes a purchase are better than interpurchase time models.

Many products used daily in the household can be consumed over a long period. Examples are detergents, soap, flour, sugar, oil, and salt. Consumers have low purchase frequencies for these products (Julander 1984). When the purchase frequency is much lower than the frequency of shopping trips, the household has several purchase occasions for the product when the stocks approach the repurchase level. In many product categories, the frequency of promotion is high compared to the purchase frequency. This implies that consumers can make their purchase decision partially dependent on the availability of promotions for a preferred brand when the household's stocks are running low. They may shop from deal to deal, to use the terminology of Blattberg and Neslin (1990).

To summarize, when household inventories are high, the probability of purchase incidence is low. Sales promotion shortens the interpurchase time, and thus, increases the probability of purchase incidence. It is better to model the consumer's category decision as whether or not to buy than when to buy, because the purchase timing is largely dependent on the occurrence of a shopping trip.

## 2.5. Sales Promotion and the Purchase Quantity Choice

When deciding to buy from a product category on a shopping trip, the consumer has in some sense made the most basic purchase quantity decision, i.e., the decision to buy more than zero units. Having decided to buy a product category the consumer has to decide how much to purchase. This decision may involve choosing a package size and a number of units to buy of that size.

The quantity that the consumer chooses to buy depends on the household's rate of consumption of the product and the interpurchase time. A promotion that lowers the unit price could make the consumer buy a larger quantity of the good. If the household's inventory holding costs are low, it could make economic sense the household to take on extra inventory of the product (Blattberg, Eppen, Lieberman 1981). Julander (1984) points out that if the availability of the product in the consumer's home increases the consumption, this strategy is less attractive for the household that seeks to minimize the cost of its consumption bundle. Further, the consumer would not use sales promotion to build inventories of perishable product.

The purchase quantity decision has not yet been subject to much study. Some pioneering work has been done by Neslin, Henderson, and Quelch (1985), Gupta (1988), Chiang (1991), Krishnamurthi and Raj (1988, 1991), and Krishnamurthi, Mazumdar, and Raj (1992). All used scanner panel data for coffee.

Chiang (1991) found that promotion induced increases in purchase quantity represented 6 percent of the brand sales increase due to promotion. Gupta (1988) found the purchase quantity's share of the increase to be 2 percent. Neslin, Henderson, and Quelch (1985) found that increased purchase quantity is more important than shortened interpurchase time in purchase acceleration due to sales promotion. They defined purchase acceleration as shortened interpurchase time or increased purchase quantity, or both.

Krishnamurthi and Raj (1988) found that only the price of the chosen alternative determines the consumer's purchase quantity while prices of other alternatives have no impact on the purchase quantity. Krishnamurthi and Raj (1991) found that the purchase quantity elasticity of brand loyal consumers is higher than the purchase quantity elasticity of brand switchers.

In summary, there is evidence that sales promotion may increase the consumer's purchase quantity.

## 2.6. Sales Promotion and the Brand Choice

The consumer's brand choice is the favorite modeling object in the consumer behavior and marketing literature. Bass (1974) viewed the consumer's brand choice as stochastic. Bass *et al.* (1984) investigated the order of the brand choice process. They found that consumers' choices of soft drinks are zero-order, i.e., a consumer's choice probabilities are the same in each period. Givon (1984) used a stochastic brand choice model to study consumers' variety-seeking through brand-switching.

Lattin (1987) found that consumers seek variety on some product characteristics but are loyal to other characteristics. The product category was soft drinks. Bawa (1990) found the consumer's purchase history to explain the consumer's variety-seeking and inertia in the brand choice. The product categories Bawa studied were facial tissue, paper towels, and ready-to-eat cereals. Dodson *et al.* (1978) found sales promotion to increase the consumer's choice probability of the brand. They also found evidence that the retraction of the deal had a negative effect on the consumer's repeat purchasing of that brand. Dodson *et al.* used data for margarine and flour.

Corstjens and Gautschi (1983) reviewed formal (individual level) choice models in marketing. These models are derived from four theories: the neoclassical economic theory as extended by Lancaster, the risk-preference theory, the strict utility model, and the random utility model. The strict utility model and the random utility model are the most important brand choice models. The logit model is an example of a model that can be interpreted as a strict utility model or as a random utility model.

Guadagni and Little (1983) used a logit model to measure the effect of sales promotion on brand-switching. The model was tested on a set of scanner panel data for coffee. They found that household specific variables for brand and size loyalty were important determinants of variation across households in brand choice. The household-specific variables accounted for about one quarter of the variance in the time-series, cross-sectional data set. Sales promotion was found to explain another quarter of the variance. They showed that the logit model provides a parsimonious way of describing the consumer's brand choice.

Bucklin and Lattin (1991) modeled consumer's brand choice of saltine crackers using a multinomial logit model. Sales promotion had a significant impact on the consumer's brand choice when the consumer was in the opportunistic state. Vilcassim and Jain (1991) also found sales promotion to affect consumers' choice of saltine cracker brand. They found that the effect of sales promotion to be asymmetric between brands. Asymmetric switching between brands was also modeled by Allenby and Rossi (1991) who used margarine data to illustrate their consumer-level, brand choice model.

Gupta (1988) and Chiang (1991) both used the multinomial logit model to model the consumer's coffee brand choice as a function of sales promotion. Gupta found that brand switching accounts for 84 percent of the brand's incremental sales due to sales promotion. Chiang estimated the same figure to be 81 percent.

Krishnamurthi and Raj (1988, 1991) modeled the consumer's choice of coffee brand as a function of sales promotion. In their 1988 article, they found that the brand choice, in contrast to the quantity choice, is dependent on the attributes of all the choice alternatives. In 1991, they showed that the difference between brand loyals' and brand switchers' elasticities in the brand choice decision is larger than the overall difference in their elasticities. This is because the brand loyal consumers' purchase quantity elasticity is higher than that of the brand switchers.

Moore and Olshavsky (1989) found that very deep price discounts (75 percent) lead to fewer consumers choosing the brand than a moderate (30 percent) price discount when consumers were not familiar with the brand. When the consumers were familiar with the brand, the deep price discount attracted more consumers than the moderate price discount. The product was white long sleeve men's dress shirts.

In consumer behavior models in marketing, price is often included as an attribute that the consumer uses when forming an attitude toward the brand. The consumer chooses the brand for which he has the highest (most favorable) attitude. A promotion leads to an improved attitude toward the brand and thereby improves the brand's position in the brand choice process of the consumer.

The consumer's brand choice can come out as a repurchase of the brand last bought or as a purchase of another brand. The latter is referred to as a brand switch.

Closely related to brand-switching as a consequence of promotions is the impact of promotions on repeat purchasing. This is one link between short-term effects and long-term effects of sales promotion. It has been suggested that two different psychological processes operate simultaneously in connection with the impact of promotions on repeat purchasing. On the one hand, classical conditioning is thought to imply that the purchasing of a product in itself leads to a higher repurchase probability. Blattberg and Neslin (1990) call this the *purchase effect.* On the other hand, the attribution theory implies that the consumer's attitude toward the brand may be negatively affected by a purchase when the product is on deal. This is dubbed the *promotion usage effect* (Blattberg and Neslin 1990). Studies reporting decreased repurchase probabilities after promotional purchases have failed to recognize the importance of measurement of this phenomenon on the individual level (Blattberg and Neslin 1990).

In summary, the literature provides ample evidence that sales promotion affects the consumer's brand-choice decision.

## 2.7. Combining the Decisions

Blattberg and Neslin (1990) recognized a trend toward modeling efforts combining purchase incidence, purchase quantity, and brand choice models. Whether the decisions should be regarded as independent or correlated is being debated and as yet unresolved.

Neslin, Henderson, and Quelch (1985) model interpurchase time and purchase quantity as functions of sales promotion and previous inventory (i.e., the consumer's inventory directly after the previous purchase). Further, they investigate the possible impact of interpurchase time on the consumer's purchase quantity. They find this effect to be small in their sample.

Wagner and Taudes (1986) model brand choice and purchase incidence. Their integrated model was tested on panel data for detergents and was found to outperform simpler models.

Currim and Schneider (1991) outline five expected purchasing strategies that consumers might use as response to sales promotion. The consumer may exhibit: (1) brand preference without purchase acceleration, (2) promotion-motivated brand-switching without purchase acceleration, (3) promotion-motivated brand-switching and purchase acceleration, (4) promotion-motivated purchase acceleration of preferred brand, and (5) switch to other brand, not motivated by promotion. Their empirical illustration (scanner panel data for 200 heavy users of coffee) provides support for four of the five hypothesized purchase strategies.

Gupta (1988) developed a model for purchase timing, brand choice, and purchase quantity. The three decisions are independent in Gupta's model. Chiang's (1991) model differs from Gupta's in that Chiang models purchase incidence rather than interpurchase time. It also differs in that Chiang regards the consumer's three decisions as interrelated.

Krishnamurthi and Raj (1988, 1991) and Krishnamurthi, Mazumdar, and Raj (1992) model the consumer's purchase quantity decision and the brand choice decision. They regard the quantity decision as dependent on the brand choice.

Bucklin and Lattin (1991) model purchase incidence and brand choice using a nested logit approach, where the probability of purchase incidence is dependent on the maximum expected utility of the brand choice. Vilcassim and Jain (1991) also model purchase timing and brand choice as correlated decisions.

Bucklin and Gupta (1992) segment households buying liquid laundry detergent by their sensitivity to sales promotion. They model the brand choice and purchase incidence decisions using a nested logit approach. Sales promotion is found to affect some households' purchase incidence decision and others' brand choice decision. More specifically, they found that households whose purchase incidence is accelerated by sales promotion do not switch brands. Other households, whose brand choice decisions are affected by sales promotion, do not accelerate their purchases because of the sales promotion.

Dalal *et al.* (1984) modeled the purchase incidence and brand choice. Their model is very general and assumes neither dependence nor independence between the decisions.

Keng and Ehrenberg (1984) modeled the store choice and the brand choice using the NBD model. They found that the individual consumers tend to spread their purchases of the product to over stores and over brands in proportion to the market shares of the products and the stores.

Grover and Srinivasan (1992) investigate the multiple effects of sales promotion using a brand choice model, a store choice model, and a purchase quantity model. The decisions are dependent in their framework.

In summary, there is a trend toward modeling two or more of the consumer's decisions simultaneously. However, there is no model that has integrated all four decisions.

## 2.8. Dynamic Effects of Sales Promotion

The dynamic effects of sales promotion are of a different kind than intertemporal effects or lags caused by inventory effects of sales promotion. Dynamic effects of sales promotion here refer to its impact on the effectiveness of sales promotion in later periods.

Winer (1986) proposed and found empirical support for a model where demand is a function of current observed price and the consumer's internal reference price. The data set used in the empirical test was panel data for heavy users of coffee. The model implies that frequent sales promotions make the deal price to the consumer's reference price. The regular price is then regarded as a premium price.

Lattin and Bucklin (1989) built a model incorporating reference effects of sales promotion. They model the consumer as perceiving a brand as either promoted or nonpromoted. If the consumer perceives the brand as promoted, i.e., a brand that regularly is offered on a deal, the consumer is unlikely to purchase at regular price. Sales promotions for brands that are perceived as nonpromoted are regarded as purchase opportunities. Empirical support for the model was found in a test using scanner panel data for regular ground coffee.

Jacobson and Obermiller (1990) stress the importance of consumers' expectations of future prices and promotions. Using grocery store data for canned tuna, they found empirical support for their serial correlation model of price expectation formation.

Kalwani and Yim (1992) found that the promotion frequency and the depth of the price discounts have impact on consumers' price expectations. The consumers' price and promotional expectations were found to affect brand choice. Kalwani and Yim conducted an experiment with 200 undergraduate students as respondents. The product stimuli were two hypothetical brands of liquid laundry detergents.

Krishna, Currim, and Shoemaker (1991) used a survey to study consumers' perception of promotional activity. They found that about half of the respondents were reasonably accurate in their perception of the deal frequency. The expected deal frequency was found to be positively correlated with the perceived past deal frequency. The accuracy of recall of sale price was better the higher the frequency of promotion.

Bawa, Landwehr, and Krishna (1989) found that the in-store marketing environment is correlated with consumers' sensitivity to sales promotion. Consumers tended to be more price sensitive in stores with a high price variability. Bawa *et al.* (1989) used panel data for regular ground coffee in their study.

Krishna (1991) showed that the price which consumers are willing to pay is correlated with the actual deal frequency of the brand. However, the perceived deal frequency was more important for consumers' willingness to pay than the actual deal frequency. She used a computer-simulated experiment with 159 undergraduate and graduate students who made 12 weekly purchase decisions for two hypothetical brands of soft drinks. Using a similar computer-simulated shopping experiment, Krishna (1994) showed that consumers who have information about future prices behave differently from consumers without such information.

Bolton (1989) studied the relationship between market characteristics and promotional price elasticities. Promotional price elasticity is found to be positively correlated with feature advertising activity in the category. The display activity in the category and for the brand were found to be negatively correlated with the elasticity. The correlation between category price activity and elasticity was insignificant. The study was conducted on store-level scanner data for three brands in four categories in 12 stores. The product categories were waffles, bleach, tissue, and ketchup.

Raju (1992) studied the determinants of variability in product category sales. Using scanner data from 63 homogeneous product categories Raju found that the magnitude of deals increase the variability in category sales. The frequency of deals had the opposite effect, i.e., more frequent deals lead to less variability in category sales. Raju did not study the effect on variability of brand sales.

Helsen and Schmittlein (1992) found that the deal frequency is positively correlated with the price sensitivity. They found forward buying to be more common in product categories with high mean depth-of-discount. The study employed scanner panel data for ketchup, canned tuna, margarine, toilet tissue, and peanut butter.

Summarizing the literature on dynamic effects of sales promotion, it seems that the frequency of sales promotion and the size of the price deals have an impact on the consumers' deal sensitivity. The sign of the dynamic effects has not been conclusively determined. The correlational nature of the studies implies that the causal direction between promotional sensitivity and promotional pattern cannot be determined. The implication for the retailer of dynamic effects of sales promotion is that the consumer response to sales promotion cannot be assumed to be constant. Retailers trying to improve the effectiveness of their sales promotion would consequently need to constantly monitor, or track, the sales response.

## 2.9. Summary

This chapter started with an informal illustration of the shopper's decisions before and during a shopping trip. These decisions have been modeled formally in earlier research in: (1) store choice models, (2) purchase incidence and interpurchase time, (3) purchase quantity models, (4) brand choice models and (5) models of two or more decisions. Previous research has found that sales promotion may affect all four decisions. However, its importance varies across the four decisions and across products. The weakest effects of sales promotion were found for the store choice.

There is a trend toward an integrated modeling approach of the consumer's decisions. The integrated modeling efforts described in the literature have modeled two or three of the consumer's decisions. None of the models has integrated all four consumer decisions.

Dynamic effects of sales promotions have been found in previous research. The consumers sensitivity to promotion may depend on the actual and perceived promotional pattern. Changing the promotional pattern may thus lead to changing promotional effectiveness.

# 3. PROMOTIONAL SALES RESPONSE

## 3.1. Introduction

This chapter examines the outcome of the consumers' responses to sales promotion from a retailer's point of view. It starts with a discussion about the sources of a retailer's incremental item sales and present some empirical findings from previous research. Thereafter, different modeling approaches are discussed and some important promotional sales-response models used in previous research are presented. These models include brand-sales models, market-share models, category-sales models, store-sales models, and store-traffic models.

## 3.2. Sources of Retailer's Incremental Item Sales

Previous research has shown that the impact of sales promotion on the promoted brand's sales in a store is often substantial (e.g., Chevalier 1975; Curhan 1974; Holmberg 1992; Wilkinson, Mason, and Paksoy 1982). According to Blattberg and Neslin (1990), retailer incremental brand-sales volume comes from four sources:

- other retailers
- competitive brands
- purchase and quantity acceleration
- increased consumption

This classification of the sources of incremental sales volume provides a good framework for analyzing promotional effects. However, we need to modify the classification slightly to make the sources mutually exclusive and collectively exhausting.

Since total consumption can be regarded as fixed, increased consumption of the promoted item must logically come from other items and product categories. Thus, sales promotion for an item in a particular store may steal sales from other items during the promotional period, from its own future sales, as well as from other items' future sales in that store and other stores. The sources can be seen as relating to the three dimensions product, time, and store, as illustrated by Figure 3.1.

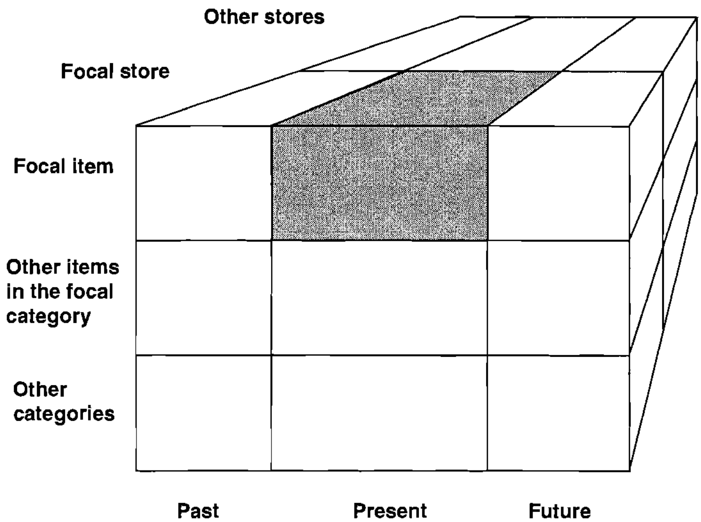


*Figure 3.1. Sources of retailer's incremental item sales volume.*

Figure 3.1 shows a 3×3×2 cube. The shaded compartment represents the present sales volume of the focal brand in the focal store. The remaining 17 compartments represent possible sources of incremental sales volume. Assuming that the total possible sales are fixed, sales promotion may move sales from one compartment to another. We shall examine these effects one at a time, concentrating on the question *where* the retailer's incremental sales of the promoted item come from. In other words, we are here concerned with the substitution effects. The possible positive effect on the retailer's sales of other products through increased store traffic was treated earlier, in the discussion about the consumer's store choice.

### 3.2.1. Other Brands

The retailer's sales increase of a promoted product may come from other brands. Figure 3.1 suggests that the promoted brand may steal from other brands' past, present, and future sales in that store as well as in other stores. What we will discuss here is the effect on the store's present sales of other brands in the same category.

Using an in-store experiment, Chevalier (1975-76) investigated substitution patterns caused by special display. The increase in category unit-sales was found to be slightly larger than the increase in brand unit-sales on average. Chevalier concludes that most of the increased unit sales of the item due to special display come from additional category sales.

Wilkinson, Paksoy, and Mason (1981) reported elasticities and cross-elasticities from an in-store experiment. Special displays were found to have a strong positive impact on the promoted brand's sales and significant negative impact on other brands' sales. The product categories studied were pie shells, rice, apple juice, and soap.

Kumar and Leone (1988) found price deals, feature advertising, and special displays significant determinants of the promoted brand's sales. The only significant cross-elasticities were those for price deals. Feature advertising and special displays did not have any significant impact on sales of other brands than the promoted.

Blattberg and Wisniewski (1989) found asymmetric patterns in the promotional cross-elasticities. When higher-price and quality brands are offered on a deal, they steal sales from other high-priced brands and from lower-priced brands. Lower-priced brands, on the other hand, were found to steal sales only from other lower-priced brands. Blattberg and Wisniewski used store level scanner data for flour, margarine, bathroom tissue, and canned tuna.

Bemmaor and Mouchoux (1991) studied short-term deal-price elasticities using an in-store experiment. They found that while the direct elasticities ranged between 2 and 11 in absolute value, cross-elasticities fell in the range from 2 to 2.7.

Walters (1991) found that price promotion for one brand in a store reduced sales of other brands in the same category. The product categories were spaghetti, spaghetti sauce, cake mix, and cake frosting.

To summarize, previous research has found that sales promotion for one brand may have negative effects on sales of other brands in the product category. The importance of such negative cross-effects may vary across product categories and between promotional tools. Asymmetries in cross-elasticities between products within a category have been found in several studies.

### 3.2.2. Other Categories

The impact of sales promotion in one product category on sales of other categories in a store has received little attention in previous research. The category management concept, as a specific example, category space management (see e.g., Bultez and Naert 1988) assumes that space redistribution within a product category has negligible effects on other categories.

No study was found that explicitly dealt with the promotion-induced substitution across product categories within a store. The extent of such substitution is unknown, but at least two reasons speak for its existence. First, product categories are often narrowly defined, which places fairly close substitutes outside the category. For example, when a product category is defined as regular ground coffee, then decaffeinated coffee, coffee beans, and instant coffee are not part of the category. However, substitution could occur. Second, the household's total consumption of grocery products is restricted by biological and pecuniary constraints. Incremental consumption and purchases of one category would thus have to imply decreased consumption and purchases of other categories.

One piece of evidence for cross-category substitution was provided by Walters (1988) who was surprised to observe a negative relationship between promotional sales of notions and unrelated sales in a study using data from two fabric stores. The study mainly focused on the substitution within categories and the positive effect on other categories' sales expected from complementarity and from the effect on store traffic.

Walters (1991) investigated the effects on sales promotion on sales of complementary categories. He found significant positive effects on spaghetti sales when spaghetti sauce was offered on a deal and vice verse. The results were replicated on the cake mix and cake frosting pair of complementary product categories.

In summary, the substitution effect between product categories in retail stores has been neglected in previous research. Research investigating the extent of such substitution, as well as the complementarity among product categories, is needed.

### 3.2.3. Other Stores

Some of the promotion-induced sales increase of an item in one store may come from other retailers. As Keng and Ehrenberg (1984) note: *"Most customers of a given chain also buy the product elsewhere."* Empirical evidence of such interstore competition was provided by Kumar and Leone (1988) who reported that price dealing in one store affected sales of that brand and sales of competing brands in closely located stores. They also found that feature advertising and special display in one store had negative effects on the same brand in other stores. The product category was disposable diapers.

Walters (1991) found some evidence that a price deal on a brand in one store reduced sales of that brand and its close substitutes in another store. However, Walters hesitates to accept the evidence.

Grover and Srinivasan (1992) found that the promotional attractiveness of a product category in one store significantly affected that store's share of the sales in that category. The product category used in the study was coffee.

Bucklin and Lattin (1992) note that store competition comes in two flavors. The direct component of store competition is the effect on the consumer's store choice and leads to reallocation of store traffic. The indirect component of store competition is the effect on category sales in another store in the absence of any direct effect. The indirect effect occurs because consumers are not loyal to a single store but rather shop regularly in a set of stores. A promotion in one store may then increase the consumer's probability of purchase incidence when visiting that store. If the increased probability of purchase incidence results in a purchase, then the consumer's probability of purchase incidence is decreased in subsequent periods when other stores are visited.

The concept of indirect store competition integrates the concept of cross-shopping and the purchase acceleration concept. Indirect store competition is more subtle than direct store competition, but might be more important. Bucklin and Lattin (1992) found no significant direct effect but observed significant indirect competition in their empirical illustration using data on liquid laundry detergents.

In summary, the literature shows that sales promotion in one store may reduce other stores' sales of that product and its substitutes. Such store competition can be either direct, affecting store traffic, or indirect, affecting the consumers' purchase timing. The indirect effect might be the more common.

### 3.2.4. Other Periods

Sales promotion may cause substitution of current sales for other periods' sales. Note that shifts in sales may be due to changes in the timing of the consumption, inventory build-up, or a combination of the two.

Purchase acceleration is the shift of sales volume from future periods to the present period. Previous research has found that the purchase acceleration effect exists at the consumer level (e.g., Blattberg and Neslin 1990; Neslin, Henderson, and Quelch 1985). It seems that consumers do take advantage of promotions to build inventories. A post-promotional dip, or trough, would consequently be expected. Neslin and Shoemaker (1983) produce a post-promotional dip in sales in a model which simulates consumer behavior. However, studies using sales data have seldom observed any trough after the promotion period (Blattberg and Neslin (1990). The existing evidence comes from panel data, i.e., individual level data.

The high frequency of promotions may mean that the inter-promotion period is too short for sales to return to their normal level. Doyle and Saunders (1985) suggested that promotions might be anticipated, causing a pre-promotion dip, which would make the post-promotion dip difficult to detect. Blattberg and Neslin (1990) note that if a promotion does accelerate households' purchase quantity, then the promotion will steal sales from several periods. That would make the post-promotional dip difficult to observe.

Another explanation for the difficulty in observing troughs after sales promotions when using store level data is that other brands' and other stores' sales in future periods are affected. The effect on the store's future sales of the brand is diluted by brand- and store-switching, making the effect difficult to measure. The exception would be a store with a large proportion of store loyal customers. In that case, the store would steal mostly from its own future sales. Such a retailer may observe post-promotional troughs, provided that not a large number of the store loyal customers shop from deal to deal.

In summary, although sales promotion leads to household level substitution of current purchases for future purchases, the effect for a retailer might be small.

## 3.3. Response Modeling: Direct and Indirect Approach

Response models or demand models constitute a special class of predictive models used in marketing (Naert and Leeflang 1978). The purpose of a response model is to relate changes in marketing variables (and other decision and environmental variables) to changes in demand. Response models are important for evaluating the effectiveness of past promotions and for making conditional predictions for future promotions.

The performance measure in a sales response model is a measure of demand. Sales response models may be classified according to the level of demand. Three levels of demand are usually recognized. Product class demand (or primary demand) refers to the demand for a product class and is modeled by *product-class sales models*. The second level of demand (secondary demand) is demand for a particular brand. This is modeled in *brand-sales models*. The third level is the relative number of units that is sold by a particular brand relative to the total number of units sold in the product class. This is modeled in *market-share models*. The relationships between the different levels of demand are given by the following equations.

$$Q_{jt} = \sum_{i=1}^{I_j} q_{ijt} \tag{3.1}$$

and

$$m_{ijt} = \frac{q_{ijt}}{Q_{jt}} \tag{3.2}$$

where,

| | | |
|---|---|---|
| $Q_{jt}$ | = | total demand in product class $j$ period $t$ |
| $q_{ijt}$ | = | demand for brand $i$ in product category $j$ period $t$ |
| $m_{ijt}$ | = | market share brand $i$ in product category $j$ period $t$ |
| $I_j$ | = | number of brands in category $j$ |

The definition of market share implies that if we know demand at two of the three levels, then demand at the third level can be calculated. That is, if the product-class demand and the market share are known, then the demand for the brand can be calculated. This makes two modeling alternatives available for building brand-sales models. The first alternative is to model brand sales directly as a function of a set of explanatory variables, $X_{ijt}$.

$$q_{ijt} = q(X_{ijt}) \tag{3.3}$$

The second alternative is to model brand sales indirectly, by building models of primary demand and brand market-share as functions of some sets of explanatory variables. Brand sales are then computed as the product of primary demand and the brand's market share.

$$Q_{jt} = Q(X_{jt}) \tag{3.4}$$

$$m_{ijt} = m(X_{ijt}) \tag{3.5}$$

$$q_{ijt} = Q_{jt} \cdot m_{ijt} = Q(X_{jt}) \cdot m(X_{ijt}) \tag{3.6}$$

According to Naert and Leeflang (1978), modeling brand sales indirectly is preferable for a number of reasons. The indirect modeling approach distinguishes between changes in brand sales caused by changes in product-class sales and changes caused by changes in its market share. The different levels of demand may be influenced by different sets of variables. For example, environmental variables and seasonal or cyclical variables may cause changes in primary demand but may leave the market shares unaffected. The market share model need not include such variables and focuses attention on the competitive interaction among the brands (Naert and Leeflang 1978).

The indirect modeling of brand sales is an example of hierarchical modeling. The category or product-class sales is modeled in the higher level model while market shares are modeled in the lower level model. When the outcome at the higher level is modeled as a function of the outcome at the lower level, we have a nested hierarchical model.

## 3.4. Brand Sales Response Models

The focus here is retail level brand-sales models of response to sales promotions. This is the direct modeling approach of sales response. Four types of models will be described in this section. Each of these models will be exemplified with a model used in previous research. The four types of models are: (1) linear models, (2) multiplicative models, (3) exponential models, and (4) time-series models.

### 3.4.1. Linear Models of Brand Sales

Kumar and Leone (1988) developed a model for studying the effect of store competition on brand sales in the stores. They used the following linear sales-response model.

$$\begin{aligned} S_t(AP) &= b_0 + b_1 \cdot P_t(AP) + b_2 \cdot P_t(AS) + b_3 \cdot P_t(CP) + b_4 \cdot P_t(CS) \\ &+ b_5 \cdot \left[F_t(AP) - F_t(AS)\right] + b_6 \cdot \left[D_t(AP) - D_t(AS)\right] \end{aligned} \tag{3.7}$$

where

| | |
|---|---|
| $S_t(AP)$ | = sales of brand A in the primary store P period $t$ |
| $P_t(AP)$ | = price of brand A in the primary store P period $t$ |
| $P_t(CS)$ | = price of brand C in the secondary store S period $t$ |
| $F_t(\cdot)$ | = dummy variable indicating feature advertising period $t$ |
| $D_t(\cdot)$ | = dummy variable indicating in-store special display period $t$ |
| $b_i$ | = model parameters |

This model must be seen as primarily a research model used for testing whether or not sales promotion has a statistically significant impact on sales of the promoted brand as well as other brands in the promoting store and in a competing store. The model does not seem to be suited for managerial use because of its lack of detail and its linear structure. A drawback of the Kumar and Leone model is that store traffic is not included in the model.

### 3.4.2. Multiplicative Models of Brand Sales

An important multiplicative model is the SCAN*PRO model developed by Wittink *et al.* (1987). According to Blattberg and Neslin (1990), the model was designed to help manufacturers understand the retailers' decision-making. The SCAN*PRO model is:

$$S(i,1,t) = \alpha_{i1} \cdot \prod_{j=1}^{J} \left[ P(i,j,t)^{\beta_{ij}} \cdot \gamma_{1,i,j}^{D(1,i,j,t)} \cdot \gamma_{2,i,j}^{D(2,i,j,t)} \cdot \gamma_{3,i,j}^{D(3,i,j,t)} \right] \cdot \exp\left(u_{i,1,t}\right) \tag{3.8}$$

where

| | |
|---|---|
| $S(i,1,t)$ | unit sales for brand 1 in store $i$, week $t$ |
| $P(i,j,t)$ | unit price for brand $j$ in store $i$, week $t$ |
| $D(1,i,j,t)$ | indicator variable for feature only, brand $j$, store $i$, week $t$ |

| | |
|---|---|
| $D(2,i,j,t)$ | indicator variable for display only, brand *j*, store *i*, week *t* |
| $D(3,i,j,t)$ | indicator variable for display and feature, brand *j*, store *i*, week *t* |
| $u(i,1,t)$ | error term |
| $\alpha, \beta, \gamma$ | model parameters |

The SCAN*PRO model is estimated at the store level, giving store specific estimates for the promotional response parameters. This is to avoid the aggregation bias that would occur if the model was estimated on data aggregated across stores.

An interesting feature in the SCAN*PRO model is the way display and feature advertising are modeled. This modeling approach recognizes that a special display in combination with a feature advertisement may cause an interaction effect on sales.

Prices of competing brands are included in the model at the store level. That is, the price competition is a competition within the store. Only one price variable is used per brand. The price variable gives the actual price of the brand. The different effects of regular prices and price deals are not modeled separately.

The marketing research giant A.C. Nielsen uses the SCAN*PRO model. According to Parsons *et al.* (1993), A.C. Nielsen's model has been used in 500 different commercial applications. Another model that has had considerable commercial success is the Abraham and Lodish (1993) PROMOTIONSCAN model. Information from PROMOTIONSCAN is bought by approximately half of all major packaged goods marketers in the U.S. (Parsons *et al.* 1993). We shall discuss the PROMOTIONSCAN model in the description of time-series models.

### 3.4.3. Exponential Models of Brand Sales

The Blattberg and Wisniewski brand-sales response model was developed to be used by retailers. The sales response function is:

$$
\begin{aligned}
S_{it} = \exp\Bigg[ & \alpha + \beta_1 \cdot R_{it} + \beta_2 \cdot \frac{1}{1-D_{it}} + \sum_{k \neq i} \left( \delta_k \cdot \frac{1}{P_{kt}} \right) + \sum_{j=1}^{3} \gamma_j \cdot A_{i,j,t} \\
& + \phi_1 \cdot X_{i,t} + \phi_2 \cdot E9_{i,t} + \phi_3 \cdot NF_{i,t} + \lambda \cdot T_{i,t} + \phi_4 \cdot C_{i,t} + \varepsilon_{it} \Bigg]
\end{aligned}
\tag{3.9}
$$

where

| | | |
|---|---|---|
| $S_{it}$ | = | unit sales of brand *i* in period *t* |
| $R_{it}$ | = | regular price of brand *i* in period *t* |
| $P_{it}$ | = | actual price of brand *i* in period *t* |
| $D_{it}$ | = | deal discount, defined as $(P_{it} - R_{it})/R_{it}$ |

| | | |
|---|---|---|
| $A_{i,j,t}$ | = | dummy variable for A, B, and C advertisements |
| $X_{i,t}$ | = | display activity (number of stores that display the brand) |
| $E9_{i,t}$ | = | dummy variable for promotion ending in 9 (e.g., \$1.99) |
| $NF_{i,t}$ | = | dummy variable for an "*N* for" promotion (e.g., 3 for \$1.19) |
| $T_{i,t}$ | = | time since the promotion began with 0 being the first week |
| $C_{i,t}$ | = | scanner week/deal week correction |
| $\varepsilon_{i,t}$ | = | error term |
| $\alpha, \beta, \gamma, \delta, \phi, \lambda$ | = | model parameters |

Blattberg and Wisniewski include regular price and the deal price in the model, because the responses to these differ. The price deal discount enters the model as a fraction of the regular price. This is important because problems with multicollinearity could arise otherwise. Other brands' prices in the store are also included in the model. Only one price variable was used for each of the other brands. Advertising was modeled using dummy variables indicating the type of the advertisement.

The model was developed for a retailer with seven stores. Therefore, the special display factor was modeled as the number of stores that displayed the brand. An alternative would have been to have store-specific dummy variables. Dummy variables were used to model the effect of "*N* for" (i.e., e.g., 3 for \$1.19) and "Ending in 9" promotions. The deals often run over several weeks, and a decay variable was included to account for the decaying effectiveness of the promotion over the weeks.

A variable was included in the model to adjust for the mismatch between the scanner week and the promotion week: the scanner week started on Sunday and ended on Saturday while the promotion week started on Thursday and ended on Wednesday. The weight used for the adjustment was the share of weekly sales that Thursday, Friday, and Saturday account for on the average.

Blattberg and Wisniewski (1989) used this model when studying price-induced patterns of competition among brands (or items).

### 3.4.4. Time-Series Models of Brand Sales

PROMOTER is a system for automatic evaluation of manufacturers' trade promotions. It was designed by Abraham and Lodish (1987). The model in PROMOTER is a one-product model based on time-series decomposition.

$$S(t) = T(t) \cdot SI(t) \cdot X(t) \cdot [b(t) + p(t) + e(t)] \tag{3.10}$$

where

$S(t)$ = sales level at time $t$

$T(t)$ = trend of sales not due to promotion at time $t$

$SI(t)$ = seasonal index of consumer demand at time $t$

$X(t)$ = exception index representing the effect of special factors at time $t$

$b(t)$ = base-level sales after trend, seasonal, and exception index adjustment

$p(t)$ = promotion effect at time $t$

$e(t)$ = noise term at time $t$

Adjusted sales is defined as:

$$AS(t) = \frac{S(t)}{T(t) \cdot SI(t) \cdot X(t)} \tag{3.11}$$

Inserting (3.10) into (3.11) gives:

$$AS(t) = b(t) + p(t) + e(t) \tag{3.12}$$

In other words, adjusted sales is the sum of baseline sales, incremental sales due to sales promotion, and a noise term. The promotion effect index $p(t)$ is defined to be zero during normal, i.e., nonpromotion, periods. The exception index $X(t)$ is modeled as the product of a number of exception sub-indices. Each sub-index equals unity during periods when that exception does not occur. When the exception occurs, the sub-index assumes a value representing the effect of that exception on sales. Examples of events modeled by sub-index are all commodity volume distribution, the number of trading days, the introduction of new items, price changes, major competitive deals, sales force incentives, strikes, shortages, and product recalls.

Abraham and Lodish (1993) describe an implemented system for improving promotion productivity. The system, PROMOTIONSCAN, is a brand management model similar to PROMOTER. The main difference is that PROMOTIONSCAN is implemented using store-level scanner data whereas PROMOTER uses shipment data.

## 3.5. Market-Share Models

Applying the indirect modeling approach, the market shares of the items or brands must be modeled. Market-share models call for somewhat more complex structures than brand-sales models in order to be robust. Robustness or logical consistency criteria are important when specifying market-share models.

A logically consistent market-share model should ensure (1) that predicted market shares are not negative or greater than one and (2) that the sum of market shares should at all times be one. These criteria are not satisfied by the linear model, the multiplicative model, the exponential model, and the time-series model presented in the previous section.

This section presents the attraction model, a type of model that satisfies the robustness criteria for market-share models. First, we describe the general formulation of the attraction model. Then, some specific attraction-type models used in previous research are described.

### 3.5.1. Attraction Models

The attraction model is a class of models satisfying the logical consistency criteria of market-share models (Naert and Leeflang 1978).

In the general formulation of an attraction model, the market share of brand $i$ is:

$$m_{it} = \frac{a_{it}}{\sum_{j=1}^{J} a_{jt}} \tag{3.13}$$

where

$a_{it}$ = attraction of brand $i$ period $t$

A brand's attraction is a non-negative function of the relevant marketing variables. The market share of brand $i$ is given by the ratio of the brand's attraction and the sum of all brands' attractions.

The attraction function can be specified in different ways. One specification is the multiplicative competitive interaction model (MCI) of Nakanishi and Cooper (1974). The attraction function in the MCI model is a multiplicative model. The market share of brand $i$ is given by:

$$m_{it} = \frac{a_{it}}{\sum_{j=1}^{J} a_{jt}} = \frac{\alpha_i \cdot \prod_{k=1}^{K} X_{kit}^{\beta_k}}{\sum_{j=1}^{J} \left( \alpha_j \cdot \prod_{k=1}^{K} X_{kjt}^{\beta_k} \right)} \tag{3.14}$$

This model was thought to be intrinsically nonlinear until Nakanishi and Cooper (1974) showed that a linearizing transformation exists. The first step of the transformation is to divide the brands' market shares pairwise. In this way we get rid of the complicated denominator, since the sum of all brands' attractions obviously is the same in all brands' market share expressions.

$$\frac{m_{i,t}}{m_{i+1,t}} = \frac{a_{i,t}}{\sum_{j=1}^{J} a_{j,t}} \Bigg/ \frac{a_{i+1,t}}{\sum_{j=1}^{J} a_{j,t}} = \frac{a_{i,t}}{a_{i+1,t}} = \frac{\alpha_i \cdot \prod_{k=1}^{K} X_{ki,t}^{\beta_k}}{\alpha_{i+1} \cdot \prod_{k=1}^{K} X_{ki+1,t}^{\beta_k}} \tag{3.15}$$

The second step is to take logarithms. This gives

$$\ln\left(\frac{m_{i,t}}{m_{i+1,t}}\right) = \ln(\alpha_i) + \sum_{k=1}^{K} \left(\beta_k \cdot \ln X_{ki,t}\right) - \ln(\alpha_{i+1}) - \sum_{k=1}^{K} \left(\beta_k \cdot \ln X_{k+1i,t}\right) \tag{3.16}$$

Rearranging the terms makes the equation look simpler.

$$\ln\left(\frac{m_{i,t}}{m_{i+1,t}}\right) = \ln\left(\frac{\alpha_i}{\alpha_{i+1}}\right) + \sum_{k=1}^{K} \left[\beta_k \cdot \ln\left(\frac{X_{ki,t}}{X_{ki+1,t}}\right)\right] \tag{3.17}$$

Nakanishi and Cooper (1982) provided a simplified estimation procedure for the model. They showed that regression analysis using dummy variables can be used to estimate the MCI model. Cooper and Nakanishi (1988) provide an excellent description of different formulations of the attraction model. They show that the logit model is a special case of the attraction models, where the attraction function is an exponential model.

For an interesting debate over the pros and cons of attraction models please refer to: Naert and Bultez (1973), Beckwith (1973), McGuire and Weiss (1976), Naert and Weverbergh (1981), Brodie and Kluyver (1984), Gosh, Neslin, and Shoemaker (1984), Leeflang and Reul (1984), Naert and Weverbergh (1985), and Wittink (1987). The main advantage of the attraction model is that the logical consistency criteria are satisfied. Its disadvantage is that the number of parameters to estimate rapidly increases with the number of brands and marketing variables (Hanssens *et al.* 1990).

### 3.5.2. Examples of Attraction Models

Surprisingly few market-share models have been reported in the recent literature. Most recent studies use panel data to estimate individual choice probabilities using logit and multinomial logit models. Important examples of such studies are Guadagni and Little (1983) and Gupta (1988).

A store-level application of the attraction model to the measurement of brand market-share is the shelf space allocation model by Bultez and Naert (1988). An attraction model is estimated and used to determine the optimal shelf space allocation. A brand's attraction is given by:

$$a_i = \alpha_i \cdot s_i^{\beta_i} \tag{3.18}$$

where

| | | |
|---|---|---|
| $a_i$ | = | attraction of item *i* |
| $s_i$ | = | shelf space allocated to item *i* |
| $\alpha_i, \beta_i$ | = | model parameters specific to brand *i* |

Bultez *et al.* (1989) extended the model to incorporate the effects of asymmetric competition in retail assortments. This was done by assuming that items of the same variety are more likely to compete with each other than items from different varieties, *ceteris paribus*. Similarly, items from the same brand are likely to be closer substitutes than items from different brands. They showed that a space allocation based on the symmetric competition model was inferior to an allocation allowing asymmetric competition.

Grover and Srinivasan (1992) used a logit model to model the variations in store-level market shares caused by sales promotion. The market share of brand *j* in period *t* was modeled as:

$$m_{jt} = \frac{\exp\left(\sum_{k=1}^{K} \alpha_k \cdot X_{kjt}\right)}{\sum_{l=1}^{J} \exp\left(\sum_{k=1}^{K} \alpha_k \cdot X_{klt}\right)} = \frac{a_{jt}}{\sum_{l=1}^{J} a_{lt}} \tag{3.19}$$

$$a_{jt} = \exp\left(\alpha_1 \cdot P_{jt} + \alpha_2 \cdot F_{jt} + \alpha_3 \cdot C_{jt} + \alpha_4 \cdot D_{jt} + \sum_{g=1}^{J-1} \alpha_{4+g} \cdot B_{gjt}\right) \tag{3.20}$$

where

| | | |
|---|---|---|
| $a_{jt}$ | = | attraction of brand *j* period *t* |
| $P_{jt}$ | = | price of brand *j* period *t* |
| $F_{jt}$ | = | feature advertising indicator brand *j* period *t* |
| $C_{jt}$ | = | coupon indicator brand *j* period *t* |
| $D_{jt}$ | = | display indicator brand *j* period *t* |
| $B_{gjt}$ | = | dummy indicator of brand, 1 when $g=j$, 0 otherwise |
| $\alpha_k$ | = | model parameters |

Foekens *et al.* (1992) described the nested multinomial logit (NMNL) modeling framework. In the NMNL model, the choice outcomes at each level in the hierarchy are dependent on the alternatives' attributes defined at that level and a summary measure of the attractiveness of lower levels of that branch. The summary measure is named the inclusive variable of the alternative. The dependence of higher level models on lower level models implies that the model estimation must take a bottom up approach, starting with models of the lowest level decisions. Assuming that the choice of a variety of a brand is the lowest level choice, the variety *i*'s share of brand *j*'s sales is given by:

$$\frac{s_{ijkt}}{s_{jkt}} = \frac{\exp\left(\sum_m \alpha_{mjk} \cdot X_{mijkt}\right)}{\sum_h \exp\left(\sum_m \alpha_{mjk} \cdot X_{mhjkt}\right)} \tag{3.21}$$

where

| | | |
|---|---|---|
| $X_{mijkt}$ | = | the *m*th marketing variable of variety *i* of brand *j* in category *k* period *t* |
| $\alpha_{mjk}$ | = | response parameter associated with the *m*th marketing variable of brand *j* in category *k* |

At the next higher hierarchical level (i.e., the brand choice in this example), brand *j*'s share of category *k* is:

$$\frac{s_{jkt}}{s_{kt}} = \frac{\exp\left(\sum_n \beta_{nk} \cdot Y_{njkt} + \beta_{ok} \cdot I_{jkt}\right)}{\sum_g \exp\left(\sum_n \beta_{nk} \cdot Y_{ngkt} + \beta_{ok} \cdot I_{gkt}\right)} \tag{3.22}$$

where

$Y_{njkt}$ = the *n*th marketing variable of brand *j* in category *k* period *t*
$\beta_{nk}$ = response parameter associated with the *n*th marketing variable in category *k*
$I_{jkt}$ = the inclusive variable of brand *j* in category *k*, period *t*

The inclusive variable is a summary measure of the attractiveness of all varieties of the brand. It is defined as

$$I_{jkt} = \ln\left[\sum_h \exp\left(\sum_m \alpha_{mjk} \cdot X_{mhjkt}\right)\right] \tag{3.23}$$

which is the logarithm of the denominator in the variety share model. In attraction model terms, it is the logarithm of the sum of all varieties' attractions. Modeling the next higher hierarchical level is a straightforward extension of this method. At each hierarchical level, the marketing variables relevant at that level and the inclusive variables defined at the next lower level are included in the model.

## 3.6. Category Sales Models

Cooper and Nakanishi (1988) suggest that a store's sales of a product category can be modeled using the following general model:

$$Q_t = \exp(a + u_t) \cdot Q_{t-1}^b \cdot \prod_{j=1}^{J} \left[ P_{jt}^{c_j} \cdot \prod_{k=2}^{K} \exp\left(b_{kj} \cdot X_{kjt}\right) \right] \tag{3.24}$$

where

| | | |
|---|---|---|
| $Q_t$ | = | category sales in period $t$ |
| $P_{jt}$ | = | price of brand $j$ in period $t$ |
| $X_{kjt}$ | = | marketing variable $k$ for brand $j$ in period $t$ |
| $u_t$ | = | error term |
| $a,b,c$ | = | model parameters |

This model allows all brands and marketing variables to have a fferent impact on category volume. It is a flexible model which contains a general interaction among the marketing variables. This general interaction may be disturbing when applied to a product category. An example will show why.

Think of a promotion each for brand A and brand B that, if run when no other promotion is run, will increase category sales by 50 percent, or., multiply category sales by 150 percent. What would category sales be if both promotions were run the same week? Intuition says that sales would be in the range of 150 to 200 percent of baseline sales. The model proposed by Cooper and Nakanishi predicts 225 percent of baseline sales. However, if the restriction that only one brand at the time may be promoted is imposed on the model, then the positive interaction is no longer a problem.

The lagged sales term is questionable since the model does not include last period's marketing activities. Large category sales in the previous period may be due to a seasonal factor or to some promotional activity. The implication for the relation between the previous period's sales and sales in the present period would be rather different in these two cases.

Mason (1990) modeled product-class sales as a function of the product-class attraction. Although Mason only used product characteristics in her model, she suggested that marketing mix variables also could be included in the attraction measure. Mason defines four alternative operationalizations of the total attraction of a product category. Total attraction as the sum of the individual products' attraction implies that anyaddition to the product category would increase its attraction. In the averaging model, a category's total attraction is the average attraction of the individual products. Adding a product with below average attraction would decrease the total attraction. The maximum model defines total attraction as the highest individual attraction in the category, while the minimum model defines total attraction as the attraction of the least attractive product in the category.

Mason used the maximum model to model product-class sales. The sales-response model was

$$Q = L + (U - L) \cdot \frac{\exp(b \cdot TA)}{B + \exp(b \cdot TA)} \tag{3.25}$$

where

| | | |
|---|---|---|
| $Q$ | = | product-class sales |
| $L$ | = | lower limit on demand |
| $U$ | = | upper limit on demand |
| $TA$ | = | total product-class attraction |
| $B, b$ | = | model parameters, ($B$>0) |

Grover and Srinivasan (1992) modeled a store's share of the sales in a product category using an attraction model. The total category sales was then modeled as a function of the category's overall attractiveness. They defined the category's attractiveness as the log of the sum of the stores' attractiveness with respect to that category. A store's attractiveness with respect to a specific category was modeled as the log of the sum of the individual products' attractiveness. That is, the store's attractiveness is calculated in the same way as the inclusive variable used as input at lower hierarchical levels of their model

$$a_{jt} = \exp\left(\sum_{k=1}^{K} \alpha_k \cdot X_{kjt}\right) \tag{3.26}$$

$$a_t = \ln\left(\sum_{j=1}^{J} a_{jt}\right) \tag{3.27}$$

where

| | |
|---|---|
| $a_{jt}$ | = attraction of brand *j* period *t* in the store |
| $a_t$ | = the store's attraction with respect to the category |
| $X_{kjt}$ | = determinants of brand attractiveness |
| $\alpha_k$ | = model parameters |

Grover and Srinivasan note that this model has the intuitively appealing feature that a price cut of 50 cents on one brand contributes more to the total attractiveness than a price cut of 25 cents on two brands (assuming that the brands are equally preferred).

A drawback of Grover and Srinivasan's (1992) approach of linking attraction at different levels is that they constrain the effects of sales promotion on the store's category sales to be directly related to the gain in market share within the category. This seems to be an unnecessarily restrictive assumption.

Grover and Srinivasan model the store's share of the sales in one product category. Using a similar modeling approach, it should also be possible to model a category's share of a store's sales.

## 3.7. Store Sales and Store Traffic

This section presents models that have been used to study sales promotion's impact on store sales and store traffic. Walters and Rinne (1986) used a linear model to investigate the impact of double couponing and loss leader portfolios on store sales. They estimated the following model:

$$S_t = \alpha + \delta \cdot H_t + \eta \cdot M_t + \sum_{i=1}^{10} \tau_i \cdot P_{it} + \varepsilon_t \tag{3.28}$$

where

| | | |
|---|---|---|
| $S_t$ | = | store sales in dollars, week *t* |
| $H_t$ | = | dummy variable indicating holiday weeks |
| $M_t$ | = | dummy variable indicating double-couponing in week *t* |
| $P_{it}$ | = | dummy variable indicating use of loss leader portfolio *i* week *t* |
| $\varepsilon_t$ | = | error term |

$\alpha, \delta, \eta, \tau$ = model parameters

The linear model with dummy variables is a rather crude model that would not be useful as a management tool. However, the aim was to test whether the promotions have impact on store sales and for that aim the model may be good enough. A methodologically interesting issue is that they concluded that sales promotion has no effect because the model parameters were insignificantly different from zero. A better model might have had the power to reject the null hypothesis of no effect. Store traffic and store profit were modeled with the same model as store sales, but with other model parameters.

Walters and MacKenzie (1988) provided a structural model for studying the impact of sales promotion on store profits. Figure 3.2 presents their structural model. This model will be examined here in some detail because it provides a useful framework for analyzing the profitability of retail promotions. However, the model has some undesirable features which shall be addressed.

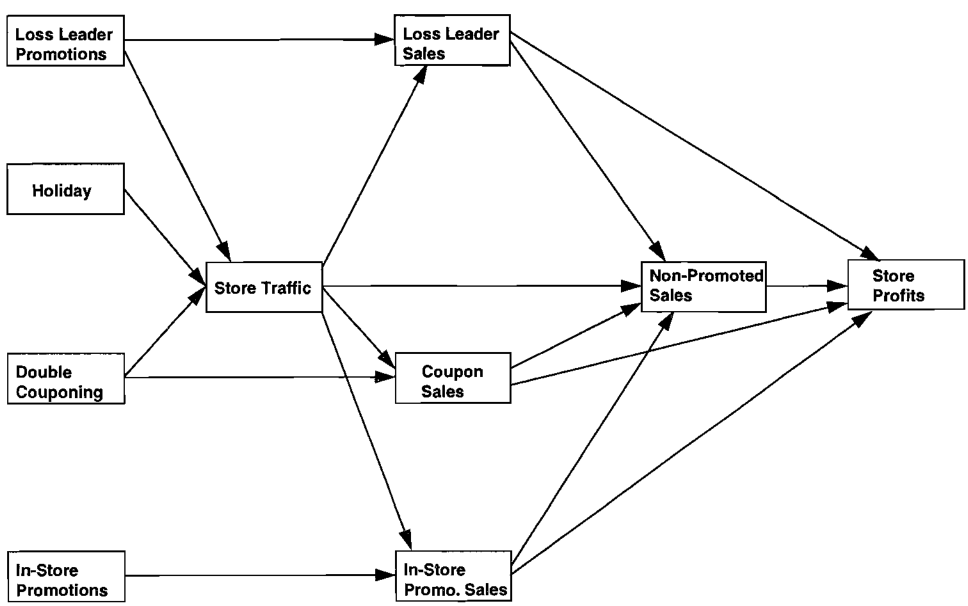


*Figure 3.2. The effects of price promotions on store performance according to Walters and MacKenzie (1988)*

This model explains the variation in store profits with variation in promotional efforts and seasonal variation. Loss leader sales, non-promoted sales, coupon sales, and in-store promotion sales are the variables that directly affect store profits in this model. It is important to note two things about these four sales measures. First, sales is measured in dollars and not in quantity. Second, it appears that the four sales variables measure the dollar value of products sold with a certain type of promotion (or without promotion). For example, loss leader sales are sales of products promoted as loss leaders that week while nonpromoted sales are sales of products that were not promoted that week. The weeks an item is on in-store promotion, its sales are added up together with sales of all other products on in-store promotion. Other weeks, when the item is not promoted, its sales enter the calculation of the non-promoted sales variable. This means that part of the variation in the non-promoted sales variable is due to the composition of the basket of non-promoted products. Another source of variation is the number of products on deal. If all products would be on deal, non-promoted sales would of course be zero. This is not a desirable feature of the model because it makes the results difficult to interpret and makes some results trivial. For example, that in-store specials increases sales of products on in-store promotion is not too surprising.

A very interesting feature of the model is that store traffic is explicitly included in the model. Store traffic is a determinant of sales of all products in the store, and is consequently an indirect determinant of store profits. The model measures the effect of loss leader promotions and double couponing on store traffic. In-store specials are assumed to have no impact on store traffic in the short run. The effect of the December holiday season on store traffic is measured.

The modeling of non-promoted sales as a function of loss-leader sales, coupon sales, and in-store promotion sales is questionable because we can expect a positive and a negative effect simultaneously. The negative effect between promoted sales and non-promoted sales arises because of substitution and because of the way the variables are defined (as was discussed above). The positive effect would arise from variation in store sales that is not caused by store traffic variation. For example, the season may affect the average purchase. It would be better to model the effect of sales promotion on non-promoted sales directly rather than indirectly through promoted sales.

Walters (1988) used a model similar to the Walters and MacKenzie (1988) model. An important improvement in Walters's model is that he models sales for each product category separately. Unfortunately, within each category, he measures sales of promoted and unpromoted products in the same way as Walters and MacKenzie (1988). The conceptual model of promotional effects suggested by Walters (1991) (see Figure 3.3) is from this aspect more appealing.

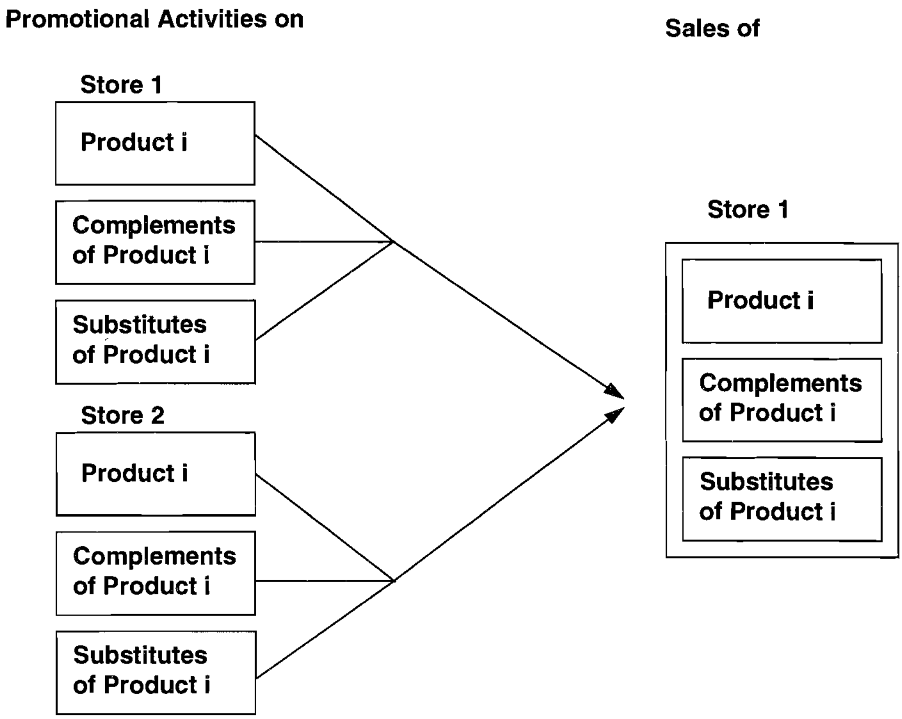


*Figure 3.3. Walters's (1991) conceptual model of retail promotional effects*

The drawback of this model is that store traffic is not included in the model. It would have been very interesting to see how store traffic and store sales were affected by the stores' promotions.

## 3.8. Summing Up

The aggregate results of consumers' purchase decisions translate into retailer sales. In the previous chapter, it was found that sales promotion affects the outcomes of consumers' purchase decisions. It can therefore be expected that sales promotion affects sales. This chapter started by noting that previous studies have found that sales promotion has a large effect on sales of the promoted item. The possible sources of the retailer's incremental sales of the promoted item were identified as other items, other categories, other stores, and other time periods. Note that these sources can be visualized in three dimensions as product, store, and time.

Empirical results reported in the literature suggest that other items (or brands) in the same category, in the same store, at the same time, constitute an important source of promotion-induced incremental sales volume. Concerning other categories, previous research has focused on complements rather than substitutes. Consequently, no study examining whether other product categories' sales suffer from promotions was found. This is clearly a knowledge gap that needs to be filled.

Further, other stores have been found to be a source for incremental sales volume. Promotion in one store has been found to have impact on competing stores' sales of the promoted item and its close substitutes. Such effects may be either direct, by affecting store traffic, or indirect by affecting the consumers' timing of the purchase. Indirect effects may occur because households are not completely loyal to one store.

The previous chapter reported that sales promotion has been found to affect consumers' purchase timing and that household inventories moderate that effect. However, the research presented in this chapter found that the retailer's sales of the promoted item in periods following the promotion did not suffer. This suggests that retailer-oriented models of sales promotions can disregard effects on future sales.

We have seen that retail sales can be modeled at different levels of demand. Further, brand sales can be modeled directly as well as indirectly as the product of category sales and market share. A number of models of retail sales' response to promotions were described. These included models of promotional brand-sales response, market-share response, category-sales response, store-sales response, and store-traffic response. However, none of the models included all of these important responses.

# 4. PROMOTION PROFITS

## 4.1. Introduction

A basic principle in economic decision theory is that only the incremental or marginal effects of a decision are relevant. Costs and revenues that are equal across decision alternatives can be disregarded when evaluating the outcomes of the decision alternatives. Promotional decision-making should be no exception from this basic economic principle. Thus, the profit of a promotion should be evaluated on an incremental basis, comparing the change in profits caused by the promotion. Evaluating a promotion *ex post* implies that the profits that would have been if the promotion had not taken place must be estimated.

As will be seen in this chapter, several authors have suggested models for defining and measuring promotion profits. All the models presented here define promotion profits on an incremental basis. However, the models differ in the definition of the relevant incremental costs and revenues.

Although the main focus in this report is profits of retail promotion, models and results concerning trade promotion are presented as well. The reason for this is that these models and results provide additional insight because they have important features in common with store-related models.

## 4.2. Profit Impact of Sales Promotion

This section presents results and empirical evidence concerning the profit impact of sales promotion as reported in previous research.

### 4.2.1. Manufacturer Profits

Only a small number of studies investigating the impact of sales promotion on manufacturers' profits have been reported. The results of these studies are discussed here.

Strang (1976) called attention to the increasing use of sales promotion and the lack of effect evaluation. The effects on profits were particularly unknown. He showed an example from a consumer goods market where an increased usage of sales promotion led to higher sales but lower profits.

Hardy (1986) found that only 30 out of 45 promotions that managers reported as successful were actually financially successful. At the same time, 19 out of 46 promotions reported to be overall failures increased profits. Hardy explained the discrepancy between the reported degree of success and incremental profits with the managers' concern about sales volume.

Blattberg and Levin (1987) developed a method to measure the profitability of trade promotions. The model shows the importance of incremental consumer sales for the profitability of trade promotions. If consumer sales do not increase, incremental shipments only mean increased pipeline inventories. The retailers' pass-through of the trade deal to the consumers is therefore paramount for trade promotion profits. Blattberg and Levin found negative net profits for the manufacturer for most trade promotions.

According to Abraham and Lodish (1990), only 16 percent of the trade promotion events they studied were profitable. They found that the cost of obtaining one dollar extra sales often exceeded one dollar. The following example of a hypothetical trade promotion was presented to illustrate the weak results of trade promotions. They assume weekly base sales of 100 cases and a list price of $10 per case.

| | ***Cases*** | ***Gross Dollars*** |
|---|---|---|
| Baseline sales that would have occurred during the four weeks | 400 | 4,000.00 |
| + Incremental sales to consumers | 430 | 4,300.00 |
| + Ten weeks of forward buying by retailers | 1,000 | 10,000.00 |
| = Total sales during promotion | 1,830 | 18,300.00 |
| | | |
| Cost of promotion ($18,300x 15% discount) | | 2,745.00 |
| | | |
| **Cost per incremental dollar of sales** | | **0.64** |

*Table 4.1. The cost of incremental sales according to Abraham and Lodish (1990).*

In their hypothetical example the cost of one dollar's incremental sales is 64 cents. If the manufacturer's margin is less than that, the promotion would not be profitable. The high cost of the incremental sales arises because the manufacturer gives the discount also on the normal sales. Abraham and Lodish stress that although this is hypothetical example, it is based on extensive empirical experience. Further, they claim that the example gives a conservative estimate of the manufacturer's cost of increased sales.

Jones (1990) tabulates the sales and profit outcomes of a 10 percent price discount for different combinations of variable costs, net profits, and price elasticities. The levels are chosen to reflect typical costs, profits, and elasticities for real brands. Although the effect on sales volume is positive and fairly large, the price discount reduces profits in 21 out of the 24 cell entries. The loss would be even greater if the mortgage effect on future sales were included in the calculation.

Neslin (1990) measured the incremental sales due to manufacturers' coupon promotions. Incremental sales were shown to be important for the profitability of couponing. None of the seven instant coffee brands studied by Neslin reached the levels of incremental sales that would be necessary to make the coupon promotion profitable.

In summary, the literature suggests that trade promotions in general are unprofitable. One reason for this seems to be that sales volume is used to evaluate the performance of sales promotion, although sales volume and profits behave differently. Blattberg and Levin (1987) put forth the explanation that many trade promotions are defensive rather than offensive. The gain from a promotion would then be that the decline in profits is reduced.

### 4.2.2. Retailer Profits

Empirical reports on the profitability of retailer promotions are scarce. Doyle and Gidengil (1977) complained that most in-store experiments up to that time had failed to consider "*even the basic characteristics of retailing economics*". These characteristics are the high cross-elasticities of demand between items in a supermarket, the low gross margins, and the high variable costs. These characteristics imply that store profits are inelastic to volume changes but elastic to price changes. A second implication is that isolated item elasticities are of limited value for the retailer who is more interested in the impact on overall store profitability.

One attempt to measure the impact of a retail couponing on retail profits was done by Chapman (1986) who conducted a low-cost field experiment for a pizza parlor's couponing. He found that the couponing increased the pizza parlor's profits by five percent during a six-week period. The incremental profit corresponded to eleven percent of the fixed cost of the couponing. A sensitivity analysis showed that the profits could be increased considerably if the fixed cost could be reduced.

Walters and Rinne (1986) tried to measure the impact of double couponing and loss leader portfolios on overall profits. They recalculated the gross margins for each product every week in three supermarkets. The weekly store profit was calculated as the sum of the gross margins times sales volume for all products, minus labor and material costs. They found that double couponing had a significant impact on store profits in one of the three stores. Loss leader portfolios were found to affect store profits significantly in only four cases. Walters and Rinne concluded that loss leader portfolios and double couponing might leave profits unaffected although the impact on store sales may be significant.

This study by Walters and Rinne is interesting because it is the first attempt to measure the impact of double couponings and loss leader promotions on store profits.

Unfortunately, their model is too aggregate to provide insight into the mechanisms by which sales promotion affects retail profits.

Dhebar, Neslin, and Quelch (1987) measured the incremental retailer profit from a sales promotion launched by a automobile dealer. They found that the increased sales volume more than offset the lower margins and the fixed costs of the promotion. The immediate result of the promotion was increased profits for the automobile dealer. When adding the estimated long-term effects on service and repeat purchases, the promotion was even more profitable.

However, the automobile dealership setting is fairly remote from grocery retailing. The long-term effects are certainly more important for the automobile dealer than for the grocery retailer. The effects of the promotion on the dealership's sales of other cars and sales of the promoted model in the periods after the promotion was negligible and not included in the model.

Walters and MacKenzie (1988) can be seen as an extension of the study by Walters and Rinne (1986). They use a similar way of measuring store profits. Weekly store profit is the dependent variable in a structural equations model relating store profit to loss leader portfolios, double couponing, and in-store specials. Store traffic is an endogenous variable that is affected by the independent variable. The model also tests the impact of store traffic on store profit. They found that most loss leader promotions had no effect on store profits. The loss leaders that had an effect on store profit did so because they created incremental store traffic. Double couponing, on the other hand, affected store profits by increasing sales of products sold with coupons rather than affecting store traffic. In-store specials did not have any impact on store profits, store traffic, or store sales.

Walters (1988) used a model similar to Walters and MacKenzie (1988) in a fabric store setting. He found that sales promotion had a positive effect on store profits by their impact on store traffic. Sales of promoted products had a negative impact on store profit because of their depressed profit margins.

Inman, McAlister, and Hoyer (1990) found that consumers respond also to signal-only promotions. Based on this observation, Inman and McAlister (1993) developed a promotion-policy model for retailers. They found that a retailer can improve category profits by offering negligible price discounts accompanied with a promotion signal, e.g., a special display and a one percent price cut. The model draws attention to the effect of the signal-only promotion. However, their resulta are a consequence of the restrictive assumptions made. Promotions are assumed to have no effect on category sales volume; their only effects are on the market shares of the brands within the store. Inman and McAlister also assume that the retailer can improve gross profits by absorbing the trade promotion.

Gijsbrechts (1993) made an extensive review of pricing and sales promotion research in consumer marketing. She concludes by giving directions for future research, stating the importance of studies on pricing and retail profits:

> *"Theoretical and empirical insight is needed on the impact of price strategies on intra- and interstore brand substitution, and on sales of complementary products. The role of price in store choice and the formation of store price images should be further investigated, since they are closely linked to retailer profitability".*

In summary, it has been found that sales promotion may have a positive impact on the store profit if it increases store traffic and thus the retailer's sales of other products. Store profits may also increase if the retailer can improve the margins by absorbing some of the trade promotion. More research is clearly needed in this important area.

## 4.3. Manufacturer Induced Promotions

This section presents models for measuring the manufacturer's profits of manufacturer induced promotions. First, a normative framework developed by Aaker is presented. Then, trade promotion models are discussed, followed by models of the profits of couponings.

### 4.3.1. A Normative Framework

Aaker (1973) developed a framework model for normative promotional decision-making. The core of the framework is the objective function to maximize, the net present value expected from a promotion

$$\begin{aligned} &\text{select } \theta \text{ to max } V(\theta) \\ &\text{subject to: } V(\theta) > 0, \text{ Budget Constraints} \end{aligned} \tag{4.1}$$

where $\theta$ is a decision parameter vector describing the promotion and $V(\theta)$ is the net present value of the promotion. The parameters included in Aaker's decision parameter vector are $(p)$ the promotional vehicle or type, $(s)$ the size or unit value of the promotion, $(x)$ describes the target audience, and $(t)$ is the number of months since the last promotion. The vector can be expanded or modified to fit the problem at hand. The objective function is specified as:

$$V(\theta) = S(\theta) - A - C(\theta) + L(\theta) + W(\theta) \tag{4.2}$$

where

| | | |
|---|---|---|
| $S(\theta)$ | = | total gross margin contributed by the brand during and just after the promotion |
| $A$ | = | total gross margin that would have been generated in the absence of the promotion during a comparable time period |
| $C(\theta)$ | = | direct promotion cost, excluding the unit cost |
| $L(\theta)$ | = | the value of any increase in the loyalty among existing customers as a result of the promotion |
| $W(\theta)$ | = | the long-run value of a group of new triers of a brand attracted during promotion |

We are interested in the short-run effects of sales promotion and will concentrate on the first three terms of the equation. While the direct promotion cost is straightforward to calculate, the difference $S(\theta) - A$ must be estimated. It is important to note that the "immediate effect" in Aaker's model is measured "during and just after" the promotion. In this way, Aaker includes a possible post-promotional dip in the model.

Aaker developed the model from a manufacturer's viewpoint, but stresses that it would be identical for an analysis of the retailer's situation. The model was developed to structure the thinking about the immediate and long-run effects of sales promotion. For our purposes, the model does not contain enough detail concerning the short-run effects of sales promotion.

The two most important aspects of this model are (1) that it clearly defines the profit of a promotion as the change in profits caused by the promotion, and (2) that its essence is that all such changes should be considered.

### 4.3.2. Trade Promotion Profits

Hardy (1986) also used the change in profits as the measure of the profit of a trade promotion. He used the following equation to calculate the profits of a trade promotion:

$$\text{Incremental Profit} = [S(p) - c] \cdot q(p) - [S(r) - c] \cdot q(N) - C(p) \tag{4.3}$$

where

| | | |
|---|---|---|
| $S(p)$ | = | selling price during the promotion |
| $S(r)$ | = | regular selling price |
| $c$ | = | average variable cost of product |
| $q(p)$ | = | sales volume during the promotion |
| $q(N)$ | = | normal sales volume |

$C(p)$ = fixed promotional cost

It is not clear from Hardy's equation how the promotion period and the normal sales volume are specified. However, it appears that the promotion period refers to the period when the promotion was run, not including the period immediately after the promotion, as Aaker suggested.

Blattberg and Levin (1987) used the following method to compute the profitability of a trade promotion. They computed the average unit price charged per period since not all units were sold with the promotional allowance.

Econometric models and historical data were used to estimate the sales volume that would have occurred had the promotion not taken place. The incremental unit shipments due to the promotion were computed as the cumulative difference between actual unit sales and projected unit sales. Incremental dollar shipments were calculated by multiplying the period's incremental unit sales by the relevant price. Incremental gross profit was computed by multiplying the monthly incremental dollar shipments by each month's product gross margin. The deal cost was computed by multiplying the total promoted shipments sold during the period by the dollar discount.

Blattberg and Levin (1987) provided the following example to illustrate the profit calculation. The regular price of the product was \$12, its gross margin \$6, and the discount \$1. During normal periods, sales were 20,000 units per period.

| Period | Total Shipments | Percent on Deal | Deal Cost * | Incremental Shipments | Cum. Incremental Shipments |
|---|---|---|---|---|---|
| 1 | 50,000 | 80% | 40,000 | 30,000 | 30,000 |
| 2 | 30,000 | 80% | 24,000 | 10,000 | 40,000 |
| 3 | 25,000 | 80% | 20,000 | 5,000 | 45,000 |
| 4 | 30,000 | 80% | 24,000 | 10,000 | 55,000 |
| 5 | 35,000 | 50% | 17,500 | 15,000 | 70,000 |
| 6 | 5,000 | 0% | 0 | -15,000 | 55,000 |
| 7 | 5,000 | 0% | 0 | -15,000 | 40,000 |
| 8 | 10,000 | 0% | 0 | -10,000 | 30,000 |
| 9 | 10,000 | 0% | 0 | -10,000 | 30,000 |
| 10 | 15,000 | 0% | 0 | -5,000 | 15,000 |
| 11 | 20,000 | 0% | 0 | 0 | 15,000 |
| 12 | 20,000 | 0% | 0 | 0 | 15,000 |
| Total | 255,000 | | 125,500 | 15,000 | 15,000 |

*Table 4.2. Calculating profits from a trade promotion. *) Deal Cost = Total Shipments × Percent on deal × Discount*

The total deal cost was \$125,500. Incremental unit sales due to this promotion were 15,000 units. With a gross margin of \$6 per unit the total additional gross margin was \$90,000. Thus, the manufacturer lost \$35,500 on this sales promotion.

A similar model was used by Abraham and Lodish (1990). Their model emphasizes the importance of incremental consumer sales for the profitability of trade promotion (see Table 4.1). Retailers' forward buying explicitly enters the cost calculation. They calculate the cost of an additional dollar's sales as follows. Total sales volume during the promotion consists of three parts: (1) baseline consumer sales, i.e., the sales that would have occurred during the period even without the sales promotion; (2) incremental sales to consumers; and (3) retailers' forward buying. The total sales value in gross dollars is calculated as the sales volume times the list price.

Abraham and Lodish calculate the cost of the promotion as the total gross dollar sales times the discount percentage. The incremental sales dollars are incremental sales to consumers times the list price. Dividing the cost of the promotion by the incremental sales dollars gives the promotional cost per incremental dollar sales. If the cost per dollar sales exceeds the manufacturer's gross margin, the promotion is not profitable.

### 4.3.3. Couponing Profits

This sub-section presents two models developed to measure the profit of couponings. Neslin and Shoemaker (1983) showed the importance of calculating the net incremental impact of a coupon on consumer sales volume when evaluating the profitability of a couponing. Neslin (1990) defined incremental unit sales per redemption as net incremental unit sales to the number of redeemed coupons. The incremental unit sales per redemption enters the profitability calculation. Neslin illustrated the profitability calculation with an example calculation. The couponing profit calculation by Neslin was then formalized by Blattberg and Neslin (1990). They define the following variables.

| | | |
|---|---|---|
| $C$ | = | distribution cost per coupon |
| $D$ | = | number of coupons distributed |
| $F$ | = | face value of coupon |
| $P$ | = | processing cost per redeemed coupon |
| $R$ | = | redemption rate as fraction of distributed coupons redeemed |
| $L$ | = | fraction of redemptions that are legitimate, i.e., not misredemptions |
| $M$ | = | profit margin per unit sold (in dollars) |
| $I$ | = | fraction of redemption sales that is incremental |

The total incremental costs are the sum of distribution costs and redemption costs. The total incremental profit is given by the number of incremental sales times the profit margin. The net incremental profit of the couponing is the difference between the incremental profits and the incremental costs. Expressed as an equation, the net incremental profit is:

$$\Delta\pi = (D \cdot R \cdot L \cdot I \cdot M) - [C \cdot D + D \cdot R \cdot (F + P)] \tag{4.4}$$

or

$$\Delta\pi = D \cdot [R \cdot (L \cdot I \cdot M - F - P) - C] \tag{4.5}$$

The equations show that the profit margin from redemptions that represent incremental sales is the only source of profits from a couponing. Given that the face value and the processing costs do not exceed the profit margin from the incremental sales, a couponing is more profitable when the redemption rate is high. If the incremental profit per distributed coupon would exceeds the distribution cost, then the couponing is more profitable the more coupons that are distributed. However, it is unlikely that the variables in this equation are independent. The redemption rate may be lower when the total number of coupons distributed increases. The distribution cost per coupon, on the other hand, is likely to be lower for a large couponing than for a smaller drop.

Blattberg and Neslin (1990) show that the break-even point for incremental sales per coupon is given by setting the incremental profit to zero and solving for $I$. The necessary incremental sales per coupon to break even is:

$$I^* = \frac{C}{R \cdot L \cdot M} + \frac{F + P}{L \cdot M} = \frac{1}{L \cdot M} \cdot \left[\frac{C}{R} + F + P\right] \tag{4.6}$$

Equation (4.6) shows that the break-even point is reached at lower levels of incremental sales per coupon when profit margins are high. The incremental sales per coupon must be higher to break even when the coupon has a high face value, when the processing costs per redeemed coupon are high, and when the distribution cost per redeemed coupon is high.

Although the model gives the incremental profit of a couponing, it could be used to evaluate the profitability of a price deal. The number of coupons distributed would then be equal to the total sales and the redemption rate would be unity. The discount would correspond to the face value of the coupon.

Chapman (1986) measured the profitability of a pizza parlor's couponing. Although a pizza parlor is a retailer, the model will be presented in this section because the model is more related to manufacturer couponing than to retailer price deals.

The incremental profit from the couponing was calculated with the following equation.

$$G = u \cdot c \cdot S + (1 - u) \cdot m \cdot S - m \cdot B - F \tag{4.7}$$

where

$G$ = the incremental profit from the couponing

| | | |
|---|---|---|
| $u$ | = | the proportion of sales for which a coupon was used |
| $c$ | = | the contribution margin (in percent) from coupon sales |
| $m$ | = | the contribution margin (in percent) from sales without coupon |
| $S$ | = | total sales revenue during the promotion |
| $B$ | = | base sales revenue that would have occurred without the coupon |
| $F$ | = | the fixed costs of the coupon promotion |

The equation can be interpreted as the sum of the gross margin from sales with and without the coupon, less the gross margin that would have been in the absence of the promotion, less the fixed cost of the promotion. Chapman showed that the equation can be rearranged to:

$$G = m \cdot (S - B) - u \cdot S \cdot (m - c) - F \tag{4.8}$$

The profit from the couponing is the regular margin from the incremental sales less the face value of redeemed coupons less fixed costs of the couponing.

In summary, the profit of a couponing promotion is calculated as the change in gross profits due to the couponing.

## 4.4. Retailer Promotions

This section presents models developed to measure the profits of retailer promotions. The models are of three types: (1) models measuring only the impact of sales promotion on the retailer's gross profits from the promoted item; (2) models considering also the promotion's effect on other items in the category; and (3) models considering effects on other categories as well.

### 4.4.1. Item Profits

Dhebar *et al.* (1987) developed a model for planning retailer sales promotions. The aim of the model is to help an automobile dealer to design an individual promotion. The retailer's profit is the focus of the model. Figure 4.1 shows the conceptual model for the short-term impact of a sales promotion on profit. Dhebar *et al.* link the conceptual model of short-term and long-term impact on profit through immediate sales. We will concentrate on the short-term part of the model, which is relevant to the current purpose.

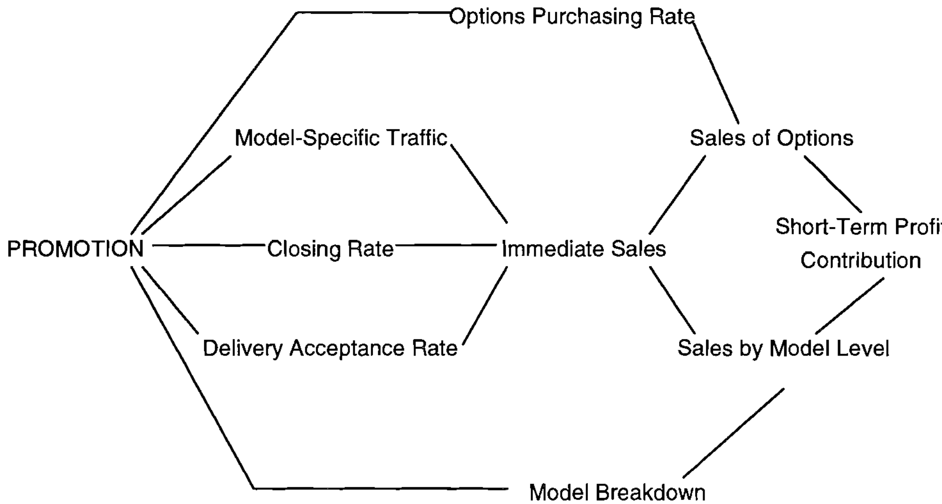


*Figure 4.1. Promotion's Short-Term Impact on Profit. Source: Dhebar* et al. *(1987)*

Dhebar *et al.* (1987) model immediate sales of the promoted model *(ISALES)* as the product of four factors: *TRAFFIC* is the number of customers visiting the store per day; *RELTRAFFIC* is the percentage of traffic that represent a potential sale of the promoted model; *CLOSE* is the percentage of model relevant store visits that result in a sale; and *DELIVER* is the percentage of closed sales accepted by the customer for delivery. Thus,

$$ISALES = TRAFFIC \cdot RELTRAFFIC \cdot CLOSE \cdot DELIVER \tag{4.9}$$

Each of the four factors is potentially affected by the sales promotion. They model the sales of various options as percentages of immediate sales. The profit is calculated as contribution margins less commission cost and fixed promotion cost. The profit of a promotion is then calculated as the profit with the promotion less the profit that would have been without the promotion. In other words, the incremental profit due to the promotion is calculated.

The model is a powerful tool for evaluating the effects of a sales promotion for an automobile dealership. However, the effect of sales promotion on other cars than the promoted model is assumed to be negligible and is not included in the model. Such an assumption may be relevant for an automobile dealer, but in grocery retailing we must include such effects in the model. Dhebar *et al.* indicate that the effect on sales of other car models could be included by estimating the cross-elasticities of sales promotion.

Blattberg and Neslin (1990) describe how the optimal price discount for a product can be determined. The profit function is defined as:

$$\pi = (p - c + DISA + TD) \cdot q - D \cdot q - DISC + FAA - FAC \tag{4.10}$$

where

| | | |
|---|---|---|
| $p$ | = | regular retail price per unit |
| $c$ | = | cost per unit |
| $q$ | = | quantity in units |
| $DISA$ | = | display allowance per unit |
| $D$ | = | deal discount (in dollars) |
| $DISC$ | = | cost of a display |
| $FAA$ | = | feature advertising allowance |
| $FAC$ | = | feature advertising cost |
| $TD$ | = | trade deal in dollars per unit |

Specifying a sales-response model to model unit sales ($q$), the profit maximizing price can be calculated using standard calculus. The model can be used to analyze the retailer's passthrough of trade deals. The higher the price deal elasticity, the larger the passthrough. At high elasticities, the retailer will add their own money to the price deal. On the other hand, when the elasticity is low, the retailer will absorb most of the trade deal.

In summary, the item profits modelspresented in this section show how the prmotions affects the profit from sales of the promoted item. This is sufficient when only one item is sold. However, the item profit models are of limited value for the grocery retailer evaluating the profit of a sales promotion because these models fail to consider effects on other items. As there are complex interdependencies among the products in a retailer's assortment, these models thus have to be extended to include the effects on other items.

### 4.4.2. Category Profits

Cannibalization within the category is an important issue that the item sales models failed to consider. Blattberg and Neslin (1990) extended their item profit model (presented above) to include interdependencies among the items in a category. In this model, the retailer's objective is to maximize the profits in the category. The category profit equation is:

$$\pi = \sum_{i=1}^{I} m_i \cdot q_i - \sum_{i=1}^{I} d_i \cdot q_i \tag{4.11}$$

where

| | | |
|---|---|---|
| $m_i$ | = | item $i$'s gross margin per unit in dollars including the trade deal |
| $d_i$ | = | item $i$'s deal discount per unit in dollars |

$q_i$ = quantity sold of item $i$

$I$ = number of items in the category

A sales-response function is defined for each item. The sales of item $i$ are dependent on other items' deals. The category margin and the degree of cannibalization determine the optimal price discount for an item. When cannibalization is the dominant source of incremental brand volume, the optimal price discount is smaller. Thin margins also lead to smaller optimal discount.

Blattberg and Neslin (1990) show that a model of this type can be used to determine whether to display an item or not, or whether to include an item in the feature advertisement or not. They argue that the direct cost of a display or a feature advertisement may be approximately the same independent of which products are displayed or featured. However, the retailer has limited space to display products in the store and the space in the newspaper feature advertisement is also limited. Thus, the relevant costs of display and feature advertising are the opportunity costs of display space and space in the feature advertisement.

Inman and McAlister (1993) developed an interesting model of category profits of sales promotion. The aim of their model is to maximize a retailer's category profits for a given week. The model recognizes that signal-only promotions may affect consumers' brand choice (Inman, McAlister, and Hoyer 1990). Given the brands' margins, available trade deals, and consumer response to sales promotions for the brands, the retailer has to choose which brand to promote, if any, and the discount level. The discount can be either significant or negligible. Inman and McAlister refer to promotions with negligible price discounts as signal-only promotions.

Inman and McAlister used a very restrictive response function to derive the profit from the different promotions on the brands. They specified the negligible discount to 1 percent and the significant discount to 15 percent. At these discounts, the sales response is the same for all brands in a category, and is only dependent on the market shares of the brands. The consumers are thought of as members of one of three segments: (1) brand loyals (never react to any promotion); (2) switchers responding only to significant discounts; and (3) switchers reacting to all promotions. In the three-brand setting in which the model was tested, the market shares are completely determined by six parameters: the market preferences for each brand and the sizes of the three segments.

Inman and McAlister assume that sales promotion only affects brand-switching. Category sales are thus not affected by sales promotion and other periods' sales are also unaffected. Also, sales promotion has no effect on store traffic and there are no effect on sales of other categories. Only one brand may be promoted each period.

The retailer receives the offered trade promotion only if he promotes the brand, but receives the same trade support per unit whether the brand is promoted using a significant discount or a negligible discount. This means that the retailer can choose to absorb most of the trade promotion or to pass it through to the consumers.

The most interesting aspect of this model is that it provides the retailer with a two-step procedure for defining the profit-maximizing promotion in a product category; to select the brand to put on a negligible discount promotion, the retailer has to calculate, for each brand, the category profits that would occur if that brand were promoted with a negligible discount promotion. The maximum category profits that can be obtained by using a negligible discount can then be found. The same procedure is then repeated for the significant discount promotion. Having found the maximum category profits from a negligible discount as well as from a significant discount, the retailer calculates the category profits that would occur if no promotion were used. Then, the strategy giving the highest estimated category profit is chosen.

Although allocation of display space is not addressed with this model, it would not be difficult to extend the model to this decision. The opportunity cost (or the value) of display space is then important. The value of the display space when allocated to the product category is the difference between the maximum category profit the retailer would gain when a display is used in the category and the maximum category profit the retailer could reach without the display.

In conclusion, the category profit models presented here are much more relevant for the retailer than the single item models presented above. While the model developed by Blattberg and Neslin (1990) allows sales promotion to expand the category sales, the model developed by Inman and McAlister assumes complete cannibalization within the category. Both models ignore the possible impact on other product categories.

### 4.4.3. Store Profits

A completely different approach to measuring the effect of sales promotion on retailers' profits was suggested by Walters and Rinne (1986). They measured weekly store profits by adding the weekly gross margin for all products sold and subtracting labor and material costs. The profit impact of sales promotion was measured by regression analysis with store profit as dependent variable and the promotional activities as independent, or explanatory, variables. Their model is important because it is the first attempt to measure the effect of sales promotion on the total store profit. However, their model is aggregate and does not address the question of how sales promotion works to affect retail profits.

Walters and MacKenzie (1988) carried the analysis of Walters and Rinne (1986) further by providing a structural model for studying the impact of sales promotion on store profits.

They calculated weekly aggregate store profits in the same way as Walters and Rinne (1986). Their model was presented in Section 3.7.

These models are important because they represent unique attempts to make empirical observations of the store level profit impact of sales promotion. The profit impact is defined as the change in a store's gross profits resulting from a change in the promotion portfolio. Unfortunately, the models are too aggregate to reveal the causal structure transforming changes in the promotion portfolio into changes in store profits. This also makes the models unlikely to reject a null hypothesis of no impact of sales promotion when there is insufficient variation in the overall promotional portfolio.

These models are clearly research models and not models intended to be used by retailers as decision support or decision models. The aim of these models is to test hypotheses concerning the existence of a profit impact of sales promotions.

A very interesting modeling framework was suggested by Mulhern and Leone (1991). They recognize the importance of a multiproduct perspective when studying retailer pricing and promotion policies. Products within a product line are substitutes in their model. Across product lines, products can be substitutes, complements, or independent. They note that complementary relationships between products are of two types: products can be *use* complements or *purchase* complements, or both. The retailer perspective makes purchase complementarity important, and Mulhern and Leone note that purchase complementarity may occur for all items in the store because consumers buy baskets of products when visiting a grocery store.

A price deal thus influences sales of three groups of products in the Mulhern and Leone model. While a price deal increases the sales volume of (1) the promoted item and of (2) its purchase complements, it reduces sales of (3) the item's purchase substitutes. The major weakness of their model is that it fails to explicitly include store traffic. They test the model on the cake mix and cake frosting categories where direct and cross effects for all items within and across these two categories were tested for statistical significance. Effects on other categories' items were implicitly assumed to be zero.

Mulhern and Leone calculate the profit impact of the promotion as the difference between the profits with the promotion and the profits if the promotion were not run. They define the promotion profit for the store as the sum of the change in profits for the promoted item, the change in profits from substitutes, and the change in profits from the complements.

In conclusion, the model developed by Mulhern and Leone is the most promising of the models trying to measure sales promotion's impact on store profits. However, it would be valuable to have a model that more clearly accounts for all effects outside the promoted item's category.

## 4.5. Summing Up

This chapter presented a number of models and definitions of promotion profits. Common for all these models is that promotion profit is defined on an incremental basis, i.e., as the change in profits caused by the sales promotion. A general observation is that the models are adapted to the problem at hand in order to take the relevant incremental costs and revenues into consideration in the definition of promotion profits.

The profit impact of sales promotion is to a large extent unknown. However, there is evidence and logical arguments indicating that many sales promotions are not profitable (at least not in the short run). It was also argued that consumers usually buy a basket of products when visiting a grocery store. The consumer's store choice is consequently important for the retailer as it means store traffic for the retailer. Empirical evidence indicated that sales promotion's impact on store traffic is important for the profitability of retail promotions. At the same time, there is evidence that sales promotion has small impact on store traffic.

None of the models presented here seems to be ideal for a grocery retailer who wants to measure the profit impact of sales promotion for individual items. The single product models are clearly much too limited to catch the complex impact of sales promotion on other items in the store. The category profit models are better but failed to look outside the focal product category for effects on other categories.

The store level models developed by Walters and his colleagues include effects on other product categories. The store level models that include store traffic, however, are too aggregate to help the retailer. The most promising model is the model developed by Mulhern and Leone. Their model is detailed and recognizes the importance of effects on other categories, but fails to include store traffic.

The retailer perspective implies that store traffic must enter the model for two reasons. First, store traffic is commonly assumed to be a driver of sales of all products in the store. This could be tested, and the result would contribute to the retailers' and researchers' knowledge. If store traffic is a determinant of sales, then any model of item sales would be incomplete without taking store traffic into consideration. Second, some sales promotions are assumed to influence store traffic, and thereby sales of unrelated products. The model should measure this influence.

Thus, there is a need for a model defined for the retailer's specific decision problem. Such a model should the consider all costs and revenues relevant for the retailer. It should also contain considerable detail concerning the effects on other items and should explicitly include store traffic. A model of that kind will be developed in the next chapter.

# 5. MODEL DEVELOPMENT

## 5.1. Introduction

In this chapter we develop a system of models for the measurement of the profit impact of sales promotion. First, a framework model which decomposes the retailer's sales into four factors is developed. Then, the framework is model is filled with with more specific sub-models of the four factors. Third, the retailer's promotion profit is defined and and modeled within the framework model. Last, the profit-maximizing deal is defined and the factors affecting the size of the profit-maximizing deal discount are examined.

## 5.2. Decomposing Retailer Sales

This section shows how that the retailer's of an individual item can be decomposed in a number of factors. First, the important issues the model should include are defined and the general modeling approach is proposed. Then follows a discussion and definition of the framework model's dependent variable. Last, the model is specified a formal definition of sales cannibalization is proposed.

### 5.2.1. General Considerations and Modeling Approach

The task here is to develop a model of retailer sales of individual items. Such a model should include the following important aspects:

- Grocery shoppers generally buy baskets of items.
- The average basket size is a source of sales for all items in the store.
- Store traffic is a generator for sales of all items in the store, including the focal item.
- Sales promotion may increase the size of the average shopping basket.
- Sales promotion may increase store traffic and thereby cause sales of other items to increase.

- Sales promotion may cause cannibalization among the items in the retailer's assortment.

A model of retailer sales should include all these aspects. Hypotheses regarding the importance or existence of each phenomena can then be tested. Such a model could also be used to track the effectiveness of the retailer's sales promotional activities.

A very interesting approach was suggested by Cooper and Nakanishi (1988) as an avenue for future research:

> *"If we have data on the total transaction of each consumer, someone is going to try to model them. Extrapolating the approach in this book to that task, we would divide the market basket into categories, model the total expenditures as we would a category-volume model, and model the shares among categories as we would a market-share model. Within each category we would have a nested pair of models for category volume and brand shares" (Cooper and Nakanishi 1988, p.264).*

This is basically the approach that will be used in this study, but it will be extended and adapted to suit the present problem of modeling retailer sales of individual items. The store's sales volumes of all items could be modeled using this hierarchical approach. For example, on the lowest level, consumers choose between different package sizes (purchase quantities) or varieties or both. On the next higher level, consumers choose between brands. There may be a level where the consumer chooses between groups of similar brands. On a higher hierarchical level, the consumer chooses between product categories. Again, there may be one or more hierarchical levels of groups of product categories before the store choice level is reached.

This modeling approach can be described as the indirect approach because the ultimate dependent variable is modeled as the product of variables that are modeled as functions of the independent variables.

### 5.2.2. Selecting the Quantity Measure

When building market-share models, it must be decided what kind of shares to use. This is not an easy decision; there are many aspects that need to be considered when defining a market share measure for practical use. It will be argued that a share of sales valued at regular (as opposed to actually paid) prices should be an appropriate market share measure when modeling the retailer's sales.

According to Cooper and Nakanishi (1988), market shares can be measured as shares of sales volume (e.g., units or weight) or shares of monetary sales (e.g., dollars or kronor). We shall here use monetary market shares for the following reason. A necessary condition for the definition of market shares is that the sales volumes of the items can be aggregated.

This implies that sales volumes of all items must be expressed in some common unit, which becomes harder and harder to find the more heterogeneous the items are. Grocery retailers have very large and heterogeneous assortments. The most relevant unit common to all items in such assortments is money. Monetary sales volumes can always be aggregated. In addition, monetary sales have direct managerial relevance.

The monetary market share measure used in the model will however be modified to overcome a major drawback of monetary market shares in response models. The drawback of monetary sales is that it is the product of the number of units sold and the price charged. This makes changes (and even the absence of changes) in monetary sales difficult to interpret. It also makes sales-response models difficult to interpret, because price would occur on both sides of the model equation. The model would thus explain price changes with price changes, which is not very helpful. A solution would be to get the price out of the sales measure.

Fortunately, actual price, i.e., the price charged, can be removed from the monetary sales measure. Instead of using actual prices for valuing the unit sales volume, we can use the regular price. This gives the sales volume valued at regular price. Sales valued at regular price can be seen as a Laspeyres quantity index, i.e., a quantity index that uses the base period's prices as weights (see e.g., Chou 1984, p.669). The base period here corresponds to the case when the promotion is not used and the current period is the case when the item is promoted.

What happens when the regular prices changes? Regular price changes could be handled as follows. Instead of using the current period's regular prices to calculate sales valued at regular prices, sales could be valued at the regular price of some base period.

The difference between current period valuation and base period valuation would then be regarded as a gain or a loss depending on whether current prices are higher or lower than the base period's. These considerations are mainly of interest when estimating the sales model parameters from a long time-series with large changes in the price level and in relative prices. In such cases, however it may be better to use a subset of the data set, since structural changes in prices can change the parameters as well.

In conclusion, the market-share measure chosen here is a monetary market-share measure. In the preferred measure, sales is valued at the regular prices valid at a specified point in time.

### 5.2.3. Decomposing Retailer Item Sales

This section develops a model for analyzing retailer sales of single items by expressing item sales as the product of four factors. The model can be seen as an extension and adaption of the indirect modeling approach (e.g., Naert and Leeflang 1978). Recall that indirect modeling of item sales means modeling product class sales and market shares separately. Item sales is then received as the product of the two models' output. The model developed here is an extension in the respect that a hierarchy of sales shares is introduced. It is also an adaption of the general model to the retail setting in the respect that store sales are modeled as the product of store traffic and average basket value. A model similar to the one developed here was used by Persson (1992) for decomposing the promotional sales effect into a purchase quantity effect and a effect on the number of buyers. That model was later formalized by Persson (1994).

Following the conclusion of the previous section, we define sales of item $i$ in category $j$, period $t$ as:

$$s_{ijt} = p_{ij} \cdot q_{ijt} \tag{5.1}$$

where

| | | |
|---|---|---|
| $p_{ij}$ | = | base period's regular price of item $i$ in category $j$ |
| $q_{ijt}$ | = | unit sales of item $i$ in category $j$, period $t$ |

Sales valued at regular prices can be aggregated to the desired level of detail and overview. Three relevant levels of aggregation are assumed: the item-level, the category-level, and the store-level. Then, category sales of category $j$ in period $t$ is the sum of the sales of all items belonging to that category. That is,

$$s_{jt} = \sum_{i=1}^{I_j} s_{ijt} \tag{5.2}$$

where $I_j$ is the number of items in category $j$. The $J$ categories can then be aggregated to yield store sales in period $t$:

$$s_t = \sum_{j=1}^{J} s_{jt} \tag{5.3}$$

We now have market-share measures that can be applied at all levels of aggregation in a supermarket. Assuming three hierarchical levels (store, category, and item), sales of an item (valued at regular price) can be expressed as the product of three factors:

$$s_{ijt} = s_t \cdot \frac{s_{jt}}{s_t} \cdot \frac{s_{ijt}}{s_{jt}} \tag{5.4}$$

In period $t$, the sales of item $i$ in product category $j$ is the product of three factors: (1) the total store sales valued at regular prices; (2) the product category $j$'s share of store sales; and (3) the item $i$'s share of category $j$'s sales.

In this example, we assume that the hierarchical levels are store-level, product category, and item. Obviously, the hierarchy could be extended to any number of levels. For example, categories could be grouped into departments of related categories, or categories could be split into sub-categories based on brands or varieties.

Store traffic is another important consideration for the retailer. The model is not complete on important issues if store traffic is not included in the model. Using the hierarchical modeling approach, inclusion of store traffic is a fairly straightforward extension of the model. The model can be written as:

$$s_{ijt} = B_t \cdot \frac{s_t}{B_t} \cdot \frac{s_{jt}}{s_t} \cdot \frac{s_{ijt}}{s_{jt}} \tag{5.5}$$

where $B_t$ is the number of receipts produced by the EPOS in period $t$. This is a direct measure of the number of shopping baskets that shoppers purchased. The second factor is the average value of the shopping baskets (valued at regular prices).

The shopping basket concept makes alternative models of item sales feasible. At each hierarchical level, the number of shopping baskets that contain an item, or at least one item from a group of items, can be counted. Sales of an item can then be written:

$$s_{ijt} = B_t \cdot \frac{b_{jt}}{B_t} \cdot \frac{b_{ijt}}{b_{jt}} \cdot \frac{s_{ijt}}{b_{ijt}} \tag{5.6}$$

or

$$s_{ijt} = B_t \cdot \frac{b_{jt}}{B_t} \cdot \frac{s_{jt}}{b_{jt}} \cdot \frac{s_{ijt}}{s_{jt}} \tag{5.7}$$

where

| | | |
|---|---|---|
| $b_{ijt}$ | = | number of baskets that contain item $i$ in category $j$, period $t$ |
| $b_{jt}$ | = | number of baskets that contain at least one item from category $j$, period $t$ |

Although these three models look similar to the previous model, there are important differences. The ratios between basket counts at different levels give percentages that can be interpreted as conditional probabilities, i.e., the probability the category $j$'s item $i$ is bought, given that the category $j$ is bought. However, these ratios are different from the sales ratios, because more than one sub-class may be chosen. This is most obvious at the category-level where the sum of category-to-total baskets is unity only when each basket contains exactly one product category. It is also easy to see that the sum can never be less than unity, because empty shopping baskets are not counted. Thus we have the following relation between the basket counts:

$$B_t \leq \sum_{j}^{J} b_{jt} \tag{5.8}$$

and

$$b_{jt} \leq \sum_{i}^{I_j} b_{ijt} \tag{5.9}$$

The ratios are useful because they are easy to understand and highlight the importance of the number of buyers for the sales of an item or a category. Knowing, for example, that about five percent of all baskets contain coffee would be useful as a heuristic device when making back-of-the-envelope calculations to forecast sales.

The hierarchical model proposed here is similar to the model proposed by Grover and Srinivasan (1992) but differs in the hierarchical structure. Grover and Srinivasan define store share at the category-level as the store's share of total category sales. In their model, the category sales are a function of the attractiveness of the category in all stores. The present model defines category share as the share of a store's sales. The store's sales are regarded as a function of the attractiveness of all the store's categories.

A further difference is that, while the Grover and Srinivasan model is specified at consumer segment level, the present model regards the store's market as unsegmented. On the other hand, the present model is more explicit concerning store traffic than the model by Grover and Srinivasan.

### 5.2.4. Degree of Cannibalization Defined

Sales cannibalization is an important issue in grocery retailing, and the retailer thus needs an efficient way to describe and measure this phenomenon. It is not immediately clear how such a measure should be defined. Cannibalization could be measured in absolute and relative terms, and relative category or store sales. We shall here use a measure relating absolute changes at the item-level to absolute changes at the store-level, and absolute changes at the category-level to absolute changes at the store-level.

Define $\Delta s_{ijt}$, $\Delta s_{jt}$, $\Delta s_t$ as the changes in item, category, and store sales respectively caused by a promotion for item *i*, in category *j*, period *t*. The degree of intra-category cannibalization can then be described by $\Phi_{12}$, defined such that:

$$\Phi_{12}\Delta s_{ijt} = \Delta s_{jt} \tag{5.10}$$

This measure is zero when there is complete intra-category cannibalization and unity in the absence of intra-category cannibalization. Values greater than one would be interpreted as sales increase multipliers rather than in terms of cannibalization. For example, if the intra-category cannibalization variable is 1.5, then an increase of SEK 100 in sales of the focal item would mean that category sales increase by SEK 150.

Inter-category cannibalization can be described by defining $\Phi_{23}$ such that:

$$\Phi_{23}\Delta s_{jt} = \Delta s_t \tag{5.11}$$

The notation of the cannibalization variables anticipates definitions used later in this report where the item-level is denoted as the first level, the category-level as the second level, and store-level as the third level. The subscript 23 is thus based on the logic that the intra-category cannibalization measure relates the second level to the third.

These definitions of cannibalization are useful for describing the impact of a promotion. However, it may sometimes be useful to describe the rate of cannibalization, i.e., the cannibalization that would occur for a small change in the promotion variable. We define the rates of intra- and inter-category cannibalization $\phi_{12}$ and $\phi_{23}$ such that:

$$\phi_{12}\left(\frac{\partial s_{ijt}}{\partial \theta_{ijt}}\right) = \frac{\partial s_{jt}}{\partial \theta_{ijt}} \tag{5.12}$$

and

$$\phi_{23}\left(\frac{\partial s_{jt}}{\partial \theta_{ijt}}\right) = \frac{\partial s_{t}}{\partial \theta_{ijt}} \tag{5.13}$$

where $\theta_{ijt}$ denotes the promotional status of item *i*, category *j*, period *t*. Similar to the cannibalization measures relating sales changes at different levels, the variables $\Psi_{12}$ and $\Psi_{23}$ can be defined to relate changes in the number of baskets at different levels. Let,

$$\Psi_{12}\Delta b_{ijt} = \Delta b_{jt} \tag{5.14}$$

and

$$\Psi_{23}\Delta b_{jt} = \Delta B_t \tag{5.15}$$

The variable $\Psi_{23}$ can be interpreted as the share of the increase in category baskets that represent increased store traffic. When the variable is zero, store traffic is not affected by the promotion and all incremental category baskets belong to customers who would visit the store anyway. A value of unity implies that all incremental buyers of the category represent increased store traffic. Likewise, the variable $\Psi_{12}$ is interpreted as the share of the increase in item baskets representing incremental buyers of the category.

The corresponding variables defined for small changes in the promotion are:

$$\psi_{12}\left(\frac{\partial b_{ijt}}{\partial \theta_{ijt}}\right) = \frac{\partial b_{jt}}{\partial \theta_{ijt}} \tag{5.16}$$

and

$$\psi_{23}\left(\frac{\partial b_{jt}}{\partial \theta_{ijt}}\right) = \frac{\partial B_t}{\partial \theta_{ijt}} \tag{5.17}$$

Note that the these measures cannot be interpreted in terms of cannibalization. Even if the number of category buyers is unaffected by a promotion while the number of buyers of the promoted item increases, the number of buyers of other items need not decrease. This is because the incremental buyers of the promoted item may still buy other items in the category.

## 5.3. Specifying the Response Models

The framework model developed in the previous section will here be filled with response models. First, a series of assumptions that guides the model specification is made. Then, the promotional response models are defined for the factors of the framework model.

### 5.3.1. Model Assumptions and Constraints

We can impose some constraints on the variables and ratios in the model. The constraints guide the model specification in two ways. First, some of the assumptions guide the choice of the response models. Second, the assumptions lead to constraints restricting the valid range of the model parameters. This is useful when specifying the model parameters without empirical data. If empirical data are available, the second type of assumptions are to be treated as hypotheses.

By definition of the variables, the following inequalities are always satisfied:

$$s_t \geq s_{jt} \geq s_{ijt} \geq 0 \tag{5.18}$$

$$B_t \geq b_{jt} \geq b_{ijt} \geq 0 \tag{5.19}$$

If the retailer promotes item $i$ in category $j$ in period $t$ with the sales promotion $\theta_{ijt}$, we can assume that the effect on sales is positive or neutral at all levels of aggregation. That is, the partial derivatives of sales with regard to the promotion are positive or zero:

$$\frac{\partial s_{ijt}}{\partial \theta_{ijt}} \geq 0; \frac{\partial s_{jt}}{\partial \theta_{ijt}} \geq 0; \frac{\partial s_t}{\partial \theta_{ijt}} \geq 0 \tag{A1}$$

This assumption is not very restrictive and simply means that promotion for the focal item does not hurt sales of the focal item, sales of the focal category, or store sales. At least at the item-level, it is generally expected that the promotion increases sales of the promoted item. Moore and Olshavsky (1989) state that the exception to this general pattern is when an unknown item is promoted with a deep price cut. However, sales of other items in the focal category, as well as sales of other categories, may be hurt by the promotion without violating this assumption. This assumption may be violated if the focal item is considerably cheaper (at regular price) than the items it cannibalizes. However, results from previous research (e.g., Blattberg and Wisnievski 1989) show that cheaper products rarely cannibalize more expensive products when promoted.

The number of item baskets, number of category baskets, as well as the total number of baskets would be expected to rise or remain constant as a result of the promotion. That is,

$$\frac{\partial b_{ijt}}{\partial \theta_{ijt}} \geq 0; \frac{\partial b_{jt}}{\partial \theta_{ijt}} \geq 0; \frac{\partial B_t}{\partial \theta_{ijt}} \geq 0 \tag{A2}$$

However, we could make a somewhat stronger assumption for the changes in the number of baskets. We can assume that the increase in item buyers would be at least as large as the increase in category buyers. In general it is reasonable to believe that the promotion would not increase the number of category buyers more than the number of item buyers, since the new category buyers would be attracted to the category by the promotion on the focal item. Using the same logic, store traffic would not increase more than the number of category buyers. We have the following inequalities:

$$\frac{\partial b_{ijt}}{\partial \theta_{ijt}} \geq \frac{\partial b_{jt}}{\partial \theta_{ijt}} \geq \frac{\partial B_t}{\partial \theta_{ijt}} \geq 0 \tag{A3}$$

This implies that the ratio of item baskets to category baskets, and the ratio of category baskets to total baskets increase (or remain constant) as a result of the sales promotion. In other words, the following two inequalities must be satisfied:

$$\frac{\partial\left(b_{ijt}/b_{jt}\right)}{\partial\theta_{ijt}} \geq 0; \frac{\partial\left(b_{jt}/B_t\right)}{\partial\theta_{ijt}} \geq 0 \tag{A4}$$

Note that if (A3) holds, then (A4) will automatically hold, while the opposite is not true. We can also assume that the promotion would increase the focal item's share of category sales, and the focal category's share of store sales (valued at regular prices). This means that

$$\frac{\partial\left(s_{ijt}/s_{jt}\right)}{\partial\theta_{ijt}} \geq 0; \frac{\partial\left(s_{jt}/s_t\right)}{\partial\theta_{ijt}} \geq 0 \tag{A5}$$

It should be noted that this does not imply that sales of the focal item increases more than sales of the focal category, or that the focal category's sales increase would be larger than the increase in store sales. In some cases, this may be the result, but in general we would expect store sales to increase more than category sales, which is likely to happen if store traffic increases. The relative sizes of the changes, however, should satisfy the following inequality:

$$\frac{\partial s_{ijt}/\partial\theta_{ijt}}{s_{ijt}} \geq \frac{\partial s_{jt}/\partial\theta_{ijt}}{s_{jt}} \geq \frac{\partial s_t/\partial\theta_{ijt}}{s_t} \geq 0 \tag{A6}$$

Assumption (A5) constrains the cannibalization rates, $\phi_{23}$ and $\phi_{12}$, by the following boundaries:

$$0 \leq \phi_{23} \leq \frac{s_t}{s_{jt}} \tag{A7}$$

and

$$0 \leq \phi_{12} \leq \frac{s_{jt}}{s_{ijt}} \tag{A8}$$

The verbal interpretation is that the multipliers are greater or equal to zero and smaller than the inverse of the sales share. If the multiplier were equal to the inverse of the sales share, the sales share would not be affected by the promotion. For example, the multiplier for an item with a 20 percent share of category sales would be lower than five. If the multiplier were greater than five, the promotion would reduce the promoted items share of category sales.

Assumption (A3), about changes in the number of baskets at different levels, is stronger than assumption (A5) about the changes in sales sales at different levels. This constrains the variables $\psi_{12}$ and $\psi_{23}$ to the zero to unity range, i.e.,

$$0 \leq \psi_{23} \leq 1 \tag{A9}$$

and

$$0 \leq \psi_{12} \leq 1 \tag{A10}$$

It should be noted that these assumptions are mainly proposed to guide the specification of the response models. The modeling framework would, however, not break down if the assumptions turn out to be unrealistic. The two most basic assumptions, (A1) and (A2), which state that promotions have positive effects on sales and on the number of baskets, are not very controversial. Assumptions (A4) and (A5) are used in the specification of the response functions and guide the estimation of the empirical models. Assumption (A3) is the strongest of the assumptions; it is used to facilitate the parameterization of the simulation model. In the empirical part, this assumption has no importance and would rather be seen as a hypothesis than an assumption. The remaining assumptions, (A6), (A7), (A9), and (A10) , were all specified for convenience, and can be derived from (A3) and (A5). Thus, they should also be seen as assumptions guiding the parameterization of the simulation model and be regarded as hypotheses in the empirical use of the model.

### 5.3.2. Specification of Response Models

In this section, we specify seven response models for the factors of the framework model. Three models relate to store traffic, category-to-store baskets, and item-to-category baskets. Store sales, category-to-store sales, and item-to-category sales are modeled by three further models. The last model is a model of average basket value, i.e., store sales to store traffic. Before defining the models, we shall define the independent variables used to represent sales promotion.

The response models specified here consider two types of sales promotion for the focal item. Most of the attention will be given to the price deal promotion, which is modeled by the *DEAL* variable. The *DEAL* variable is defined as the deal discount expressed as a fraction of the regular price. That is, *DEAL* is zero when there is no price deal for the focal item and 0.15 when there is a 15 percent price deal discount.

The second promotion variable in the models is a dummy variable indicator for in-store special display of the focal item. The variable is named *DISPLAY* and assumes the value zero when there is no special display allocated to the focal item. When the focal item is on special display, then *DISPLAY* becomes unity. Note that both *DEAL* and *DISPLAY* would have subscripts for the focal item, the category, and the time period. These subscripts were however omitted.

There are, of course, numerous other variables that could be included in the response models. For example, newspaper feature advertising, coupons, leaflet advertising, all types of sales promotion for other items, seasons, and holidays. In order to avoid overloading the models with unnecessary detail, such variables have not been included in the model. However, this should not be seen as a limitation because the response models can easily accommodate these variables as well.

The four dependent variables, item-to-category baskets, item-to-category sales, category-to-store baskets, and category-to-store sales, are all logically constrained to the range of zero to unity. A robust model formulation should ensure that the model output falls within this range. It was noted in chapter three that the attraction type of model satisfies this criteria. One well-known model of that type is the binomial logit model, which is the model chosen here.

The binomial logit model used to describe the ratio of item baskets to category baskets can be written as:

$$\frac{b_{ijt}}{b_{jt}} = \frac{u_1}{1+u_1} \tag{5.20}$$

where

$$u_1 = \exp(\alpha_{u1} + \beta_{u1} DEAL + \delta_{u1} DISPLAY) \tag{5.21}$$

The promotion response parameters are non-negative to satisfy assumptions (A4) and (A5). Thus, the three functions are strictly positive and their partial derivatives with respect to price deal and special display are non-negative. In the same way, we define the binomial logit models for category-to-store baskets, item-to-category sales, and category-to-store sales as follows:

$$\frac{b_{jt}}{B_t} = \frac{u_2}{1+u_2}, \text{ where } u_2 = \exp(\alpha_{u2} + \beta_{u2} DEAL + \delta_{u2} DISPLAY) \tag{5.22}$$

$$\frac{s_{ijt}}{s_{jt}} = \frac{v_1}{1+v_1}, \text{ where } v_1 = \exp(\alpha_{v1} + \beta_{v1} DEAL + \delta_{v1} DISPLAY) \tag{5.23}$$

$$\frac{s_{jt}}{s_t} = \frac{v_2}{1+v_2}, \text{ where } v_2 = \exp(\alpha_{v2} + \beta_{v2} DEAL + \delta_{v2} DISPLAY) \tag{5.24}$$

The remaining three models to be defined are not restricted to the range of zero to one. They do have zero as a lower boundary, but have no upper boundary. These variables can be seen as scaling factors in the framework model. We shall here use the exponential model to model store traffic, store sales, and average basket value. The exponential model has previously been used successfully to model promotional sales-response by Blattberg and Wisnievski (1989), for example. Thus, we define the following models:

$$B_t = u_3 = \exp(\alpha_{u3} + \beta_{u3} DEAL + \delta_{u3} DISPLAY) \tag{5.25}$$

$$s_t = v_3 = \exp(\alpha_{v3} + \beta_{v3} DEAL + \delta_{v3} DISPLAY) \tag{5.26}$$

The promotion response parameters are non-negative in the store traffic and store sales models. This means that the functions (5.25) and (5.26) are strictly positive, and their partial derivatives with respect to the price deal and the special display are non-negative.

The average basket value is modeled using the follwing model:

$$\frac{s_t}{B_t} = w_3 = \exp(\alpha_{w3} + \beta_{w3} DEAL + \delta_{w3} DISPLAY) \tag{5.27}$$

The assumptions above do not imply that the parameters in equation (5.27) have to be positive. In other words, sales promotion may decrease the value of the average shopping basket. This happens if the store traffic increases more than the store sales. It can be shown that the model parameters are related as follows:

$$\alpha_{w3} = \alpha_{v3} - \alpha_{u3} \qquad (5.27)$$

$$\beta_{w3} = \beta_{v3} - \beta_{u3} \tag{5.28}$$

$$\delta_{w3} = \delta_{v3} - \delta_{u3} \tag{5.29}$$

This section specified seven promotional-response models for the factors of the framework model. In four models, the binomial logit model was used, as it represents a robust model form when the dependent variable is constrained to the range of zero to unity. The remaining three models were specified using an exponential structure. The sales-promotion variables entering the models as independent variables were also specified. The relationships between the cannibalization measures and the model parameters are presented in the appendix to this chapter.

## 5.4. Modeling Retailer Promotion Profits

This section defines a model for measuring retailer promotion profits from a sales promotion on a single item. First, a general and exact model defining promotion profits of a promotion for an item as the change in the total gross profits of the store is developed. Second, the model is simplified by introducing some approximations in order to make it more parsimonious. Third, it is shown that retailer promotion profits can be measured at the item, category, and store-level, and that the item and category measures are myopic in the sense that not all the effects are measured. Fourth, cannibalization's impact on promotion profits is investigated.

### 5.4.1. Retailer Promotion Profits

This section defines promotion profits as the incremental profits due to the promotion. For determining the promotion profits, we first need to define the equations for the retailer's profits (or gross margin) with and without the promotion. The retailer's profit ($\pi$) in period $t$ can be described by the following equation:

$$\pi_t = \sum_{j=1}^{J}\sum_{i=1}^{I_j}\left[q_{ijt}\left(p_{ijt} - c_{ijt} - d_{ijt} + \tau_{ijt}\right) - D_{ijt} + T_{ijt}\right] - F_t \tag{5.30}$$

where

| | | |
|---|---|---|
| $q_{ijt}$ | = | unit sales of item $i$, category $j$, period $t$ |
| $p_{ijt}$ | = | regular price of item $i$, category $j$, period $t$ |
| $c_{ijt}$ | = | unit cost of item $i$, category $j$, period $t$ |
| $d_{ijt}$ | = | deal discount (in monetary units) for item $i$, category $j$, period $t$ |
| $\tau_{ijt}$ | = | trade deal per unit of item $i$, category $j$, period $t$ |
| $D_{ijt}$ | = | lump sum deal cost for item $i$, category $j$, period $t$ |
| $T_{ijt}$ | = | lump sum trade deal for item $i$, category $j$, period $t$ |
| $F_t$ | = | fixed costs in period $t$ |
| $J$ | = | number of product categories |

$I_j$ = number of items in category $j$

We will examine small changes in the retailer's promotional portfolio; specifically, the marginal effect of a change in the promotional status of one item, assuming that retailer keep the promotional status of all other items unchanged. It is assumed that the retailer faces a number of trade deal offers which may or may not be made conditional on the retailer's promotional activity.

The profit of a suggested promotion for item $m$ in category $n$ in period $t$ is the difference in store profit with and without the promotion. The superscripts * and $\theta$ denote variables that relate to the baseline (i.e., without the promotion) and the promoted cases respectively. So, the profit of the promotion for the focal item is:

$$\Delta\pi_t^{\theta} = \pi_t^{\theta} - \pi_t^{*} \tag{5.31}$$

where

$\pi_t^{*}$ = profit in period $t$ without the promotion on the focal item in period $t$
$\pi_t^{\theta}$ = profit in period $t$ with the promotion on the focal item in period $t$

Inserting the profit expression (5.30) in (5.21) gives:

$$\begin{aligned}\Delta\pi_t^{\theta} = &\left\{\sum_{j=1}^{J}\sum_{i=1}^{I_j}\left[q_{ijt}^{\theta}\left(p_{ijt}^{\theta} - c_{ijt}^{\theta} - d_{ijt}^{\theta} + \tau_{ijt}^{\theta}\right) - D_{ijt}^{\theta} + T_{ijt}^{\theta}\right] - F_t^{\theta}\right\} \\ &-\left\{\sum_{j=1}^{J}\sum_{i=1}^{I_j}\left[q_{ijt}^{*}\left(p_{ijt}^{*} - c_{ijt}^{*} - d_{ijt}^{*} + \tau_{ijt}^{*}\right) - D_{ijt}^{*} + T_{ijt}^{*}\right] - F_{ijt}^{*}\right\}\end{aligned} \tag{5.32}$$

The retailer's fixed costs are the same whether or not the promotion is run. Also, other items' promotional status are supposed to be given when calculating the profit from the suggested promotion on the focal item. All items' regular prices and the regular wholesale prices are unaffected by the promotion. It is assumed that the focal item would be sold at regular price if the suggested promotion did not occur.

Dividing the profit from the promotion into the effect on the focal item, other items in the focal category, and items in other categories, the promotion profit equation can be written:

$$\Delta\pi_t^\theta = \underbrace{\left[q_{mnt}^\theta\left(p_{mnt}^* - c_{mnt}^* - d_{mnt}^\theta + \tau_{mnt}^\theta\right) - D_{mnt}^\theta + T_{mnt}^\theta\right] - \left[q_{mnt}^*\left(p_{mnt}^* - c_{mnt}^* + \tau_{mnt}^*\right) + T_{mnt}^*\right]}_{\text{change in gross profit from the focal item } m \text{ in category } n}$$

$$+ \underbrace{\sum_{i \neq m}^{I_n}\left[\left(q_{\text{int}}^\theta - q_{\text{int}}^*\right)\left(p_{\text{int}}^* - c_{\text{int}}^* - d_{\text{int}}^* + \tau_{\text{int}}^*\right)\right]}_{\text{change in gross profits from other items } i \text{ in the focal category } n} + \underbrace{\sum_{j \neq n}^{J}\sum_{i=1}^{I_j}\left[\left(q_{ijt}^\theta - q_{ijt}^*\right)\left(p_{ijt}^* - c_{ijt}^* - d_{ijt}^* + \tau_{ijt}^*\right)\right]}_{\text{change in gross profits from other categories}} \quad (5.33)$$

Define the change in sales quantity of item $i$ as:

$$\Delta q_{ijt} = q_{ijt}^\theta - q_{ijt}^* \quad (5.34)$$

Inserting (5.34) in (5.33) gives the profit of the sales promotion for the focal item as:

$$\Delta\pi_t^\theta = \underbrace{\Delta q_{mnt}\left(p_{mnt}^* - c_{mnt}^*\right)}_{(1)} + \underbrace{\Delta q_{mnt}\left(\tau_{mnt}^\theta - d_{mnt}^\theta\right)}_{(2)} + \underbrace{q_{mnt}^*\left(\tau_{mnt}^\theta - \tau_{mnt}^* - d_{mnt}^\theta\right)}_{(3)}$$

$$+ \underbrace{\left(T_{mnt}^\theta - T_{mnt}^* - D_{mnt}^\theta\right)}_{(4)} + \underbrace{\sum_{i \neq m}^{I_n}\Delta q_{\text{int}}\left(p_{\text{int}}^* - c_{\text{int}}^* - d_{\text{int}}^* + \tau_{\text{int}}^*\right)}_{(5)} + \underbrace{\sum_{j \neq n}^{J}\sum_{i=1}^{I_j}\Delta q_{ijt}\left(p_{ijt}^* - c_{ijt}^* - d_{ijt}^* + \tau_{ijt}^*\right)}_{(6)}$$

$$(5.35)$$

The promotion profit can thus be seen as the sum of six terms, which are interpreted as follows: (1) the increased sales volume of the focal item makes a positive contribution to the store's gross profits.

(2) The gross profit of the incremental sales is corrected for the per unit trade deal and the per unit price discount. Whether this term is positive or negative depends on the size of the trade deal and the retailer's pass-through of the trade promotion to the consumers.

(3) the gross profit from the sales of the focal item that would have occurred had the promotion not taken place must be adjusted for the per unit trade deal and the retailer's price deal. Note that it is the difference between the per unit trade deal the retailer would receive with the promotion and the trade deal the retailer would receive without the promotion that is of importance for the promotion profits. The sign of this term is again dependent on whether the trade deal would be received independently of the promotion or not, the size of the trade deal, and the retailer's pass-through.

(4) the net effect of lump-sum trade deals and fixed costs of the promotion must be considered. (5) the sales volumes of other items in the focal category may be affected by the promotion. (6) the sales of items in other categories may also be affected by the promotion. The sign of the last two terms can be positive or negative. Term five would in general be expected to contribute negatively to the promotion profits.

The profitability of a sales promotion thus heavily depends on its effect on sales of the promoted item as well as its effect on sales of all other items in the store.

We rewrite the promotion-profit equation (5.35) in terms of sales valued at regular prices. Define sales valued at regular price as:

$$s_{ijt} = p_{ij} \cdot q_{ijt} \tag{5.36}$$

Inserting (5.36) in the equation for the profit of a sales promotion (5.35), we receive the following expression:

$$\Delta\pi_t^\theta = \Delta s_{mnt}\left(1-\frac{c_{mnt}^*}{p_{mnt}^*}\right)+\Delta s_{mnt}\left(\frac{\tau_{mnt}^\theta}{p_{mnt}^*}-\frac{d_{mnt}^\theta}{p_{mnt}^*}\right)+s_{mnt}^*\left(\frac{\tau_{mnt}^\theta}{p_{mnt}^*}-\frac{\tau_{mnt}^*}{p_{mnt}^*}-\frac{d_{mnt}^\theta}{p_{mnt}^*}\right)$$
$$+\left(T_{mnt}^\theta-T_{mnt}^*-D_{mnt}^\theta\right)+\sum_{i\neq m}^{I_n}\Delta s_{\mathrm{int}}\left(1-\frac{c_{\mathrm{int}}^*}{p_{\mathrm{int}}^*}-\frac{d_{\mathrm{int}}^*}{p_{\mathrm{int}}^*}+\frac{\tau_{\mathrm{int}}^*}{p_{\mathrm{int}}^*}\right)+\sum_{j\neq n}^{J}\sum_{i=1}^{I_j}\Delta s_{ijt}\left(1-\frac{c_{ijt}^*}{p_{ijt}^*}-\frac{d_{ijt}^*}{p_{ijt}^*}+\frac{\tau_{ijt}^*}{p_{ijt}^*}\right) \tag{5.37}$$

It is useful to define the *effective* margin for all items except the focal item as:

$$m_{ijt} = 1-\frac{c_{ijt}^*}{p_{ijt}^*}-\frac{d_{ijt}^*}{p_{ijt}^*}+\frac{\tau_{ijt}^*}{p_{ijt}^*} \tag{5.38}$$

For the focal item, it is more useful to define the *regular* margin as:

$$m_{mnt} = 1-\frac{c_{mnt}^*}{p_{mnt}^*} \tag{5.39}$$

The promotion profits can now be written:

$$\Delta\pi_t^\theta = \Delta s_{mnt}m_{mnt}+\Delta s_{mnt}\left(\frac{\tau_{mnt}^\theta}{p_{mnt}^*}-\frac{d_{mnt}^\theta}{p_{mnt}^*}\right)+s_{mnt}^*\left(\frac{\tau_{mnt}^\theta}{p_{mnt}^*}-\frac{\tau_{mnt}^*}{p_{mnt}^*}-\frac{d_{mnt}^\theta}{p_{mnt}^*}\right)$$
$$+\left(T_{mnt}^\theta-T_{mnt}^*-D_{mnt}^\theta\right)+\sum_{i\neq m}^{I_n}\Delta s_{\mathrm{int}}m_{\mathrm{int}}+\sum_{j\neq n}^{J}\sum_{i=1}^{I_j}\Delta s_{ijt}m_{ijt} \tag{5.40}$$

This is the exact version of the retailer promotion-profit model proposed and used in this study. The next section will propose a simplified version of the retailer's promotion-profits model.

### 5.4.2. A Simplified Promotion-Profit Model

This section develops a simplified or approximate version of the promotion profit model. The reason for developing an approximate version of the model is that it facilitates analysis and notation. The model is modified as follows:

First, the lump-sum trade deal and the fixed promotional costs are omitted from the model. This makes the model easier to handle and the loss of generality is minimal. The lump-sum trade deal and fixed promotional costs can easily be included again in the model.

Second, average effective margins are used for other items in the category and for other categories than the focal category. This makes the notation of the model much simpler and facilitates the analysis. However, it introduces the assumption that the margins of other products are homogeneous or that the promotional effects are fairly evenly distributed over the other items and categories. This should be a useful approximation because the retailer's margin for items within a category tends to be fairly homogeneous. Across categories, margins may vary somewhat more, but the promotional response may be fairly similar. However, if the violations to this assumption would be too large, we could split the sales of other items in the focal category and the sales of other categories into groups of items and categories with similar margins and sales response.

Third, the manufacturers' promotion requirements are formally modeled. This is done by defining the size of the trade deal offered and the minimum deal discount the retailer has to use in order to be entitled to the trade deal. Note that the deal discount and the trade deal are both expressed in percent of the regular retail price. This facilitates comparisons between the trade money received by the retailer and what is passed through to the consumers as price deals. It is important for the interpretation of the results to remember this definition, because the common way to express the size of the trade deal would be in percent of the wholesale price. The advantage of a clear interpretation of pass-through was judged to be much greater than the inconvenience of the somewhat unusual way to express the size of the trade deal. Lastly, we simplify the notation by omitting the time subscript, *t*, from the model.

We define the following variables:

| | |
|---|---|
| $s_1$ | = sales of focal item valued at regular price |
| $s_2$ | = sales of focal category valued at regular prices |
| $s_3$ | = store sales valued at regular prices |
| $m_1$ | = gross margin of item (in percent of regular retail price) |
| $m_2$ | = average effective gross margin of other items in the focal category |
| $m_3$ | = average effective gross margin of products in other categories |
| *DEAL* | = deal discount on focal item (in percent of regular retail price) |
| *DISPLAY* | = display indicator for focal item |
| *t* | = trade deal received by the retailer (in percent of regular retail price) |
| *TROFFER* | = trade deal offered on focal item (in percent of regular retail price) |
| *DEALREQ* | = minimum deal required to obtain the trade deal |

$DISPREQ$ = indicator of display requirement to obtain the trade deal

The manufacturer's deal requirement is modeled using the expression:

$$t = \begin{cases} TROFFER \text{ if } (DEAL \geq DEALREQ) \text{ and } (DISPLAY \geq DISPREQ) \\ \quad 0 \text{ otherwise} \end{cases} \tag{5.41}$$

Although not included in this model, the manufacturer could demand that the retailer includes the item in the feature advertisement. The model could easily be extended to implement a feature advertising requirement.

Denote the promotion induced changes (i.e., the sales that would occur with the promotion less the sales that would occur without the promotion) in sales of the focal item, the focal category, and store-level sales, by the three differences:

$$\Delta s_1 = s_1^{\theta} - s_1^{*}; \Delta s_2 = s_2^{\theta} - s_2^{*}; \Delta s_3 = s_3^{\theta} - s_3^{*} \tag{5.42}$$

The store-level promotion profit, or the promotion profit for short, can now be written:

$$\Delta \pi_3 = \Delta s_1 m_1 + \Delta s_1 \left(t^{\theta} - DEAL\right) + s_1^{*}\left(t^{\theta} - t^{*} - DEAL\right) + m_2\left(\Delta s_2 - \Delta s_1\right) + m_3\left(\Delta s_3 - \Delta s_2\right) \tag{5.43}$$

This is the simplified and final version of the promotion-profit model proposed in this study. This is the model that will be used throughout the analyses in this and following chapters. Equation (5.43) is an approximation of equation (5.40). The most important modification is that the average effective margins of other items in the focal category and the average effective margin of other categories are used instead of the effective margin of each item.

Note that both the trade deal and the retail deal discount are expressed in percent of the regular retail price and the net effect of fixed costs and lump-sum trade deals are assumed to be zero.

It should also be noted that the definition of equation (5.43) is neither dependent on the specific response models used, nor whether a direct or indirect modeling strategy is used. The definition of retailer's promotion profits would remain the same, but the numerical results may be different should the response models be defined differently.

### 5.4.3. Three Promotion Profit Measurement Levels

This section shows that a retailer may evaluate promotional (and other) profits at three hierarchical levels. Promotion profits may be evaluated at the item-level, the category-level, or the store-level. The model developed in the preceding section measures the promotion profits at the store-level, the level defined as the correct level of promotion profit measurement. Item and category-level measures are incomplete and can be viewed as myopic measures of the retailer's promotion profits.

We now define promotion profits at the item, category, and the store-level. The change in the retailer's gross profits from the item is the item-level profit from the promotion. Thus, the item-level promotion profit is given by:

$$\Delta\pi_1 = \pi_1^\theta - \pi_1^* = \Delta s_1 m_1 + \Delta s_1\left(t^\theta - DEAL\right) + s_1^*\left(t^\theta - t^* - DEAL\right) \tag{5.44}$$

At the item-level, the promotion profit is the sum of three effects. The first effect is the incremental gross profit from the incremental sales valued at the regular price. This is adjusted by the second term, the difference between the trade deal and the retail promotion. The third term is the effect of the change in effective margin on the sales that would have occurred even if the promotion had not taken place. This is in general negative but may also be positive if the retailer can absorb some of the trade deal. The third term will be negative if the retailer would receive the trade deal irrespective of the pass-through.

As already noted, the retailer is more interested in store performance than item performance. The promotion profits must therefore be measured at the category and store-level as well. The category-level promotion profit is defined as:

$$\Delta\pi_2 = \pi_2^\theta - \pi_2^* = \Delta\pi_1 + m_2\left(\Delta s_2 - \Delta s_1\right) \tag{5.45}$$

The category-level profit of the promotion is the sum of the item-level promotion profit and the change in gross profits from other items in the focal category.

The store-level promotion profit is defined by the difference:

$$\Delta\pi_3 = \pi_3^\theta - \pi_3^* = \Delta\pi_2 + m_3\left(\Delta s_3 - \Delta s_2\right) \tag{5.46}$$

Like the category-level promotion profits, the store-level promotion profits is the sum of the category-level promotion profits and the promotion's impact on gross profits from other categories than the focal category. This means that the total effect of the promotion, i.e., the store-level promotion profits, can be written as the sum of the change in profits from the focal item, the change in the profit from other items in the focal category, and the change in profits from other categories than the focal category. That is:

$$\Delta\pi_3 = \underbrace{\underbrace{\underbrace{\overbrace{\Delta\pi_1}^{\text{focal item}}}_{\text{item level promotional profit}} + \overbrace{\left(\Delta\pi_2 - \Delta\pi_1\right)}^{\text{other items in focal category}}}_{\text{category level promotional profit}} + \overbrace{\left(\Delta\pi_3 - \Delta\pi_2\right)}^{\text{other categories}}}_{\text{store level promotional profit}} \tag{5.47}$$

This equation clearly shows that the promotion profit can be decomposed into three parts: (1) the effect on the gross profit from the focal item, (2) the effect on the gross profits from other items in the focal category, and (3) the effect on the gross profits from other categories. Further, this suggests that three measures of promotion profits can be defined, depending on the number of effects that are considered.

The item-level promotion profit considers only the effects on the focal item. The category-level promotion profit includes the effect on other items in the focal category. The store-level promotion profit includes the effect on all other categories as well. Obviously, the three measurement levels will generally provide different estimates of the profit of a promotion.

As already noted, the store-level promotion-profit is the relevant measure for the retailer. The item- and category-level measures are myopic, because they do not include all the effects of the promotion.

### 5.4.4. The Profit Impact of Cannibalization

The promotion profit model shows the importance of sales effects on other items in the focal category as well as on other categories in the store. In the development of the sales model, formalized measures of the intra-category and inter-category cannibalization were defined. We shall here use these measures to examine the profit impact of cannibalization by re-writing the promotion-profit model to include the cannibalization measures. Define $\Phi_{12}$ and $\Phi_{23}$ such that:

$$\Phi_{12}\Delta s_1 = \Delta s_2 \tag{5.48}$$

and

$$\Phi_{23}\Delta s_2 = \Delta s_3 \tag{5.49}$$

Insert $\Phi_{12}$ and $\Phi_{23}$ into the store promotion profits equation and rearrange terms:

$$\Delta\pi_3 = s_1^*\left(t^\theta - t^* - DEAL\right) + \Delta s_1\left[\left(m_1 + t^\theta - DEAL\right) + m_2\left(\Phi_{12} - 1\right) + m_3\Phi_{12}\left(\Phi_{23} - 1\right)\right] \tag{5.50}$$

The equation for promotion profits would be more general if the incremental sales were expressed as the increase relative to the baseline sales. Therefore, define the relative incremental sales:

$$\sigma_1 = \frac{\Delta s_1}{s_1^*} = \frac{s_1^\theta - s_1^*}{s_1^*} \tag{5.51}$$

The relative incremental sales (5.51) are inserted into the promotion-profit equation (5.50), which yields:

$$\Delta\pi_3 = s_1^* \left\{ \underbrace{\left(t^\theta - t^* - DEAL\right)}_{\text{term 1}} + \sigma_1 \left[ \underbrace{\left(m_1 + t^\theta - DEAL\right)}_{\text{term 2}} + \underbrace{m_2\left(\Phi_{12} - 1\right)}_{\text{term 3}} + \underbrace{m_3\Phi_{12}\left(\Phi_{23} - 1\right)}_{\text{term 4}} \right] \right\} \tag{5.52}$$

This equation can be interpreted by examining its parts in detail. First, it can be noted that the sales volume valued at regular price if the deal would not be launched, $s_1^*$, enters the equation only as a scaling factor. This means that it does not affect whether or not the promotion is profitable, but determines the size of the profit or loss. All other factors being equal, the larger the regular sales volume, the more pronounced the impact on the profit.

The expression within the brackets consists of four terms which shall here be analyze one at a time beginning from the left, after distributing the relative incremental sales to each of the three terms within the brackets. The first term, $\left(t^\theta - t^* - DEAL\right)$, is the change in gross margin on sales of the focal item that would have occurred had the promotion not taken place. This term is in general negative and can be regarded as an opportunity loss caused by the promotion. The second term, $\sigma_1\left(m_1 + t^\theta - DEAL\right)$, is the effect on profit from the item that stems from increased sales volume. In this term, $\left(m_1 + t^\theta - DEAL\right)$ is the effective margin on the incremental sales while $\sigma_1$ is the size of the sales increase. The effective margin can be interpreted as the regular margin adjusted for the deal and the trade deal received from the manufacturer. Given that the effective margin is positive, the size of the sales increase is obviously very important for the profitability of the promotion.

The first two terms together give the promotion-induced change in the retailer's gross margin from sales of the focal item. The third term expresses the effect on the retailer's gross profits from other items in the focal category, while the last term expresses the effect on gross profits from other categories.

Assuming that the average gross margin for the other items in the focal category is positive, the third term, $\sigma_1 m_2\left(\Phi_{12} - 1\right)$, is zero if $\Phi_{12}$ equals one. This would mean that sales of other products in the category are unaffected from the sales promotion on the focal item. The full increase in sales of the focal item translates into increased sales of the category, which can be interpreted as the absence of intra-category cannibalization. In the absence of intra-category cannibalization, the promotion has no impact on profits from other items in the category. If the focal item does cannibalize on sales of other items in the category, the value of the third term is negative. With full intra-category cannibalization, i.e., when $\Phi_{12}$ equals zero, the sales promotion reduces the gross profits from other items in the category by $\sigma_1 m_2$. Whether or not the promotion is profitable is dependent on the relative size of the effective gross margin on the focal item compared to the gross margin on other items in the focal category. The third term may sometimes become positive, implying that gross profits from other items in the category increase due to the promotion. This would be rare if the category is narrowly defined with only substitute items, but more common if the category contains complements to the focal item. The third term is positive when $\Phi_{12}$ is greater than one.

The effect on the retailer's gross profit from other categories than the focal category is given by the fourth term, $\sigma_1 m_3 \Phi_{12}(\Phi_{23}-1)$. This term is more likely than the third term to be positive because there is more complementarity in the purchase of products at this level than within a category. The complementarity in purchase may come from complementarity in use or simply from the fact that it is convenient to buy a basket of groceries rather than making one store visit for each product. The fourth term may also become negative. This occurs when the promoted category cannibalizes on other categories' sales, indicated by a $\Phi_{23}$ between zero and one. When $\Phi_{23}$ is exactly one, the incremental store sales are equal to the incremental sales of the focal product category. The effect on the gross profits from other categories than the focal one is zero. The fourth term can be zero for another reason, too—when there is complete intra-category cannibalization in the focal category, i.e., $\Phi_{12}$ equals zero. This is because complete intra-category cannibalization means that all incremental sales of the focal item come from other items in the category. The effect on sales in other categories is consequently zero.

## 5.5. Maximizing Promotion Profits

The previous section showed how the effect of sales promotion on a retailer's profits can be computed using changes in sales and margins caused by a promotion. *Ex post*, that model can be used to analyze the components of promotion profits. The model can also be used to analyze the profit impact of different values of the variables in the model. This section defines the optimal deal and how that can be found, starting with the optimal size of a deal discount. Then, the value of a special display is discussed as well as how to determine whether or not to allocate a special display to an item. The concept of myopic deal optimization is defined together with a discussion of its costs. Last, we discuss the impact of cannibalization, margins, and deal elasticity for the size of the optimal deal as well as for the myopic deal. It should be noted that the results in this section are general and not specific to any particular response model, except for the last discussion where a particular response model is used.

### 5.5.1. Profit Maximization and Optimal Deal Discount

This section describes how the profit-maximizing retailer would set the size of the deal discount for the focal item. It is assumed that the retailer wants to maximize store-level gross profits. Note that the retailer's gross profits can be written:

$$\pi_3 = s_1(m_1 + t - DEAL) + m_2 s_2\left(1 - \frac{s_1}{s_2}\right) + m_3 s_3\left(1 - \frac{s_2}{s_3}\right) \tag{5.53}$$

This can be rewritten as:

$$\pi_3 = s_1(m_1 + t) - s_1 DEAL + (s_2 - s_1)m_2 + (s_3 - s_2)m_3 \tag{5.54}$$

Define the rate of intra-category cannibalization, $\phi_{12}$, and the rate of inter-category cannibalization, $\phi_{23}$, such that:

$$\phi_{12}\frac{\partial s_1}{\partial DEAL} = \frac{\partial s_2}{\partial DEAL} \tag{5.55}$$

and

$$\phi_{23}\frac{\partial s_2}{\partial DEAL} = \frac{\partial s_3}{\partial DEAL} \tag{5.56}$$

Assuming that the trade deal received by the retailer is not dependent on the size of the deal, differentiation with respect to *DEAL* yields:

$$\frac{\partial \pi_3}{\partial DEAL} = -s_1 + \frac{\partial s_1}{\partial DEAL}(m_1 + t - DEAL) + \left(\frac{\partial s_2}{\partial DEAL} - \frac{\partial s_1}{\partial DEAL}\right)m_2 + \left(\frac{\partial s_3}{\partial DEAL} - \frac{\partial s_2}{\partial DEAL}\right)m_3 \tag{5.57}$$

Inserting $\phi_{12}$ and $\phi_{23}$ and simplifying gives the following equation:

$$\frac{\partial \pi_3}{\partial DEAL} = -s_1 + \frac{\partial s_1}{\partial DEAL}\left[(m_1 + t - DEAL) + (\phi_{12} - 1)m_2 + \phi_{12}(\phi_{23} - 1)m_3\right] \tag{5.58}$$

If the gross profit is a continuous function of the deal discount, then the derivative of the gross profit function with respect to *DEAL* is zero at the profit maximizing deal discount. This means that the rate of change in store-level gross profits is zero when the profit-maximizing deal is used. Thus, the profit maximizing deal, $DEAL^{\omega}$, satisfies the equation:

$$0 = -s_1 + \frac{\partial s_1}{\partial DEAL}\left[(m_1 + t - DEAL^{\omega}) + (\phi_{12} - 1)m_2 + \phi_{12}(\phi_{23} - 1)m_3\right] \tag{5.59}$$

When $DEAL \neq 0$ we can define the deal elasticity as:

$$\eta_{DEAL} = \frac{DEAL}{s_1} \cdot \frac{\partial s_1}{\partial DEAL} \tag{5.60}$$

Inserting the deal elasticity and rearranging the equation gives:

$$DEAL^{\omega} = \frac{m_1 + t + (\phi_{12} - 1)m_2 + \phi_{12}(\phi_{23} - 1)m_3}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.61}$$

This expression looks fairly simple and may be used to evaluate whether a profit maximizing deal discount has been found. Using the sales response models defined earlier in this chapter, it seems unlikely that the profit-maximizing deal discount can be found analytically by solving for $DEAL^{\omega}$. This is because $\phi_{12}$ and $\phi_{23}$, as well as the rate of change of sales due to the price deal, are all functions of the price deal in that model. Using that model, numerical methods are needed in order to find the profit-maximizing deal discount.

However, we can evaluate the derivative for a given size of deal discount in order to determine whether this is a profit maximizing deal discount. If the derivative does not indicate a profit maximum, its sign tells whether a larger or smaller deal would be better. In order to check whether a price deal could be profitable we can evaluate the derivative when the deal discount is set to zero. A non-positive value indicates that nothing can be gained by a price deal (given that the trade promotion is not conditional on a certain size of the deal discount). A negative derivative indicates that a negative deal discount, i.e., a higher price, would be more profitable than the current price. However, since we cannot have negative deal discounts and the response function is specified for price deals (not for regular price changes), it cannot be concluded that the regular price should be increased.

If the trade promotion is made conditional on a certain deal discount, we need to evaluate the profit when the deal discount is zero and when it is at the minimum level at which the retailer receives the trade deal. If the gross profit is higher when the deal is zero than when set equal to the deal requirement, it is sufficient to evaluate the derivative when deal is zero. If the profit would be higher when the retailer receives the trade deal, the derivative at the smallest deal discount that still gives the retailer the trade deal should be evaluated. If this is non-positive, this is the optimal deal discount. If it is positive, a larger deal discount would be more profitable.

A perhaps less elegant but simpler and fail safe method is to evaluate the promotion profit for all possible deal discounts. This is the method that will be used in the illustrations of the model in Chapters 6, 8, 9, and 10.

### 5.5.2. Display Profits

In principle, the profit of a display is defined in the same way as the profit from a price deal, i.e., as its impact on the retailer's store-level profits. However, there are two important differences: First, display does not have any impact on the margin of the focal item. Second, display is not a continuous variable. This means that derivatives are not useful for determining whether the display should be used or not.

As already noted, the value of a display allocated to an item is equal to its impact on retailer profits, measured at the store-level. Its value is dependent on whether or not the size of the deal discount has already been fixed. If the deal discount is pre-determined, for example by an agreement with the manufacturer, the display profit is the difference between the retailer's gross profits with the display allocated to the item and the gross profits without the display. Although this approach gives a correct estimate of the value of the display given that the deal discount is fixed, it is not useful when the deal discount can be changed. In fact, setting the deal discount first and subsequently determining the value of display is likely to lead to sub-optimal performance. The better alternative when the retailer can set the size of the deal is to determine the optimal deal discount with and without a display. The value of the display is then the difference between the promotion profit of the optimal deal discount with the display and the promotion profit of the optimal deal discount without the display allocated to the focal item.

The manufacturer may offer the retailer a lump-sum display allowance that is made contingent on the retailer allocating a special display to the item. Such a lump-sum allowance can easily be handled by the model. The effect is to increase the value of the display by the lump sum. Note that a lump-sum display allowance that is not contingent on the actual allocation of a display for the focal item has no effect on the value of the display, because the retailer receives the money irrespective of the display. The lump sum would then be added to the gross profits with the display as well as without the display. Thus, the difference, i.e., the value of the display, is unaffected by the allowance.

### 5.5.3. Myopic Optimization

It has been argued that the retailer should measure promotion profits as the change in store-wide gross margins caused by the promotion. The optimal promotion is thus the promotion that has the greatest positive effect on the store's profits. Using the more myopic approach of measuring promotion profits as the change in gross margin of the promoted item and designing promotions that maximize these profits is likely to be sub-optimal. We shall here investigate what the myopic approach means for the size of the deal discount and what it costs in terms of forgone profits.

If the retailer uses a myopic approach when determining the size of the deal discount, then the deal discount will be determined by maximizing the item-level gross profits:

$$\pi_1 = s_1\left(m_1 + t - DEAL\right) \tag{5.62}$$

This implies differentiation with respect to the size of the deal discount:

$$\frac{\partial \pi_1}{\partial DEAL} = -s_1 + \frac{\partial s_1}{\partial DEAL}\left(m_1 + t - DEAL\right) \tag{5.63}$$

The myopic deal discount, $DEAL^{\mu}$, is obtained when the rate of change in item-level profit is zero.

$$0 = -s_1 + \frac{\partial s_1}{\partial DEAL}\left(m_1 + t - DEAL^{\mu}\right) \tag{5.64}$$

Inserting the price deal elasticity defined above (5.60) and rearranging the terms means that the following equation holds at the myopic optimal deal discount:

$$DEAL^{\mu} = \frac{m_1 + t}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.65}$$

Note that this equation in general cannot be used to determine the size of the myopic deal discount unless the elasticity is constant. Myopic deal optimization and store-level deal optimization occasionally lead to the same deal discount. However, in general, myopic deal optimization cannot be expected to set the same deal discount as store-level optimization.

Whenever the deal discount determined at the item-level deviates from that determined at the store-level, it is likely that the store-level gross profits would be lower if the myopic deal discount were used. This means that there is an opportunity loss associated with myopic optimization, i.e., there is a cost to myopic deal optimization.

The cost of myopia can be estimated as the difference between the profits from the optimal deal and the profits from the myopically determined deal. Zenor (1994) used a similar approach to measure the manufacturer's profit from category management as compared to brand management. Symbolically, the cost of myopia can be written:

$$\mu_c = \pi_3^{\omega} - \pi_3^{\mu} = \Delta\pi_3^{\omega} - \Delta\pi_3^{\mu} \tag{5.66}$$

Trying to find a general analytical solution to this cost leads to a complex equation which is difficult to interpret. The cost of myopia should be evaluated using the relevant sales-response models and the promotion profits equations.

Myopic optimization was defined as the deal set by maximizing item-level gross profits. The cost of such myopic optimization was defined as the difference between store-level promotion profits from the optimal deal and the store-level profits from the myopically determined deal. Maximization of category-level profits is also a myopic approach and that the cost of category-level deal optimization is defined in the same way as the cost of item-level deal optimization.

### 5.5.4. Determinants of Optimal Deal Discount

In this section, comparative statics are used to examine how the optimal deal discount changes when the degree of cannibalization, the margins, and the deal elasticity change. We also examine the effect that changes in these factors have on the myopic deal discount. To simplify the analysis, we assume that $\phi_{12}$, $\phi_{23}$, and $\eta_{DEAL}$ are exogenously determined and independent of one another. This means that the results presented here are not directly applicable when the factors show complex interdependencies, as in the sales model developed earlier in this chapter.

Recall that the optimal deal discount satisfies the equation:

$$DEAL^{\omega} = \frac{m_1 + t + (\phi_{12} - 1)m_2 + \phi_{12}(\phi_{23} - 1)m_3}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.67}$$

As the factors on the right side of the equation are assumed to be exogenously determined, i.e., not dependent on the deal discount, the equation determines the optimal deal discount. Thus, we can investigate how the optimal deal discount changes when the factors on the right side change. Beginning with the intra-category cannibalization, the following partial derivative gives the rate of change in optimal deal discount for small changes in $\phi_{12}$:

$$\frac{\partial DEAL^{\omega}}{\partial \phi_{12}} = \frac{m_2 + m_3(\phi_{23} - 1)}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.68}$$

The derivative shows that as long as there is no inter-category cannibalization, i.e., as long as $\phi_{23}$ is not lower than one, increasing $\phi_{12}$ leads to larger optimal deal discounts. In other words, the optimal deal discount will be larger the less cannibalization within the category when sales of other categories are positively affected by the deal. When $\phi_{23}$ is lower than one and the average margin of other categories is higher than the average margin in the focal category (excluding the focal item), increasing $\phi_{12}$ may lead to a lower optimal deal discount.

Increasing the value $\phi_{23}$ means to reduce the degree of inter-category cannibalization (or to increase the store sales increase multiplier if its value is greater than unity). The effect on the optimal deal discount of increasing $\phi_{23}$ is always positive (or zero); that is, the optimal deal discount will be larger. The rate of change is given by:

$$\frac{\partial DEAL^{\omega}}{\partial \phi_{23}} = \frac{m_3 \phi_{12}}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.69}$$

Larger trade deals and higher margins on the focal item obviously lead to larger optimal deal discounts. The effect on the size of the optimal deal discount of increasing margins of other items in the category is in general negative as can be seen from the following derivative:

$$\frac{\partial DEAL^{\omega}}{\partial m_2} = \frac{\phi_{12} - 1}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.70}$$

The effect of higher margins on other categories than the focal category on the size of the optimal deal discount depends on $\phi_{23}$. When $\phi_{23}$ is lower than one, i.e., when the focal category cannibalizes on other categories' sales, increased margins on other categories mean lower optimal deal discount. On the other hand, when sales of other categories increase due to the promotion, the optimal deal discount will be larger. The rate of change of the optimal deal discount for changes in the average margin of other categories is given by:

$$\frac{\partial DEAL^{\omega}}{\partial m_3} = \frac{\phi_{12}(\phi_{23} - 1)}{1 + \dfrac{1}{\eta_{DEAL}}} \tag{5.71}$$

The effect of increasing the price deal elasticity is an increase in the size of the optimal deal discount.

### 5.5.5. Determinants of the Deviation from Optimal Deal Discount

Next, we examine the effect of cannibalization, margins, and deal elasticity on the deviation of the myopic deal discount from the optimal deal discount. We still assume that

$\phi_{12}$, $\phi_{23}$, and $\eta_{DEAL}$ are exogenously determined and independent of each other. The myopically determined deal satisfies the equation:

$$DEAL^{\mu} = \frac{m_1 + t}{1 + \frac{1}{\eta_{DEAL}}} \tag{5.72}$$

The difference between the optimal deal discount and the myopically determined deal discount is:

$$DEAL^{\omega} - DEAL^{\mu} = \frac{(\phi_{12} - 1)m_2 + \phi_{12}(\phi_{23} - 1)m_3}{1 + \frac{1}{\eta_{DEAL}}} \tag{5.73}$$

This difference will be zero when $\phi_{12}$ and $\phi_{23}$ are both equal to one, indicating that the promotion has no effect on items or categories in the store other than the focal item. The difference may be zero for other reasons, too. If the average margin of other items in the focal category and the average margin of other categories relate as

$$m_2 = \frac{m_3\phi_{12}(\phi_{23} - 1)}{(1 - \phi_{12})} \tag{5.74}$$

the difference will again be zero. In these cases, there will be no loss incurred by using the myopic approach to find the optimal deal discount. However, this would of course only be a coincidence. Therefore, it is interesting to examine the sign of the difference in order to determine whether the myopically determined deal discount is too large (negative difference) or too small (positive difference). We will assume positive average margins for items in the focal category and in other categories.

When there is some degree of intra-category cannibalization as well as inter-category cannibalization, i.e., both $\phi_{12}$ and $\phi_{23}$ are smaller than one, the difference is always negative, indicating that the myopic deal is too large. The situation is more complex when there is some intra-category cannibalization, but positive effects on sales in other categories than the focal category. Large store sales change multiplier values may offset the effect of the intra-category cannibalization, making the myopic deal too small compared to the optimal deal discount. The margins are here of considerable importance for how large $\phi_{23}$ has to be before the myopically determined deal discount becomes too small. The higher the average margin of other categories, the faster the myopic deal turns out to be too small.

Another factor affecting the difference between optimal and myopic deal discount is the deal elasticity. The difference between the optimal deal discount and the myopic deal discount approaches zero as the deal elasticity approaches zero. High elasticities, on the other hand, tend to inflate the difference, making the sub-optimization more severe.

## 5.6. Summary

This chapter presented a framework model for decomposing retailer item sales as the product of four factors. Item sales are modeled as the product of store traffic, average basket value, the category's share of store sales, and the item's share of category sales. That is,

$$\underbrace{s_1}_{\text{sales of focal item}} = \underbrace{B}_{\text{store traffic}} \times \underbrace{\frac{s_3}{B}}_{\text{average basket value}} \times \underbrace{\frac{s_2}{s_3}}_{\text{focal category's share of store sales}} \times \underbrace{\frac{s_1}{s_2}}_{\text{focal item's share of category sales}} \qquad (5.75)$$

where $B$ is store traffic measured as the number of shopping baskets checked out, and $s_1$, $s_2$, and $s_3$ are sales of the focal item, sales of the focal category, and store sales. It was noted that the three-level framework model can be extended to any number of levels. The framework model was filled with response models for each of the four factors, i.e., response models for (1) the store traffic, (2) the average basket value, (3) the focal category's share of store sales, and (4) the focal item's share of category sales.

Two types of cannibalization were formally defined. It was shown that there may be intra-category cannibalization, $\Phi_{12}$, and inter-category cannibalization, $\Phi_{23}$, in the three-level framework. These were defined such that:

$$\Phi_{12}\Delta s_1 = \Delta s_2 \qquad (5.76)$$

and

$$\Phi_{23}\Delta s_2 = \Delta s_3 \qquad (5.77)$$

where $\Delta s_1$, $\Delta s_2$, $\Delta s_3$ are the changes in item-, category-, and store-sales respectively caused by a promotion on the focal item.

The retailer's promotion profit from a promotion of a single item were defined as the change in store-level gross profit caused by the promotion of that item. The promotion profit of a promotion of the focal item is:

$$\Delta\pi_3 = \underbrace{\underbrace{\underbrace{\Delta s_1 m_1 + \Delta s_1\left(t^\theta - DEAL\right) + s_1^*\left(t^\theta - t^* - DEAL\right)}_{\text{item level promotional profit}} + m_2\left(\Delta s_2 - \Delta s_1\right)}_{\text{category level promotional profit}} + m_3\left(\Delta s_3 - \Delta s_2\right)}_{\text{promotional profit or store level promotional profit}} \tag{5.78}$$

It was shown that promotion profits could falsely be measured at the item or category-level, and that such measurement would lead to different estimates of the promotion profits.

The deal discount that maximizes the store-level promotion profit was defined as the optimal deal discount and it was shown how the optimal deal discount can be recognized and found. Myopic deal optimization was defined as optimization of the item-level or the category-level promotion profits. The cost of myopic optimization was defined as the difference between maximum store-level promotion profits and the store-level promotion profits resulting from the myopic optimal deal.

We examined how cannibalization affects promotion profits measured at different-levels and how cannibalization affects the optimal deal discount as well as its impact on the myopic deal.

# Appendix

## 5.A.1. Relationship between Cannibalization and Model Parameters

This appendix shows how the measures of cannibalization and the parameters of the response models are related. It shows (1) how to calculate the rate of cannibalization when the response model parameters are known, and (2) how the model parameters are related when the cannibalization rates are known. The first is useful when the model has been estimated on empirical data, while the second is more appropriate when specifying the model parameters for a simulation because the degree of cannibalization should be more intuitive measures than the response parameters.

$$\phi_{23} = \left(\frac{1+v_2}{v_2}\right) \Big/ \left(1+\frac{\beta_{v2}}{\beta_{v3}(1+v_2)}\right) \tag{5.79}$$

$$\phi_{12} = \left(\frac{1+v_1}{v_1}\right) \Big/ \left(1+\frac{\beta_{v1}[1+v_2(1-\phi_{23})]}{\beta_{v2}(1+v_1)}\right) \tag{5.80}$$

$$\phi_{23} = \left(\frac{1+v_2}{v_2}\right) \Big/ \left(1+\frac{\beta_{v2}}{(\beta_{w3}-\beta_{u3})(1+v_2)}\right) \tag{5.81}$$

$$\psi_{23} = \left(\frac{1+u_2}{u_2}\right) \Big/ \left(1+\frac{\beta_{u2}}{\beta_{u3}(1+u_2)}\right) \tag{5.82}$$

$$\psi_{12} = \left(\frac{1+u_1}{u_1}\right) \Big/ \left(1+\frac{\beta_{u1}[1+u_2(1-\psi_{23})]}{\beta_{u2}(1+u_1)}\right) \tag{5.83}$$

$$\beta_{v2} = \beta_{v1}\phi_{12}\left(\frac{v_1}{1+v_1}\right)\left[\frac{1+v_2(1-\phi_{23})}{1+v_1(1-\phi_{12})}\right] \tag{5.84}$$

$$\beta_{v3} = \beta_{v2}\phi_{23}\left(\frac{v_2}{1+v_2}\right)\left(\frac{1}{1+v_2(1-\phi_{23})}\right) \tag{5.85}$$

$$\beta_{v3} = \beta_{v1}\phi_{12}\phi_{23}\left(\frac{v_1}{1+v_1}\right)\left(\frac{v_2}{1+v_2}\right)\left[\frac{1}{1+v_1(1-\phi_{12})}\right] \tag{5.86}$$

$$\beta_{u2} = \beta_{u1}\psi_{12}\left(\frac{u_1}{1+u_1}\right)\left[\frac{1+u_2(1-\psi_{23})}{1+u_1(1-\psi_{12})}\right] \tag{5.87}$$

$$\beta_{u3} = \beta_{u2}\psi_{23}\left(\frac{u_2}{1+u_2}\right)\left(\frac{1}{1+u_2(1-\psi_{23})}\right) \tag{5.88}$$

$$\beta_{u3} = \beta_{u1}\psi_{12}\psi_{23}\left(\frac{u_1}{1+u_1}\right)\left(\frac{u_2}{1+u_2}\right)\left[\frac{1}{1+u_1(1-\psi_{12})}\right] \tag{5.89}$$

# 6. SIMULATING PROMOTION PROFITS

## 6.1. Introduction

In this chapter, the model developed in Chapter 5 is used to measure the profit impact of sales promotion for hypothetical model parameters. The chapter starts with a description of the sales model parameters. Then, the promotional sales-responses of the item, the category, and the store are described. The profit impact and the profit-maximizing deals are described next. It is shown that measurement of the promotion profit at the item-level, the category-level, and the store-level gives different estimates of the promotion profit. Thereafter follows an investigation of the promotion profit's dependence on the sales-response model parameters. The sensitivity to changes in margins, size of trade deal, and deal requirement are examined next. The chapter ends with a summariy of the conclusions of the simulation study and a discussion of the implications for retailers and manufacturers.

Note that the simulation here is deterministic and what Kotler (1991) denotes a marketing plan simulator and Cooper and Nakanishi (1988) refer to as "[to] simulate the consequences of [plans]". This should not be confused with stochastic simulations like the Monte Carlo method.

## 6.2. Definition of the Promotional Response Models

This section specifies the model parameters used in the simulation. Further, it shows the sales-response and the basket-response to various sizes of the price deal discount.

### 6.2.1. Model Structure and Parameters

To illustrate and investigate how the deal discount and the special display for an item affect retailer gross profits at different levels, a set of response models was specified. It is assumed that the retailer decides on the promotional activities for one item (the focal item) in a product category (the focal category). The specific promotional instruments the retailer has to choose are the size of the price deal discount and whether or not to allocate special display space to the item. The manufacturer offers the retailer a trade deal in the form of a price discount on the units sold by the retailer during the promotion. Gross margins are treated as homogeneous across items in the focal category (except for the focal item), and as homogeneous across categories for other categories than the focal category. The promotional status of other categories is assumed to be unaffected by the promotion of the focal item.

The response models and promotional-profit model developed in Chapter 5 are used. After consultations with industry experts, the model parameters were set to reasonable values. The response model constants were selected to give the following baseline figures:

- When the focal item is sold at regular price and not on special display, its share of the category sales is 30 percent and its share of the number of category baskets is 25 percent.
- The category's share of store sales is then 1 percent while its share of the total number of baskets is 5 percent.
- Store traffic is 3,000 baskets per day, averaging SEK 100 per basket.

Table 6.1 presents all the response model parameters of the base case model.

| **Sales-response Models** | |
|---|---|
| Item-level constant | $\alpha_{v1} = -0.847$ |
| Category-level constant | $\alpha_{v2} = -4.595$ |
| Store-level constant | $\alpha_{v3} = 12.61$ |
| Item-level deal response | $\beta_{v1} = 5$ |
| Category-level deal response | $\beta_{v2} = 1$ |
| Store-level deal response | $\beta_{v3} = 0.002$ |
| Item-level display response | $\delta_{v1} = 0.5$ |
| Category-level display response | $\delta_{v2} = 0.1$ |
| Store-level display response | $\delta_{v3} = 0.002$ |
| | |
| **Basket Response Models** | |
| Item-level constant | $\alpha_{u1} = -1.099$ |
| Category-level constant | $\alpha_{u2} = -2.944$ |
| Store-level constant | $\alpha_{u3} = 8.006$ |
| Item-level deal response | $\beta_{u1} = 5$ |
| Category-level deal response | $\beta_{u2} = 1.0$ |
| Store-level deal response | $\beta_{u3} = 0.001$ |
| Item-level display response | $\delta_{u1} = 0.5$ |
| Category-level display response | $\delta_{u2} = 0.1$ |
| Store-level display response | $\delta_{u3} = 0.001$ |
| | |
| **Basket Value Model** | |
| Constant | $\alpha_{w3} = 4.605$ |
| Deal response | $\beta_{w3} = 0.001$ |
| Display response | $\delta_{w3} = 0.001$ |

*Table 6.1. Parameters of the response models (Scenario 1: base case).*

The response model structure and parameters have now been described. In the next section, we use the model and its parameters to calculate how sales respond to sales promotion.

### 6.2.2. Sales Response

This section investigates how the sales-responses at the item-, category-, and store-levels depends on the size of the price deal discount and whether or not a special display is allocated to the focal item. More specifically, we look at the sales of the focal item, other items in the focal category, category sales, sales of other categories, and store sales. It should be pointed out again that, at all levels, sales refer to sales valued at regular prices, which means that sales can be interpreted as a type of quantity index (see section 5.2.2).

The deal discount is varied between 0 and 30 percent in two-percent steps. For each step, the item sales, category sales, and store sales are estimated for the price deal only and for the price deal combined with a special display. The sales-responses are reported in Table 6.2.

| *Deal* | *Item Sales* | | *Category* | | *Store Sales* | |
|---|---|---|---|---|---|---|
| *Discount* | *No Display* | *Display* | *No Display* | *Display* | *No Display* | *Display* |
| 0% | 900 | 1374 | 3000 | 3319 | 300000 | 300601 |
| 2% | 984 | 1484 | 3060 | 3385 | 300012 | 300613 |
| 4% | 1073 | 1599 | 3121 | 3453 | 300024 | 300625 |
| 6% | 1167 | 1719 | 3184 | 3522 | 300036 | 300637 |
| 8% | 1267 | 1843 | 3248 | 3592 | 300048 | 300649 |
| 10% | 1372 | 1972 | 3313 | 3664 | 300060 | 300661 |
| 12% | 1482 | 2104 | 3379 | 3737 | 300072 | 300673 |
| 14% | 1597 | 2239 | 3447 | 3812 | 300084 | 300685 |
| 16% | 1716 | 2377 | 3516 | 3888 | 300096 | 300697 |
| 18% | 1840 | 2517 | 3586 | 3966 | 300108 | 300709 |
| 20% | 1968 | 2660 | 3658 | 4045 | 300120 | 300721 |
| 22% | 2100 | 2805 | 3731 | 4126 | 300132 | 300733 |
| 24% | 2235 | 2951 | 3805 | 4208 | 300144 | 300745 |
| 26% | 2373 | 3098 | 3881 | 4292 | 300156 | 300757 |
| 28% | 2513 | 3245 | 3959 | 4378 | 300168 | 300769 |
| 30% | 2655 | 3394 | 4038 | 4465 | 300180 | 300781 |

*Table 6.2. Sales of focal item, focal category, and store sales by deal discount with and without special display.*

The absolute sales levels presented in Table 6.2 are important as they provide the starting point for the further analysis of promotional effects. Sales of other items in the focal category and sales of other categories are not reported explicitly in Table 6.1, but can easily be calculated; sales of other items in the category are the difference between category sales and item sales. Sales of other categories are the difference between store sales and categry sales. For example, when there is no deal or special display for the focal item, then sales of the focal item are 900, sales of other items in the focal category are 2,100, and sales of other categories are 297,000.

As can be seen from the definition of promotion profit (equation 5.43), the changes in sales caused by the promotion may be even more important than the absolute levels. Figure 6.1 shows the change in sales for different sizes of the price deal when there is no special display. The changes, calculated from Table 6.1, relate to the sales that would occur in the absence of a price deal and special display. For example, the change in item sales for a 20 percent deal discount is thus 1,968 less 900 or 1,068 if the item is not on display. A deal discount of 20 percent combined with a special display increase item sales by 2,660 less 900 or 1,760.

Sales of the focal item are more responsive to the price deal than category sales and store sales. This implies that the promoted item cannibalizes on other item's sales. This can be seen in Figure 6.1 in the decreasing sales of other items in the focal category.

The effect on store sales is a small increase. However, Figure 6.1 shows that sales of other categories decrease as a consequence of the price deal on the focal item.

Figure 6.2 shows the changes in sales when the focal item is on display. Note that all changes are calculated as changes from the zero deal discount and no special display case. This causes the intercepts observed in Figure 6.2. The change in item sales caused by a special display alone is 474, i.e., 1,374 less 900.

When the focal item is on special display, this model predicts that store sales will increase more than category sales when the price deal is smaller than ten percent. This means that sales of other categories increase until the deal is ten percent. At larger price deal discounts, sales of other categories decrease. The change in sales of other items in the category is negative for all deal siscounts which indicates that there is intra-category cannibalization.

Cannibalization was formally defined in Section 5.2.4 and we shall now use that definition. Recall that intra-category cannibalization, $\Phi_{12}$ (*phi12*), was defined as the ratio of the change in category-sales to the change in item-sales (see equation 5.10). The inter-category cannibalization, $\Phi_{23}$ (*phi23*) was defined as the ratio of store-sales change to category-sales change (see equation 5.11).

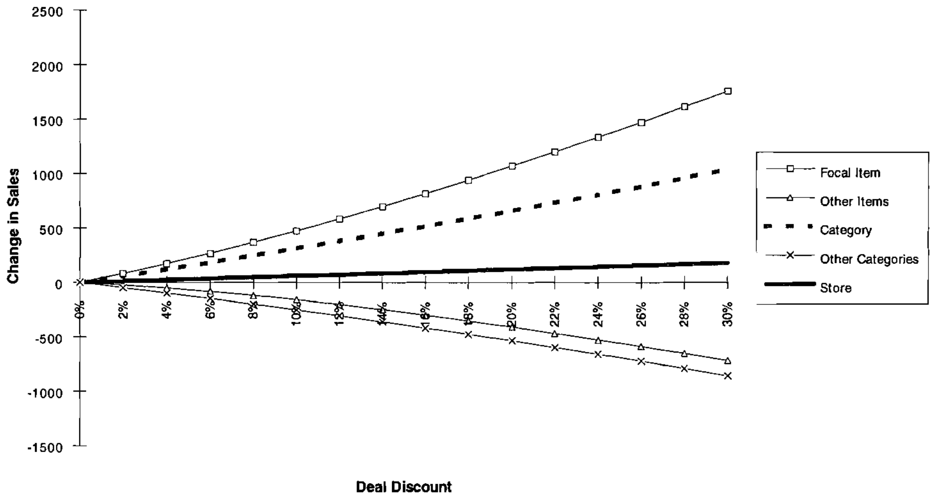


*Figure 6.1. Changes in sales at different levels by deal discount when the focal item is not on special display.*

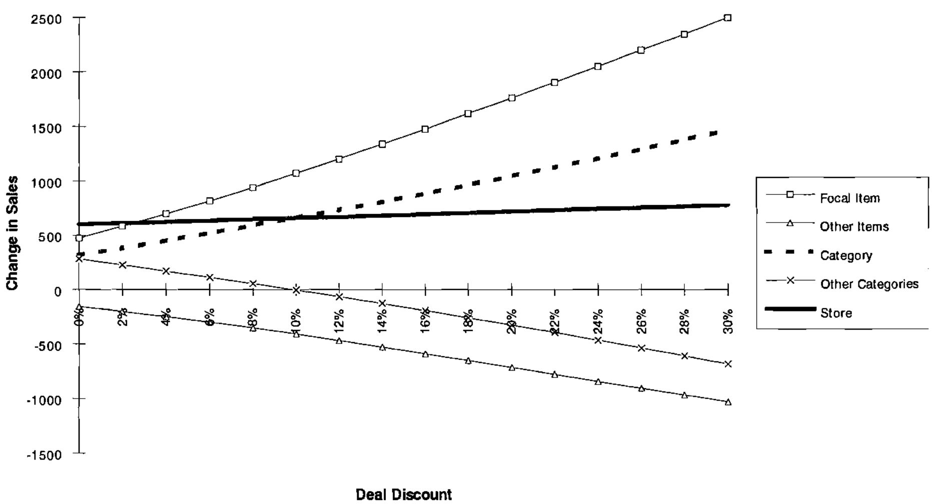


*Figure 6.2. Changes in sales at different levels by deal discount when the focal item is on special display.*

Table 6.3 presents the degree of intra- and inter-category cannibalization for different deal discounts, with and without special display. An example will clarify how the Table entries in Table 6.3 were calculated. Normal sales of the focal item are 900 and normal category sales are 3,000 as we know from Table 6.1. A promotion consisting of a 12 percent price deal plus a special display increases item sales to 2,104 and category sales to 3,737. This means that the promotion increased item sales by 1,204 and category sales by 737. The ratio of category change to item change is 0.61, which can be seen in Table 6.3.

| Deal | Without Display | | With Display | |
|---|---|---|---|---|
| Discount | phi12 | phi23 | phi12 | phi23 |
| 0% | | | 0.67 | 1.88 |
| 2% | 0.72 | 0.20 | 0.66 | 1.59 |
| 4% | 0.70 | 0.20 | 0.65 | 1.38 |
| 6% | 0.69 | 0.20 | 0.64 | 1.22 |
| 8% | 0.68 | 0.19 | 0.63 | 1.10 |
| 10% | 0.66 | 0.19 | 0.62 | 0.99 |
| 12% | 0.65 | 0.19 | 0.61 | 0.91 |
| 14% | 0.64 | 0.19 | 0.61 | 0.84 |
| 16% | 0.63 | 0.19 | 0.60 | 0.78 |
| 18% | 0.62 | 0.18 | 0.60 | 0.73 |
| 20% | 0.62 | 0.18 | 0.59 | 0.69 |
| 22% | 0.61 | 0.18 | 0.59 | 0.65 |
| 24% | 0.60 | 0.18 | 0.59 | 0.62 |
| 26% | 0.60 | 0.18 | 0.59 | 0.59 |
| 28% | 0.59 | 0.18 | 0.59 | 0.56 |
| 30% | 0.59 | 0.17 | 0.59 | 0.53 |

*Table 6.3. Cannibalization (phi) by deal discount, with and without special display.*

The interpretation of the table entry (0.61) is that 61 percent of the sales increase of the focal item translates into a sales increase of the category. The remaining 39 percent of the increase in the focal item's sales come from the other items in the category. Small values indicate severe cannibalization while 1.0 indicates no cannibalization. If the ratio is greater than unity, it is interpreted as a multiplier. Ratios greater than 1.0 can be found in the upper right corner of Table 6.3 for the store-to-category sales changes. The combination of special display and a deal of eight percent increases category sales by SEK 0.63 for each SEK 1.00 increase in item sales. Each SEK 1.00 increase in category sales in turn increases store sales by SEK 1.10.

### 6.2.3. Basket Response

The previous section examined the effect of price deal and special display for the focal item on sales of that item, sales of other items in the focal category, and sales of other categories. This section shows how the retailer's promotional efforts for the focal item affect the number of buyers of the focal item, the number of buyers of the focal category, and the total number of baskets (i.e., store traffic). The aim is to provide some intuition for the mechanism by which sales promotions affects sales, i.e., by having an impact on the number of buyers.

Table 6.4 shows the number of buyers of the item, the focal category, and store traffic (i.e., the total number of baskets) for different magnitudes of the price deal, with and without special display. It can be seen that sales promotion has little impact on store traffic for the hypothetical item in the simulation model. The number of category baskets is somewhat more affected by sales promotion and the number of item baskets is fairly responsive to sales promotion.

| Deal | Item | | Category | | Store | |
|---|---|---|---|---|---|---|
| Discount | No Display | Display | No Display | Display | No Display | Display |
| 0% | 38 | 59 | 150 | 165 | 3000 | 3003 |
| 2% | 41 | 64 | 153 | 168 | 3000 | 3003 |
| 4% | 45 | 69 | 156 | 171 | 3000 | 3003 |
| 6% | 49 | 74 | 159 | 175 | 3000 | 3003 |
| 8% | 54 | 80 | 162 | 178 | 3000 | 3003 |
| 10% | 58 | 86 | 165 | 181 | 3000 | 3003 |
| 12% | 64 | 92 | 168 | 185 | 3000 | 3003 |
| 14% | 69 | 99 | 171 | 188 | 3000 | 3003 |
| 16% | 74 | 106 | 175 | 192 | 3000 | 3003 |
| 18% | 80 | 112 | 178 | 196 | 3001 | 3004 |
| 20% | 86 | 119 | 181 | 199 | 3001 | 3004 |
| 22% | 92 | 126 | 185 | 203 | 3001 | 3004 |
| 24% | 99 | 134 | 188 | 207 | 3001 | 3004 |
| 26% | 105 | 141 | 192 | 211 | 3001 | 3004 |
| 28% | 112 | 148 | 195 | 215 | 3001 | 3004 |
| 30% | 119 | 156 | 199 | 219 | 3001 | 3004 |

*Table 6.4. Number of baskets containing the focal item, the focal category, and store traffic by deal discount with and without special display.*

Note that in contrast to the sales models, where category sales are the sum of sales of the focal item and sales of other items in the category, the number of category baskets is not the sum of the number of item baskets and the number of baskets containing other items. This is because category baskets may contain more than one item from the focal category. Therefore, it is not necessarily so that the number of other item baskets must decrease even if the number of category baskets remains constant while the number of baskets containing the focal item increases. Figures 6.3 and 6.4 illustrate the increases in the number of item baskets, the number of category baskets, and store traffic for different sizes of the price deal discount. In Figure 6.3, there is no special display allocated to the focal item, while in Figure 6.4, the price deal is accompanied by a special display.

Figures 6.3 and 6.4 clearly show that the change in the number of item baskets is larger than the change in the number of category baskets. The change in the number of category baskets is in turn larger than the change in store traffic. A way to quantify the relation between the increases in item baskets, category baskets, and store traffic is to calculate the ratio of the increase in category baskets to the increase in item baskets $\Psi_{12}$ (*psi12*), and the ratio of increase in store traffic to the increase in category baskets $\Psi_{23}$ (*psi23*). The first of these ratios is the share of the increase in item buyers that are also new buyers of the category. The second ratio is the share of new buyers of the category who represent extra store traffic. Table 6.5 shows these ratios for different sizes of deal discounts, with and without special display, for the focal item.

| Deal | No Display | | Deal and Display | |
|---|---|---|---|---|
| Discount | psi12 | psi23 | psi12 | psi23 |
| 0% | | | 0.72 | 0.20 |
| 2% | 0.79 | 0.02 | 0.70 | 0.17 |
| 4% | 0.77 | 0.02 | 0.68 | 0.15 |
| 6% | 0.75 | 0.02 | 0.67 | 0.13 |
| 8% | 0.73 | 0.02 | 0.66 | 0.12 |
| 10% | 0.71 | 0.02 | 0.64 | 0.11 |
| 12% | 0.69 | 0.02 | 0.63 | 0.10 |
| 14% | 0.68 | 0.02 | 0.62 | 0.09 |
| 16% | 0.67 | 0.02 | 0.62 | 0.08 |
| 18% | 0.65 | 0.02 | 0.61 | 0.08 |
| 20% | 0.64 | 0.02 | 0.60 | 0.07 |
| 22% | 0.63 | 0.02 | 0.60 | 0.07 |
| 24% | 0.62 | 0.02 | 0.59 | 0.07 |
| 26% | 0.61 | 0.02 | 0.59 | 0.06 |
| 28% | 0.61 | 0.02 | 0.58 | 0.06 |
| 30% | 0.60 | 0.02 | 0.58 | 0.06 |

*Table 6.5. Psi by deal discount, with and without special display.*

Table 6.5 should be read as explained by the following example: If the retailer allocates a special display to the focal item and sets the deal discount at 18 percent, then 61 percent of the extra buyers of the item are also extra buyers of the category, i.e., they would not have been buyers of the category had the promotion not been executed. Eight percent of the extra buyers of the category represent an increase in store traffic. These are consumers attracted to the store by the sales promotion for the focal item.

For this hypothetical item, sales promotion mainly serves to increase the number of buyers of the item while its effect on store traffic is assumed to be small.

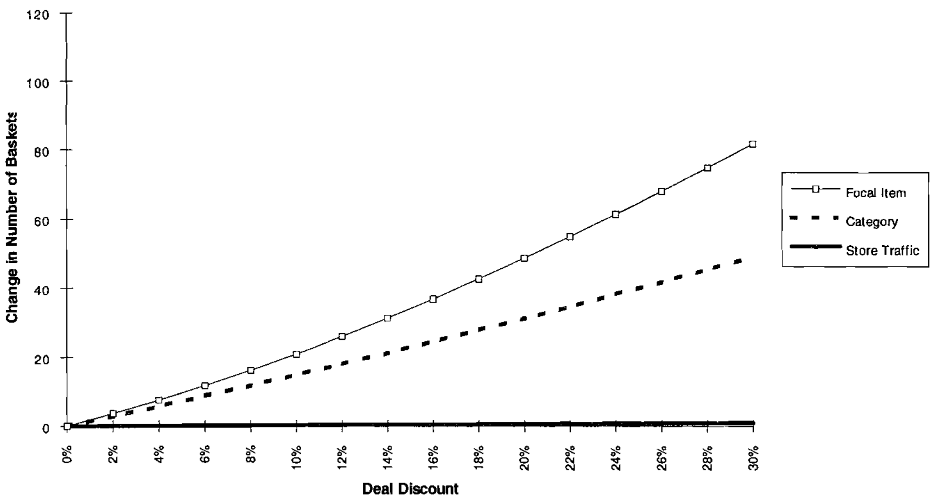


*Figure 6.3. Changes in the number of item baskets, category baskets, and store traffic by deal discount when the focal item is not on special display.*

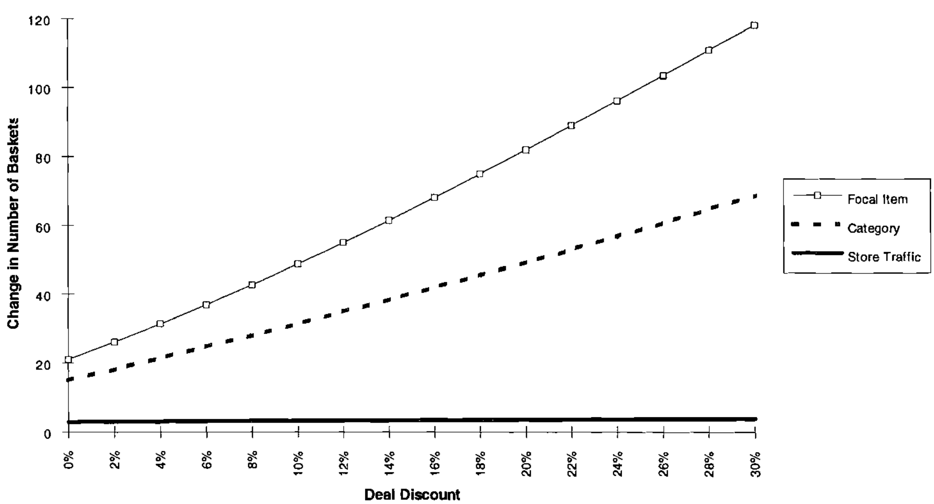


*Figure 6.4. Changes in the number of item baskets, category baskets, and store traffic by deal discount when the focal item is on special display.*

## 6.3. Promotion Profits Measured at Three Levels

Promotional sales-response may be interesting in its own right, but our main interest in this study is to define and investigate the retailer's profit of sales promotion. The aim of this section is thus to demonstrate the profit impact of the sales-responses reported above. In order to do that, we need to specify the parameters of the promotion-profit model defined in Chapter 5. The following parameter values were used:

| | | |
|---|---|---|
| Gross margin of item (percent of regular retail price) | $m_1$ | $= 0.20$ |
| Average effective gross margin of other items in the focal category | $m_2$ | $= 0.20$ |
| Average effective gross margin of items in other categories | $m_3$ | $= 0.20$ |
| Trade deal offered on focal item (percent of regular retail price) | $TROFFER$ | $= 0.20$ |
| Minimum discount required to obtain the trade deal | $DEALREQ$ | $= 0$ or $0.10$ |
| Indicator of display requirement to obtain the trade deal | $DISPREQ$ | $= 0$ |

This section will show that, given the models and the parameters specified above, the retailer will come to different conclusions concerning the profitability of the promotion and set different price deal discounts depending on the level at which the promotion profit is evaluated.

As the parameters indicate, we assume that the retailer is offered a per unit trade deal of 20 percent of the retail price (i.e., 25 percent of the retailer's product cost when the retailer cost of the product is 80 percent of the retail price). We evaluate the promotion profits for two cases: (1) the retailer receives the trade money irrespective of the deal discount; and (2) the retailer receives the trade money only if the deal discount is set at 10 percent or more. In both cases, we investigate the promotion profits at the item-, category-, and store-levels.

### 6.3.1. Level of Analysis, Deal Discount, and Special Display

We start with the profit impact of sales promotion when there is no deal requirement, i.e., when the retailer can absorb any part of the trade money. Figure 6.5 shows the promotion profit measured at the item-, category-, and store-level at different deal discounts when the focal item is not on special display. The retailer's promotion profit is evaluated at two-percent intervals.

Note that the promotion profit measured at the item-level is higher than the promotion profit measured at the category- and store-level for all deal discounts evaluated. This means that the item-level measurement of promotion profit overestimates the retailer's profit of the promotion. Figure 6.5 shows that the promotion profit is negative for all deal discounts. The point here is that the item-, category-, and store-level measurement come to different estimates of the promotion profit. In other words, the estimated promotion profit is dependent on the level of analysis used.

Even more important is that the three measures reach their highest value at different deal discounts. This implies that the measurement level determines the deal discount that the profit-maximizing retailer will set.

The discount that leads to highest gross margin from sales of the promoted product is a discount of 14 percent. The category-level promotion profit peaks at a deal discount of 8 percent while the store-level promotion profit is highest when the deal discount is 0 percent.

Figure 6.6 shows the promotion profits of a special display allocated to the focal item combined with different deal discounts. This time, the store-level promotion profit is higher than the item-level and the category-level promotion profits for small deal discounts. For larger discounts, the item-level and the category-level promotion profit measurement again overestimate the promotion profit.

The deal discount which the profit-maximizing retailer will use depends, again, on the level of analysis. Item- and category-level analyses lead to larger deal discounts than store-level evaluation.

Note that the figures show the change in the retailer's gross profit from the item, from the category, and from all categories. This is calculated as the gross margin from sales of the item at each discount level and display status less the gross margin when the discount is zero and the item is not on special display. In this case, the baseline implies that the retailer absorbs the whole trade deal offered by the manufacturer.

The effect on category-level gross margin is small when the item is not on special display and the discount is smaller than 20 percent. At larger discounts, the promoted item has a lower margin than the other items in the category. This means that cannibalization hurts gross profits. Special display also leads to cannibalization of other items' sales, but as long as the effective margin of the promoted item is higher than that of the cannibalized items, the retailer's gross profit from the category increases.

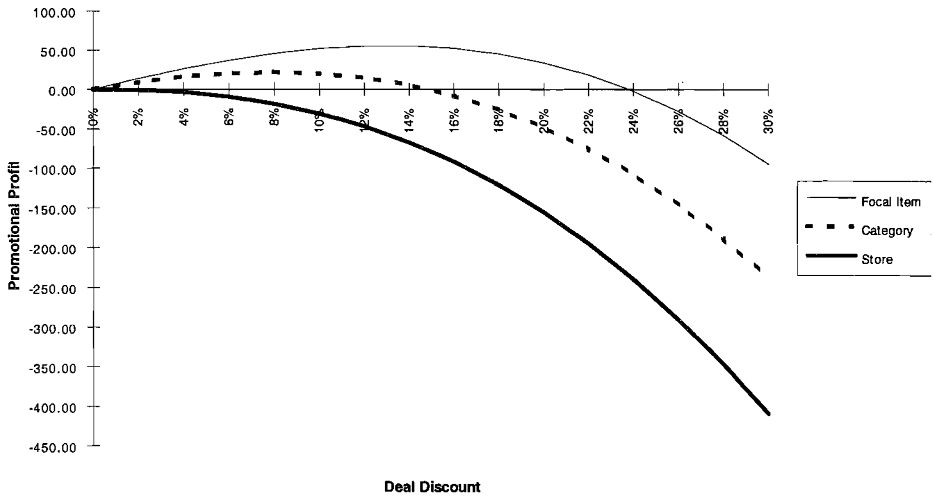


*Figure 6.5. Promotion profits measured at item-, category-, and store-level when the focal item is promoted without special display.*

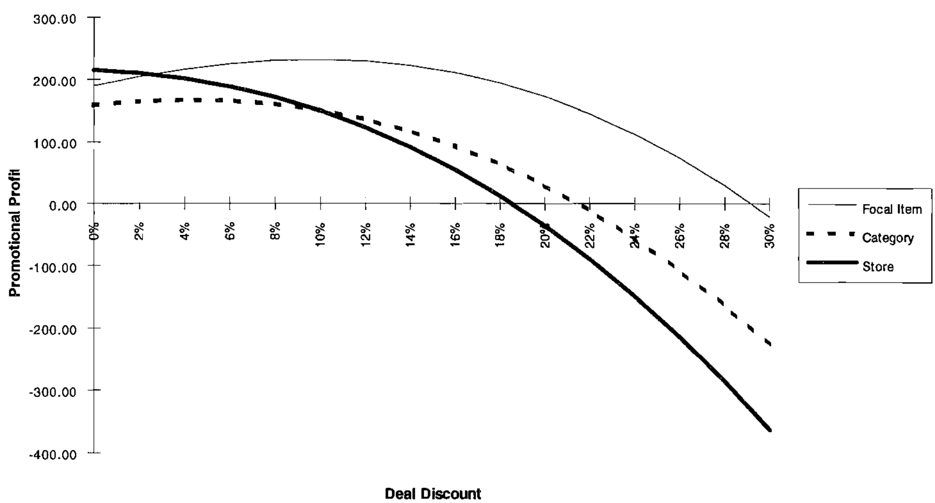


*Figure 6.6. Promotion profits measured at item-, category-, and store-level when the focal item is on special display.*

The store-level promotion profit is the real concern of the retail manager (see Chapter 5). Figure 6.6 shows that the retailer would maximize promotion profit by absorbing all of the trade deal, not passing anything on to the consumers. Allocating a special display to the item would increase gross profits by SEK 215 (see Table 6.5). If the display space would not be worth more than SEK 215 when used for another item or category, the retailer would maximize profits by displaying the item without a price deal.

The retailer's profits from different combinations of deal discount and special display for the focal item are shown in Table 6.5. The profit-maximizing deal discount depends on the level of analysis. If item-level gross profit is maximized when deciding on the deal discount, the deal discount would be set to 14 percent when not on display while the discount would be set to 10 percent when on special display. At the category-level, the profit-maximizing deal would be 8 percent deal discount without display and 4 percent with special display. The store-level analysis suggests a deal discount of 0 regardless of the special display.

The cost (or opportunity loss) incurred by the retailer when using item-level analysis rather than store-level analysis can be calculated as follows: Assume that the focal item is not on display. The item-level analysis would lead the retailer to use a deal discount of 14 percent. The store-level result of that deal is SEK 67.40 lower than when the retailer absorbs the whole trade deal, which is the optimal decision according to the store-level analysis. If the item were displayed, the loss due to sub-optimization would be 214.93 less 149.31, or SEK 65.62.

| *Deal* | *Item level Profit* | | *Category Level Profit* | | *Store Level Profit* | |
|---|---|---|---|---|---|---|
| *Discount* | *No Display* | *Display* | *No Display* | *Display* | *No Display* | *Display* |
| 0% | 0.00 | 189.62 | 0.00 | 158.54 | 0.00 | 214.93 |
| 2% | 13.75 | 204.04 | 9.06 | 164.19 | -0.56 | 209.70 |
| 4% | 26.10 | 215.82 | 15.88 | 166.48 | -3.60 | 200.85 |
| 6% | 36.74 | 224.57 | 20.15 | 165.08 | -9.44 | 188.04 |
| 8% | 45.31 | 229.92 | 21.53 | 159.69 | -18.41 | 170.96 |
| 10% | 51.47 | 231.51 | 19.70 | 150.00 | -30.84 | 149.31 |
| 12% | 54.86 | 229.00 | 14.33 | 135.77 | -47.07 | 122.84 |
| 14% | 55.12 | 222.07 | 5.12 | 116.75 | -67.40 | 91.28 |
| 16% | 51.89 | 210.44 | -8.24 | 92.73 | -92.15 | 54.43 |
| 18% | 44.84 | 193.84 | -26.02 | 63.54 | -121.59 | 12.12 |
| 20% | 33.63 | 172.03 | -48.48 | 29.03 | -156.00 | -35.83 |
| 22% | 17.96 | 144.84 | -75.86 | -10.91 | -195.59 | -89.51 |
| 24% | -2.44 | 112.09 | -108.34 | -56.37 | -240.58 | -149.04 |
| 26% | -27.84 | 73.65 | -146.10 | -107.40 | -291.15 | -214.46 |
| 28% | -58.45 | 29.43 | -189.27 | -164.05 | -347.42 | -285.83 |
| 30% | -94.46 | -20.65 | -237.96 | -226.32 | -409.53 | -363.15 |

*Table 6.5. Retailer's profits from a sales promotion evaluated at the item-level, category-level, and store-level.*

### 6.3.2. The Effect of a Deal Requirement

In the analysis above, it was assumed that the retailer could absorb the whole trade deal offered by the manufacturer (although only for the products actually sold). We shall now see how the results change when the manufacturer imposes the condition that the retailer must discount the item by at least 10 percent to receive the trade deal worth 20 percent of the retail price. Figures 6.7 and 6.8 show the retailer's promotion profits when the manufacturer imposes a 10 percent deal discount requirement.

Figure 6.7 shows the promotion profit measured at the item-, category-, and store-level when the focal item is on deal without display. Item- and category-level measurement again overestimate the promotion profit as compared with the store-level measurement.

All three measures are negative for small deal discounts. This is because the retailer does not receive the trade money unless the focal item is awarded a 10 percent deal discount or more and the deal price elasticity is not large enough to increase the sales volume enough to compensate for the lower per unit (effective) margin. The retailer's effective margin on the item decreased because the deal discount is entirely financed by the retailer at discounts below ten percent.

When the deal discount reaches 10 percent, all three promotion profit measures jump to positive values because the retailer receives the trade money. (The jumps are actually more direct than it appears in the figures).

The category-level and the store-level profit measures both peak at a deal discount of 10 percent, i.e., the minimum deal discount required by the manufacturer. The maximum item-level profit is obtained at a deal discount of 14 percent.

Figure 6.8 presents the promotion profits from the combination of a special display and a price deal. The item-level and the category-level promotion profit measures overestimate the profit at deal discounts greater than (or equal to) 10 percent. All three measures reach their maxima when the deal discount is 10 percent. This means that the profit-maximizing retailer would set the same deal discount irrespectively of the measurement-level if the focal item is allocated a special display.

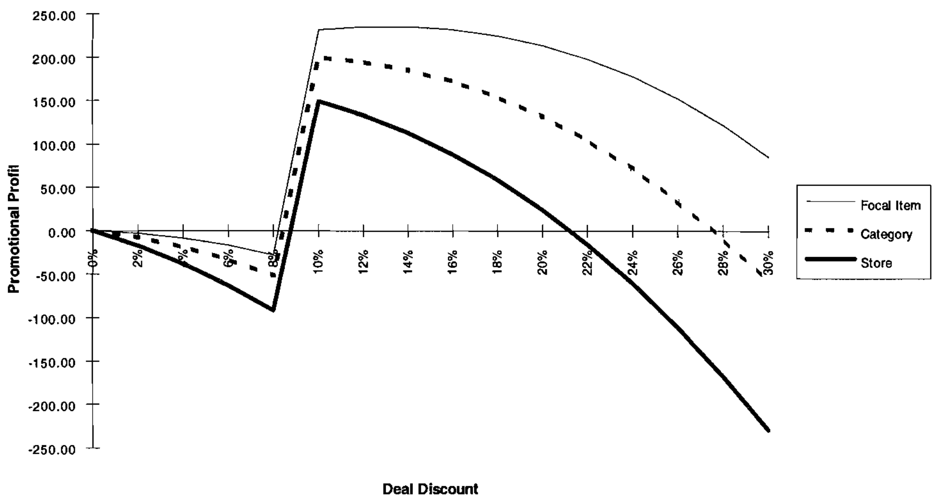


*Figure 6.7. Promotion profits measured at item-, category-, and store-level when the focal item is promoted without special display and the manufacturer requires the retailer to discount the item by 10 percent.*

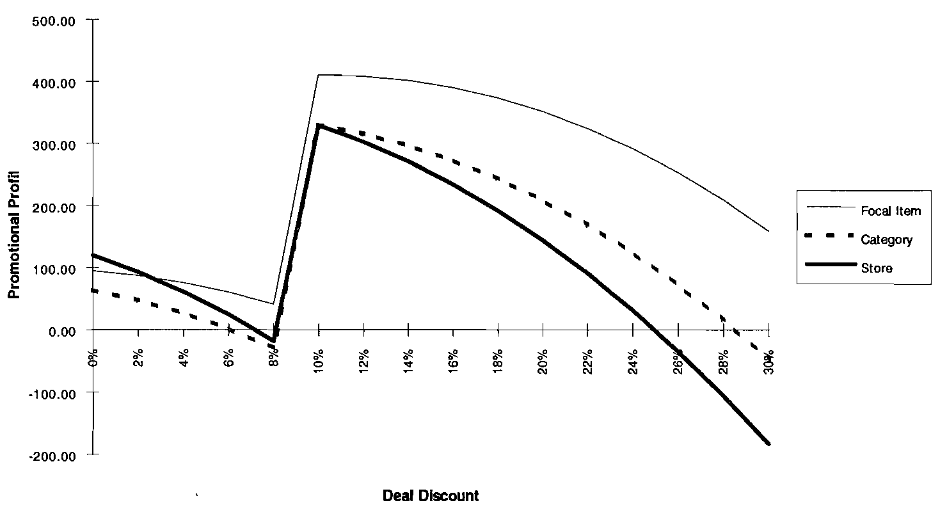


*Figure 6.8. Promotion profits measured at item-, category-, and store-level when the focal item is on special display and the manufacturer requires the retailer to discount the item by 10 percent.*

The numerical values underlying the figures 6.7 and 6.8 are supplied in Table 6.6. The retailer profit maximizes when the focal item is discounted at ten percent. The optimal discount is the same when the item is on special display and when it is not allocated any extra display space. Store-level promotion profit is SEK 180 higher when the focal item is allocated a special display. If the opportunity cost of display space is lower than SEK 180, the retailer would maximize profits by displaying the item.

Again, the retailer would choose a too large price discount if promotion profits were evaluated at the item-level rather than at the store-level. The manufacturer's deal requirement, i.e., that the item must be discounted by at least 10 percent, leads to a store-level optimal deal discount equal to the manufacturer's requirement. Thus, the profit-maximizing retailer would pass through half of the trade deal to the consumers.

Since the optimal deal discount is 10 percent at all levels of analysis when the focal item is displayed, there is no loss incurred by the myopic optimization. Under tha assumption that the focal item is not displayed, the retailer would set the deal discount to 14 percent if item-level analysis were used. Store-level analysis would lead to a 10 percent deal. The loss due to using the myopic approach is SEK 36.56 (i.e., 149.16 - 112.60).

| ***Deal*** | ***Item level Profit*** | | ***Category Level Profit*** | | ***Store Level Profit*** | |
|---|---|---|---|---|---|---|
| ***Discount*** | ***No Display*** | ***Display*** | ***No Display*** | ***Display*** | ***No Display*** | ***Display*** |
| 0% | 0.00 | 94.81 | 0.00 | 63.73 | 0.00 | 120.12 |
| 2% | -2.96 | 87.18 | -7.65 | 47.33 | -17.27 | 92.84 |
| 4% | -8.40 | 75.92 | -18.62 | 26.58 | -38.10 | 60.95 |
| 6% | -16.64 | 60.70 | -33.23 | 1.22 | -62.81 | 24.18 |
| 8% | -28.01 | 41.22 | -51.79 | -29.01 | -91.73 | -17.74 |
| 10% | 231.47 | 411.51 | 199.70 | 330.00 | 149.16 | 329.31 |
| 12% | 234.86 | 409.00 | 194.33 | 315.77 | 132.93 | 302.84 |
| 14% | 235.12 | 402.07 | 185.12 | 296.75 | 112.60 | 271.28 |
| 16% | 231.89 | 390.44 | 171.76 | 272.73 | 87.85 | 234.43 |
| 18% | 224.84 | 373.84 | 153.98 | 243.54 | 58.41 | 192.12 |
| 20% | 213.63 | 352.03 | 131.52 | 209.03 | 24.00 | 144.17 |
| 22% | 197.96 | 324.84 | 104.14 | 169.09 | -15.59 | 90.49 |
| 24% | 177.56 | 292.09 | 71.66 | 123.63 | -60.58 | 30.96 |
| 26% | 152.16 | 253.65 | 33.90 | 72.60 | -111.15 | -34.46 |
| 28% | 121.55 | 209.43 | -9.27 | 15.95 | -167.42 | -105.83 |
| 30% | 85.54 | 159.35 | -57.96 | -46.32 | -229.53 | -183.15 |

*Table 6.6. Retailer's promotion profits at the item-, category-, and store-level for different levels of discount and special display status.*

These analyses show that the manufacturer has reason to worry about the retailer's pass-through of the trade deal to the consumers. The analysis of store-level profit of the promotion shows that the retailer may be better off absorbing the whole trade deal. However, if the manufacturer can design the trade deal in such a way that the retailer must pass through at least a part of the trade deal in order to receive the discount, it may be optimal for the retailer to offer the consumers a discount.

This is very important for the manufacturer because the retailer's pass-through has a considerable impact on the manufacturer's sales volume. Recall that normal sales of the item (in this store) are SEK 900. When the item is on a ten percent deal, its sales rise to SEK 1,372 valued at regular price, while sales increase to SEK 1,972 if the price deal is combined with a special display. The sales volume increase of the focal item is thus 52 percent when only on price deal and 119 percent when the deal is accompanied by special display.

## 6.4. Promotion Profits of Four other Response Patterns

The previous sections have examined the impact of sales promotion on sales and profits for a hypothetical item in a hypothetical store. The results are obviously influenced by the choice of model parameters and the assumptions implied by the parameters. Therefore, this section examines four additional sets of model parameters, or scenarios, each implying a different type of sales-response pattern. In these scenarios, the price deal response parameters were varied as shown in Table 6.7. All other parameters were held constant across the scenarios. Note that scenario 1 was described above.

| | *Scenario* | | | | |
|---|---|---|---|---|---|
| *Model* | *1* | *2* | *3* | *4* | *5* |
| Focal item's share of category sales | 5 | 5 | 5 | 10 | 10 |
| Focal category's share of store sales | 1 | 1.5 | 1.5 | 1.5 | 1 |
| Basket value | 0.001 | 0.015 | 0.015 | 0.015 | 0.001 |
| Store traffic | 0.001 | 0.001 | 0.015 | 0.015 | 0.001 |
| Category baskets' share of all baskets | 1 | 1.5 | 1.5 | 1.5 | 1 |
| Item baskets' share of category baskets | 5 | 5 | 5 | 10 | 10 |

*Table 6.7. Response model's price deal response parameters for scenario by model. Other parameters remain constant across the scenarios.*

In scenario 2, the price deal response of the category is stronger than in the base scenario. The average basket size is also more responsive to the price deal in this scenario. The other parameters are the same as in scenario 1. Scenario 3, differs from Scenario 2 by assuming that store traffic is also responsive to the price deal. The item-level response is assumed to be stronger in Scenario 4 while the other parameters are at the same level as in Scenario 3. The last scenario keeps the strong item-level response from Scenario 4 while all other parameters are set at the levels used in the base scenario.

The analysis in this section focuses on the effects of price deal on sales and profits. The effects of special display are not analyzed in this section to save space and enhance clarity.

### 6.4.1. Scenario 2: Moderate Cannibalization

This scenario assumes that the category's response to the deal discount is stronger than in the base scenario. The average basket size is also more responsive in this scenario. The combination of stronger category- and store-level responsiveness yields a scenario with modest intra- and inter-category cannibalization. This can be seen in Figure 6.9 depicting the changes in sales for various sizes of the deal discount.

The degree of cannibalization is very low for deal discounts below ten percent, but increases progressively for larger deal discounts. The promotion profits measured at the item-level, the category-level, and store-level are presented in Figure 6.10. In this scenario (in contrast to Scenario 1), deal discounts below 20 percent are profitable at all measurement levels.

Figure 6.10 suggests that the item-level measurement as well as the category-level measurement gives upwardly biased estimates of the promotion profits. Table 6.8 shows that using item-level analysis to determine the optimal deal discount leads to a 16 percent deal discount while category- and store-level analyses both set deal discount at 12 percent.[8]

| Deal | Sales | | | Promotional Profits | | |
|---|---|---|---|---|---|---|
| Discount | Item | Category | Store | Item | Category | Store |
| 0% | 900 | 3000 | 300000 | 0.00 | 0.00 | 0.00 |
| 2% | 994 | 3091 | 300096 | 17.57 | 17.13 | 18.05 |
| 4% | 1095 | 3186 | 300192 | 34.04 | 32.25 | 33.54 |
| 6% | 1203 | 3283 | 300288 | 49.03 | 44.94 | 46.05 |
| 8% | 1319 | 3383 | 300384 | 62.14 | 54.80 | 55.15 |
| 10% | 1443 | 3485 | 300480 | 72.93 | 61.40 | 60.39 |
| 12% | 1575 | 3591 | 300577 | 80.95 | $\boxed{64.28}$ | $\boxed{61.30}$ |
| 14% | 1714 | 3701 | 300673 | 85.72 | 63.00 | 57.41 |
| 16% | 1862 | 3813 | 300769 | $\boxed{86.76}$ | 57.10 | 48.26 |
| 18% | 2016 | 3929 | 300865 | 83.58 | 46.14 | 33.37 |
| 20% | 2178 | 4048 | 300962 | 75.69 | 29.68 | 12.31 |
| 22% | 2348 | 4171 | 301058 | 62.60 | 7.31 | -15.38 |
| 24% | 2524 | 4298 | 301154 | 43.85 | -21.38 | -50.12 |
| 26% | 2707 | 4428 | 301251 | 18.97 | -56.76 | -92.30 |
| 28% | 2896 | 4563 | 301347 | -12.46 | -99.18 | -142.29 |
| 30% | 3091 | 4701 | 301443 | -50.86 | -148.97 | -200.45 |

*Table 6.8. Scenario 2: Sales and promotion profits measured at the item-, category-, and store-level for different sizes of the deal discount.*

[8]Category- and store-level analyses give the same "optimal" price deal here because the promotion profits are evaluated for every 2-percent (as opposed to every 1-percent as used later) increase in deal size.

In comparison with the store-level promotion profit of a 12 percent deal discount, the store-level promotion profit is SEK 13.04 lower for the 16 percent deal discount. This opportunity cost may not seem large. However, this implies that a retailer determining the deal discount by ising the myopic-level analysis improve the promotion profit by 27 percent by switching to the store-level model. Another way to appreciate the value of the store-level (holistic) analysis approach is to multiply the SEK 13.04 loss by seven to get the profits forgone for this promotion during the week the promotion runs. Multiply again by the number of promoted products during one week, say 300, and by the 52 weeks of the year. This is, of course, an overly simplistic way to measure the value of the holistic approach, but it gives at least an indication of the potential of a less myopic analysis.

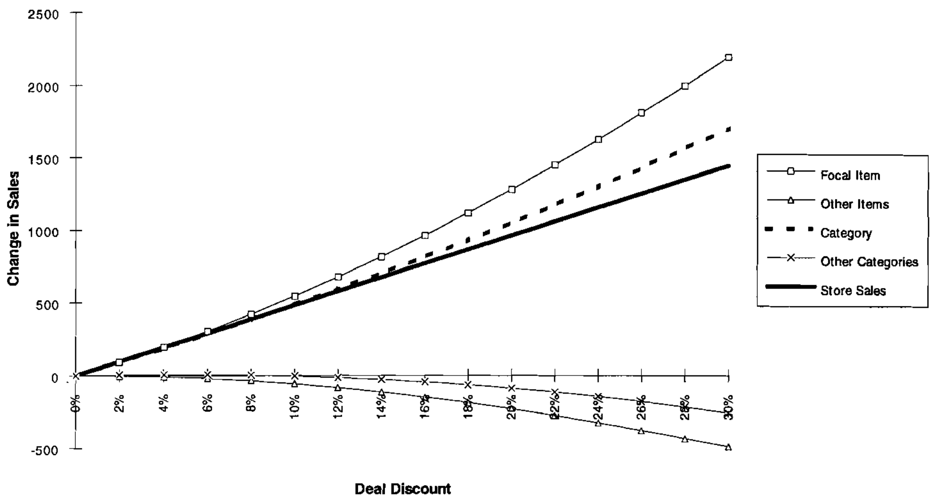


*Figure 6.9. Scenario 2: Changes in sales by deal discount.*

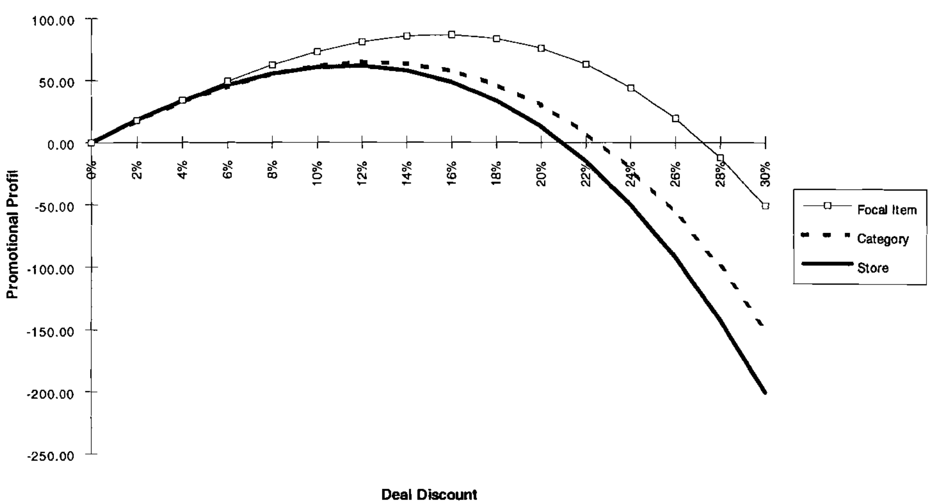


*Figure 6.10. Scenario 2: Promotion profit measured at the item-level, category-level, and store-level for different deal discounts.*

### 6.4.2. Scenario 3: Store Traffic Generation

In this scenario, the price deal has a stronger impact on store traffic than in the previous scenarios. In combination with the effect on average basket size, the impact on store traffic leads to more responsive store sales. Figure 6.11 shows that the increase in store sales is larger than the increase in sales of the focal item. There is some intra-category cannibalization in this scenario, too, but category sales are more responsive to the deal discount. Between categories, on the other hand, there is no cannibalization. Sales of other categories than the focal category also respond positively to the deal discount. This is a consequence of the price deal's impact on store traffic.

The profit impact of the price deal shows a different pattern in this scenario (Figure 6.12). The myopic (i.e., the item-level) profit measure understates the true promotion profit. What is interesting in this scenario is that the category-level analysis understates the promotion profits even more than the item-level analysis.

The optimal deal discount is 18 percent when evaluated at the store-level. This is to be compared with the 16 percent deal discount suggested by the item-level model and the 12 percent deal discount suggested by the category-level model. The intriguing point here is that the sub-optimization is more severe when using a category-level model than when using the most myopic model. Using a category management model can, thus, be counter productive when intra-category cannibalization is combined with positive effects on other categories. Table 6.9 gives the promotion profits needed to calculate the cost of myopia. The item-level model leads to a loss of SEK 1.98 while the loss caused by the category-level model is SEK 22.71.

| Deal | Sales | | | Promotional Profit | | |
|---|---|---|---|---|---|---|
| Discount | Item | Category | Store | Item | Category | Store |
| 0% | 900 | 3000 | 300000 | 0.00 | 0.00 | 0.00 |
| 2% | 994 | 3092 | 300180 | 17.68 | 17.36 | 34.91 |
| 4% | 1095 | 3187 | 300360 | 34.26 | 32.70 | 67.27 |
| 6% | 1204 | 3285 | 300540 | 49.38 | 45.64 | 96.66 |
| 8% | 1321 | 3386 | 300721 | 62.61 | 55.74 | 122.65 |
| 10% | 1445 | 3490 | 300901 | 73.54 | 62.58 | 144.78 |
| 12% | 1577 | 3598 | 301082 | 81.69 | $\boxed{65.70}$ | 162.59 |
| 14% | 1718 | 3708 | 301263 | 86.60 | 64.65 | 175.59 |
| 16% | 1866 | 3822 | 301443 | $\boxed{87.76}$ | 58.97 | 183.32 |
| 18% | 2021 | 3939 | 301624 | 84.70 | 48.22 | $\boxed{185.30}$ |
| 20% | 2185 | 4060 | 301805 | 76.91 | 31.95 | 181.08 |
| 22% | 2355 | 4184 | 301987 | 63.91 | 9.73 | 170.21 |
| 24% | 2533 | 4312 | 302168 | 45.21 | -18.83 | 152.26 |
| 26% | 2717 | 4444 | 302349 | 20.35 | -54.12 | 126.82 |
| 28% | 2908 | 4580 | 302531 | -11.10 | -96.50 | 93.52 |
| 30% | 3104 | 4721 | 302712 | -49.56 | -146.31 | 52.00 |

*Table 6.9. Scenario 3: Sales and promotion profits measured at the item-, category-, and store-level for different deal discounts.*

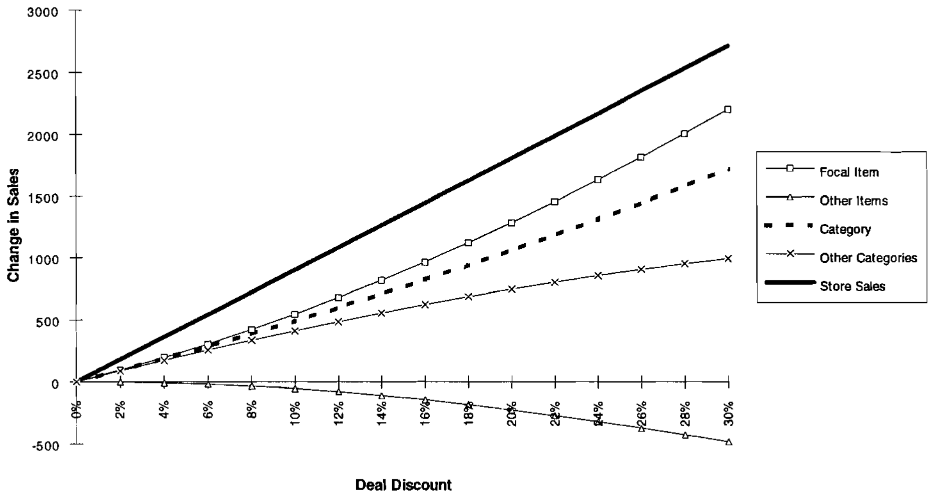


*Figure 6.11. Scenario 3: Changes in sales by deal discount.*

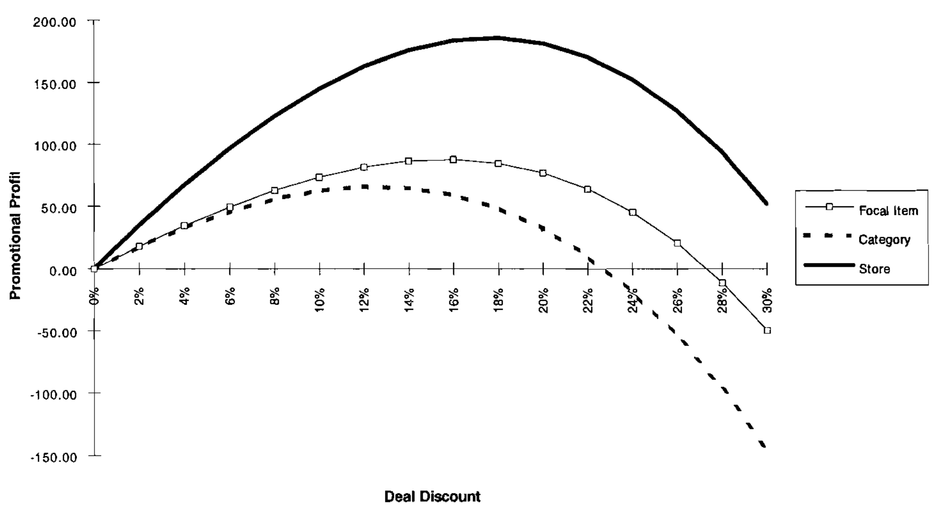


*Figure 6.12. Scenario 3: Promotion profit measured at the item-level, category-level, and store-level for different deal discounts.*

### 6.4.3. Scenario 4: Intra-Category Cannibalization and Store Traffic Generation

Intra-category cannibalization is more pronounced in scenario 4 than in scenario 3. The responsiveness of store sales and category sales are equal to the previous scenario. Figure 6.13 shows the change in sales at different measurement levels for various deal discounts.

Item-level measurement exaggerates the promotion profits and leads to larger than optimal deal discounts in this scenario. The effect of using category-level measurement is the opposite, leading to smaller than optimal deal discounts (see Figure 6.14).

The optimal deal discount according to item-level analysis is 18 percent, while the category-level analysis sets the deal discount at 12 percent. According to the store-level evaluation of deal profits, the optimal deal discount is 14 percent. The sub-optimization cost of the item-level model is SEK 12.02 while the loss incurred by using the category-level model is SEK 8.34 calculated from the promotion-profit figures in Table 6.10.

| Deal | Sales | | | Promotional Profit | | |
|---|---|---|---|---|---|---|
| Discount | Item | Category | Store | Item | Category | Store |
| 0% | 900 | 3000 | 300000 | 0.00 | 0.00 | 0.00 |
| 2% | 1063 | 3092 | 300180 | 43.75 | 29.71 | 47.26 |
| 4% | 1243 | 3187 | 300360 | 87.51 | 56.37 | 90.94 |
| 6% | 1441 | 3285 | 300540 | 129.80 | 78.75 | 129.78 |
| 8% | 1653 | 3386 | 300721 | 169.00 | 95.63 | 162.55 |
| 10% | 1878 | 3490 | 300901 | 203.44 | 105.88 | 188.09 |
| 12% | 2113 | 3598 | 301082 | 231.56 | 108.52 | 205.41 |
| 14% | 2354 | 3708 | 301263 | 251.95 | 102.81 | 213.75 |
| 16% | 2598 | 3822 | 301443 | 263.49 | 88.26 | 212.61 |
| 18% | 2843 | 3939 | 301624 | 265.37 | 64.64 | 201.73 |
| 20% | 3085 | 4060 | 301805 | 257.08 | 31.95 | 181.08 |
| 22% | 3325 | 4184 | 301987 | 238.43 | -9.66 | 150.82 |
| 24% | 3559 | 4312 | 302168 | 209.44 | -59.89 | 111.20 |
| 26% | 3788 | 4444 | 302349 | 170.32 | -118.39 | 62.55 |
| 28% | 4011 | 4580 | 302531 | 121.36 | -184.81 | 5.22 |
| 30% | 4229 | 4721 | 302712 | 62.93 | -258.80 | -60.50 |

*Table 6.10. Scenario 4: Sales and promotion profits measured at the item-, category-, and store-level for different sizes of the deal discount.*

Note that the category-level model performs better than the item-level model in this scenario in spite of the positive effects on store sales. The reason is that the intra-category cannibalization is too strong compared with the increase in store sales.

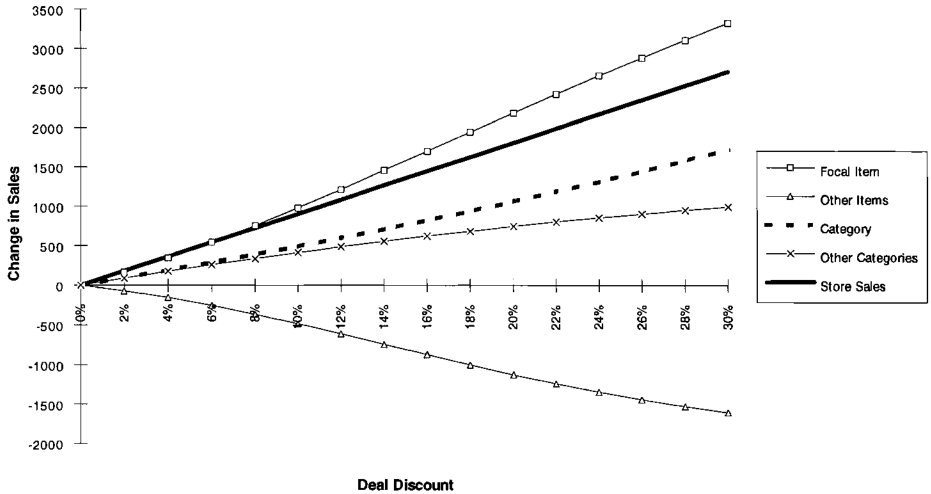


*Figure 6.13. Scenario 4: Changes in sales by deal discount.*

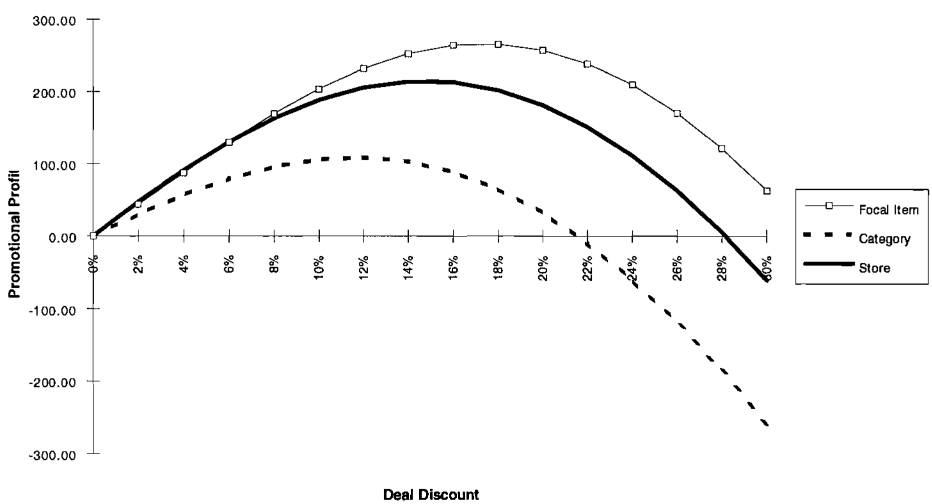


*Figure 6.14. Scenario 4: Promotion profits measured at the item-level, category-level, and store-level for different deal discounts.*

### 6.4.4. Scenario 5: More Cannibalization

The last scenario is characterized by responsive item-sales and fairly inelastic category- and store-sales. The implication is considerable intra-category and inter-category cannibalization. Figure 6.15 shows how the sales-responses depend on the deal discount.

As expected, the item-level analysis grossly overstates the promotion profits. Also the category-level analysis leads to an overly optimistic view of promotion profits. The store-level profit (loss) of the promotion is almost unaffected by deal discounts on the focal item up to deals of about 12 percent. Above this point, the store-level profit of the deal rapidly becomes negative.

According to Table 6.11, the optimal deal discount is 6 percent. Retailers using category-level analysis would set the deal at 10 percent, while those planning deal discounts using the item-level model would reduce the price by 16 percent.

| Deal | Sales | | | Promotional Profit | | |
|---|---|---|---|---|---|---|
| Discount | Item | Category | Store | Item | Category | Store |
| 0% | 900 | 3000 | 300000 | 0.00 | 0.00 | 0.00 |
| 2% | 1051 | 3060 | 300012 | 39.55 | 21.28 | 11.66 |
| 4% | 1217 | 3121 | 300024 | 78.25 | 39.06 | 19.58 |
| 6% | 1396 | 3184 | 300036 | 114.68 | 52.24 | $\boxed{22.66}$ |
| 8% | 1585 | 3248 | 300048 | 147.34 | 59.79 | 19.85 |
| 10% | 1783 | 3313 | 300060 | 174.77 | $\boxed{60.79}$ | 10.26 |
| 12% | 1984 | 3379 | 300072 | 195.63 | 54.55 | -6.85 |
| 14% | 2188 | 3447 | 300084 | 208.82 | 40.59 | -31.93 |
| 16% | 2390 | 3516 | 300096 | $\boxed{213.54}$ | 18.70 | -65.21 |
| 18% | 2588 | 3586 | 300108 | 209.31 | -11.07 | -106.64 |
| 20% | 2780 | 3658 | 300120 | 195.95 | -48.48 | -156.00 |
| 22% | 2964 | 3731 | 300132 | 173.57 | -93.15 | -212.88 |
| 24% | 3140 | 3805 | 300144 | 142.48 | -144.57 | -276.81 |
| 26% | 3308 | 3881 | 300156 | 103.12 | -202.22 | -347.27 |
| 28% | 3467 | 3959 | 300168 | 56.03 | -265.59 | -423.74 |
| 30% | 3618 | 4038 | 300180 | 1.76 | -334.19 | -505.75 |

*Table 6.11. Scenario 5: Sales and promotion profits measured at the item-, category-, and store-level for different deal discounts.*

The 12 percent deal discount is SEK 2.81 worse than the optimal deal while the 16 percent deal costs the retailer SEK 87.87 in foregone gross profits. This indicates that using the myopic analysis for setting the size of the deal discount can be costly when (1) item sales are responsive to deal discounts and (2) cannibalization is an important source of that incremental sales volume.

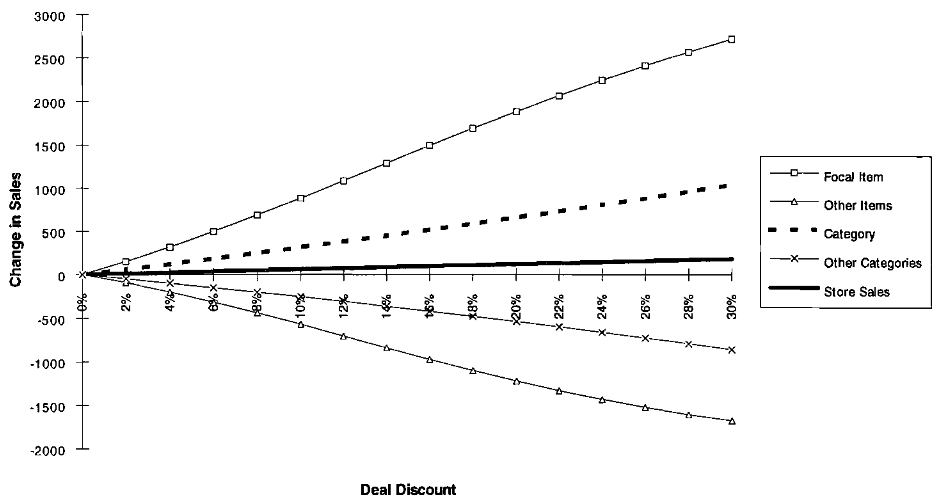


*Figure 6.15. Scenario 5: Changes in sales at by deal discount.*

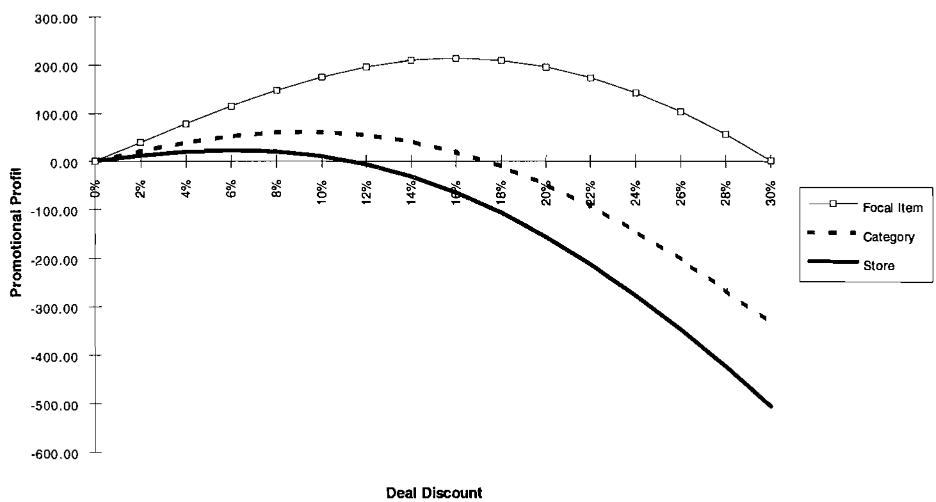


*Figure 6.16. Scenario 5: Promotion profits measured at the item-level, category-level, and store-level for different deal discounts.*

## 6.5. Determinants of the Size of the Deal Discount

In this section, we examine some determinants of the size of the deal discount under the assumption that the retailer maximizes current promotion profits. The determiants we consider are: (1) the level of analysis, (2) the size of the trade deal discount, (3) deal requirements imposed by the manufacturer, and (4) the gross margins of the focal category.

The size of the trade deal discount as a determinant of the retailer deal discount is directly related to the question of retailer pass-through of trade deals. It will be seen that three factors moderate the effect of the trade deal on deal discount. First, the level of analysis that the retailer uses for determining the deal discount influences the deal discount. It is assumed that the retailer will set the deal discount that maximizes promotion profits, given the level of analysis used. Second, the gross margins of the focal category is positively related to the deal discount. Third, the sales-response parameters (the scenarios described above) are also important determinants of the deal discount.

Three additional issues are addressed in this section. The first is the promotion profit's dependence on the trade deal. The second issue is how the trade deal influences the opportunity loss due to myopic deal optimization. The third issue is the gross margin's impact on the deal discount and the pass-through.

### 6.5.1. Level of Analysis, Trade Deal Discount, and Response Pattern

In order to investigate the impact of the level of analysis and the size of the trade deal discount on the size of the retailer deal discount we need to define three variables; the retailer determining the deal discount by using the item-level analysis would set the deal discount to *Deal1*. If the category-level analysis were used, the retailer would set the deal to *Deal2* while the store-level analysis would lead to *Deal3*.

These three variables were determined by evaluating the profit (measured at the item-level, the category-level, and the store-level) for each 0.1 percent step of the deal discount between zero and 100 percent. While this procedure does not find the exact optimal deal discount, it provides reasonable precision and can be seen as an approximation of the reality where the deal discount is not a perfectly continuous variable.

We start with the Scenario 1. Figure 6.17 shows how the deal discount depends on the trade deal offered by the manufacturer and the level of analysis used by the retailer for setting the deal discount. In general, the larger the trade deal, the larger the deal offered to the consumers.

In Scenario 1, the item-level analysis leads to the largest deals and the largest pass-through of trade deal money to the consumers, while store-level analysis leads to the lowest pass-through.

Indeed, small trade deals will be totally absorbed by the profit-maximizing retailer using store-level or category-level analysis. Trade deals larger than 19 percent (of the retail price) lead to small deal discounts in the store. The deal discount then increases linearly with the size of the trade deal. This means that the relative pass-through (deal discount divided by the trade deal) is higher the larger the trade deal, assuming that the retailer seeks to maximize store-level promotion profits.

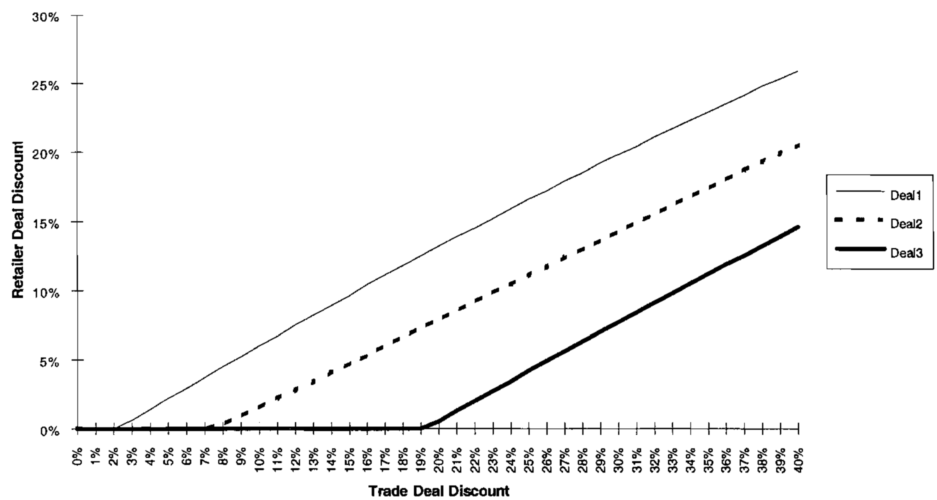


*Figure 6.17. Scenario 1: Deal discount based on item (Deal1), category (Deal2), and store (Deal3) level deal optimization as functions of the size of the trade deal offered.*

Figure 6.18 presents the results for Scenario 2. Item-level analysis again leads to larger deal discounts than the category-level and the store-level analyses. The difference between the deal discounts determined by the three methods is smaller than in Scenario 1, but increases with the size of the trade deal.

The deal discounts are approximately proportional to the trade deal discount. This implies that the relative pass-through is constant. Retailers using the item-level deal optimization pass through three quarters of the trade money while the relative pass-through of retailers who use the store-level deal optimization is about 50 percent.

The results of Scenario 3 (Figure 6.19) differ from those of the first two scenarios; the store-level deal optimization leads to larger deals than category- and store-level deal optimization for most trade deals. Substantial trade deals, however, lead to larger deal discounts when the retailer optimizes the deal discount at the item-level rather than at the store-level.

The relative pass-through is constant for category- and store-level deal optimization but decreases with the size of the trade deal when using store-level optimization. The retailers using store-level optimization would add their own resources to the trade deal on those smaller than 16 percent. This is due to the rather strong store sales effect of the price deal in scenario 3.

In Scenario 4, store-level deal optimization leads to smaller deal discounts than item-level optimization but larger than the deals determined by category-level optimization (see Figure 6.20). Relative pass-through is independent of the trade deal when the retailer uses category-level optimization. When using item or store-level deal optimization, the relative pass-through decreases with the size of the trade deal.

Figure 6.21 presents the results for Scenario 5. Item-level optimization leads to larger deals than category-level optimization, while deals set to optimize category-level promotion profits are larger than deals determined by store-level deal optimization. This scenario is similar to the Scenario 1. The difference is that the item-level sales-response is stronger than in Scenario 1, which leads to a larger difference between *Deal1* and *Deal3* than in Scenario 1.

In summary, these analyses show that the deal discount is positively related to the size of the trade deal. Whether the relative pass-through increases, decreases, or is constant with the trade deal depends on the sales-response (i.e., the scenario) and the level of deal optimization applied by the retailer. The retailer's level of optimization (item, category, or store) also influences the absolute pass-through, or the deal discount. Obviously, it is important for the manufacturer to understand these mechanisms and have knowledge about the sales-response and the level of analysis used by the retailer, in order to manage trade promotions effectively.

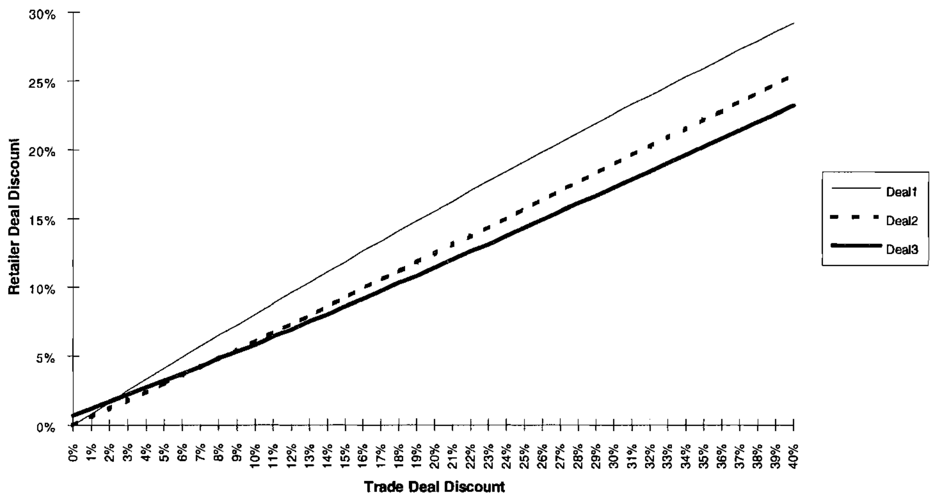


*Figure 6.18. Scenario 2: Deal discount based on item (Deal1), category (Deal2), and store (Deal3) level deal optimization as functions of the trade deal offered.*

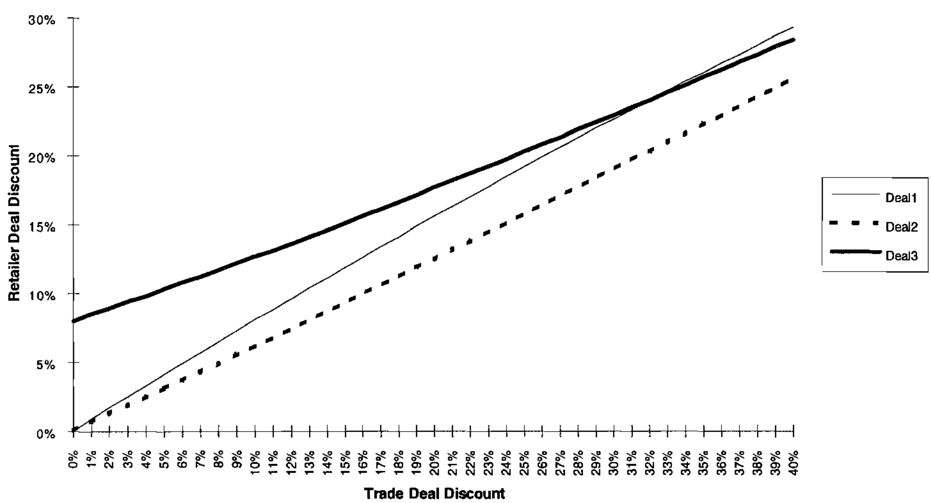


*Figure 6.19. Scenario 3: Deal discount based on item (Deal1), category (Deal2), and store (Deal3) level deal optimization as functions of the trade deal offered.*

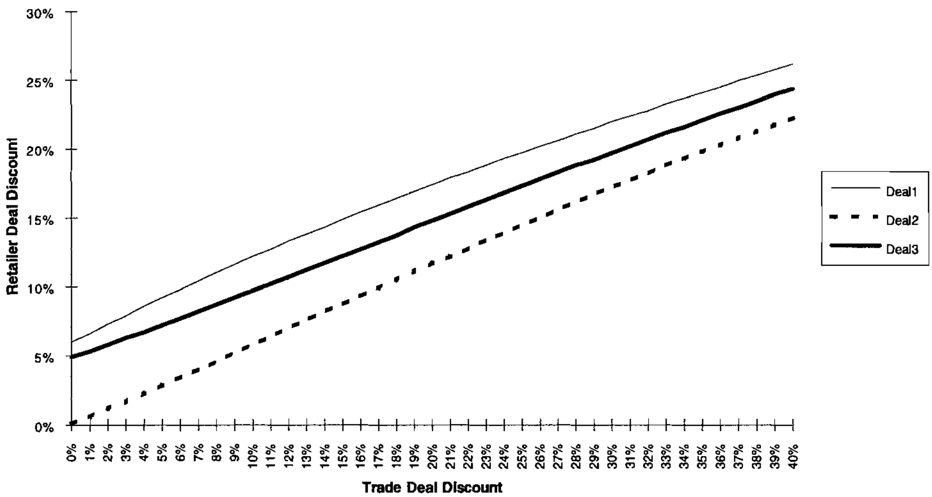


*Figure 6.20. Scenario 4: Deal discount based on item (Deal1), category (Deal2), and store (Deal3) level deal optimization as functions of the trade deal offered.*

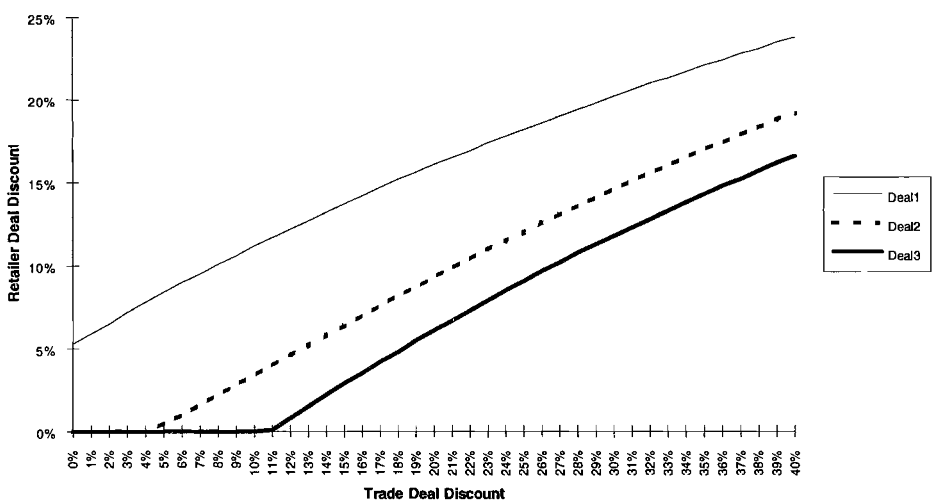


*Figure 6.21. Scenario 5: Deal discount based on item-, category-, and store-level deal optimization as functions of the trade deal offered.*

### 6.5.2. The Cost of Myopic Optimization

We have seen how the deal discount depends on the size of the trade deal and the level of optimization that the retailer uses. Now, we shall see how these two factors influence the promotion profits measured at the store-level. In the following, *Profit3* is the store-level promotion profit of *Deal3*. Similarly, *Profit1* and *Profit2* are the store-level promotion profits resulting from *Deal1* and *Deal2*,respectively. The opportunity losses caused by myopic deal optimization are *Loss1 = Profit3 - Profit1* and *Loss2 = Profit3 - Profit2*.

Figure 6.22 presents the store-level promotion profits of *Deal1*, *Deal2*, and *Deal3* in Scenario 1. It should be noted that the irregularities of the curves presented in this section were introduced by the search routine used; the curves should really be smooth and regular.

Starting with *Profit3*, i.e., the store-level promotion profit of the deal optimized at the store-level, Figure 6.22 shows that the promotion profits are zero for small trade deals. This is because small trade deals do not induce the retailer to pass anything of the trade deal through to the consumers. Recall that the trade money pocketed by the retailer is not included in the promotion profit because this money has no effect on the retailer's decision when the trade deal is not made conditional on a retail promotion. The retailer's promotion profit increases rapidly with the size of the trade deal.

The store-level profit of category-level deal optimization, denoted *Profit2*, is zero as long as the trade deal is small enough not to induce a price deal. As *Deal2* and *Deal3* are equal when the trade deal is small, the sub-optimization cost is also zero. Moderate-sized trade deal discounts lead to larger than optimal retailer deal discounts, causing opportunity losses for the retailer. Large trade deals lead to positive promotion profits (*Profit2*). The the opportunity loss is approximately constant for moderate and large trade deals (see Figure 6.23).

A similar pattern can be observed for the store-level profit of item-level deal optimization, i.e., *Profit1*. Large trade deals induce the retailer to use deal discounts that generate positive store-level profits. The opportunity cost due to sub-optimization is constant for moderate and large trade deals.

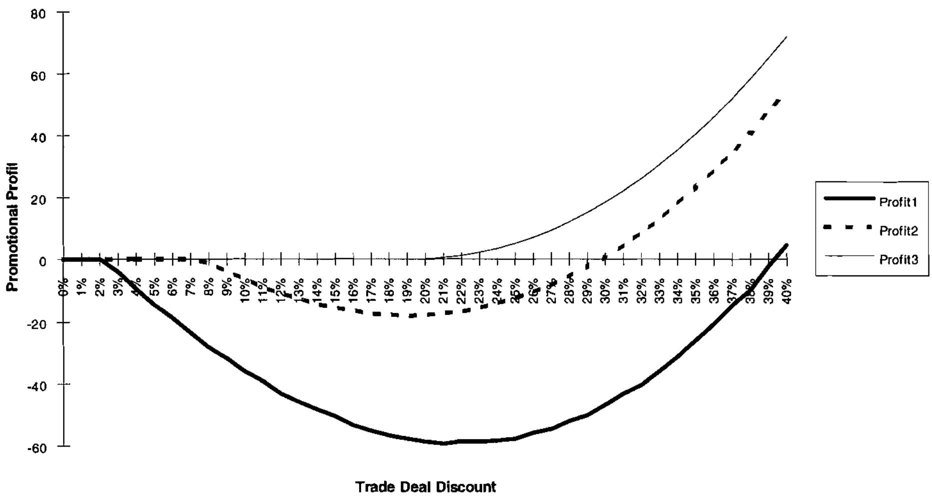


*Figure 6.22. Scenario 1: Store-level promotion profit of deal discount optimized at item-, category-, and store-level as functions of the trade deal offered.*

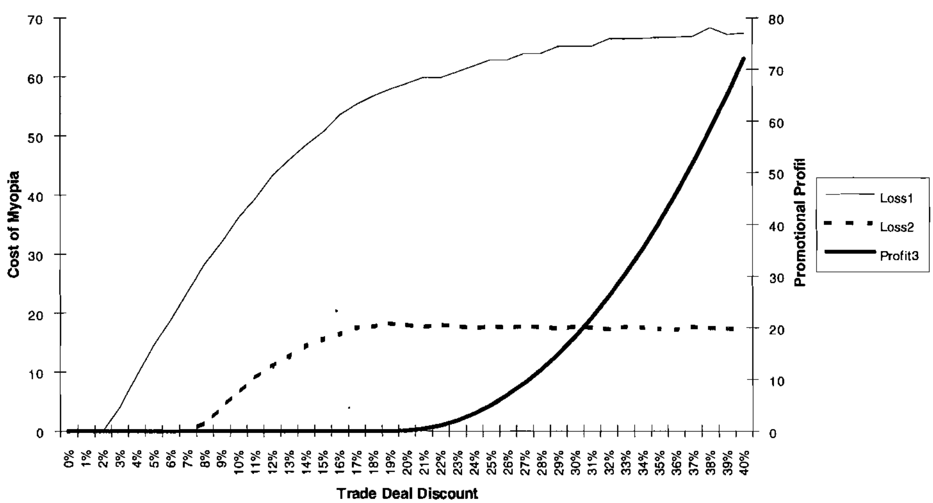


*Figure 6.23. Scenario 1: Sub-optimization costs and maximum promotion profit as functions of the trade deal offered.*

Figure 6.24 shows that the promotion profits rise sharply with the size of the trade deal in Scenario 2. As category- and store-level deal optimization lead to almost the same deal discount in this scenario, the opportunity loss due to category-level optimization is small.

The item-level deal optimization causes somewhat larger opportunity losses than the category-level optimization. Figure 6.24 shows that the opportunity losses increase slowly with the size of the trade deal.

The retailer's promotion profit, again, rises progressively with the size of the trade deal in Scenario 3 (Figure 6.25), . Larger trade deals reduce the opportunity losses due to myopic deal optimization. In this scenario, the opportunity loss due to category-level deal optimization is larger than the opportunity losses caused by item-level optimization.

Figure 6.26 depicts the profit outcome and opportunity losses in Scenario 4 as functions of the trade deal discount. Large trade deal discounts are much more profitable for the retailer than small trade deals. The use of myopic deal optimization leads to small opportunity losses for the retailer in this scenario.

The picture is different for Scenario 5 (see Figure 6.27). Small trade deals lead to no incremental profits for the retailer (except for the absorbed trade money). For larger trade deals, the retailer's profits rise fairly rapidly.

Category-level deal optimization costs the retailer little in terms of foregone promotion profits. Item-level optimization, on the other hand, is more costly. Item-level optimization leads to store-level promotional losses for small trade deals and to 20 percent lower than maximum profits for large trade deals.

To summarize, the retailer's promotion profit is positively related to the size of the trade deal. The severity of myopic deal optimization depends on the sales-response model. The promotional sales-response also influences the relation between the trade deal discount and the cost of sub-optimization. In addition, it determines whether the item-level deal optimization is better or worse than the category-level deal optimization.

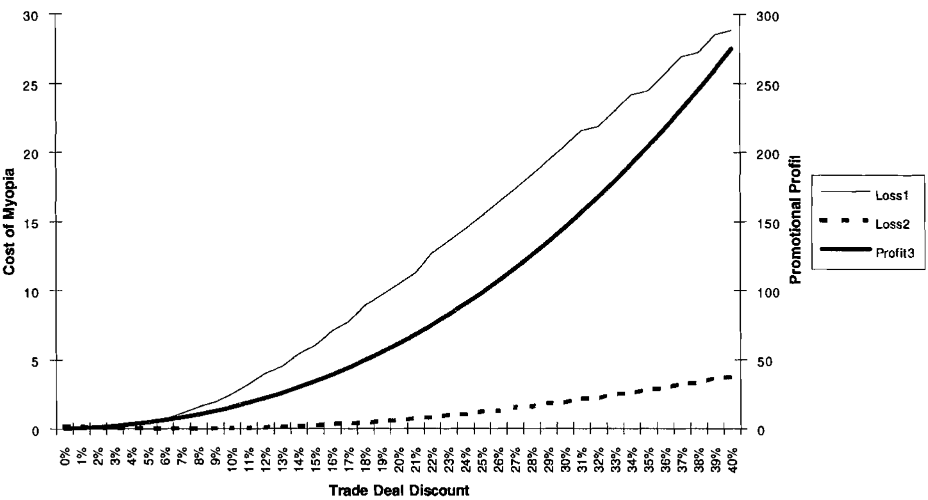


*Figure 6.24. Scenario 2: Sub-optimization costs and maximum promotion profit as functions of the trade deal offered.*

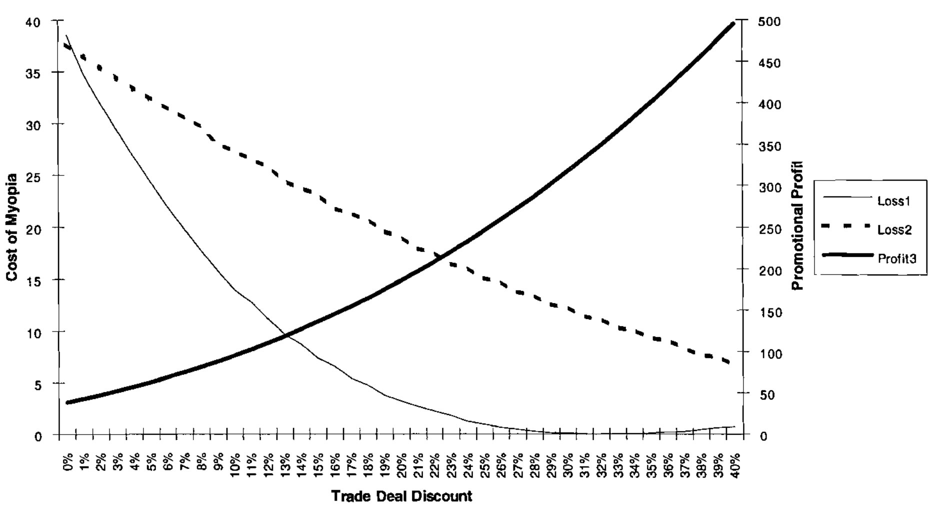


*Figure 6.25. Scenario 3: Sub-optimization costs and maximum promotion profit as functions of the trade deal offered.*

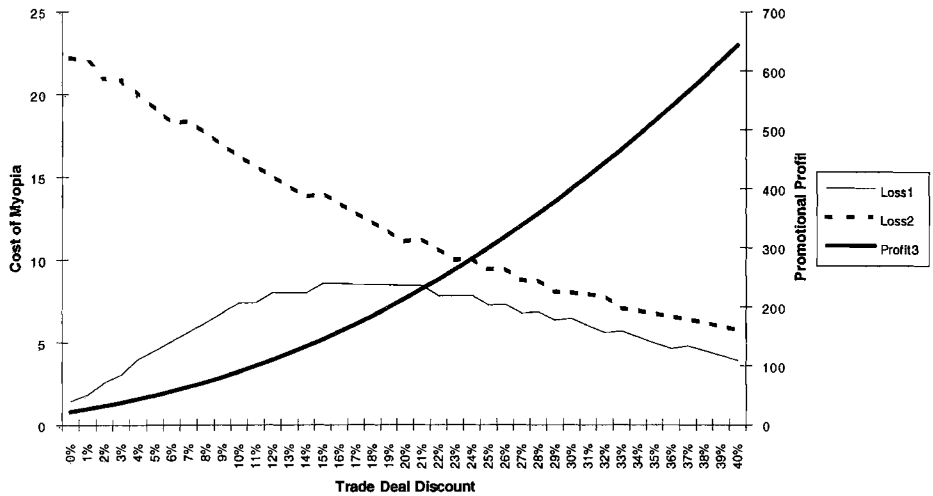


*Figure 6.26. Scenario 4: Sub-optimization costs and maximum promotion profit as functions of the trade deal offered.*

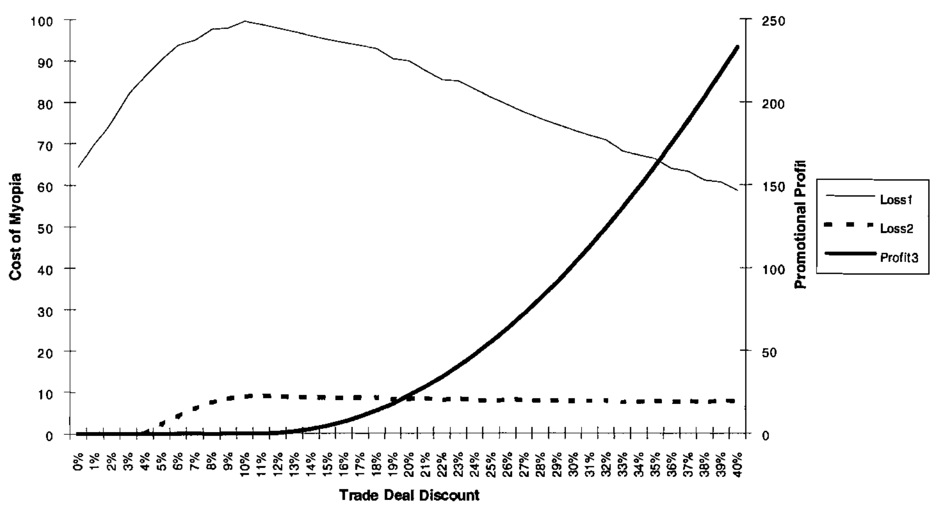


*Figure 6.27. Scenario 5: Sub-optimization costs and maximum promotion profit as functions of the trade deal offered.*

### 6.5.3. The Effects of a Deal Requirement

We shall here investigate the effects of a deal requirement on (1) the optimal deal discount, (2) the maximum promotion profit, and (3) the cost of myopic optimization of the deal discount. It is assumed that the profit margins of the focal item, other items in the focal catgeory, as well as other categories are 20 percent and the trade deal offered is 20 percent. Changing only the deal requirement and the scenario, we get the results presented in Table 6.12.

| Item | DealReq | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|
| Scenario 1 | 0% | 13% | 8% | 1% | 56.71 | 18.42 | 0.01 |
| Scenario 2 | 0% | 16% | 12% | 11% | 13.15 | 0.12 | 61.41 |
| Scenario 3 | 0% | 16% | 13% | 18% | 1.98 | 15.59 | 185.30 |
| Scenario 4 | 0% | 17% | 12% | 15% | 5.99 | 8.98 | 214.39 |
| Scenario 5 | 0% | 16% | 9% | 6% | 87.86 | 6.70 | 22.66 |
| | | | | | | | |
| Scenario 1 | 1% | 13% | 8% | 1% | 56.71 | 18.42 | 180.01 |
| Scenario 2 | 1% | 16% | 12% | 11% | 13.15 | 0.12 | 241.41 |
| Scenario 3 | 1% | 16% | 13% | 18% | 1.98 | 15.59 | 365.30 |
| Scenario 4 | 1% | 17% | 12% | 15% | 5.99 | 8.98 | 394.39 |
| Scenario 5 | 1% | 16% | 9% | 6% | 87.86 | 6.70 | 202.66 |
| | | | | | | | |
| Scenario 1 | 10% | 13% | 10% | 10% | 25.86 | 0.00 | 149.16 |
| Scenario 2 | 10% | 16% | 12% | 11% | 13.15 | 0.12 | 241.41 |
| Scenario 3 | 10% | 16% | 13% | 18% | 1.98 | 15.59 | 365.30 |
| Scenario 4 | 10% | 17% | 12% | 15% | 5.99 | 8.98 | 394.39 |
| Scenario 5 | 10% | 16% | 10% | 10% | 75.46 | 0.00 | 190.26 |

*Table 6.12. Optimal deal discount, cost of myopia, and optimal deal profit.*

The one-percent deal requirement has no effect on the optimal deal discount, irrespective of the level of analysis. The ten percent deal requirement affects the category- and store-level optimal deal discount for scenarios 1 and 5 while the item-level optimal deal discount is not affected.

Although the store-level optimal deal discount is not affected by the one-percent deal requirement, a comparison of the promotion profits shows that the profits increase due to the deal requirement.

A comment about the effect of *DEALREQ* on *Profit3* is necessary because it may seem contra-intuitive that the deal requirement has a positive impact on *Profit3*. The reason is that the promotion profit, i.e., *Profit3*, is defined as the change in retailer gross profits caused by the deal. If the trade deal is not conditional on a price deal in the store, the effect is merely to increase the gross margin on the focal item. The margin increase leads to larger gross profits on the normal sales of the focal item. However, this is not included in the promotion profit, because the price deal does not cause this change. On the other hand, if the trade deal is made conditional on a price deal in the store, the retailer would not benefit from the higher gross margin on the normal sales of the focal item until the deal discount reaches the threshold. At the threshold, the retailer's gross margin suddenly increases by the size of the trade deal. The conclusion of this discussion is that although a deal requirement leads to higher promotion *Profit3,* it can, as any restriction in an optimization problem (see e.g., Eppen and Gould 1985), never improve the retailer's total gross profits. On the contrary, the deal requirement can only hurt, or leave unaffected, the retailer's gross profits.

In the absence of the deal requirement, the retailer could absorb all of the trade deal and thereby increase the store profits. However, this profit increment would not be regarded as a promotion profit because it would not be caused by the retailer's deal discount. The effect of the one-percent deal requirement is to make this incremental profit relevant for the promotion decision and, thus, part of the promotion profit.

For example, the increase in promotion profits for scenario 1 from 0.01 to 180.01 means that the retailer receives SEK 180 from the manufacturer without doing anything even if there were no deal requirement.

A comparison of the promotion profits for a deal requirement of one percent and ten percent shows how the deal requirement may hurt the retailer's profits. For scenario 1, the ten-percent deal-requirement leads the retailer to increase the deal discount to ten percent from the otherwise optimal 1 percent deal discount. This reduces store-level promotion profits from SEK 180.01 to 149.16. The deal requirement thus costs the retailer the difference of SEK 30.85.

### 6.5.4. Margins and Optimal Deal Discount

How does the gross margin of the focal category affect the pass-through of trade deals to the consumers? To answer this question, we will assume that the retailer uses store-level deal optimization. We also assume that the gross margin of the focal item is equal to that of all other items in the focal category. The average gross margin of other categories is, as in all the previous analyses, assumed to be 20 percent.

Figure 6.28 shows the results for scenario 1. The 20 percent category gross margin case, used in the analyses in the previous section, is marked with a thick line. In this case, the focal category and other categories have equal margins. Figure 6.28 shows that higher margins clearly lead to greater pass-through of trade money.

Results for the other four scenarios can be found in the appendix to this chapter. The pattern is the same for all scenarios; the higher the margin, the larger the deal discount.

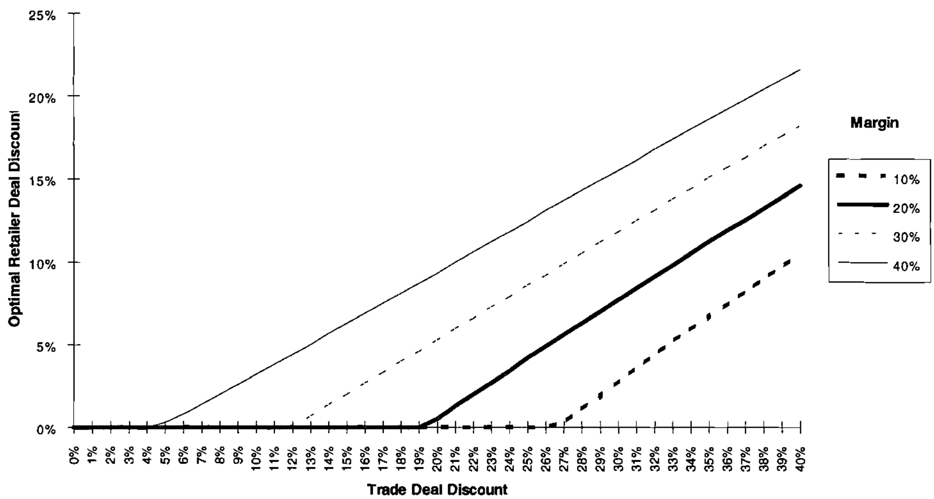


*Figure 6.28. Scenario 1: Store-level optimal deal discount as a function of the trade deal for different category gross margins.*

## 6.6. Meta Analysis of the Deal Discount and the Cost of Myopia

This section attempts to produce an overview of the impact of the level of analysis, the response patterns, the trade deal offered, the deal requirements, the margin of the focal item, and the margin of other items in the focal category on the size of the deal discount and the cost of myopic deal discount optimization. In contrast to the previous sections, we will here study average outcomes.

### 6.6.1. Procedure

The following procedure was used to produce the simulation results used as input in the meta-level analysis. For each of the five sales-response scenarios described in Section 6.4, we examine two levels for each of the four following parameters:

(1) the deal requirement (*DEALREQ*) [0, 10],

(2) the size of the trade deal offered (*TROFFER*) [10, 20]

(3) the retailer's gross margin on the focal item ($m_1$ or *m1*) [20, 30]

(4) the retailer's gross margin on other items in the focal category ($m_2$ or *m2*) [20, 30].

All four parameters are expressed in percent of the regular retail price. The symbols used for these parameters appear within parenthesis () and the levels are presented within brackets [].

The total number of combinations (or cases) examined is thus 80 (=5 × 2 × 2 × 2 × 2). Table 6.16 in the appendix to this chapter presents the complete output of these analyses. The results of these simulation runs will be presented and analyzed in a more compressed format than in the preceding sections.

The six output variables examined were: *Deal1* the myopic optimal deal discount determined by using the item-level analysis and *Deal2* is the deal discount determined by category-level analysis. *Deal3* is the optimal deal discount, which is determined by using store-level analysis. These three variables were determined by evaluating the profit (measured at the item-level, the category-level, and the store-level) for each 1 percent step between zero and 100 percent deal discount and selecting the deals with the highest profit.

*Profit3* is the store-level profit of the deal of size *Deal3*, i.e., the profit of the profit-maximizing deal. The variables *Loss1* and *Loss2*, are the losses due to sub-optimization by setting deal to *Deal1* or *Deal2*. These are calculated as described in Section 6.5.2.

### 6.6.2. The Impact of the Level of Analysis

The impact of the level of analysis on the deal discounts and the losses due to myopic optimization is examined by examination of the summary statistics of the simulation output. The summary statistics are presented in Table 6.13. In these 80 simulations, the deal discount set by item-level profit maximization is in general larger than the optimal deal. The category-level analysis, on the other hand, leads to slightly smaller deal discounts than the average optimal deal discount.

While the smallest deal discount set by the store-level and the category-level analyses was zero (i.e., no price deal), the minimum deal set by the item-level analysis was six percent. The largest optimal deal in these simulations was 23 percent, which was also the largest deal suggested by the item-level optimization. The largest deal suggested by the category-level optimization was 19 percent.

| | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|
| Min | 6.0 | 0.0 | 0.0 | 165.15 | 44.99 | 0.00 |
| Max | 23.0 | 19.0 | 23.0 | 0.00 | 0.00 | 579.62 |
| Avg. | 15.7 | 10.7 | 10.8 | 37.65 | 8.50 | 154.49 |
| Stdv. | 4.5 | 4.1 | 5.9 | 42.95 | 8.82 | 138.30 |

*Table 6.13. Summary of simulation results (all simulated cases).*

On average, the optimal deal discount returns a profit of SEK 154.49. The range and standard deviation of the maximum profit were large in this set of simulation runs. The category-level and the item-level analyses sometimes led to the same deal discount as the store-level analysis; In those cases, the losses due to myopic optimization were zero.

The item-level analysis on average led to larger losses than the category-level analysis. The largest sub-optimization cost observed in the simulations, SEK 165.15, was caused by item-level optimization of the deal discount.

Another way to analyze the outcomes of the simulation is to examine the frequency of myopic deals larger than, equal to, and smaller than the optimal deal discount. This is shown in Table 6.14, which reveals that item-level analysis is very likely to lead to larger than optimal deal discounts, but leads to smaller than optimal deal discounts in eight of the 80 cases investigated here. The item-level deal was equal to the optimal deal in nine cases.

| | Item Level Optimization | | Category Level Optimization | |
|---|---|---|---|---|
| | # | % | # | % |
| Myopic deal too small | 8 | 10% | 30 | 38% |
| Myopic deal optimal | 9 | 11% | 18 | 23% |
| Myopic deal too large | 63 | 79% | 32 | 40% |
| **Total** | 80 | 100% | 80 | 100% |

*Table 6.14. The effect of myopic determination of deal discount. Absolute and relative frequencies.*

In 18 out of 80 cases the deal discount maximizing category profits coincided with the deal discount maximizing store profits. In the remaining 62 cases, the category-level optimization led to larger than optimal deal discounts as often as it led to smaller than optimal deal discounts.

### 6.6.3. Scenarios, Trade Deals, Deal Requirements, and Margins

So far, we have seen the overall impact of the level of analysis used when the deal discount id determined. We shall now examine the effects of some intervening factors. Table 6.15 presents averages of the output variables broken down by scenario, margins, trade deal, and deal requirement.

The average deal discount suggested by the most myopic analysis (i.e., the item-level analysis) is larger than the average optimal deal discount in four out of five scenarios. Scenario 3 is the exception and we recall from the scenario descriptions in Section 6.4 that the increase in store sales is much larger than the increase in the focal item's sales. Scenario 3 is the only scenario where the average loss due to sub-optimization is larger when using category-level analysis than when item-level analysis is used. The category-level analysis leads to an average deal discount that is larger than the average optimal deal discount in three out of five scenarios.

| *Variable Name* | *Variable Level* | *Deal1* | *Deal2* | *Deal3* | *Loss1* | *Loss2* | *Profit3* | *n* |
|---|---|---|---|---|---|---|---|---|
| Scenario | 1 | 13.5 | 8.9 | 5.3 | 49.76 | 8.94 | 50.06 | 16 |
| Scenario | 2 | 16.0 | 12.2 | 11.3 | 16.74 | 0.46 | 133.13 | 16 |
| Scenario | 3 | 16.0 | 12.4 | 17.1 | 2.65 | 16.86 | 254.43 | 16 |
| Scenario | 4 | 17.0 | 11.1 | 13.7 | 16.82 | 8.77 | 261.17 | 16 |
| Scenario | 5 | 15.8 | 9.1 | 6.8 | 102.29 | 7.49 | 73.67 | 16 |
| *TROFFER* | 10 | 12.7 | 8.6 | 8.8 | 32.67 | 8.13 | 92.64 | 40 |
| *TROFFER* | 20 | 18.6 | 12.9 | 12.9 | 42.63 | 8.88 | 216.34 | 40 |
| *m1* | 20 | 12.7 | 8.6 | 8.8 | 32.67 | 8.13 | 115.14 | 40 |
| *m1* | 30 | 18.6 | 12.9 | 12.9 | 42.63 | 8.88 | 193.84 | 40 |
| m2 | 20 | 15.65 | 11.575 | 11.85 | 27.298 | 7.767 | 168.64 | 40 |
| m2 | 30 | 15.65 | 9.875 | 9.825 | 48.004 | 9.2343 | 140.34 | 40 |
| *DEALREQ* | 0 | 15.5 | 9.6 | 9.6 | 44.79 | 10.82 | 95.26 | 40 |
| *DEALREQ* | 10 | 15.9 | 11.8 | 12.1 | 30.51 | 6.19 | 213.72 | 40 |

*Table 6.15. Average deal discounts, cost of myopia, and optimal profit (bivariate analyses).*

Not surprisingly, increasing the offered trade deal (*TROFFER*) from 20 to 30 percent increases (1) the size of the optimal deal, (2) the size of the myopic deal discounts, and (3) the promotion profit. Less obvious is that the larger trade deal leads to somewhat larger costs of sub-optimization.

The effects of changing the margin on the focal item from 20 to 30 percent are the same as when changing the size of the trade deal.

Increasing the margin of other items in the focal category has no effect on the size of the deal discount determined by using the item-level analysis. The size of the optimal deal discount as well as the deal discount determined by using the category-level analysis, on the other hand, were smaller when the margin on other items in the focal category was 30 percent than when the margin was 20 percent. In other words, the higher the margin of other items, the smaller the optimal deal discount.

A requirement from the manufacturer that the retailer must pass through at least 10 percentage points of the trade deal to the consumers in order to receive the trade money leads to an increase in the (average) optimal deal. Recall that the reason for this contra-intuitive result is that the promotion profit is measured on an incremental basis, where the increment is measured in relation to the gross profit the retailer would obtain if there would be no retailer promotion for the focal item (see Section 6.5.3).

## 6.7. Conclusions

This chapter has shown that the retailer will set different deal discounts depending on whether item-level, category-level, or store-level evaluation is used to find the optimal deal discount. It is proposed that store-level deal optimization is the relevant level of analysis for the retailer.

In general, item-level deal optimization leads to larger than optimal deal discounts. The category-level optimization often leads to larger than optimal deal discounts. However. the deal discount is likely to be closer to the optimal deal discount. The item-level and the category-level deal optimization result in larger than optimal deal discounts because the intra- and inter-category cannibalization are disregarded. However, if store traffic and store sales are responsive to the sales promotion (i.e., when there is no cannibalization), the item-level and the category-level optimization may lead to smaller than optimal deal discounts.

It was found that the size of the trade deal affects the deal discount positively. The relative pass-through is also dependent on the trade deal. However, the sign of the relation depends on the sales-response and the degree of cannibalization. Deal requirements imposed on the retailer by the manufacturer increase the size of the optimal deal discount.

The implications for retailers and manufacturers are important. For the retailer, the most important observation is that item-level evaluation of promotion profits is myopic and leads to opportunity losses. Also category-level analysis is insufficient for the retailer, who should rather adopt the store-level perspective on promotion profits.

Manufacturers should also find the results interesting as the analysis shows that the size of the trade promotion will have effects on the deal discount in the store. In order to manage promotions effectively, manufacturers need to know how sales respond to retail promotions as well as to the level of deal optimization used by retail managers.

Imposing deal requirements seems to be an effective way of increasing the pass-through of trade deals to the consumers, because deal requirements alter the shape of the retailer's profit function and generally increase the size of the optimal deal. This is important for the manufacturer because the deal discount influences sales to the consumers.

Thus, retail managers as well as manufacturers should find the model described in this chapter useful in promotion management. Point-of-sales scanner data would be useful for parameterizing the models for such usage. Alternatively, the model could be regarded as a decision calculus model (Little 1975a, 1975b; Lodish 1982) that can help retailers and manufacturers to calculate the implications of the assumptions they make.

# Appendix

## 6.A.1. Gross margins, Trade Deals, and Optimal Deal discount

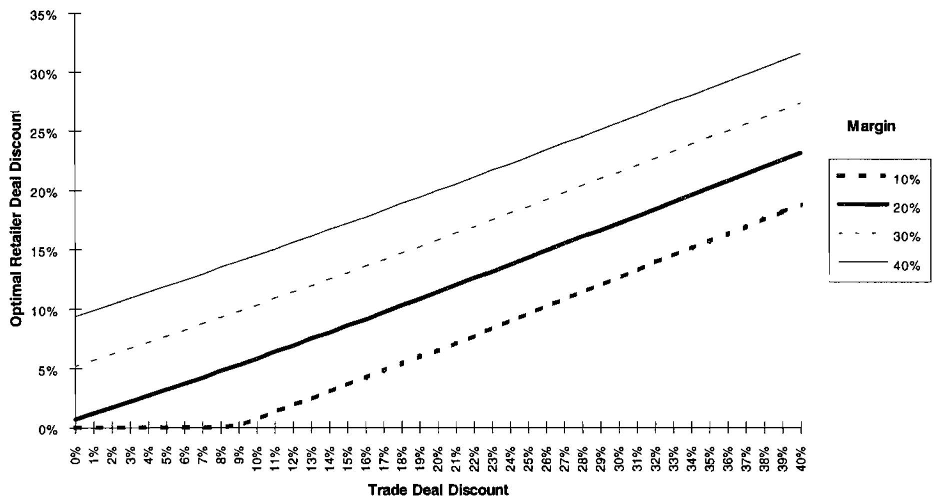


*Figure 6.29. Scenario 2: Store-level optimal deal discount for different category gross margins as functions of the trade deal offered.*

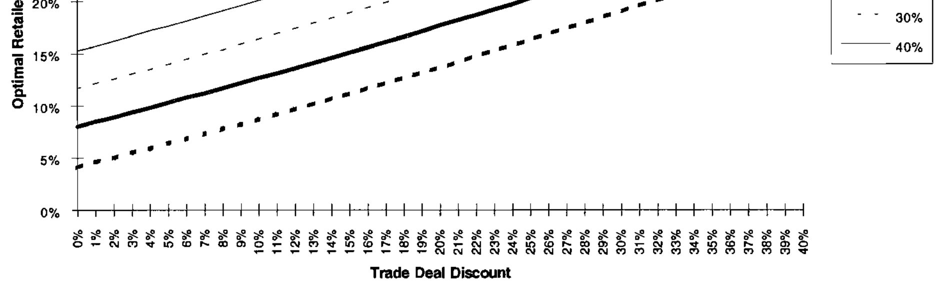


*Figure 6.30. Scenario 3: Store-level optimal deal discount for different category gross margins as functions of the trade deal offered.*

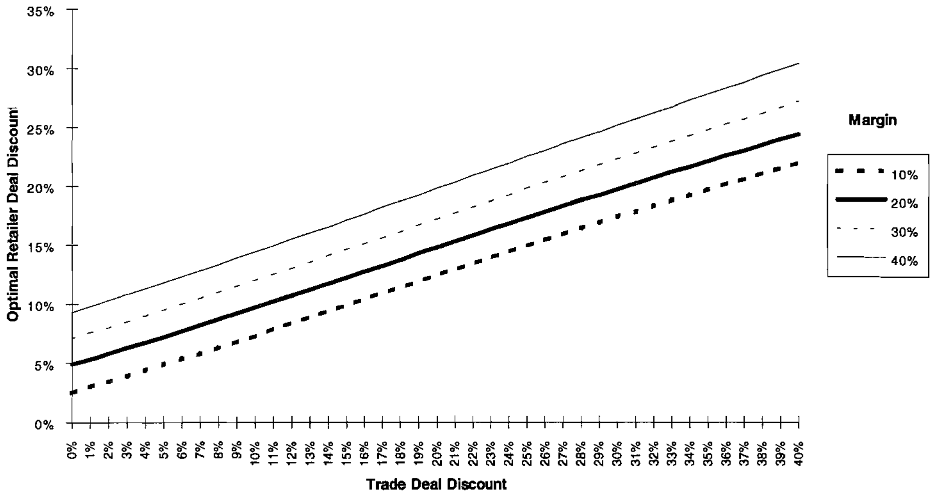


*Figure 6.31. Scenario 4: Store-level optimal deal discount for different category gross margins as functions of the trade deal offered.*

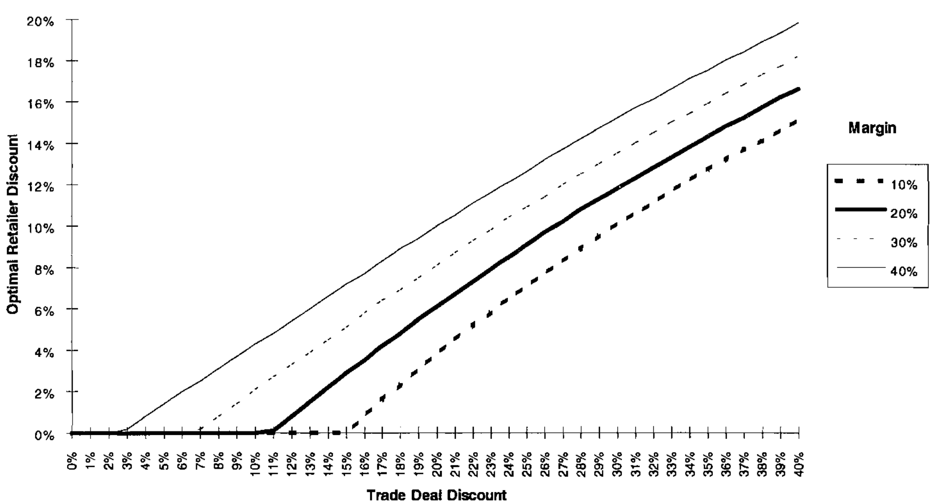


*Figure 6.32. Scenario 5: Store-level optimal deal discount for different category gross margins as functions of the trade deal offered.*

## 6.A.2. Simulation Results

| Case | Scen. | DEALREQ | TROFFER | m1 | m2 | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 10 | 20 | 20 | 6 | 2 | 0 | 36.12 | 8.92 | 0.00 |
| 2 | 1 | 0 | 10 | 20 | 30 | 6 | 0 | 0 | 44.42 | 0.00 | 0.00 |
| 3 | 1 | 0 | 10 | 30 | 20 | 13 | 8 | 1 | 56.71 | 18.42 | 0.01 |
| 4 | 1 | 0 | 10 | 30 | 30 | 13 | 6 | 0 | 79.29 | 17.73 | 0.00 |
| 5 | 1 | 0 | 20 | 20 | 20 | 13 | 8 | 1 | 56.71 | 18.42 | 0.01 |
| 6 | 1 | 0 | 20 | 20 | 30 | 13 | 6 | 0 | 79.29 | 17.73 | 0.00 |
| 7 | 1 | 0 | 20 | 30 | 20 | 20 | 14 | 8 | 67.43 | 15.99 | 18.25 |
| 8 | 1 | 0 | 20 | 30 | 30 | 20 | 12 | 5 | 99.34 | 18.27 | 9.10 |
| 9 | 1 | 10 | 10 | 20 | 20 | 10 | 10 | 10 | 0.00 | 0.00 | 12.00 |
| 10 | 1 | 10 | 10 | 20 | 30 | 10 | 10 | 0 | 3.89 | 3.89 | 0.00 |
| 11 | 1 | 10 | 10 | 30 | 20 | 13 | 10 | 10 | 25.86 | 0.00 | 59.16 |
| 12 | 1 | 10 | 10 | 30 | 30 | 13 | 10 | 10 | 32.56 | 0.00 | 43.27 |
| 13 | 1 | 10 | 20 | 20 | 20 | 13 | 10 | 10 | 25.86 | 0.00 | 149.16 |
| 14 | 1 | 10 | 20 | 20 | 30 | 13 | 10 | 10 | 32.56 | 0.00 | 133.27 |
| 15 | 1 | 10 | 20 | 30 | 20 | 20 | 14 | 10 | 65.50 | 14.06 | 196.32 |
| 16 | 1 | 10 | 20 | 30 | 30 | 20 | 12 | 10 | 90.67 | 9.60 | 180.43 |
| 17 | 2 | 0 | 10 | 20 | 20 | 8 | 6 | 6 | 2.52 | 0.00 | 15.75 |
| 18 | 2 | 0 | 10 | 20 | 30 | 8 | 5 | 5 | 4.43 | 0.00 | 14.00 |
| 19 | 2 | 0 | 10 | 30 | 20 | 16 | 12 | 11 | 13.15 | 0.12 | 61.41 |
| 20 | 2 | 0 | 10 | 30 | 30 | 16 | 11 | 10 | 21.20 | 0.20 | 54.62 |
| 21 | 2 | 0 | 20 | 20 | 20 | 16 | 12 | 11 | 13.15 | 0.12 | 61.41 |
| 22 | 2 | 0 | 20 | 20 | 30 | 16 | 11 | 10 | 21.20 | 0.20 | 54.62 |
| 23 | 2 | 0 | 20 | 30 | 20 | 23 | 19 | 17 | 23.70 | 2.07 | 145.36 |
| 24 | 2 | 0 | 20 | 30 | 30 | 23 | 17 | 16 | 38.01 | 0.95 | 129.58 |
| 25 | 2 | 10 | 10 | 20 | 20 | 10 | 10 | 10 | 0.00 | 0.00 | 96.08 |
| 26 | 2 | 10 | 10 | 20 | 30 | 10 | 10 | 10 | 0.00 | 0.00 | 90.31 |
| 27 | 2 | 10 | 10 | 30 | 20 | 16 | 12 | 11 | 13.15 | 0.12 | 151.41 |
| 28 | 2 | 10 | 10 | 30 | 30 | 16 | 11 | 10 | 21.20 | 0.20 | 144.62 |
| 29 | 2 | 10 | 20 | 20 | 20 | 16 | 12 | 11 | 13.15 | 0.12 | 241.41 |
| 30 | 2 | 10 | 20 | 20 | 30 | 16 | 11 | 10 | 21.20 | 0.20 | 234.62 |
| 31 | 2 | 10 | 20 | 30 | 20 | 23 | 19 | 17 | 23.70 | 2.07 | 325.36 |
| 32 | 2 | 10 | 20 | 30 | 30 | 23 | 17 | 16 | 38.01 | 0.95 | 309.58 |
| 33 | 3 | 0 | 10 | 20 | 20 | 8 | 6 | 13 | 14.47 | 28.80 | 95.06 |
| 34 | 3 | 0 | 10 | 20 | 30 | 8 | 5 | 12 | 9.69 | 30.61 | 86.84 |
| 35 | 3 | 0 | 10 | 30 | 20 | 16 | 13 | 18 | 1.98 | 15.59 | 185.30 |
| 36 | 3 | 0 | 10 | 30 | 30 | 16 | 11 | 16 | 0.00 | 21.35 | 168.92 |
| 37 | 3 | 0 | 20 | 20 | 20 | 16 | 13 | 18 | 1.98 | 15.59 | 185.30 |
| 38 | 3 | 0 | 20 | 20 | 30 | 16 | 11 | 16 | 0.00 | 21.35 | 168.92 |
| 39 | 3 | 0 | 20 | 30 | 20 | 23 | 19 | 23 | 0.00 | 12.24 | 316.44 |
| 40 | 3 | 0 | 20 | 30 | 30 | 23 | 17 | 21 | 1.73 | 15.60 | 288.65 |

*Table 6.16a. Simulation results.*

| Case | Scen. | DEALREQ | TROFFER | m1 | m2 | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 41 | 3 | 10 | 10 | 20 | 20 | 10 | 10 | 13 | 4.79 | 4.79 | 185.06 |
| 42 | 3 | 10 | 10 | 20 | 30 | 10 | 10 | 12 | 2.05 | 2.05 | 176.84 |
| 43 | 3 | 10 | 10 | 30 | 20 | 16 | 13 | 18 | 1.98 | 15.59 | 275.30 |
| 44 | 3 | 10 | 10 | 30 | 30 | 16 | 11 | 16 | 0.00 | 21.35 | 258.92 |
| 45 | 3 | 10 | 20 | 20 | 20 | 16 | 13 | 18 | 1.98 | 15.59 | 365.30 |
| 46 | 3 | 10 | 20 | 20 | 30 | 16 | 11 | 16 | 0.00 | 21.35 | 348.92 |
| 47 | 3 | 10 | 20 | 30 | 20 | 23 | 19 | 23 | 0.00 | 12.24 | 496.44 |
| 48 | 3 | 10 | 20 | 30 | 30 | 23 | 17 | 21 | 1.73 | 15.60 | 468.65 |
| 49 | 4 | 0 | 10 | 20 | 20 | 12 | 6 | 10 | 6.14 | 14.55 | 90.27 |
| 50 | 4 | 0 | 10 | 20 | 30 | 12 | 3 | 7 | 28.90 | 18.07 | 51.52 |
| 51 | 4 | 0 | 10 | 30 | 20 | 17 | 12 | 15 | 5.99 | 8.98 | 214.39 |
| 52 | 4 | 0 | 10 | 30 | 30 | 17 | 9 | 12 | 29.54 | 10.23 | 143.89 |
| 53 | 4 | 0 | 20 | 20 | 20 | 17 | 12 | 15 | 5.99 | 8.98 | 214.39 |
| 54 | 4 | 0 | 20 | 20 | 30 | 17 | 9 | 12 | 29.54 | 10.23 | 143.89 |
| 55 | 4 | 0 | 20 | 30 | 20 | 22 | 17 | 20 | 6.34 | 9.20 | 399.62 |
| 56 | 4 | 0 | 20 | 30 | 30 | 22 | 14 | 17 | 27.15 | 11.84 | 296.38 |
| 57 | 4 | 10 | 10 | 20 | 20 | 12 | 10 | 10 | 6.14 | 0.00 | 180.27 |
| 58 | 4 | 10 | 10 | 20 | 30 | 12 | 10 | 10 | 18.87 | 0.00 | 131.49 |
| 59 | 4 | 10 | 10 | 30 | 20 | 17 | 12 | 15 | 5.99 | 8.98 | 304.39 |
| 60 | 4 | 10 | 10 | 30 | 30 | 17 | 10 | 12 | 29.54 | 4.58 | 233.89 |
| 61 | 4 | 10 | 20 | 20 | 20 | 17 | 12 | 15 | 5.99 | 8.98 | 394.39 |
| 62 | 4 | 10 | 20 | 20 | 30 | 17 | 10 | 12 | 29.54 | 4.58 | 323.89 |
| 63 | 4 | 10 | 20 | 30 | 20 | 22 | 17 | 20 | 6.34 | 9.20 | 579.62 |
| 64 | 4 | 10 | 20 | 30 | 30 | 22 | 14 | 17 | 27.15 | 11.84 | 476.38 |
| 65 | 5 | 0 | 10 | 20 | 20 | 11 | 3 | 0 | 95.63 | 7.11 | 0.00 |
| 66 | 5 | 0 | 10 | 20 | 30 | 11 | 0 | 0 | 159.37 | 0.00 | 0.00 |
| 67 | 5 | 0 | 10 | 30 | 20 | 16 | 9 | 6 | 87.86 | 6.70 | 22.66 |
| 68 | 5 | 0 | 10 | 30 | 30 | 16 | 6 | 2 | 165.15 | 11.09 | 2.53 |
| 69 | 5 | 0 | 20 | 20 | 20 | 16 | 9 | 6 | 87.86 | 6.70 | 22.66 |
| 70 | 5 | 0 | 20 | 20 | 30 | 16 | 6 | 2 | 165.15 | 11.09 | 2.53 |
| 71 | 5 | 0 | 20 | 30 | 20 | 20 | 15 | 12 | 69.61 | 10.22 | 101.59 |
| 72 | 5 | 0 | 20 | 30 | 30 | 20 | 11 | 8 | 134.86 | 7.37 | 44.62 |
| 73 | 5 | 10 | 10 | 20 | 20 | 11 | 10 | 10 | 17.63 | 0.00 | 12.00 |
| 74 | 5 | 10 | 10 | 20 | 30 | 11 | 10 | 0 | 69.37 | 44.99 | 0.00 |
| 75 | 5 | 10 | 10 | 30 | 20 | 16 | 10 | 10 | 75.46 | 0.00 | 100.26 |
| 76 | 5 | 10 | 10 | 30 | 30 | 16 | 10 | 10 | 115.90 | 0.00 | 43.27 |
| 77 | 5 | 10 | 20 | 20 | 20 | 16 | 10 | 10 | 75.46 | 0.00 | 190.26 |
| 78 | 5 | 10 | 20 | 20 | 30 | 16 | 10 | 10 | 115.90 | 0.00 | 133.27 |
| 79 | 5 | 10 | 20 | 30 | 20 | 20 | 15 | 12 | 69.61 | 10.22 | 281.59 |
| 80 | 5 | 10 | 20 | 30 | 30 | 20 | 11 | 10 | 131.76 | 4.28 | 221.53 |

*Table 6.16b. Simulation results (continued).*

# 7. EMPIRICAL DATA AND ESTIMATION METHOD

## 7.1. Introduction

This chapter discusses the application of the promotion-profit model developed in Chapter 5 to real data and can be seen as preparation for the three following chapters. In the first section, the purpose of the empirical applications is discussed as well as the criteria used to select the cases. The second section discusses different types of data sources, with an emphasis on scanner data. The third section presents the databases used for the present research, i.e., the databases collected at the Foundation for Distribution Research. Section four shows the store-level data series, common to all three empirical illustrations. Last, the estimation procedures used to parameterize the response models are described and discussed.

### 7.1.1. Purpose of Empirical Illustrations

The purposes of the empirical illustrations are: (1) to show that the model can be applied to real data, (2) to obtain estimates of how some different items' sales response to promotion are composed, and (3) to illustrate the promotion profits for these items' response structures.

### 7.1.2. Selection of Cases

Previous research has found that the promotional response varies across product categories as well as across items within a product category (e.g., Bemmaor and Mouchoux 1991; Bolton 1989; Julander and Persson 1992; and Persson 1993). It is therefore important to test the application of the model in more than one product category. It was decided that applying the model to three product categories would suffice as empirical illustration of the model's capabilities.

The following criteria were used for selection of the product categories for this study: First, the category should have fairly large sales. Second, it had to be a category where promotion had been used rather frequently. The categories selected are regular ground coffee, breakfast cereals, and pasta.

Within each of these three product categories, the item selection followed criteria similar to those used for category selection. The items should be fairly important in the category and they must be promoted with some frequency.

The reasoning behind the case selection criteria is rather pragmatic and has to do with the estimation of the response models. Clearly, it is a prerequisite for measurement of promotional response that there have been some promotions. Promotion all the time, on the other hand, would not have been useful either. The high volume criterion is important because it reduces the problem with observations of zero sales. There are two problems of observations of zero sales volume: (1) In general, zero sales volume is problematic because it is a type of truncated data, which means that the dependent variable (sales) is cut off at zero (since we cannot observe negative sales). Truncated data tend to bias the estimates of the independent variables' effect. (2) In the binomial logit models used here, observations of zero sales are problematic because they are treated as missing data (because the logarithm of zero is not defined).

Retail managers would also face these considerations when implementing systems based on the model presented in this report. It is therefore important to note that the case-selection criteria coincide with criteria for managerial relevance. The items are large-volume products and consequently important for the store. The frequent promotion of these items means that they consume much management time for designing the promotions.

This case selection procedure obviously does not result in a random sample. Consequently, the results can not be used to make inferences about the population parameters, i.e., the promotional response and profits of items in general in the store.

## 7.2. Data Sources

The data sources that can be used for parameterizing response models are discussed in this section. First, historical data and experimental data are discussed. Then, information technology is identified as a factor making huge amounts of data available to managers. Third, different types of scanner data are presented.

### 7.2.1. Managerial Judgment, Historical Data and Experiments

There are three ways to parameterize a response function: managerial judgment, statistical analysis of historical data, and experiments. Managerial judgment may be the cheapest and quickest way to obtain and may in some situations be the only method available. The obvious disadvantage of this type of data is that it is subjective rather than objective data.

Statistical analysis is a powerful collection of methods for making sense out of historical data. It provides a systematic way of parameterizing response models. Using statistical analysis of past empirical data for making forecasts is not to assume that the future will be like the present. Then, we would not need the statistics. The assumption is rather that the mechanisms at work are fairly stable. Experience has shown that this is a reasonable assumption. Parsons *et al.* (1993) conclude that past data are useful for making many practical marketing decisions and that when past data are available they should be utilized.

Parameters obtained from analyses of past data can be used as prior estimates that are updated with judgmental inputs. Blattberg and Hoch (1990) found that statistical models combined with managerial judgment outperformed either of the methods used on its own.

The past variance and covariance of the independent variables are important when using past data for estimating the parameters in a response function. If the decision variables have not varied in the past it is impossible to know the response to a change in an independent variable. Also, even if the variable has varied enough to obtain an estimate of its effect, the range within which forecasts are valid is restricted to the range the variable has varied in the past. The response to a change in a decision variable may also be difficult to estimate if the independent variables have been highly correlated. This is known as multicollinearity and will be discussed later.

If past data do not provide enough variation or suffer from multicollinearity, an experiment may be the best way to obtain estimates of the parameters of the response model. Experiments are also useful when causality is an issue, because past data cannot really be used to make inferences about causality. In an experiment, the treatment variables are varied systematically and the response to these variations is observed.

Experiments can be conducted in a laboratory or on the field. Laboratory experiments are the experiments that allow the researcher the greatest control over the experimental stimuli and covariates. The external validity of laboratory experiments may be low. Field experiments, on the other hand, do not suffer the from low external validity but cannot be as thoroughly controlled as laboratory experiments. In-store experiments (a type of field experiment) were reviewed by Doyle and Gidengil (1977). They found that in-store experiments had not contributed much to marketing practice or marketing knowledge. However, Chapman (1987) used a field experiment to investigate the profitability of a retailer couponing. He found that an inexpensive experiment could help the retailer to increase profits.

In comparison with past data, experiments have the drawback that the data are not immediately available when a question arises. An experiment must then be designed and conducted before the data become available to the researcher. Past data, on the other hand, are available at any time the researcher needs them (provided that they have been collected and stored). Other drawbacks of experiments are that they may be expensive and usually do not give as many observations as past data.

Past data may be regarded as observations from naturally occurring experiments. A manager who recognizes the importance of variance in the decision variables in order to measure the impact of those variables can devise a long-term series of quasi-experiments by systematically varying the levels of the decision variables. This can be done within a tracking and feedback framework.

### 7.2.2. Information Technology

Recent developments in information technology, especially the rapid growth in storage and processing capacity of computers, increase the availability of business data dramatically. Companies in all kinds of industries can now store and process transaction data at a disaggregate level. This means unprecedented possibilities to base business decisions on relevant and timely data, or information.

New information technology has also entered the modern supermarket. Scanner equipped check-outs and bar-coded merchandise promise productivity improvements in the operations of the store. The immediate benefits for the retailer are faster and more accurate check-out and the merchandise need not be price-marked.

Although more productive operations are valuable for the retailers, the transaction databases that the computerized cash registers, or Electronic Point-of-Sales systems (EPOS), produce as a by-product are even more valuable. The huge databases created by the computerized check-outs may transfer power from the manufacturer to the retailer. Data may by itself be useful for the retailer, but the real potential is when statistical methods are used to combine data and models. Application of statistical methods for combining models and data can be seen as a form of refinement of raw data to decision relevant information. If retail managers learn to refine their own databases to decision support, they can improve store profits and shift power from the brand manager or manufacturer.

Sales promotion, the subject of this report, is just one of many areas where the retail manager and retail organizations could benefit from decision-support based on data and models. As Lilien notes:

> *"New data sources are having a major impact on developments in modeling markets. One of the most influential developments in the 1980s has been the impact of scanner data" Lilien (1993, p.13).*

### 7.2.3. Scanner Data in General

Measurement usually disturbs the system being studied, and the more the system is disturbed, the worse the validity of the measurement. This is especially true when human behavior is studied. Broadly speaking, there are two approaches to the study of human behavior. We can ask the individual questions concerning the past, present, or intended behavior, or, we can observe the behavior. If we choose to make observations, we can either observe the behavior directly by direct observation, or we can observe the behavior indirectly through the traces the behavior may leave. When human behavior is observed, the individual being observed may be aware or unaware of being observed. The cooperation of the observed individual may or may not be needed. The less the individual knows and perceives from the observation, the better the validity. What we are interested in is therefore an unobtrusive method of studying behavior. In retailing, such data are now available in form of transaction data collected by the point-of-sales systems.

There are five nodes on a packaged consumer good's way from the production at the manufacturer to its consumption or final disposition in the consumer's home. Data can be collected between these nodes. Curry (1989 and 1993) described the nodes and the data collection points with the scheme shown in Figure 7.1. We will in this study use data collected at the point-of-sales.

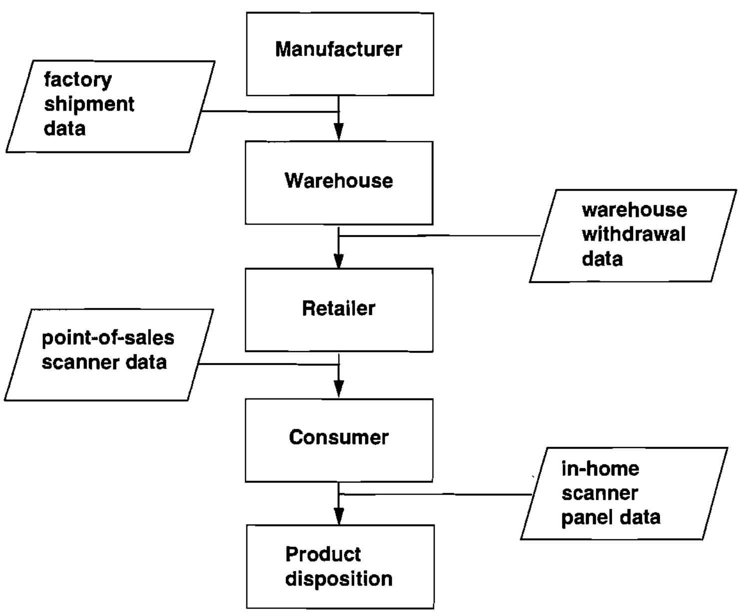


*Figure 7.1. Product flow, data collection points, and type of data.*

Julander (1987) suggested that receipt data should be a valuable complement to the traditional weekly-aggregated item sales data collected in the stores and to the panel data.

Cooper and Nakanishi (1988) note that the shopping basket is the basic transaction unit in optical scanner point-of-sale systems. However, competitive analyses or marketing-effectiveness studies focusing on a single category only utilize a subset of the information on the receipt. Traditionally this subset is recorded in two ways. The sales of each item in the basket are added to an accumulating record for each item. If the customer is a member of a scanner panel, the transaction is sent to a record keeping track of that customer's purchases in different stores (Cooper and Nakanishi 1988).

Store data contain item-level information about the sales and prices of all items in a store during a specified time period. The time period is usually one week. Panel data, on the other hand, contain household- or consumer-level information about all the purchases of that household or individual.

Julander (1992) showed how valuable information can be gained by studying the receipt data. He therefore urged retailers to collect and analyze scanner data on the receipt-level. This is in line with the principles that McCann and Gallagher (1991) outlined for merchandising databases. In order to maintain flexibility for future needs, a merchandising database should store data at the lowest levels of aggregation (McCann and Gallagher 1991). Hernant and Persson (1994) created single-source data of consumers' purchases and household characteristics by combining receipt data with data from a survey. The procedure used enabled the establishment of the exact links between questionnaires and receipts.

Much of the recent research concerns panel data, as noted by Roberts (1990):

> *"... the availability of household panel data has caused an exodus of interest from aggregate store-level data. This is unfortunate, since for many geographic areas in the U.S.A. for which scanner data is available, there is no panel. Also, in many instances, except for* ad hoc *analyses, the additional expense of a panel cannot be justified" (Roberts 1990).*

Blattberg and Neslin (1990) note that both store data and panel data are influenced by noncoverage: the stores or panelists used to generate the data may not be representative of the total market. This position is clearly a manufacturer's one. From the retailer perspective, store data are not influenced by noncoverage. The data reflect purchases by all the retailer's customers. This is in contrast to panel data, which trace the purchases of some of the store's customers in several stores.

## 7.3. The Scanner Data Project

The data used in this research were collected for a large research project at the Foundation for Distribution Research at the Stockholm School of Economics. The project aims to develop methods to extract decision relevant information from Electronic-Point-of-Sales systems (EPOS) in grocery retailing (Julander and Holmberg 1987). The largest Swedish grocery retailer, ICA, has made one store available for data collection. The store is a fairly large (annual turnover approximately MSEK 80) and modern supermarket in a Stockholm suburb. It is open between 8:00 a.m. and 8:00 p.m., seven days a week all year, except Christmas Day, Easter Friday and Midsummer's Day. The store carries about 10,000 different items.

### 7.3.1. Data Collection History and Procedures

The store has been visited weekly since the project started in the spring of 1987. Weekly sales figures, prices, and deal prices on item-level for all items in the store have been collected since the project started by copying the sales file from the EPOS. In-store special displays have been registered during the weekly visits to the store. In four product categories, in-store special displays were recorded from the beginning; from October 1987 (week 41), all in-store special displays have been registered. Since the summer of 1988, the EAN bar codes of displayed items have been registered using an optical hand-scanner. We distinguish between two types of in-store special display: (1) special display in connection to the product's regular shelf location, and (2) free-standing special display.

Newspaper feature advertising data have been collected by cutting out the advertisements appearing in *Dagens Nyheter* (thw major daily Swedish newspaper). The EAN codes for all items in these advertisements were recovered and entered in an advertising datafile. From the beginning, we searched for the EAN codes of advertised items in our article database, but now receive bar coded lists with the advertised items. We still use the advertisements for coding the relative size of the item in the advertisement. We also identify which day the advertisement occurred in the paper. The retail chain's leaflets have been collected and coded using a similar procedure.

A pilot study for testing the usefulness of receipt data was conducted in October 1987. A random sample of ten percent of the receipts during one week was manually entered in a database. The results of the analyses, reported by Julander (1989, 1992), were encouraging and led to the development of a system for the automatic logging of receipts. The system was first tested in October 1990 and during the spring of 1991. Since August 1991, the system has been continuously collecting electronic copies of all receipts generated in the store. Due to technical problems, the receipt data collection has suffered a number of interruptions which has lead to the loss of some periods' receipts.

### 7.3.2. Problems in Data

Although the data collection has proceeded relatively smoothly, it has not been without problems. Some products' bar codes can be difficult to scan but the quality of the codes and the scanners have improved over the years. Examples of products that have been difficult are some brands of beer in cans and frozen food in plastic bags. The problem with bar codes that are difficult to scan is that the check-out clerks prefer to punch in the price and product category identification into the computer rather than making repeated attempts to scan the bar code. The unit sales of such items are then understated. Another reason for understated unit sales of certain items have been some sales promotions; the monetary sales amount has then been entered on an aggregate promotional sales category. For some sales promotions, for example "buy three, pay for two", the retailer creates and uses temporary "EAN" codes. This is a good solution that does not lead to loss of information if the sales registered at the temporary "EAN" are added to the sales registered at the real EAN before analysis.

Sales of fresh meat and deli are only registered on an aggregate level in the cash register. Unit sales volume for these products were consequently not available. We have not collected information on display activity of fruits, vegetables, and bread. The reason for this is that our data collection of in-store display has been done on a weekly basis while the displays in these categories are changed several times during the week.

It may occasionally be difficult to define whether a product has a special display or not. Some products have regular displays that have the appearance of special displays. Such regular displays should not be registered as special displays. Therefore, it has been important to have one person collecting the in-store data for a longer period. As the project is now on its eigth year of data collection, it has not been possible to have the same person doing the data collection over the full period. However, great care has been taken to train new assistants in order to ensure the greatest possible continuity and reduce the variation induced by the data collection.

The researcher using scanner data should be aware of these types of problems. This makes the researcher's participation in the data collection process very valuable. However, it should be emphasized that scanner data are generally very reliable data and that problems with this kind of data should be regarded as deviations from what would be perfect data rather than as shortcomings in comparison with other data sources. It can be noted that the data for the items selected for the empirical illustrations are of very high quality.

### 7.3.3. The Database

The data collection gives us five data tables: four tables of weekly observations and one table of transaction data. The common ID-fields in the four weekly tables are the thirteen digit EAN code and a four digit number identifying the week. The four tables of weekly observations are:

- item sales table
- special display table
- feature advertising table
- leaflet table

The four tables constitute a relational database that could be used for storing and retrieving the data. However, the size of the database made data retrieval cumbersome. The four tables were therefore merged into one single table. One record in this table contain information about one item one week, and only one record exists with that combination of EAN code and week number.

In addition to the weekly data, we have collected receipt data. The receipt data, or transaction data, are stored in a separate data table.

Receipts are uniquely identified by a cash register ID, a four digit transaction number, and the date. Each record in the receipt data table contains information about one receipt line. Therefore, a receipt consists of one or more records in the receipt table.

When a customer buys two units of an item this can be represented in two ways on the receipt. Either the purchase is registered on one line with the number of units purchased registered or the purchase is registered on two lines. On the receipts produced in a cash register, both methods are used. This makes analysis difficult and error prone. Therefore, we have decided to use the first of the two alternative representations. If the same EAN code appeared more than once on a receipt the lines were merged.

Data about sales promotion are not present in the original receipt data table. This information had to be retrieved from the weekly database described above. The EAN code and the ID of the week again served as key variables.

## 7.4. Description of the Store-Level Data

In order to make the reader familiar with the data, this section describes the store-level data used in the study. First, the variables are defined. Second, some summary statistics are provided and the variables' development over time is presented. The regularity of the patterns that these variables exhibit is noteworthy.

### 7.4.1. Definition of Variables.

Three variables are important for describing the store-level performance. Store traffic is the number of shopping baskets that are checked out. This is reflected in the number of receipts produced by the store's EPOS.

In this chapter, we define store sales as the actual store sales (in contrast to store sales valued at regular price). This is the total amount paid by the store's customers and includes value added tax. However, the sales model developed in Chapter 5 is defined in terms of sales valued at regular price. Therefore, store sales valued at regular prices instead of actual store sales were used in the empirical illustrations (Chapter 8, 9, and 10).

Store sales valued at regular prices are not directly available but can be calculated. As the exact calculation turned out to be extremely cumbersome, the following approximation was used: First, actual sales of the focal category were subtracted from actual store sales which resulted in actual sales of other categories. Sales of other categories valued at regular prices were then approximated by adding five percent (a figure obtained from comparisons with the weekly sales data) to the actual sales of other categories. Finally, adding the focal category's exactly calculated sales valued at regular prices rendered the approximate store sales valued at regular prices.

The third variable is average basket value, or basket value for short. Basket value is defined as daily store sales[9] divided by daily store traffic. However, it is more useful to think of store sales as the product of store traffic and basket value because that gives an idea of how store sales are generated. Benishay (1965) used this approach and regarded the number of customers and the dollar size of an individual sale as random variables.

### 7.4.2. Data Frequency and Temporal Aggregation

Temporal aggregation refers to aggregation across periods, e.g., as weekly observations are aggregated daily observations. The longer the time period, i.e., the higher the degree of temporal aggregation, the less random noise is left in the data. However, that does not mean that the coefficient of determination must be higher when aggregated data are used. Seasonal variation may account for a large part of the variance in the disaggregate series. When the data have been aggregated, the season can no longer be used to explain the variance in the aggregate series. Also, the variance of other explanatory variables is reduced due to the temporal aggregation.

The main benefit of aggregation is a better overview than when disaggregate data are used. Data may also be aggregated in order to correspond to a relevant decision-level. A

[9]In this chapter, actual store sales; in following chapters, store sales valued at regular prices.

common reason for using aggregate data is, however, that data may not be available at a more disaggregate level. As aggregation is an irreversible operation on the data, it is advisable to store data in disaggregate format and aggregate to the preferred-level only for the analysis.

The drawbacks of aggregation are that the number of observations available for estimation of the response function decreases and that the parameter estimates may be biased. An important source of the bias is, according to Foekens, Leeflang, and Wittink (1994), that the disaggregate response function may be nonlinear while the aggregation is usually the arithmetic sum.

Scanner receipt data come at a very disaggregate level, since each receipt is marked with the date, hour, and minute of the transaction. This means that the choice of level of temporal aggregation is not restricted by the data collection procedure. The choice was therefore guided by the trade off between the need for a sufficient number of observations and long enough periods to reduce the problem caused by observations of zero sales volume. This made daily observations appear to be the preferable level of temporal aggregation.

### 7.4.3. Description of Store-Level Variables

The data were collected between May 18 and November 22, 1992. Due to technical problems, the period of September 14 to October 4 was lost, and the store was closed on June 26. Thus, the data sets available for this research contain 168 daily observations. Table 7.1. presents summary statistics for the three store-level performance variables. It should be noted that the figures presented in this section refer to actual sales (as opposed to sales valued at regular prices). In the following chapters, however, sales valued at regular prices will be used.

| | *Store traffic (Baskets)* | *Index* | *Basket value (SEK)* | *Index* | *Store sales (SEK)* | *Index* |
|---|---|---|---|---|---|---|
| Mean | 2820 | 100% | 96.21 | 100% | 277809 | 100% |
| Median | 2849 | 101% | 89.86 | 93% | 250916 | 90% |
| Standard Deviation | 520 | 18% | 18.59 | 19% | 95315 | 34% |
| Range | 3798 | 135% | 129.40 | 135% | 603124 | 217% |
| Minimum | 727 | 26% | 42.37 | 44% | 30804 | 11% |
| Maximum | 4525 | 160% | 171.77 | 179% | 633928 | 228% |

*Table 7.1. Store-level summary statistics. n = 168 daily observations.*

The average number of receipts produced by the store's EPOS was 2,820 per day with a standard deviation of 520, or 18 percent of the average number of baskets. The overall average basket value was SEK 98.52 during the measurement period. Computing the average of the daily observations of average basket value gives SEK 96.21 as the average of the averages. This is the figure occurring in Table 7.1. The standard deviation of daily average basket value was 18.59, or 19 percent of the average. The daily variation in basket value and store traffic is thus approximately equal. Store sales, on the other hand, vary more. The standard deviation of store sales is 95,315, or 34 percent of the average daily store sales (SEK 278 thousand). The larger relative variance of the store sales indicates that store traffic and the basket size are positively correlated.

Figure 7.2 shows the variation in daily store traffic over the measurement period. The pattern is fairly regular with some few exceptions.

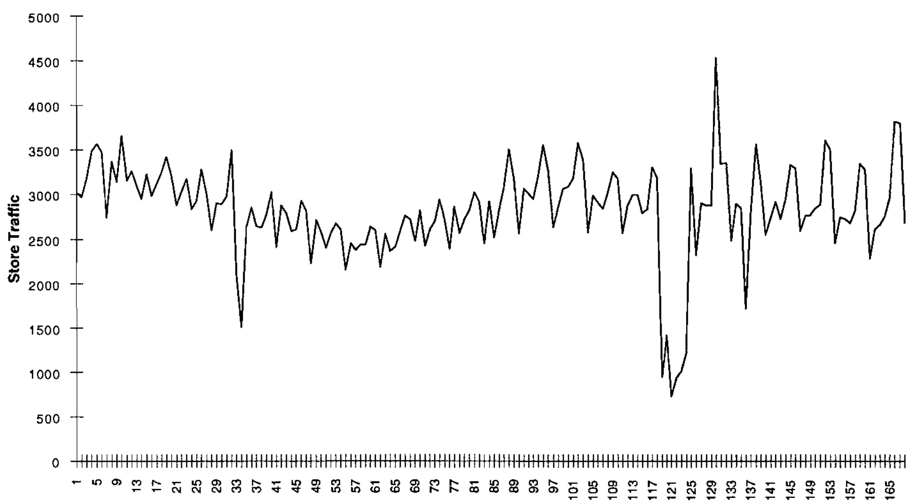


*Figure 7.2. Store traffic over 168 days.*

The large dip around period 120 needs some explanation. The explanation is that the layout of the store was changed and during the reconstruction work, some parts of the store were closed and not accessible to the customers. This made the store less attractive and reduced store traffic dramatically. The six observations affected are September 13, and October 5 to 9, i.e., one observation before and five observations after the period lost due to technical problems.

Figure 7.3 presents the variation in average basket value over the measurement period. This variable appears to follow an even more regular pattern than the store traffic variable.

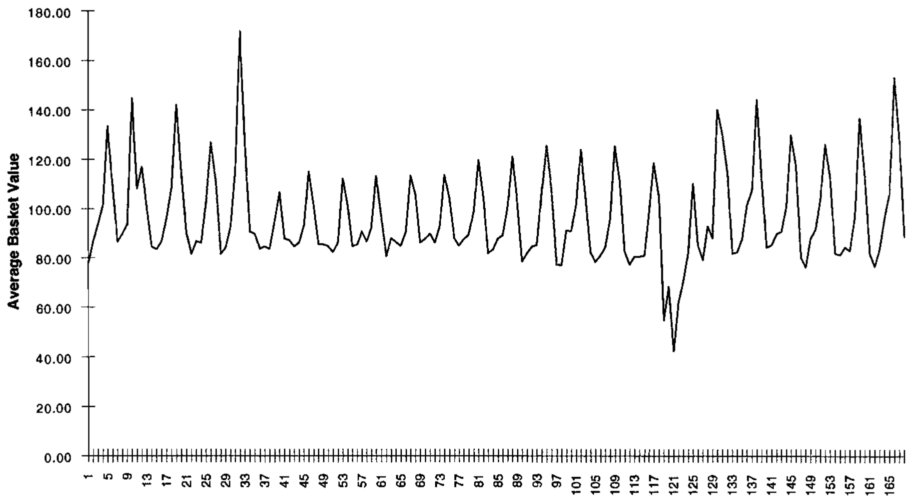


*Figure 7.3. Average basket value over 168 days.*

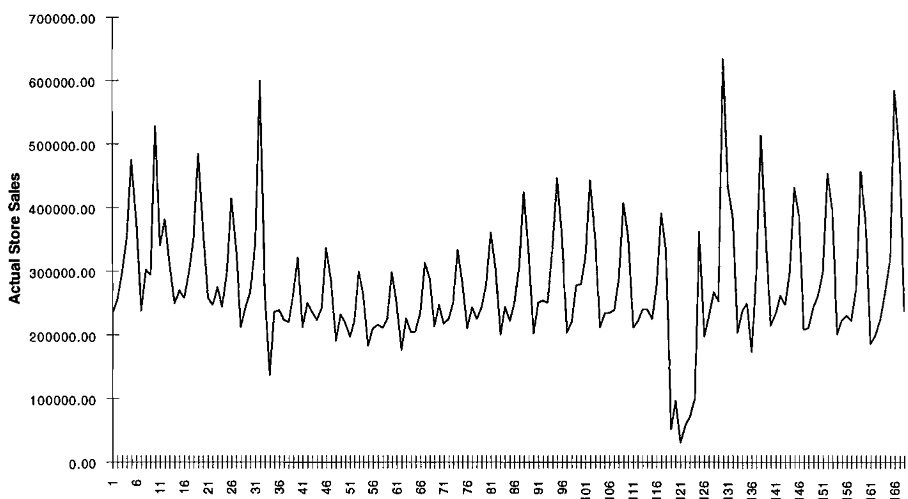


*Figure 7.4. Store sales over 168 days.*

The average basket value also dips around day 120. In other words, not only did fewer people choose to make their purchases in this store during the reconstruction period, but those who did visit the store bought less than the usual average. Part of the explanation for that is that not the whole assortment was available. The store's newspaper and tobacco kiosk was not affected by the reconstruction. These customers accounted for a larger than usual share of the store traffic which contributed to the reduction in average purchase amount.

The correlation between store traffic and basket value is 0.68. Store traffic and store sales have a correlation of 0.87 and the correlation between store sales and basket value is 0.94. The high positive correlations between store sales and the two other variables are not surprising since store sales are the product of store traffic and basket value. The correlation between store traffic and basket value indicates that the two variables tend to move together; periods when more consumers visit the store, each of them spends a larger amount on average. Being the product of two positively correlated variables, store sales vary more than either of the two variables.

The six observations during the reconstruction period can be seen as exceptional observations or outliers. Whether or not to include these observations in model building can be discussed. It is likely that the models will not be affected by the inclusion or exclusion of these observations, because the ratios should not be sensitive to store-level changes. The coefficient of determination of the store-level model, on the other hand, would be lower when these observations are included than when they are deleted from the data. This was also confirmed in tests not reported here. The reason is that the reconstruction period increases the variance of the dependent variables without affecting the variance of the independent variables. This automatically reduces the coefficient of determination. In the empirical illustrations reported in Chapters 8, 9, and 10, the six observations were excluded in the estimation of the models. However, it should be noted that all models were estimated with and without the six observations in order to test the impact of these observations. As expected, the parameters were basically not affected while the coefficient of determination increased.

We have seen that store traffic, basket value, and store sales follow fairly similar and regular patterns. It is not difficult to find the source of these patterns: the consumers purchasing behavior over the days of the week. Table 7.2 presents the averages for the three store-level variables by day-of-the-week.

| | Store traffic (Baskets) | Index | Basket value (SEK) | Index | Store sales (SEK) | Index |
|---|---|---|---|---|---|---|
| Monday | 2806 | 0.994 | 81.92 | 0.850 | 230740 | 0.828 |
| Tuesday | 2701 | 0.957 | 85.33 | 0.885 | 234202 | 0.840 |
| Wednesday | 2699 | 0.956 | 90.34 | 0.937 | 247919 | 0.890 |
| Thursday | 2917 | 1.034 | 102.85 | 1.067 | 307699 | 1.104 |
| Friday | 3128 | 1.108 | 123.90 | 1.285 | 393542 | 1.412 |
| Saturday | 3060 | 1.084 | 107.75 | 1.118 | 332246 | 1.192 |
| Sunday | 2446 | 0.867 | 82.77 | 0.859 | 204384 | 0.733 |
| **Average** | 2822 | 1.000 | 96.41 | 1.000 | 278676 | 1.000 |

*Table 7.2. Average store traffic, basket value, and store sales by day of week.*

Note that during the three heavy shopping days—Thursday, Friday, and Saturday—the number of shoppers is higher than during the rest of the week. Further, the average purchase amount is also higher during these days. This means that the total sales volume are even more concentrated on these three days than the store traffic variation alone would suggest. Store sales thus fluctuate more over the week than the store traffic and the average basket value.

## 7.5. Parameterization of the Response Models

This section describes and discusses the procedures used for estimating the parameters of the response models. First, the independent variables to be included in the models are discussed. Then, the transformations used to make the response models linear in the parameters are presented. The procedure used to select the variables to include in the final model and to estimate their parameters are described third. Fourth, the interpretation of statistical significance in this model-building is discussed, and fifth, the indirect modeling of item sales and its implications for the null hypothesis are discussed.

### 7.5.1. Selection of Independent Variables

Statistical techniques such as regression analysis can be seen as the bridge between theoretical models and empirical observations. If the theoretical model fits the data well, it provides a good representation of the data. The model can be said to correspond to the facts. It is well known that this does not mean that the model is true in some absolute sense, but it makes the model useful in several ways. The model can be seen as a shorthand description of the data set used for estimation. If we have reason to believe that a new data set would be similar to the first data set, the model would fit this data set, too. The model can then be used as a description of the population from which the original data set was drawn. A good model uses the variation in the independent variables to explain (or represent) a large part of the variation in the dependent variable. In that sense, a high value of the adjusted coefficient of determination is desirable.

Therefore, the sales promotion variables of other items and day of the week dummy variables were included in the response models in addition to the sales promotion variables of the focal brand. Competing stores' marketing variables constitute another type of variable that would have been desirable to include in the model estimation in order to explain more of the variance in the dependent variables, but these variables were not available. However, as long as competitors' promotions are not correlated with the promotions studied here, leaving them outside the model does not bias the parameter estimates. That also holds for variables such as season and sales promotions for other items and categories in the test store.

Scanner data are, as noted above, historical data reflecting the behavior of consumers and retailers. As retailers tend to use combinations of promotions, scanner data generally show a high degree of multicollinearity. In the research reported here, the sales promotion variables were highly correlated. The method that was chosen to handle the multicollinearity problem was to drop some of the promotion variables. The remaining variables should thus be interpreted as combinations of the promotions. In particular, the feature advertising variable was dropped from all models and the special display variable was dropped in several cases.

The implication of dropping these variables is that the response parameters for the price deal variable will be inflated. The most important effect of inflating the price deal response parameters that the optimal deal size determined by the model may deviate from the "true" optimum. However, the sign of the deviation depends on the specific model parameters in a complex way and could best be determined by sensitivity studies of the model parameters. An intuitive idea of the complexity can be gained by realizing that inflating the positive response for the promoted item at the same time implies that the negative effects on other items and categories are exaggerated. Retailers intending to use the model in their promotional decision-making are urged to conduct experiments in order to be able to obtain better estimated of the response parameters.

### 7.5.2. Linearizing Transformations before Estimation

The response models used in this study are the exponential model and the logistic model (see section 5.3). Both these models must be transformed before their parameters can be estimated with multiple regression. This section presents the transformations.

The general expression of the exponential model is:

$$Y = \exp(\alpha + \beta \cdot X) \tag{7.1}$$

and can be linearized by taking logarithms on both sides. This gives:

$$\ln(Y) = \alpha + \beta \cdot X \tag{7.2}$$

which is linear in the parameters. The error term, *e*, enters the original equation as follows:

$$Y = \exp(\alpha + \beta \cdot X + e) \tag{7.3}$$

The binomial logit model is in its general form:

$$Y = \frac{\exp(\alpha + \beta \cdot X)}{1 + \exp(\alpha + \beta \cdot X)} \tag{7.4}$$

That can be made linear in the parameters using the following transformation (see e.g., Aldrich and Nelson 1984):

$$\ln\left(\frac{Y}{1-Y}\right) = \alpha + \beta \cdot X \tag{7.5}$$

The error term of the original model is thus:

$$Y = \frac{\exp(\alpha + \beta \cdot X + e)}{1 + \exp(\alpha + \beta \cdot X + e)} \tag{7.6}$$

### 7.5.3. Estimation Procedure

Multiple regression was used for estimating the models. The regression models were built using the following procedure. First, a maximum model including all the relevant variables was specified and estimated. Second, the variables associated with parameters insignificant at the ten-percent level were eliminated. The new, restricted model was estimated and further variables might be eliminated. This was repeated until all parameters in the model were significant at the ten-percent level.

The procedure can thus be described as a stepwise regression using a backward elimination strategy (see e.g., Kleinbaum, Kupper, and Muller 1988). However, the automatic stepwise regression procedure of the statistical software could not be used to implement the variable selection. This is because stepwise regression programs eliminate variables using undirected hypotheses. In contrast, most of the hypotheses concerning the parameters in these models are directional; as it is assumed that a sales promotion would not reduce sales of the promoted item, we can interpret negative parameters as insignificantly positive. Variables having parameters with "wrong" signs were therefore eliminated.

In the estimation of the item-level models, the decision variables related to the focal item were treated slightly different from the other independent variables. The focal item's variables were not eliminated in early steps of the procedure even if the parameters were insignificant. Only if the sign of the parameter remained wrong when the variable was the only variable left in the regression model was it eliminated. The reason is that multicollinearity might make these parameters insignificant in the early steps of the estimation procedure, while they become significantly positive at later steps. Throwing these variables out at an early step would, however, be like throwing the baby out with the bath water, since these are the parameters we really want to estimate.

The estimation procedure can be said to be guided by a face validity criterion. A model has face validity if its parameters make sense from a theoretical and intuitive perspective. For example, if the parameter estimate implies that sales promotion reduces sales of the promoted product, the model does not have face validity. It could of course be a scientific breakthrough, but chances are good that something is wrong with the model.

### 7.4.4. Regression Diagnostics

The estimated regression models were examined for deviations from the assumptions of the classic linear regression model. The condition numbers (see e.g., Kleinbaum, Kupper, and Muller 1988) indicated that the estimated regressions did not suffer from severe multicollinearity. Further, plots of the studentized estimated error terms against the fitted value of the dependent variable showed that there was no problem with heteroscedasticity (nonconstant error variance) in the data (see e.g., Fox 1991). Ramsey's RESET test, which was used to test for nonlinearity, did not indicate further nonlinearities after the linearizing transformations described in Section 7.5.2. However, given the relatively low number of different deal discounts used, we should not be too confident that the functional form is the true model.

The Durbin-Watson $d$ statistic indicated that the regression models suffer from positive first order autocorrelation, i.e., positive errors tend to be followed by positive errors and negative errors tend to follow negative errors. Autocorrelated error terms have two consequences for the regression results: (1) the standard errors of the parameters are underestimated which implies that the significance levels are overestimated, and (2) the amount of variance explained is overestimated. Autocorrelation does not lead to biased parameter estimates (Kennedy 1992). The main problem with autocorrelation is thus that the variables included in the model may not be statistically significant.

The regression models were therefore re-estimated using the two step pseudo GLS (Generalized Least Squares) procedure suggested by Cochrane-Orcutt (see e.g., Ostrom 1978). The result was, as expected, that the amount of variance explained decreased while the parameter estimates remained (almost) unchanged. More important is that the parameters (with few exceptions) were still significant at the ten-percent level.

As the results of the pseudo GLS estimation were similar to the results of the OLS estimates, the OLS results are reported and used in this report.

### 7.5.5. Parameter Significance

Models used to make conditional forecasts of sales and profits for given values of the manager's decision variables can be regarded as normative models. When building such models, it is important that the parameters are "correct". A minimum requirement would be that the parameters have the right signs. Is it then important that the parameters are statistically significant? It will here be argued that the answer is no, but that statistical significance can be useful in order to obtain a parsimonious model.

The idea behind the significance testing of parameters in a regression model is that if the model were re-estimated on new samples from the same population, the parameters would be different in each estimation. The standard deviation of the parameter estimates could then be calculated. The estimate of the standard deviation the parameter would have is known as the parameter's standard error, and is used for hypothesis-testing. Parameters are generally tested against the null hypothesis that the population value of the parameter is zero. Thus, the numerical value of a significant parameter is not more "true" than that of other, insignificant, parameters. The "truth" of a parameter value is better described by its standard error, which can be used to estimate the confidence interval of the parameter. Thus, it is more important that all the parameter values make theoretical sense than that they are significant, and it might be suggested that all parameters having correct signs should be included in the model.

However, insignificant parameters are generally close to zero (otherwise they would be significant) and their variables have little impact on the dependent variable. We can then use statistical significance is to discard variables having little impact on the dependent variable. The problem is that the parameter may be insignificant because the variance of the independent was insufficient during the measurement period.

Parsimony was the reason for using statistical significance as the variable selection criteria when specifying and estimating the response models in the empirical illustrations. The general model-building principle of parsimony, i.e., that the model should not be more complex than necessary, has in statistical model building a special reason. Including too many parameters in the model reduces the number of degrees of freedom, i.e., the number of observations used to estimate the value of each parameter. This increases the standard errors of the parameter estimates, and consequently widens their confidence intervals.

Including variables that have no influence on the dependent variable increases the standard errors of the parameter estimates. If such an irrelevant variable is uncorrelated with the other independent variables of the model, its inclusion does not bias the other parameters. However, it is unlikely that it is perfectly orthogonal to the other independent variables, implying that other parameter values may change when the irrelevant variable is included in the model.

The conclusion of this discussion is that all variables should primarily be selected on the theoretical plausibility of their parameter estimates. Variables included in the model in order to make the model explain more of the variance should only be retained in the model when statistically significant. Statistical significance is less important for the decision variables.

### 7.5.6. Modeling Approach and the Null Hypothesis

On a methodological level, the modeling approach and the choice of null hypothesis are worth some consideration. The indirect modeling approach, i.e., modeling item sales as the product of four ratios and store traffic, is likely to provide conservative estimates of promotion profits. This is because promotion for a single item has little, if any, effect on store traffic and average basket value.

The null hypothesis in statistical estimation of model parameters is that the parameters are zero, so small effects may be disregarded because of lack of power of the statistical test. The effects at the item- and category-levels are larger (in relation to the variance of the dependent variables) and less likely to be victims of type II errors. The item and category models are ratios. An increase in the focal item's share of category sales automatically means that other items' or categories' share must decrease. If the lack of power leads us to the conclusion that the focal item's promotion had no effect on store sales, then the negative effects on sales of other items and categories become exaggerated, leading to a conservative estimate of the promotion profits.

If a direct model would be used instead of the indirect model, there is a risk that the promotion profits would be overestimated. The argument is the same as above. The item-level positive effect of the sales promotion is fairly large and type II errors are not likely. There is, however, a large risk that there will not be enough power to reject the null hypothesis that the sales promotion has no effect on other categories' aggregate sales since the effect would generally be expected to be negligible. A type II error would occur, with the consequence that promotion profits would be exaggerated.

# 8. EMPIRICAL ILLUSTRATION 1: COFFEE

## 8.1. Introduction

This chapter contains a case study of the coffee category in our test store. It is an application of the model developed in Chapter 5 and simulated in Chapter 6. The chapter starts with a description of the product category and the data. Then, response models are specified and estimated. The profit impact of sales promotion is calculated and the optimal deal discount and the retailer pass-through of trade deals are determined using the sales-response models. The chapter closes with a section in which the conclusions that can be drawn from the analyses are discussed.

## 8.2. Description of the Coffee Category

Two reasons were important for selecting the regular ground coffee as one of the case studies. The first reason is that coffee is a very frequently promoted product category. The second reason is that coffee is believed to function as a loss leader, i.e., a product that attracts more consumers to the store. As the model allows direct measurement of sales promotion's impact on store traffic and store sales, a loss-leader promoted product like coffee would seem suitable for illustrating the model.

There are eight brands of regular ground coffee sold in the test store. Each brand is available in a number of varieties and three brands are sold in 250 gram as well as the standard 500 gram package size. Pricing and sales promotion are homogeneous across the varieties within each brand-size. The brand-size is therefore the lowest level of analysis that will be used here. The term item will hereafter be used to represent a brand-size although each brand-size actually consists of more than one SKU (Stock Keeping Unit). Figure 8.1 presents market-shares of the items in the coffee category.

Figure 8.1 shows that three items dominate the coffee category. The analysis will thererfore focus on the three items: Item A, Item B, and Item C. Item C has much higher deal costs than Item A and Item B, which indicates that Item C has bought market shares by using large discounts. An examination of the store's promotion calendar showed that Item

C, on a number of occasions, was sold with a fifty percent discount to shoppers buying ten units.

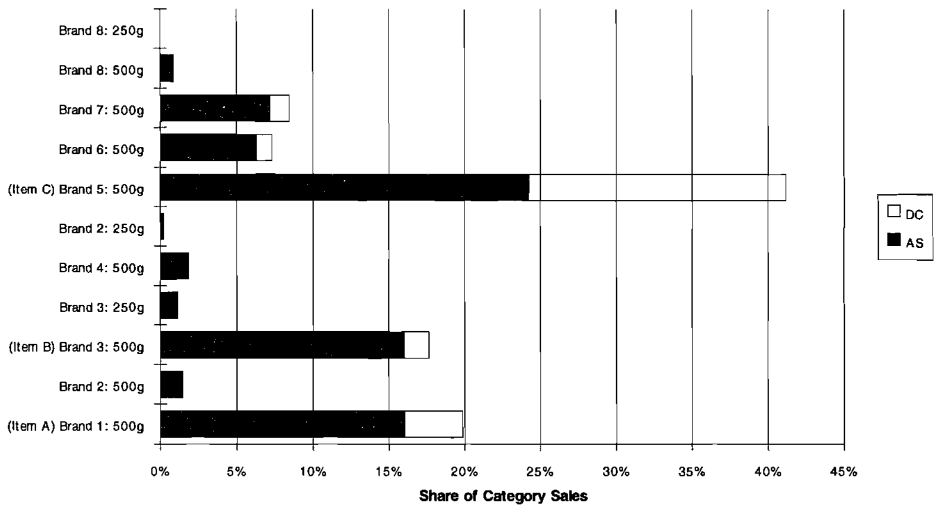


*Figure 8.1. Item sales in the coffee category during the measurement period. The bars show actual sales (AS) and deal cost (DC).*

## 8.3. Building the Promotional Response Models

This section describes the estimation of response models for the factors of the model developed in Chapter 5. The specific models used in this chapter are directly based on the model specification presented in Section 5.3.

First, the model building procedure is described. Then, the plausibility of the modeling framework is tested by examination of correlations among the variables and ratios of the decomposition model (i.e., equation 5.5). Thereafter, regression models are built for the store-level, the category-level, and the item-level measures. The section closes with an overview of the regression models, and can be seen as a further test of the modeling framework.

### 8.3.1. Model Building Procedure

The regression models were built using the procedure described in Chapter 7. The maximum model (i.e., the model containing all the independent variables that are considered potentially relevant) differed between the hierarchical levels. In the store and category-level models, the deal discount and the special display were used in the maximum model, except for Item B, where only deal discount was included. In addition to these, six dummy variables for the days Tuesday till Sunday were included in the maximum model.

In the item-level models, the maximum models were extended to include both the deal discount and the special display variable for the focal item. Other items were included with one of these variables.

Item B's the price deal and special display variables of were strongly correlated. In fact, price deal never occurred without a special display. The resulting multicollinearity made the deal discount parameter assume the wrong sign (i.e., negative instead of positive parameter). As this parameter is that of greatest interest in this study, the special display variable was dropped from the full model for Item B. It should be remembered that the price deal parameter thus is biased upwards and should be interpreted as the price deal response when Item B is on special display.

### 8.3.2. Initial Tests of the Model

The hierarchical decomposition of item sales into four factors (i.e., store traffic, average basket value, category-to-store sales, and item-to-category sales) is in itself definitional and cannot be tested. Sales of any item in the store can always be described in terms of these four factors. However, if we want to use the decomposition to explain variations in item sales as caused by variations in store traffic, some testing is needed.

It is difficult to design conclusive tests of the validity of the model, but the correlations between the variables entering the model should give some indication. Although high correlation between, for example, store-sales and category-sales may be due to a causal relation between the two variables, there may also be some common cause. Another alternative explanation for a high correlation between store-sales and category-sales is that category sales are a part of store-sales, and, if category-sales (of the focal category) make up a large share of store-sales, the correlation will be high. However, if category sales are small compared with store-sales, a high correlation would contribute to the credibility of the model.

At the same time as high correlations cannot conclusively decide the validity, low correlations *per se* cannot falsify the model. This is because even if store sales would have a causal impact on category sales, other sources of variation in category sales may reduce the correlation between store sales and category sales.

Bearing these caveats in mind, we go on examining the intercorrelations among the variables (see Table 8.1).

| | Bt | St | bjt | sjt |
|---|---|---|---|---|
| Bt | 1.00 | | | |
| St | 0.87 | 1.00 | | |
| bjt | 0.38 | 0.40 | 1.00 | |
| sjt | 0.29 | 0.26 | 0.76 | 1.00 |

*Table 8.1. Pearson correlations between store traffic (Bt), store sales (St), number of coffee category baskets (bjt), and coffee category sales (sjt). All correlations significant at the 1 percent level.*

All the correlations were significantly different from zero at the one-percent level or better. This gives an indication that the model may be useful for explaining variation in sales. The use of ratios in the decomposed model of item sales reflects the belief that sales at lower hierarchical levels vary proportionally with the next higher level's sales. Forming the ratio would then neutralize the impact of the denominator. The correlations among the ratios would then be lower than correlations among the variables. As Table 8.2 shows, correlations among the ratios are lower than the correlations among the variables.

| | Bt | St/Bt | bjt/Bt | sjt/St |
|---|---|---|---|---|
| Bt | 1.00 | | | |
| St/Bt | 0.65 | 1.00 | | |
| bjt/Bt | <u>0.13</u> | 0.21 | 1.00 | |
| sjt/St | <u>0.11</u> | <u>0.00</u> | 0.70 | 1.00 |

*Table 8.2. Pearson correlations between store traffic (Bt), basket value(St/Bt), category-to-store baskets (bjt/Bt), and category-to-store sales (sjt/St). All correlations, except those underlined, were significant at the 1 percent level. Underlined correlations were insignificant at the 10 percent level.*

As noted above, these tests cannot conclusively prove or disprove the model. However, the observed correlations do strengthen the credibility of the model. Further tests of the decomposition model are provided by the explanatory power of the sub-models. The development of the sub-models is the subject of the next few sections.

### 8.3.3. Store-Level Response Models

This section examines the store-level response to sales promotion in the coffee category. Three types of independent varaibles are used: (1) price deal variables (deal discount as fraction of regular price) for the items in the category; (2) special display indicators (coded 0 and 1) for the items in the category; and (3) day-of-the-week indicators (coded 0 and 1).

The present analyses are partial in that the independent variables included in the models are not exhaustive. For example, sales promotion in other categories and other stores' sales promotion are not included among the explanatory variables. It is thus assumed that these variables are not correlated with the coffee promotion in our test store.

Response models were built for store traffic, store sales, and the average basket value. The three response models defined at the store-level all had the same structure and the same variables in the maximum model. The of the general response model equation that was fitted is (in its linearized version):

$$\ln(y_t) = \alpha + \sum_{k=1}^{K} \beta_k x_{kt} + \varepsilon_t \tag{8.1}$$

where $t$ indexes the time period and $K$ is the number of independent variables. This type of response model is referred to as an exponential response model because the dependent variable is an exponential function of the independent variables. Note that the model parameters obviously differ between the models. Equation (8.1) is presented to show the structure of the three models. The variable $y_t$ on the left hand side of (8.1) represents store traffic expressed as number of baskets, store sales valued at regular prices, and average basket value, respectively, in the three store-level regression models that were estimated.

Table 8.3 presents the parameters (and their standard errors) of the final models of store traffic, store sales, and basket value.

| | Store Traffic coefficient | s.e. | Store Sales coefficient | s.e. | Basket Value coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | 7.95 | 0.01 | 12.41 | 0.02 | 4.48 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | 0.21 | 0.10 |
| Item C | | | | | | |
| ***Special Display*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | | |
| Item C | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | 0.07 | 0.02 |
| Thursday | | | 0.27 | 0.08 | 0.20 | 0.02 |
| Friday | 0.12 | 0.03 | 0.54 | 0.05 | 0.40 | 0.02 |
| Saturday | 0.06 | 0.03 | 0.33 | 0.04 | 0.24 | 0.02 |
| Sunday | -0.13 | 0.03 | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 22% | | 52% | | 71% | |
| n | 162 | | 162 | | 162 | |

*Table 8.3. Store-level response to sales promotion in the coffee category.*

Sales promotion in the coffee category had little impact on all three store-level dependent variables. This is what can be expected because the coffee category is just one among a large number of categories in the store. On the other hand, it may be disappointing for retailers since coffee is traditionally treated as a loss leader category whose purpose is to attract store traffic. According to Table 8.3, none of the three largest coffee brands' sales promotion had any impact on store traffic. The insensitivity to sales promotion in the coffee category could, however, also be a statistical artifact, caused by a more or less constant level of sales promotion.

Item B's price deal was the only sales promotion that had a positive effect on average basket value. The standardized coefficient of Item B's price deal variable was around 0.1 in the basket value model, indicating that the promotion explained about one percent of the variance in the dependent variable over the measurement period.

The model parameters show that there are important variations in store traffic, store sales, and the average basket value over the week. Average basket value and store traffic follow the same pattern as store sales. Store sales are low on Mondays, increase over the week until Friday. Saturday sales are slightly lower than Friday sales and Sunday sales are at the same level as Monday sales.

Note that the basket value model's parameters are defined to be the difference between the sales model's parameters and the store traffic model's parameters (see Section 5.3.2). The deviations from this found in Table 8.3 are due to the different number of parameters included in the three models.

Comparing the share of variance explained, Table 8.3 shows that the average basket value is the variable with the largest share of variance explained by the models (also after accounting for the number of independent variables included in the model.) One reason for this may be that store traffic is more stable over the week, its variance therefore relatively more attributable to other factors than the day-of-the-week and coffee promotion.

### 8.3.4. Category-Level Response Models

Two category-level response models were built, both representing category-to-store-level ratios (see Figure 8.2). The logit model was used to model these ratios (compare Section 5.3). The first response model measures the response in the ratio of the number of category baskets to the total number of baskets (i.e., store traffic). The category-to-store sales ratio is modeled in the second response model. The response models had the same structure and independent variables in both models. The estimation equation of the logit model is:

$$\ln\left(\frac{y_t}{1-y_t}\right)=\alpha+\sum_{k=1}^{K}\beta_k x_{kt}+\varepsilon_t \tag{8.2}$$

where $t$ indexes the time period and $K$ is the number of independent variables. Equation (8.2) should be interpreted in the same way as (8.1), i.e., as an illustration of the model structure. The independent variables used here are the same as those defined above. The results of the regressions are presented in Table 8.4.

Both models account for approximately half of the variance of the dependent variables. A difference between the two models is that four of the day-of-the-week dummy variables were significant in the category-to-store baskets model while only one was significant in the share of sales model.

As the category-to-store baskets and category-to-store sales are ratio measures, the *a priori* hypothesis may be that there should be no variation over the week. This is what could be expected in the share of sales model, but in the category-to-store baskets model it is not necessarily so. The reason is that the larger the shopping basket, the higher the probability that any product in the store will enter the shopping basket. As the average basket value varies over the week (as we recall from the previous section), it is logical that the category-to-store basket ratio varies too.

The category-level response to sales promotion is greater than the store-level response. It is found that the basket ratio responds to price deals for Item A and Item B, and to special displays for Item C. The price deal parameter for Item C was not significantly greater than zero even when Item C's special display variable was omitted from the model. As explained earlier, Item B's special display variable was not included in the model because of collinearity. Item B's price deal parameter is thus biased as it accounts for the effect of price deal in combination with special display. Item A's price deal variable had a significant impact on the baskets ratio while the effect of its special display variable was not significant.

In the sales ratio model, on the other hand, Item A's price deal variable and special display variable both had significant impact. Other sales promotions having significant impact on the sales ratio were Item B's price deal and Item C's special display.

It is noteworthy that the promotion response parameters are of greater magnitude in the sales ratio model than in the basket ratio model. This indicates that the average purchase in the coffee category is also affected positively by sales promotion.

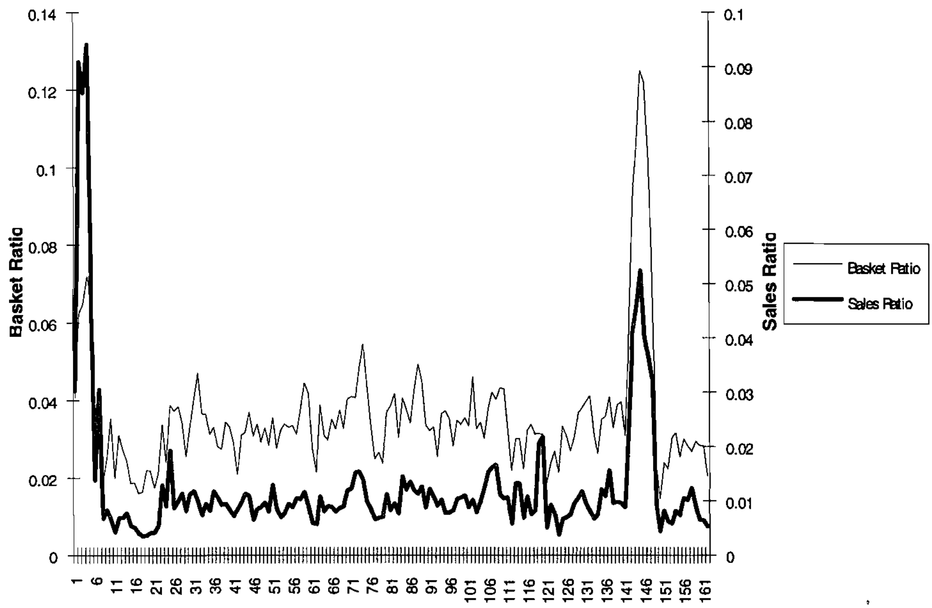


*Figure 8.2. Category development over time.*

| | Category/Store Baskets coefficient | s.e. | Category/Store Sales coefficient | s.e. |
|---|---|---|---|---|
| Constant | -3.75 | 0.04 | -5.06 | 0.06 |
| ***Price Deal*** | | | | |
| Item A | 1.12 | 0.18 | 1.36 | 0.34 |
| Item B | 3.33 | 0.29 | 5.55 | 0.48 |
| Item C | | | | |
| ***Special Display*** | | | | |
| Item A | | | 0.16 | 0.10 |
| Item B | | | | |
| Item C | 0.28 | 0.04 | 0.42 | 0.07 |
| ***Day-of-the-Week*** | | | | |
| Tuesday | | | | |
| Wednesday | 0.10 | 0.06 | 0.19 | 0.09 |
| Thursday | 0.18 | 0.06 | | |
| Friday | 0.27 | 0.06 | | |
| Saturday | 0.16 | 0.06 | | |
| Sunday | | | | |
| ***Regression Statistics*** | | | | |
| adj.Rsq. | 58% | | 53% | |
| n | 162 | | 162 | |

*Table 8.4. Category-level response to sales promotion in the coffee category.*

### 8.3.5. Item-Level Response Models

We have examined the store-level and category-level response to sales promotions for three items (brand-sizes) in the coffee category. Here, the item-level response will be studied. Three models were built for each brand, namely item-to-category basket ratio, item-to-category sales ratio, and average value of item purchase among item buyers. Hereafter, these will be referred to as the (item) basket ratio, the (item) sales ratio, and the (item) purchase size models. The two ratios were modeled using logistic regression. The transformed estimation equation is defined as:

$$\ln\left(\frac{y_t}{1-y_t}\right) = \alpha + \sum_{k=1}^{K} \beta_k x_{kt} + \varepsilon_t \tag{8.3}$$

The purchase size was modeled using an exponential model which linearized estimation equation is:

$$\ln(y_t) = \alpha + \sum_{k=1}^{K} \beta_k x_{kt} + \varepsilon_t \tag{8.4}$$

Note that the observations of zero sales of the focal item will be treated as missing values when estimationg the models using equations (8.2) and (8.3). Therefore, the number of observations used for estimation of the models will vary. The fact that observations of zero sales are not used in the estimation implies that the parameters will be biased.

In contrast to the store-level models, the purchase size variable's parameters are not defined to be the difference between salės and basket ratios (see Section 5.3.2). The response models will be presented and discussed for one item at a time.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.34 | 0.10 | -2.31 | 0.12 | 3.24 | 0.02 |
| ***Price Deal*** | | | | | | |
| Item A | 4.59 | 0.52 | 5.56 | 0.66 | 0.50 | 0.16 |
| Item B | | | | | | |
| Item C | | | | | | |
| ***Special Display*** | | | | | | |
| Item A | 1.47 | 0.15 | 1.71 | 0.19 | 0.24 | 0.04 |
| Item B | -0.97 | 0.12 | -1.31 | 0.16 | | |
| Item C | -0.34 | 0.11 | -0.54 | 0.14 | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | 0.29 | 0.15 | | | | |
| Friday | 0.41 | 0.15 | 0.35 | 0.19 | | |
| Saturday | 0.44 | 0.15 | 0.40 | 0.18 | | |
| Sunday | 0.32 | 0.15 | 0.38 | 0.18 | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 81% | | 80% | | 36% | |
| n | 161 | | 161 | | 161 | |

*Table 8.5. Response of Item A to sales promotion in the coffee category.*

Table 8.5 presents the results for Item A. The basket ratio and sales ratio models are very successful in accounting for the variance in the dependent variables. These models explain 81 and 80 percent of the variance. The purchase size model is not as successful, nevertheless it accounts for 36 percent of the variance. Recall that the situation reversed at the store-level, with little of the variance in number of baskets explained by the model while more than half of the variance in basket value was accounted for by the model.

Item A's sales promotion, price deal as well as special display, has a fairly large impact on the Item A basket ratio and the Item A share ratio. Its effect on the purchase size is somewhat smaller, however positive, implying that the sales ratio is more responsive than the basket ratio.

The competitors' sales promotion had significant negative impact on the basket ratio and the sales ratio. Their impact on purchase size was not significant.

Contrary to what would be expected, day-of-the-week variations in the basket ratio and the sales ratio were found. The effect of the day-of-the-week was insignificant in the purchase-size model.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -0.95 | 0.09 | -1.04 | 0.11 | 3.17 | 0.02 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | 7.52 | 0.79 | 6.35 | 1.00 | 1.31 | 0.21 |
| Item C | | | | | | |
| ***Special Display*** | | | | | | |
| Item A | -0.79 | 0.14 | -0.99 | 0.18 | | |
| Item B | | | | | | |
| Item C | -1.01 | 0.12 | -1.16 | 0.15 | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | -0.24 | 0.15 | -0.38 | 0.19 | | |
| Friday | -0.31 | 0.15 | -0.36 | 0.20 | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 53% | | 42% | | 19% | |
| n | 162 | | 162 | | 162 | |

*Table 8.6. Response of Item B to sales promotion in the coffee category.*

The results for Item B are presented in Table 8.6. The pattern of variance explained is the same for Item B as for Item A, but the magnitude is smaller. Again, the item basket ratio is more predictable than the item purchase size.

Item B's promotion was the only significant determinant of the purchase size and its response parameters in the ratio models were large. Note that although the basket-ratio response parameter is larger than the sales-ratio parameter, the purchase size responded positively to sales promotion. This seemingly contradictory result is explained when we recall that Item B's sales promotion had a larger effect on the category-sales ratio than on the category-baskets ratio. Purchase size is not the quotient between sales ratio and baskets ratio, but the quotient between item sales and item baskets.

Like Item A, Item B's basket and sales ratios are affected negatively by competitors' sales promotion while the purchase size is not significantly affected by other brands' promotion.

The basket ratio and the sales ratio were found to vary over the week, with both ratios being slightly lower on Thursdays and Fridays.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -3.00 | 0.09 | -3.11 | 0.12 | 3.17 | 0.05 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | | |
| Item C | 2.08 | 0.60 | 4.36 | 0.76 | 1.15 | 0.20 |
| ***Special Display*** | | | | | | |
| Item A | | | -0.40 | 0.21 | | |
| Item B | -0.65 | 0.18 | -0.44 | 0.22 | 0.51 | 0.09 |
| Item C | 2.61 | 0.21 | 2.24 | 0.29 | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | 0.26 | 0.10 |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 80% | | 82% | | 41% | |
| n | 150 | | 150 | | 150 | |

*Table 8.7. Response of Item C to sales promotion in the coffee category.*

The response models for the last of the three brands, Item C, are shown in Table 8.7. The variation in predictability is again the same as for Item A and Item B. The coefficient of determination is above 80 percent for the two ratio models and 41 percent for the purchase size model.

Item C's price deal had significant impact on all three variables. Its impact on purchase size was positive. Item C's special display had significant impact on both ratios but no effect on purchase size. An interesting observation is that while the special display coefficient is higher in the basket ratio model than in the sales ratio model, the opposite holds for price deal.

Both competitors' promotions hurt the sales ratio. In addition, Item B's promotion hurts Item C's basket ratio but has a positive impact on the purchase size. This indicates that Item B's promotion draws unproportionally from small buyers of Item C.

Unlike the models for Item A and Item B, the only day-of-the-week variable found significant was the Sunday dummy variable in the purchase-size model. The purchase size was slightly smaller on Sundays than other days. All other day-of-the-week variables were insignificant.

### 8.3.6. Overview of the Regression Results

The regression results are summarized in this section. First, the explanatory power of the regression models are compared. Then, the regression models are compared in terms of the number of independent variables retained.

Table 8.8 presents the amount of variance explained by the regression models. Item C's sales ratio model has the highest explanatory power of the 15 regression models. That model explained 82 percent of the variance in the sales ratio variable.

| | Baskets | Sales | Quantity |
|---|---|---|---|
| ***Store Level*** | 22% | 52% | 71% |
| ***Category Level*** | 58% | 53% | n.a. |
| ***Item Level Average*** | 71% | 68% | 32% |
| Item A | 81% | 80% | 36% |
| Item B | 53% | 42% | 19% |
| Item C | 80% | 82% | 41% |

*Table 8.8. Adjusted R-squares.*

Item C's basket ratio model also explained a large part of the variance. Item A's basket and sales ratio models both explained about 80 percent of the variance. Item B's models explained less variance than Item A's and Item C's models. A pattern observed for all three items is that the basket and sales ratio models explain more of the variance than the purchase quantity models.

At the store-level, the pattern is reversed. The store-level model if average basket value explains 71 percent of the variance, which is more than the 52 percent explained by the store sales model and the 22 percent explained by the store traffic model.

These observations support the indirect modeling approached used in this report. While the item-level basket and sales ratios are fairly deterministic according to the regression results, the variation in store traffic is to a large extent unexplained.

| | Sales Promotion | | | Day-of-the-Week | | |
|---|---|---|---|---|---|---|
| | Baskets | Sales | Quantity | Baskets | Sales | Quantity |
| ***Store Level*** | 0 | 0 | 1 | 3 | 3 | 4 |
| ***Category Level*** | 3 | 4 | n.a. | 4 | 1 | n.a. |
| ***Item Level Average*** | 3.3 | 3.7 | 1.7 | 2.0 | 1.7 | 0.3 |
| Item A | 4 | 4 | 2 | 4 | 3 | 0 |
| Item B | 3 | 3 | 1 | 2 | 2 | 0 |
| Item C | 3 | 4 | 2 | 0 | 0 | 1 |

*Table 8.9. Number of significant model parameters.*

Table 8.9 presents the number of significant model parameters of different types. At the store-level, only one sales promotion parameter was significant. The day-of-the-week dummy variables were the only variables retained in the store traffic and store sales models. In the store-level quantity model (i.e., the average basket value model), one sales promotion parameter and four of the day-of-the-week dummy variables were significant.

In the item-level models, the more sales promotion parameters than day-of-the-week parameters were significant. The pattern is clearly the reverse compared with the store-level models.

## 8.4. Deal Discount, Sales Response, and Profit Impact

This section integrates the sales-response models developed above to a comprehensive model for each of the three items. For each item, the sales effects of different deal discounts are exemined at the item-, category-, and store-levels. Sales promotion's effects on the number of baskets at the three hierarchical levels are also studied. Note that we are now studying absolute rather than relative measures. This is because absolute sales, not relative sales, is what translates into profits.

The absolute-sales responses are entered into the promotion-profit model developed in Chapter 5. Based on assumptions about the retailer's gross margins, coffee sales promotion's impact on retailer profits, measured as different hierarchical levels, are presented. The profit models in this section assume that:

1. The average margin of other categories is 20 percent.

2. The average margin of other coffee items is equal to the margin of the focal item, 20 percent if not otherwise noted.

3. The manufacturer offers a trade deal of 20 percent if not otherwise noted.

4. There is no requirement that the retailer must pass through any part of the trade deal to the consumers.

These assumptions were selected after consultations with industry experts. It should be noted that the qualitative results of the analyses are fairly robust to changes in the gross margins of the products. Numerical results will however depend on the choice of the margins.

The store-level profit model enables the retailer to set the optimal size of the price deal. Assuming that the retailer uses an item-level or a category-level profit model, we estimate the cost of sub-optimization.

The retailer's pass-through of trade deals to the consumers is of great concern for the manufacturers. It is shown how the retailer's pass-through depends on the gross margin, the size of the trade deal, and the level of analysis the retailer uses when setting the deal price (assuming that the deal discount is set to maximize profits).

### 8.4.1. Item A

The sales-responses to price deal for Item A are shown in Figure 8.3. Category sales increase more than item sales, implying that there is no intra-category cannibalization due to Item A's price deal. However, all of the increase in coffee sales comes from other categories in the store. In other words, the price deal for Item A leads to complete inter-category cannibalization. Store sales is thus not affected by Item A's price deal.

Formalized measures of the relations between changes in category sales and changes in item sales ($\Phi_{12}$ or *phi12*), and between changes in store sales and changes in category sales ($\Phi_{23}$ or *phi23*) were introduced earlier in this report. Table 8.10 presents these measures, as well as their basket model equivalents ($\Psi_{12}$ or *psi12* and $\Psi_{23}$ or *psi23*), for various deal discounts.

| Deal Discount | phi12 | phi23 | psi12 | psi23 |
|---|---|---|---|---|
| 2% | 2.23 | 0.00 | 2.27 | 0.00 |
| 4% | 2.12 | 0.00 | 2.18 | 0.00 |
| 6% | 2.03 | 0.00 | 2.10 | 0.00 |
| 8% | 1.93 | 0.00 | 2.01 | 0.00 |
| 10% | 1.84 | 0.00 | 1.93 | 0.00 |
| 12% | 1.75 | 0.00 | 1.86 | 0.00 |
| 14% | 1.67 | 0.00 | 1.79 | 0.00 |
| 16% | 1.59 | 0.00 | 1.72 | 0.00 |
| 18% | 1.52 | 0.00 | 1.65 | 0.00 |
| 20% | 1.45 | 0.00 | 1.58 | 0.00 |
| 22% | 1.39 | 0.00 | 1.52 | 0.00 |
| 24% | 1.33 | 0.00 | 1.47 | 0.00 |
| 26% | 1.27 | 0.00 | 1.41 | 0.00 |
| 28% | 1.22 | 0.00 | 1.36 | 0.00 |
| 30% | 1.17 | 0.00 | 1.31 | 0.00 |

*Table 8.10. Phi and psi for different deal discounts for Item A.*

Price deals for Item A lead to larger increases in category sales than item sales. This can be seen in Table 8.10 in that *phi12* is greater than unity for all deal discounts evaluated. The complete inter-category cannibalization is recognized by a column of zeroes for *phi23*. The profit impact of a price deal for Item A is thus likely to be exaggerated if measured at the item-level or at the category-level. Figure 8.4 shows that retailer profits are maximized by absorbing the whole trade deal offered by the manufacturer. However, the retailer using the myopic, item-level, analysis would set the deal discount to 22 percent. This means that the deal discount would be greater than the (20 percent) trade deal received.

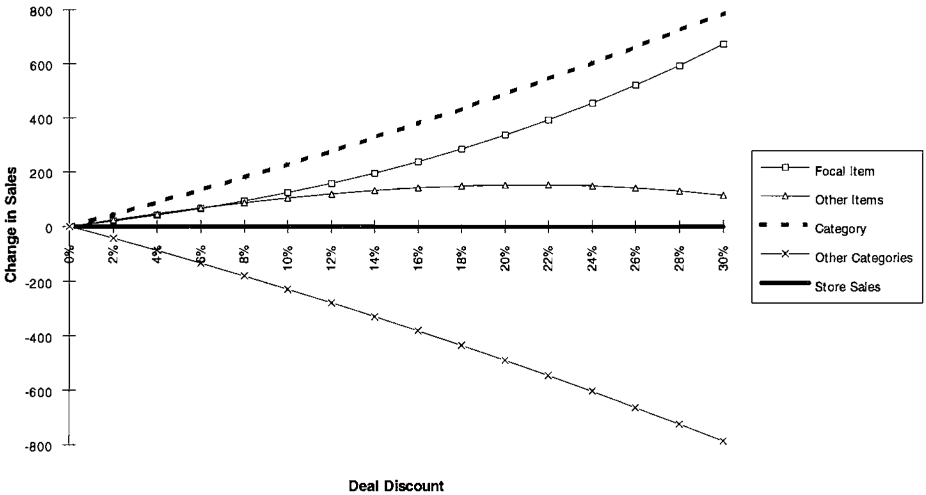


*Figure 8.3. Sales changes due to price deal for Item A coffee.*

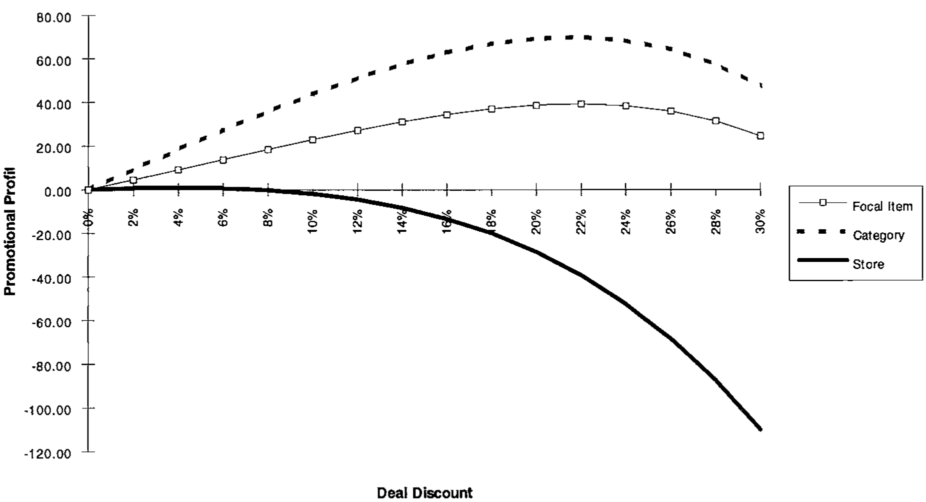


*Figure 8.4. Promotion profits of price deal for Item A measured at different levels*

### 8.4.2. Item B

The sales-responses to price deal for Item B are shown in Figure 8.5. The picture is rather different from what we saw for Item A. Store sales increase more than category sales and category sales increase more than sales of the focal item. The reader is, however, cautioned not to forget that the model parameters are likely to be biased upwards, exaggerating the sales-response to Item B's price deal. We will proceed with the analysis as if the model parameters were unbiased.

Table 8.11 presents numeric measures of the category-relative-item and store-relative-category sales and basket increases. The two columns to the right shows an approximately one to one relation between the increase in the number of category baskets and the increase in the number of item baskets. The increase in category baskets is not accompanied by an increase in store traffic. Despite this, store sales increased more than category sales, which indicates that the average basket value increased as a consequence of Item B's price deal. The effect on the average basket value as well as the effect on sales of other items in the coffee category were stronger than expected.

| Deal Discount | phi12 | phi23 | psi12 | psi23 |
|---|---|---|---|---|
| 2% | 2.02 | 5.50 | 1.29 | 0.00 |
| 4% | 1.94 | 5.20 | 1.24 | 0.00 |
| 6% | 1.87 | 4.91 | 1.19 | 0.00 |
| 8% | 1.79 | 4.63 | 1.15 | 0.00 |
| 10% | 1.72 | 4.37 | 1.11 | 0.00 |
| 12% | 1.66 | 4.11 | 1.08 | 0.00 |
| 14% | 1.60 | 3.87 | 1.05 | 0.00 |
| 16% | 1.54 | 3.63 | 1.02 | 0.00 |
| 18% | 1.48 | 3.41 | 0.99 | 0.00 |
| 20% | 1.44 | 3.20 | 0.97 | 0.00 |
| 22% | 1.39 | 3.00 | 0.95 | 0.00 |
| 24% | 1.35 | 2.81 | 0.94 | 0.00 |
| 26% | 1.31 | 2.63 | 0.93 | 0.00 |
| 28% | 1.28 | 2.46 | 0.92 | 0.00 |
| 30% | 1.25 | 2.30 | 0.91 | 0.00 |

*Table 8.11. Phi and psi for different deal discounts for Item B.*

The strong store sales-response to Item B's price deal means that store-level profits of the promotion are underestimated when the item-level (myopic) analysis is used. Figure 8.10 shows the extreme profitability of Item B's promotion when evaluated at the store-level. The profit-maximizing deal discount cannot be seen in Figure 8.10; the store-level profit of Item B's promotion peaks at 34 percent.

Item-level deal discount optimization would lead to a price deal of 26 to 28 percent. Due to the steep slope of the store-profit curve, the cost of suboptimization would be large.

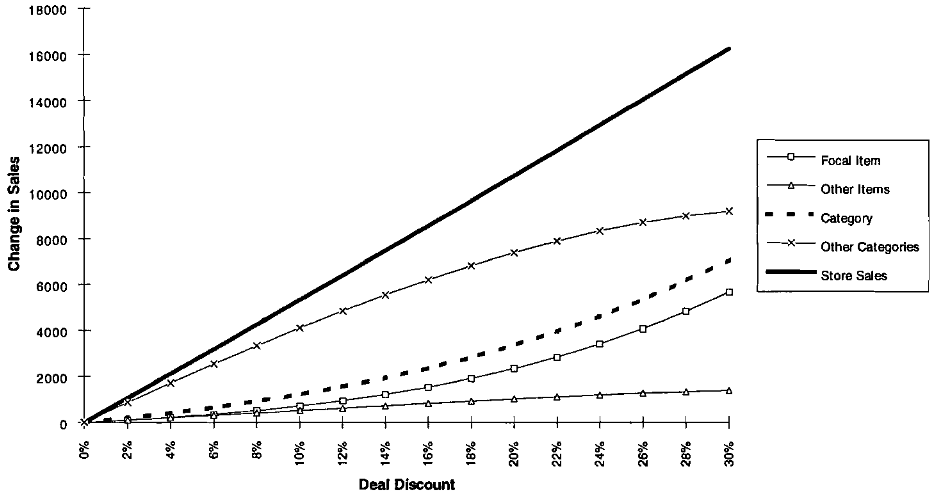


*Figure 8.5. Changes in sales due to price deal for Item B coffee.*

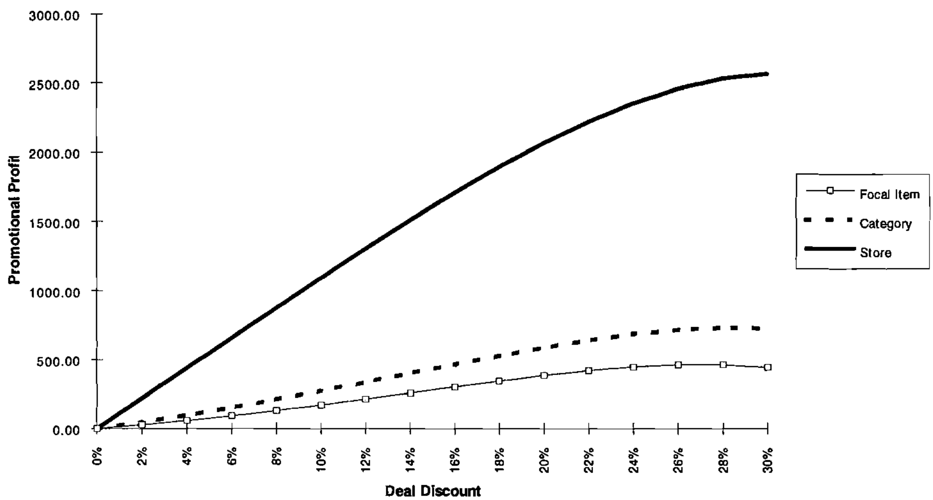


*Figure 8.10. Promotion profits of price deal for Item B measured at different levels*

### 8.4.3. Item C

The effect of Item C's price deal is simple to describe. The increase in sales of Item C comes entirely from other items in the coffee category. In other words, intra-category cannibalization is complete and category sales are not affected by the promotion. The effects on other categories' sales are zero. Figure 8.11 illustrates these effects.

Table 8.12 puts exact numbers on lack of effect of Item C's price deal on store- and category-sales. The store-relative-category increase is undefined because the category increase was zero.

The implication of the sales effect pattern for promotion profits is not difficult to conjecture. Gross profits from other items drop because their sales decrease, and the increase in sales of Item C is not strong enough to improve category-level gross margins.

The store and category-level profit impact coincide, because the price deal for Item C has no impact on other categories' sales. Figure 8.12 depicts the profit impact of Item C's price deal.

The item-level promotion profit is positive but small. Compared to the category- and store-level, item-level analysis gives a too positive picture of the true promotion profits.

| Deal Size | phi12 | phi23 | psi12 | psi23 |
|---|---|---|---|---|
| 2% | 0.00 | n.a. | 0.00 | n.a. |
| 4% | 0.00 | n.a. | 0.00 | n.a. |
| 6% | 0.00 | n.a. | 0.00 | n.a. |
| 8% | 0.00 | n.a. | 0.00 | n.a. |
| 10% | 0.00 | n.a. | 0.00 | n.a. |
| 12% | 0.00 | n.a. | 0.00 | n.a. |
| 14% | 0.00 | n.a. | 0.00 | n.a. |
| 16% | 0.00 | n.a. | 0.00 | n.a. |
| 18% | 0.00 | n.a. | 0.00 | n.a. |
| 20% | 0.00 | n.a. | 0.00 | n.a. |
| 22% | 0.00 | n.a. | 0.00 | n.a. |
| 24% | 0.00 | n.a. | 0.00 | n.a. |
| 26% | 0.00 | n.a. | 0.00 | n.a. |
| 28% | 0.00 | n.a. | 0.00 | n.a. |
| 30% | 0.00 | n.a. | 0.00 | n.a. |

*Table 8.12. Phi and psi for different deal discounts for Item C.*

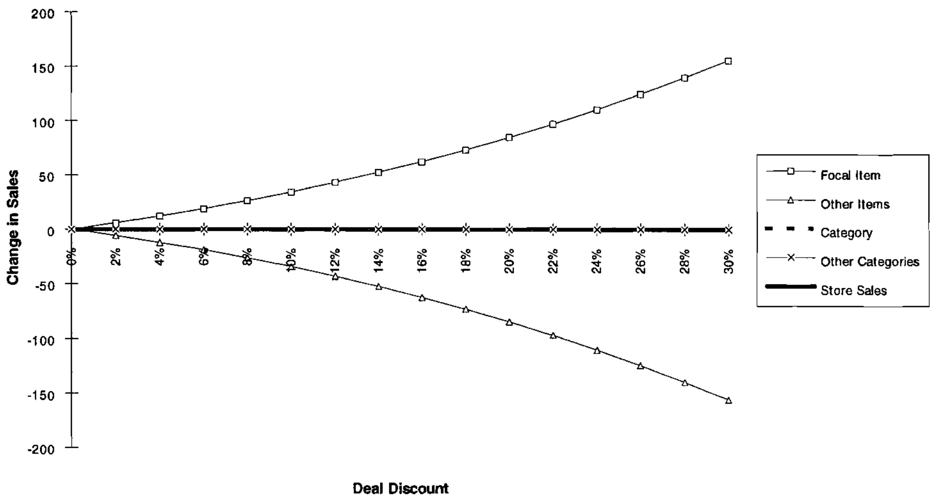


*Figure 8.11. Sales changes due to price deal for Item C coffee.*

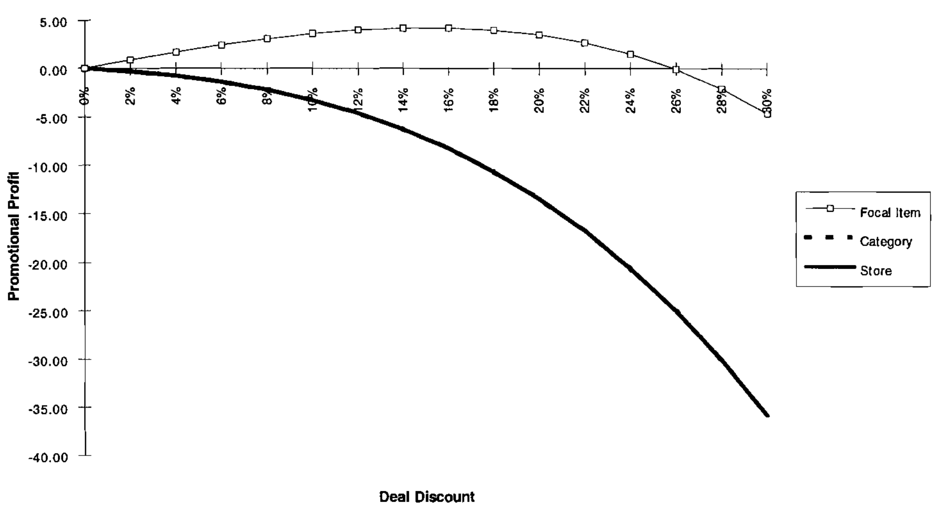


*Figure 8.12. Promotion profits of price deal for Item C measured at different levels. Category- and store-level profits coincide.*

## 8.5. Determinants of the Size of the Deal Discount

### 8.5.1. Level of Analysis

This section deals with the question of how the level of analysis that the retailer uses for optimizing promotion profits affects the size of the deal discount. The effect of a deal requirement imposed on the retailer by the manufacturer will also be examined. All amounts are expressed in SEK per day.

Item-, category-, and store-level promotion profits were evaluated for each percentage point of deal discount between zero and 100. The deal with the highest item-level profits is called *Deal1* while category and store-level optimal deals are called *Deal2* and *Deal3.*

The store-level promotion profit of *Deal3* is *Profit3.* The store-level profits of the sub-optimal price deals are denoted *Profit1* and *Profit2,* respectively. The cost of myopic deal optimization (opportunity loss) can then be denoted *Loss1* and *Loss2,* where *Loss1* = *Profit3* - *Profit1* and *Loss2* = *Profit3* - *Profit2* (see equation 5.66 in Section 5.5.3).

Table 8.13 provides the numerical results of the analysis.

| Item | DealReq | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|
| Item A | 0% | 22% | 22% | 4% | 40.10 | 40.10 | 0.90 |
| Item B | 0% | 27% | 28% | 30% | 65.25 | 33.38 | 2562.97 |
| Item C | 0% | 15% | 0% | 0% | 7.24 | 0.00 | 0.00 |
| | | | | | | | |
| Item A | 1% | 22% | 22% | 4% | 40.10 | 40.10 | 29.39 |
| Item B | 1% | 27% | 28% | 30% | 65.25 | 33.38 | 2645.37 |
| Item C | 1% | 15% | 1% | 1% | 7.11 | 0.00 | 13.34 |
| | | | | | | | |
| Item A | 10% | 22% | 22% | 10% | 37.35 | 37.35 | 26.64 |
| Item B | 10% | 27% | 28% | 30% | 65.25 | 33.38 | 2645.37 |
| Item C | 10% | 15% | 10% | 10% | 3.95 | 0.00 | 10.18 |

*Table 8.13. Deal requirement, deal discounts, loss due to myopia, and optimal deal profit.*

We first examine the results for Item A when the deal requirement is zero. The item-level and the category-level optimal deal discount are both 22 percent, while store-level optimal deal discount is only 4 percent. The 4 percent deal increases the retailer's profits by SEK 0.90 compared with absorbing all of the trade money and selling Item A at regular price. Using item-level or category-level optimization would cost the retailer SEK 40.10.

A deal requirement of 1 percent does not change the optimal deal discount for Item A. The store-level promotion profit, however, increases to SEK 29.39. The increase reflects the value of the trade money absorbed by the retailer if the trade deal could be fully absorbed (compare Sections 6.5.3). The loss caused by myopic deal maximization is unaffected by the one percent deal requirement.

Setting the deal requirement at 10 percent increases the store-level optimal deal to 10 percent. The decrease in promotion profits caused by the deal requirement is fairly small, SEK 29.39 less SEK 26.64, or SEK 2.75. The opportunity loss caused by myopic deal optimization is at the same time reduced by this amount.

While myopic optimization leads to larger than optimal price deals for Item A, the effect of myopic optimization is the opposite for Item B. This is because of the positive sales-response of other categories and other items in the focal category. The deal discount and pass-through are large irrespective of the level of analysis. Thus, deal requirements have no effect on the optimal deal discounts. The change in promotion profit between the zero and the one percent deal requirement is the value of the trade money the retailer could have absorbed.

For Item C, it is only the item-level optimal deal discount that is unaffected by the deal requirements. The reason is that item-level optimal deal discount is 15 percent (i.e., larger than the 10 percent deal requirement) while the category-level and the store-level optimal deal discounts are 0 when no deal is required.

Category-level and store-level optimization lead to the same optimal deal for Item C. Consequently, there is no opportunity loss due to category-level optimization. The opportunity loss caused by item-level deal optimization decreases with the size of the deal requirement.

### 8.5.2. Trade Deal and Margins

This section examines how the size of the trade deal affects the size of the deal discount, under the assumption that the retailer maximizes store-level promotion profits. It is also illustrated how the profit margin of coffee affects the pass-through of the trade deal to the consumers. Twenty percent margins of the focal item, the focal category, and other categories are regarded as the base case and is marked by a fat line in the figures.

Figure 8.13 depicts the (store-level) optimal price deal discount for Item A as a function of the size of the trade deal for different profit margins of the coffee category.

Small trade deals will not be passed through at all but are fully absorbed by the retailer when the coffee margin is 20 percent. The retailer would find it optimal to pass through a small part of the trade deal when the trade deal exceeds 15 percent. In fact, with a trade deal above 15 percent, the size of the deal discount is a linear function (with a slope close to unity) of the trade deal. The relative pass-through is therefore larger for large trade deals than for small trade deals.

The first 15 percent of the trade deal can (in this particular case) be seen as an entry ticket for the manufacturer. The implication for the manufacturer is that small trade deals have no effect on consumer purchases because they fail to induce action from the retailer's side. However, there may be other reasons for the manufacturer to use small trade deals, such as, for example, to load the retailer with inventories in order to keep competitors out of the store, or to improve the retailer's margin without having to reduce the regular wholesale price.

Figure 8.13 shows the effect on the optimal deal discount of different margins. The higher the coffee margins, the larger the optimal deal discount. This is because the retailer need to be less concerned with inter-category cannibalization when the margin of the coffee category exceeds that of other categories.

The analysis highlights the importance of large trade deals in order to induce the retailer to promote Item A if the coffee margins were low. Figure 8.13 shows that very large trade deal discounts would be necessary to induce the retailer to promote Item A if coffee margins were 10 percent. The manufacturer would have to use other methods than discounting the merchandise to make the retailer offer a price deal on Item A, if margins were 10 percent or lower.

Figure 8.14 shows that the retailer would pass-through all of the trade deal and sacrifice some of the regular margin for Item B in order to maximize store-level promotion profits.

Even if gross margins in the coffee category were only 10 percent, and in the absence of a trade deal, the retailer could increase profits by a promotional discount for Item B of more than 20 percent. The gross profits from sales of Item B would obviously be negative, but the increase in store-wide gross profits would outweigh the item-level loss.

The results for Item C are presented in Figure 8.15. The minimum trade deal required to induce the retailer to a small price deal is 15 percent. The retailer will pass through about half of the trade money for trade deals larger than 30 percent. As for Item A, relative pass-through is higher the higher the trade deal.

The pass-through is very sensitive to variations in profit margins of the coffee category. If margins were ten percentage points lower, only very large trade deals would have any effect on the price deal. Raising the margins by ten percent, on the other hand, makes relative pass-through for small trade deals greater than one. The size of the price deal would increase at a slower rate than the size of the trade deal. The relative pass-through of large trade deals is, thus, lower than the relative pass-through of small trade deals.

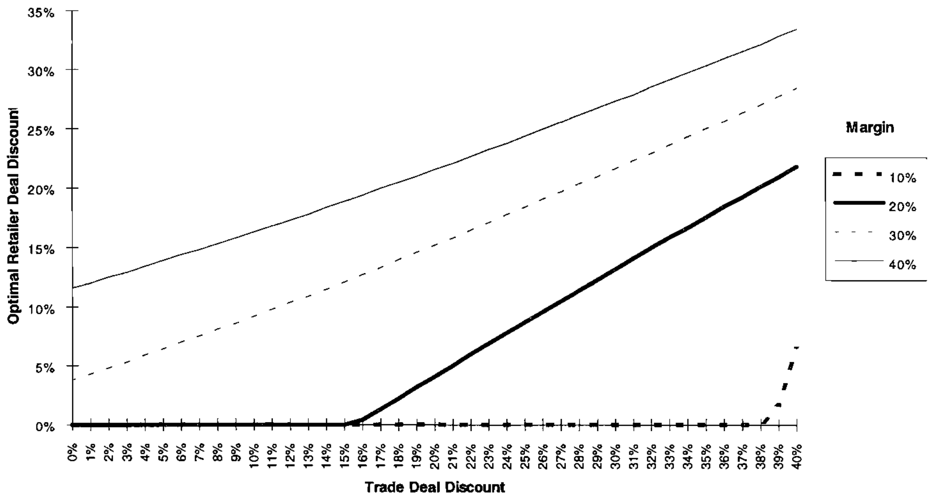


*Figure 8.13. Item A: Store-level optimal deal discount for margin by trade deal.*

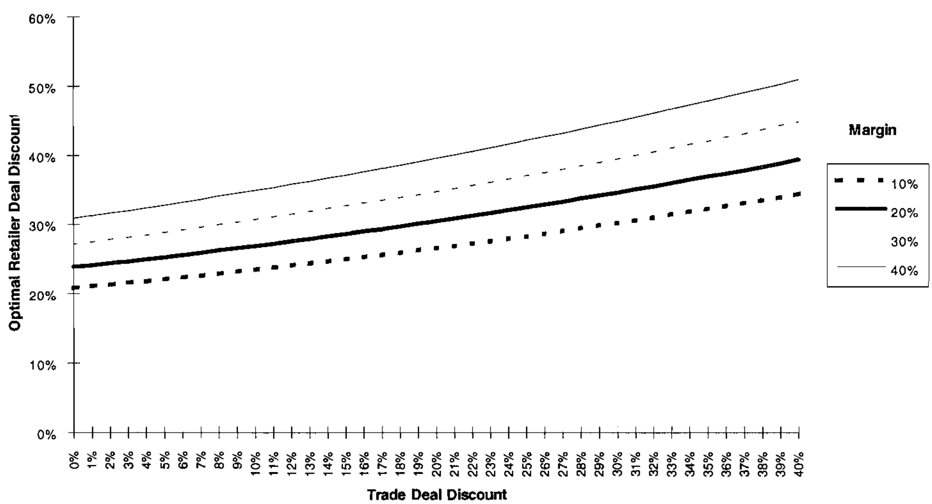


*Figure 8.14. Item B: Store-level optimal deal discount for margin by trade deal.*

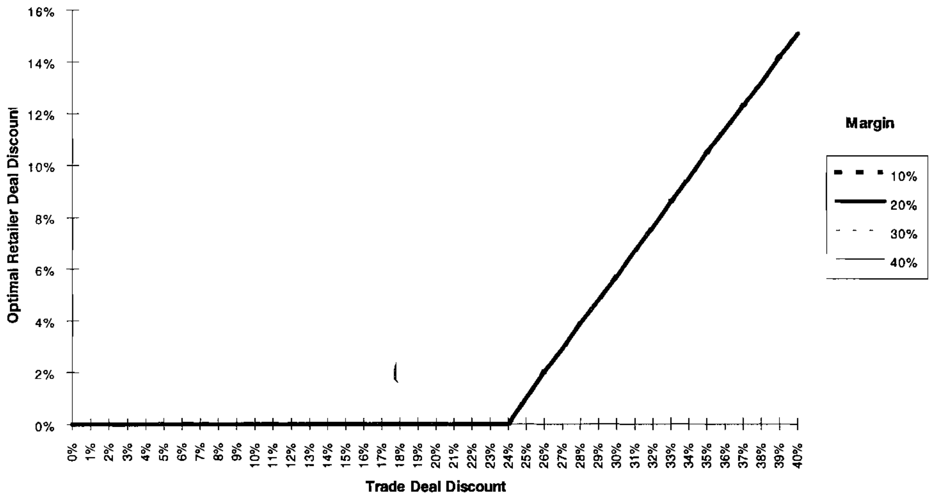


*Figure 8.15. Item C: Store-level optimal deal discount for margin by trade deal. Note that the all four margins lead to the same optimal deal discount.*

## 8.6. Conclusions

This empirical illustration of the application of the framework model and its sub-models found evidence supporting the credibility of the framework. The correlation between store traffic and store sales was, as expected, found to be high. High correlations were also found between store traffic and category baskets, and between store-sales and category-sales.

Importantly, the correlations between the ratios in the model were lower than the correlations of the variables. All this taken together support the model framework. Likewise, the coefficients of determination of the sub-models indicate that the modeling approach makes sense.

It was found that the promotion profit looks different depending on the perspective. Although not always true, item-level promotion profit often give an exaggerated estimate of the promotion profits. In the absence of effects on store sales, item-level deal optimization leads to larger than optimal price deals. The opposite can be the case if the price deal affects store traffic.

Thus, cannibalization (within and across product categories) is an important issue for the retailer who tries to optimize promotion. Item-level deal optimization fails to take positive and negative store-level effects into account. This generally reduces the profitability of promotions and may lead the retailer to run unprofitable promotions.

It was shown that the retailer's pass-through of trade money can be analyzed using the proposed framework. Strong cannibalization leads to low pass-through of small trade deals. Interestingly, the relative pass-through of large trade deal discounts is higher than the relatively pass-through of small trade deal discounts. The profit margin of the category was also found to influence the pass-through of trade deals. The higher the margin of the focal product category, the more of the trade deal will be passed through by the retailer.

The model can help retailers make better use of sales promotion. However, the manufacturer should also find the model useful as a part of a model for optimizing trade deals. The consumers' benefits of the model are perhaps more indirect; better handling of sales promotion first improves retail profits. Then, competition among stores will push the excess profits down by giving the consumers more service or lower prices.

The numerical results presented above should be regarded with some caution. The parameter estimates are not as stable as desired. This is partly due to the multicollinearity found in this kind of data due to retailers' (probably wise) practice of using price deals and special displays in combination and rarely one without the other.

# Appendix

## 8.A.1. Summary Statistics

| Item | Brand | Size | price | bij | bij/bj | sij | sij/sj | dc | dp |
|---|---|---|---|---|---|---|---|---|---|
| Item A | 1 | 500g | 23.00 . | 3533 | 21% | 125971 | 20% | 24362 | 42 |
| | 2 | 500g | 15.50 | 479 | 3% | 9223 | 1% | 0 | 0 |
| Item B | 3 | 500g | 20.80 | 4049 | 24% | 111727 | 18% | 10088 | 34 |
| | 3 | 250g | 12.00 | 575 | 3% | 7164 | 1% | 0 | 0 |
| | 4 | 500g | 21.50 | 480 | 3% | 11739 | 2% | 0 | 0 |
| | 4 | 250g | 11.50 | 105 | 1% | 1422 | 0% | 0 | 0 |
| Item C | 5 | 500g | 20.00 | 4684 | 28% | 261048 | 41% | 107316 | 56 |
| | 6 | 500g | 23.50 | 1416 | 8% | 46366 | 7% | 6342 | 35 |
| | 7 | 500g | 23.00 | 1468 | 9% | 53673 | 8% | 8160 | 42 |
| | 8 | 500g | 34.83 | 340 | 2% | 5596 | 1% | 0 | 21 |
| | 8 | 250g | 20.95 | 7 | 0% | 147 | 0% | 0 | 0 |
| Total | | | 20.60 | 17136 | 101% | 634075 | 100% | 156267 | 230 |

*Table 8.14. Summary statistics for the store's coffee sales: number of item baskets (bij), item-to-category baskets (bij/bj), sales valued at regular price (s), deal cost (dc), number of days with special display (dp). Note that the item-to-category baskets shares do not sum to 100 percent. This is because some category baskets contain more than one brand-size.*

| | Symbol | Value |
|---|---|---|
| Category purchase probability | *bjt/Bt* | 3.59% |
| Category's share of actual store sales | *(sjt-dc)/ASt* | 1.02% |
| Actual category sales per basket | *(sjt-dc)/Bt* | 1.01 |
| Actual basket value | *ASt/Bt* | 98.52 |
| Actual category sales per category basket | *(sjt-dc)/bjt* | 28.10 |
| Purchase incidences per category basket | *sum(bijt)/bjt* | 1.01 |

*Table 8.15. Summary statistics for the store's coffee sales.*

## 8.A.2. Store and Category-Level Time-Series

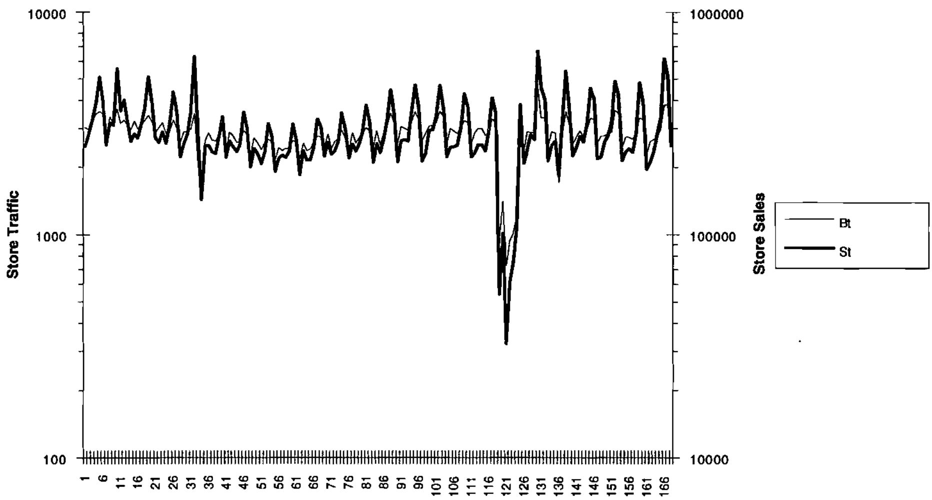


*Figure 8.16. Store traffic (Bt) and store sales (St) over time (daily observations). Logarithmic scales.*

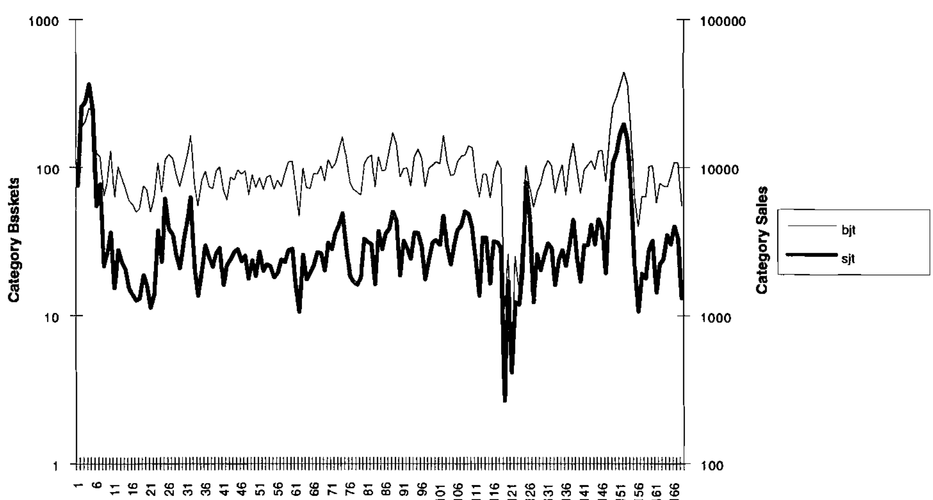


*Figure 8.17. Category baskets (bjt) and sales-response (sjt) of the coffee category over time (daily observations). Logarithmic scales.*

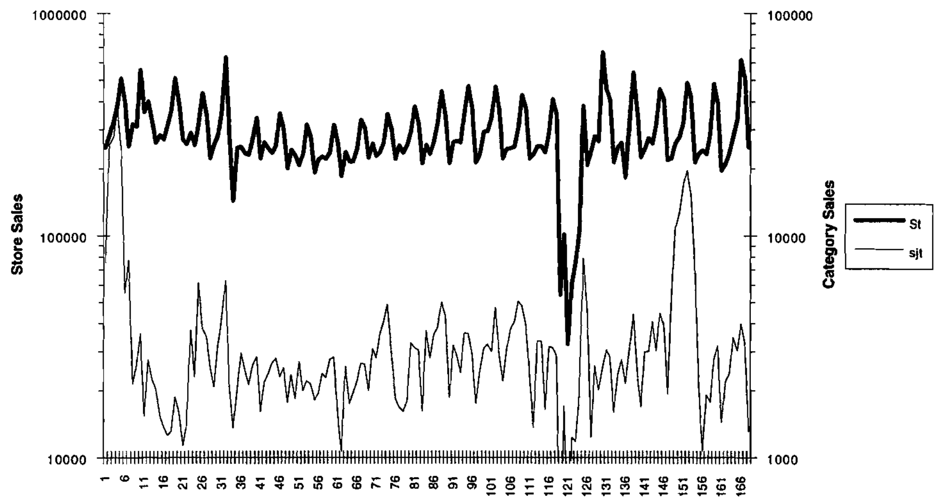


*Figure 8.18. Store sales (St) and coffee sales-response (sjt) over time (daily observations). Logarithmic scales.*

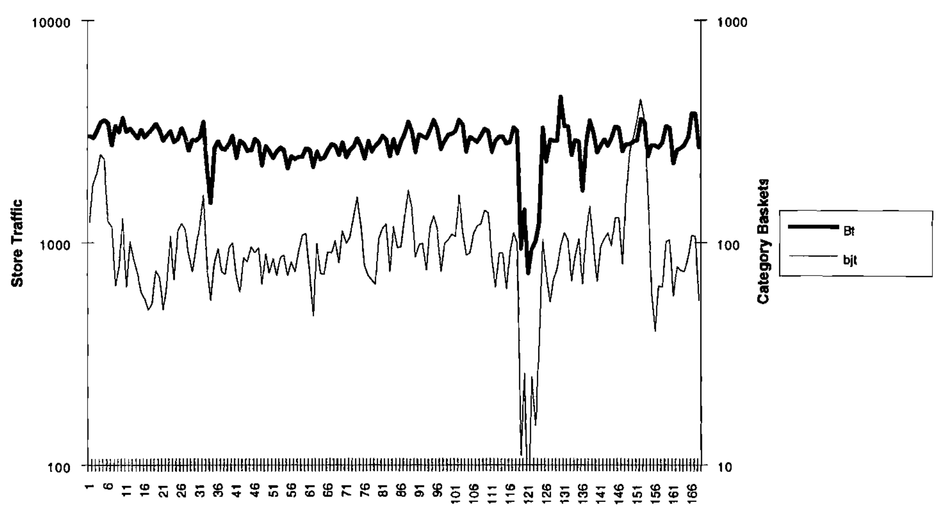


*Figure 8.19. Store traffic (Bt) and coffee category baskets (bjt) over time (daily observations). Logarithmic scales.*

## 8.A.3. Item-Level Time-Series

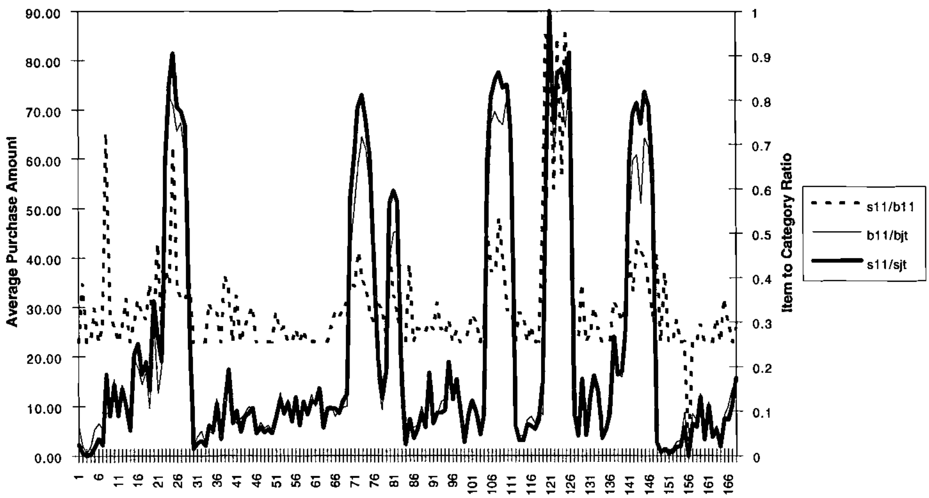


*Figure 8.20. Item A's development over time. Item sales to item baskets (sijt/bjt) on the left hand scale. Item-to-category baskets (bijt/bjt) and item-to-category sales (sijt/sjt) on the right hand scale.*

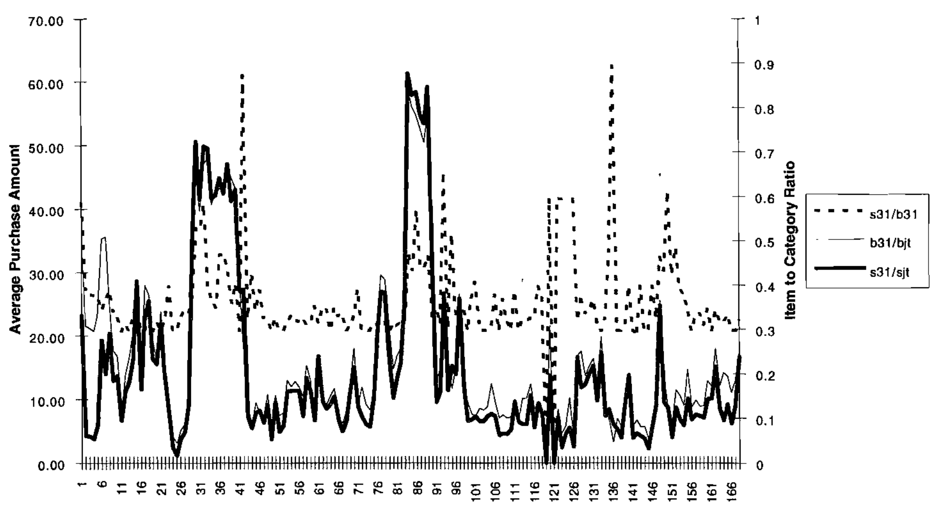


*Figure 8.21. Item B's development over time. Item sales to item baskets (sijt/bjt) on the left hand scale. Item-to-category baskets (bijt/bjt) and item-to-category sales (sijt/sjt) on the right hand scale.*

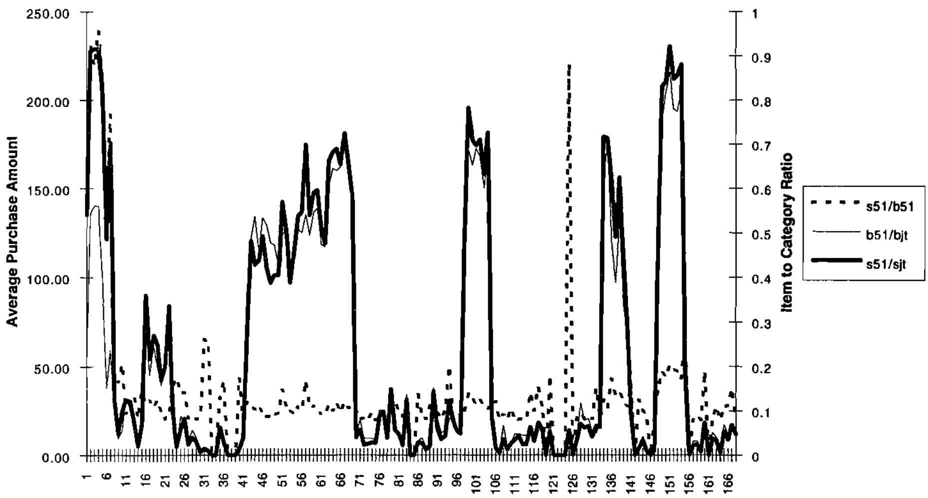


*Figure 8.22.Item C's development over time. Item sales to item baskets (sijt/bjt) on the left hand scale. Item-to-category baskets (bijt/bjt) and item-to-category sales (sijt/sjt) on the right hand scale.*

# 9. EMPIRICAL ILLUSTRATION 2: CEREALS

## 9.1. Introduction

This chapter is an empirical illustration of the model applied to the breakfast cereals product category. The structure of the chapter is similar to that of Chapter 8, starting with a description of the product category, followed by promotion sales-response models. The sales-response models are then used in the promotion-profit model. The chapter ends with a summary of the conclusions from the analysis.

Not only the structure of the chapter is similar to the preceding chapter's; the tools and concepts are also borrowed from Chapter 8. These will not be explained again, and the reader is advised to refer to Chapter 8 for more detail.

## 9.2. Description of the Cereals Category

Figure 9.1 illustrates the brand sales in the breakfast cereals market in the test store. There are seven brands of breakfast cereals available in the test store. Brand 1 dominates the category with nearly fifty percent of the sales, or three times the sales of the closest competitor.

The breakfast cereals category is divided into four sub-categories, here labeled Corn Flakes & Co, Crunchy, Muesli, and Natural. Corn Flakes & Co is the largest (64 percent) and the most difficult to describe of the four. In addition to corn flakes and frosted corn flakes, it consists of a large number of products similar in their bulkiness and light weight to cereals such as roasted and sweetened corn. The best way to describe this sub-category is by a negative definition, i.e., everything that does not qualify for any of the other three sub-categories. The sub-category Crunchy consists of sweetened ready-to-eat mix of grains, with dried fruits or nuts accounted for 13 percent of cereal sales. The Muesli product market is here defined as the ready-to-eat mix of grains, sometimes with dried fruits or nuts. Its share of sales was 22 percent. The sub-category labeled Natural consists of grains that can either be used as ingredients when mixing one's own muesli or be eaten pure. Natural has a market share of approximately 1 percent of the total cereals category. Table 9.1 provides an analysis of cereals' sales broken down by sub-category and brand.

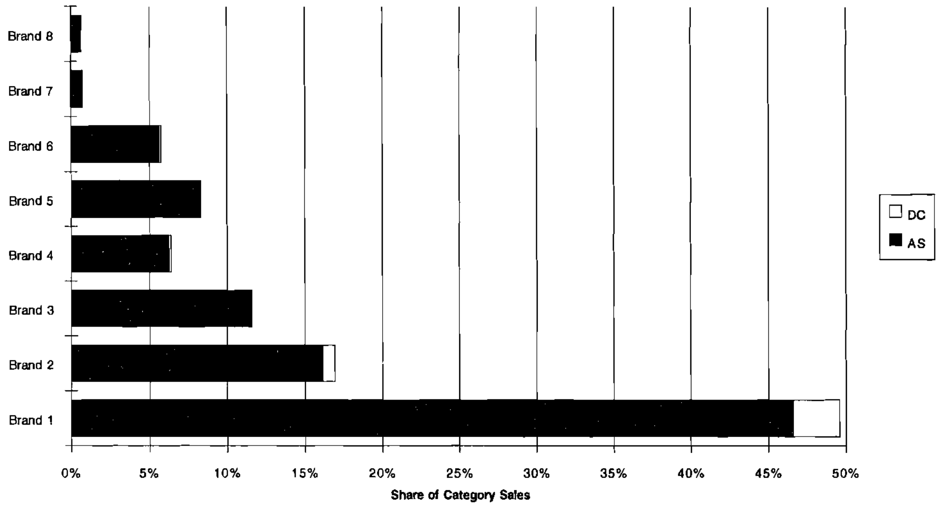


*Figure 9.1. Brand sales in the cereals category. The bars represent sales valued at regular price divided into actual sales (AS) and deal cost (DC).*

The two largest brands, Brand 1 and Brand 2, focus on the Corn Flakes & Co sub-category. Their combined sales share is above 95 percent in this sub-category. Brand 3 has a market share exceeding 90 percent in the Crunchy sub-category. Market shares are more evenly split among participants in the Muesli sub-category, with Brand 5 as the leading brand with 37 percent of sub-category sales. All brands except Brand 6 clearly focus on one of the sub-categories, while Brand 6's sales is almost evenly split between Corn Flakes & Co and Muesli.

| Brand | Corn Flakes&Co | Crunchy | Muesli | Natural | TOTAL |
|---|---|---|---|---|---|
| Brand 1 | 46.4% | 0.9% | 2.3% | | 49.6% |
| Brand 2 | 14.9% | | 1.9% | 0.2% | 16.9% |
| Brand 3 | | 11.6% | | | 11.6% |
| Brand 4 | | | 6.4% | | 6.4% |
| Brand 5 | | | 8.3% | 0.0% | 8.3% |
| Brand 6 | 2.2% | | 2.6% | 0.9% | 5.8% |
| Brand 7 | | | 0.8% | | 0.8% |
| Brand 8 | 0.7% | | | | 0.7% |
| TOTAL | 64.2% | 12.5% | 22.2% | 1.1% | 100.0% |

*Table 9.1. Sales of brands and sub-categories.*

Table 9.2 provides some summary statistics for the cereals category and the Corn Flakes & Co sub-category.

| Description | Symbol | Value |
|---|---|---|
| Average basket value | St/Bt | 103.46 |
| Cereals' share of sales | sjt/St | 0.6% |
| Corn Flakes & Co's share of Category Sales | subsjt/sjt | 64.2% |
| Cereal to total baskets | bjt/Bt | 2.3% |
| Corn Flakes & Co to Cereal Baskets | subbjt/bjt | 67.5% |
| Average purchase amount | subsjt/subbjt | 25.72 |
| Deal cost in percent of sales (Corn Flakes & co) | subdbjt/subsjt | 5.8% |
| Corn Flakes & co share of store sales | subsjt/St | 0.4% |
| Corn Flakes & co to total baskets | subbjt/Bt | 1.5% |

*Table 9.2. Descriptive measures of the cereal category.*

Although the cereals only account for 0.6 percent of the store sales, cereals can be found in 2.3 percent of the shopping baskets. The corresponding statistics for the Corn Flakes & Co sub-category to the cereals category are 64.2 percent and 67.5 percent.

### 9.2.1. Selection of Items for Analysis

Being the most important sub-category in terms of sales, the Corn Flakes & Co sub-category was selected as the focus of the following analysis. Thus, category hereafter refers to the Corn Flakes & Co sub-category of the total breakfast cereals category.

Within this sub-category, six items (SKUs, Stock Keeping Units) were chosen for detailed analysis. The two criteria used for selection of items were that (1) the items should be important in terms of sales volume and (2) that the retailer promoted the item during the measurement period. The combined market share of these six items was 61 percent of the sub-category. The items are presented in Table 9.3.

| Item | Brand | Description | Size | Relative Deal Cost | Market Share |
|---|---|---|---|---|---|
| Item A | Brand 1 | Corn Flakes | 500g | 13.3% | 10.2% |
| Item B | Brand 1 | Corn Flakes | 750g | 6.9% | 13.3% |
| Item C | Brand 1 | Other | 375g | 6.5% | 8.2% |
| Item D | Brand 1 | Sweetened Corn Flakes | 500g | 5.8% | 16.0% |
| Item E | Brand 2 | Corn Flakes | 375g | 11.0% | 6.7% |
| Item F | Brand 2 | Roasted and Sweetened Cori | 500g | 5.6% | 6.6% |
| **Total** | | | | | 60.8% |

*Table 9.3. Items selected for the further analysis. Market shares in percent of the Corn Flakes & Co sub-category.*

The reason for using single items in the analysis is that sales promotion was not homogeneous across items within the same brand-variety-size. Aggregating items would thus mean aggregation of the sales promotion which leads to biased estimates of the sales response. This is especially important when the sales response is assumed to be non-linear while aggregation is usually linear, i.e., a sum or a weighted sum (Foekens, Leeflang, and Wittink 1994).

Table 9.3 shows that each of the items selected for the analysis commands a market share of more than six percent in the test store. Item D is the best selling article in the breakfast cereals category. However, although the brand's total sales of normal corn flakes is larger, it is split on more package sizes than its sales of sweetened flakes.

## 9.3. Building the Promotion Response Models

### 9.3.1. Data Manipulations

As in the coffee case study, sales valued at regular prices of other categories than the focal category were estimated as actual sales plus five percent.

The regular prices of a number of items in the breakfast cereal category were changed during the measurement period. As suggested in Chapter 5, regular prices from one week (week 25, 1992) were used as weights when computing sales volumes of the items and the category. Deal size, however, was calculated as the deal's fraction of the actual regular price of the item.

Price deal and special display were almost always used in combination with each other. Due to the high degree of multicollinearity, special display was omitted from the regression models. The price deal parameters should consequently be interpreted as the sales response to a price deal in combination with a special display.

### 9.3.2. Initial Tests of the Model

It was argued in Chapter 8 that one way to test whether the decomposition of item sales makes sense is to examine the correlations among the variables. Table 9.4 shows that the correlation between store traffic and store sales is high. The correlations between store traffic and sub-category baskets and sub-category sales are also high.

| | *Bt* | *St* | *subbjt* | *subsjt* |
|---|---|---|---|---|
| *Bt* | 1.00 | | | |
| *St* | 0.87 | 1.00 | | |
| *subbjt* | 0.49 | 0.45 | 1.00 | |
| *subsjt* | 0.51 | 0.47 | 0.96 | 1.00 |

*Table 9.4. Pearson correlations between store traffic (Bt), store sales (St), number of Corn Flakes & Co baskets (subbjt), and Corn Flakes & Co sales (subsjt).*

Also the correlations between store sales and sub-catgegory baskets and sub-category sales are high. The correlation between sub-category baskets and sub-category sales is very high. These correlations indicate that the decomposition model may be useful.

Further evidence is provided by Table 9.5 which shows the correlations between store traffic and basket value, category-to-store baskets, and category-to-store sales. If store traffic is an important determiniant of store sales, category baskets, and category sales, then we would expect the correlations to be lower than those in Table 9.4.

| | Bt | St/Bt | subbjt/Bt | subsjt/St |
|---|---|---|---|---|
| Bt | 1.00 | | | |
| St/Bt | 0.64 | 1.00 | | |
| subbjt/Bt | 0.10 | 0.11 | 1.00 | |
| subsjt/St | -0.23 | -0.42 | 0.80 | 1.00 |

*Table 9.5. Pearson correlations between store traffic (Bt), average basket value (St/Bt), sub-category-to-store baskets (subbjt/Bt), and subcategory-to-store sales (subsjt/St).*

Table 9.5 shows that the correlation between store traffic and basket value (i.e., the ratio between store sales and store traffic) is 0.64 which is lower than the correlation between store traffic and store sales. This supports the model. It is not a problem that the correlation between store traffic and basket value is still fairly high. The high correlation indicates that store traffic and average basket value may be driven by a common underlying factor, such as the day-of-the-week.

The correlations between store traffic and category-to-store baskets and category-to-store sales also support the model. These correlations are much lower than the correlations between store traffic and category baskets, and between store traffic and category sales.

In summary, the correlations presented in this section clearly indicate that the decomposition model may be useful. Further evidence will be provided by the response-model estimation.

### 9.3.3 Store-Level Response Models

The exponential model structure was used for the three models estimated at the store-level. The regression equations were described in equation (8.1) in Chapter 8. The variables are defined in the same way as above.

The maximum model included price deal variables for all six items and six dummy variables indicating the day of the week. After estimating the maximum models, variables not significant at the 20 percent level were dropped before re-estimating the model. Regression coefficients were examined for significance at the 10 percent level and the new models were estimated. This was iterated until all coefficients were significant at the 10 percent level. As explained in the coffee case study, regression coefficients having "wrong signs" were treated as insignificant and consequently dropped from the model. The general null hypothesis was that the parameters were equal to zero. In the store traffic and store sales models, the null hypothesis for the price deal parameters wase that the parameters were non-positive. No directed hypotheses were specified in the basket-size model. The results of the model estimation are presented in Table 9.6.

| | Store Traffic coefficient | s.e. | Store Sales coefficient | s.e. | Basket Size coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | 7.92 | 0.01 | 12.43 | 0.02 | 4.47 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | | |
| Item C | 0.62 | 0.14 | 0.84 | 0.21 | | |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | 0.06 | 0.02 |
| Wednesday | | | | | 0.10 | 0.02 |
| Thursday | 0.07 | 0.03 | 0.24 | 0.04 | 0.22 | 0.02 |
| Friday | 0.13 | 0.03 | 0.49 | 0.04 | 0.41 | 0.02 |
| Saturday | 0.07 | 0.03 | 0.28 | 0.04 | 0.26 | 0.02 |
| Sunday | -0.11 | 0.03 | -0.16 | 0.04 | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 33% | | 59% | | 71% | |
| n | 160 | | 160 | | 160 | |

*Table 9.6. Store-level response to sales promotion in the cereal category.*

The only sales promotion found to have a positive effect on store traffic and store sales was Item C's price deal. The regression results indicate some variation over the days of the week. The most important variation seems to be in the average basket size. The explained variance in this dependent variable was 71 percent. Store traffic, on the other hand, showed the smallest variation over the week, with only 33 percent of its variance explained.

### 9.3.4 Category-Level Response Models

We shall now examine how the Corn Flakes & Co category responds to sales promotion. Before building regression models, the dependent variables will be examined graphically. The development over time of the ratio of category-to-store baskets and the category-to-store sales ratio are illustrated in Figure 9.2.

It can be seen that the two ratios follow each other closely over the measurement period. The correlation between the two measures is 0.80 whether the six exceptional observations are included or not.

The two ratios were modeled using logistic regression as previously described in Chapter 8 (see equation 8.2). First, the maximum models, including all variables appearing in Table 9.7 were estimated. Variables whose effect on the dependent variable was insignificant at the 20 percent level were discarded and the new, restricted, regression equation was re-estimated. Variables were then eliminated until all remaining parameters were significant at the ten percent level. The formal null hypotheses associated with the price deal variables were that sales promotion would have no positive effect on the category-to-store ratios. The hypotheses pertaining to the day-of-the-week dummy variables were that they would have no effect on the ratios.

It was found that the sales ratio varied more over the days of the week than did the basket ratio. The unexpected finding in this result was that we know from the store-level response models that the average basket size varies over the week and it would be logical that the probability of any category entering the shopping basket would be positively related to the basket size. According to the regression results, the cereals category accounts for a larger proportion of store sales on Mondays than on other days.

Table 9.7 also shows that sales promotion for five of the six items studied here had a positive impact on the category-to-store sales ratio. The category-to-store traffic ratio was positively affected by sales promotion for four of the items.

The models explained approximately half of the variance in the (transformed) dependent variables, with 48 percent of the variance in the basket ratio and 52 percent of the variance in the sales ratio explained.

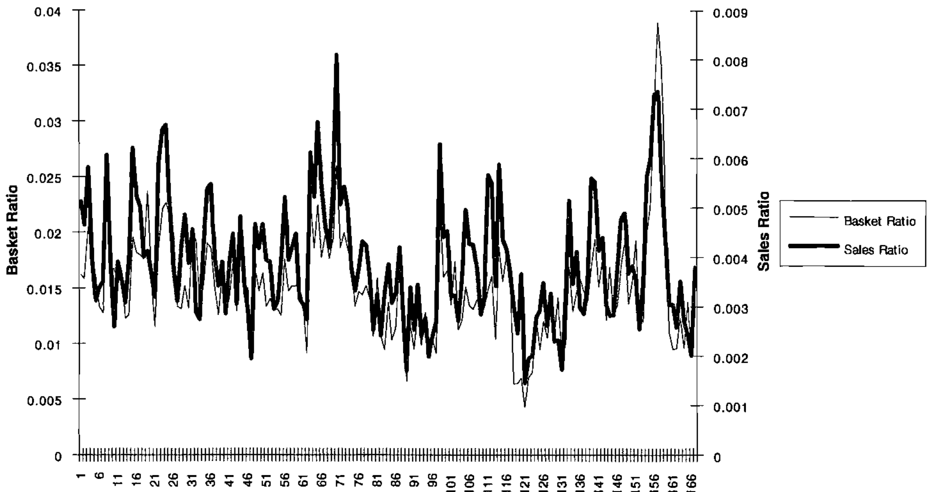


*Figure 9.2. Category development over time.*

| | Category/Store Baskets coefficient | s.e. | Category/Store Sales coefficient | s.e. |
|---|---|---|---|---|
| Constant | -4.21 | 0.02 | -5.44 | 0.05 |
| ***Price Deal*** | | | | |
| Item A | 1.14 | 0.19 | 1.38 | 0.21 |
| Item B | | | 0.69 | 0.30 |
| Item C | 0.96 | 0.27 | 0.96 | 0.28 |
| Item D | 0.61 | 0.29 | 0.69 | 0.30 |
| Item E | 0.94 | 0.25 | 0.47 | 0.26 |
| Item F | | | | |
| ***Day-of-the-Week*** | | | | |
| Tuesday | -0.09 | 0.05 | -0.19 | 0.06 |
| Wednesday | | | -0.13 | 0.06 |
| Thursday | | | -0.28 | 0.06 |
| Friday | | | -0.44 | 0.06 |
| Saturday | -0.27 | 0.05 | -0.53 | 0.06 |
| Sunday | -0.25 | 0.05 | -0.26 | 0.06 |
| ***Regression Statistics*** | | | | |
| adj.Rsq. | 48% | | 52% | |
| n | 160 | | 160 | |

*Table 9.7. Category-level response to sales promotion in the cereal category.*

### 9.3.5 Item-Level Response Models

At the item level, three models were built for each item. Item-to-category baskets and item-to-category sales were both modeled using the logistic regression model also used at the category level (see equation 8.3). For modeling the average item purchase among shoppers buying the item, the exponential model was used (equation 8.4).

The maximum models included all variables found in Table 9.8 and were identical across all six items. Final models were found using the procedure described above, with the only difference the formal null hypotheses for sales promotion for items other than the focal item; their promotion would have a positive or zero effect on the ratios.

Regression results will be presented and discussed for one item at the time, starting with Item A. Table 9.8 shows that Item A's basket and sales ratios did not vary due to the day of the week. The day-of-the-week had only small effects on the purchase amount of Item A among shoppers buying Item A on Saturdays and Sundays.

Item A's price deal had a fairly strong impact on the item's basket ratio and sales ratio. The impact on average purchase amount was small. Two of the other items' sales promotion, Item B and Item D, affected Item A's basket and sales ratios. None of these had any significant impact on the average purchase amount. Item E's sales promotion had a small but significant positive impact on the average purchase amount.

While the purchase amount model only explained 22 percent of the variance, the ratio models explained 53 percent and 55 percent of the variance in the basket ratio and the sales ratio, respectively.

The regression models for Item B are less successful than those for Item A in terms of explained variance. Only 4 percent of the variance in average purchase size could be explained, while the basket ratio and sales ratio models each explained 36 percent of the variance in their dependent variables. The final regression models for Item B are presented in Table 9.9.

The response parameters for Item B's price deal are almost identical in the basket-ratio and the sales-ratio models. Their magnitude indicates that the price deal has a strong impact on these ratios. Item B's sales promotion had no significant impact on the average purchase amount of Item B. In fact, the only variable found to have a significant impact on the average purchase amount of Item B was the dummy variable for Thursday.

Item E was the only other item whose sales promotion had an impact on the ratios. Neither the basket ratio nor the sales ratio was affected by the day-of-the-week dummy variables. Thus, there was no evidence that these ratios would vary over the days of the week.

| | *Item/Category Baskets* coefficient | s.e. | *Item/Category Sales* coefficient | s.e. | *Average Item Purchase* coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.55 | 0.07 | -2.60 | 0.07 | 3.18 | 0.00 |
| ***Price Deal*** | | | | | | |
| Item A | 5.93 | 0.55 | 6.13 | 0.55 | 0.14 | 0.04 |
| Item B | -1.91 | 0.92 | -2.14 | 0.92 | | |
| Item C | | | | | | |
| Item D | -2.77 | 0.83 | -3.10 | 0.83 | | |
| Item E | | | | | 0.12 | 0.05 |
| Item F | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | | | | | 0.03 | 0.01 |
| Sunday | | | | | 0.03 | 0.01 |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 53% | | 55% | | 22% | |
| n | 149 | | 149 | | 149 | |

*Table 9.8. Item A: Item-level response to sales promotion in the cereal category.*

| | *Item/Category Baskets* coefficient | s.e. | *Item/Category Sales* coefficient | s.e. | *Average Item Purchase* coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.65 | 0.08 | -2.34 | 0.08 | 3.52 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | 8.47 | 1.09 | 8.66 | 1.09 | | |
| Item C | | | | | | |
| Item D | | | | | | |
| Item E | -3.29 | 0.92 | -2.96 | 0.91 | | |
| Item F | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | 0.04 | 0.02 |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 36% | | 36% | | 4% | |
| n | 145 | | 145 | | 145 | |

*Table 9.9. Item B: Item-level response to sales promotion in the cereal category.*

Table 9.10 presents the regression results for Item C. Again, none of the day-of-the-week dummy variables had any significant impact on the ratios and only one of them had a small impact on the average purchase amount of the item.

Item C's own promotion affected the two ratios approximately equally, with a somewhat larger effect on the sales ratio. The promotion also had a small significant impact on the average purchase amount.

Other items whose sales promotion affected Item C's basket and sales ratios were Item A and Item D. Item D's price deal had a significant impact on the average purchase amount of Item C as well.

In comparison with the models for Item A and Item B, the models for Item C performed worse in terms of variance explained in the ratio models. The models of Item C's basket and sales ratios accounted for 29 percent each.

The model of the average purchase amount of Item C among buyers of the item explained 15 percent of the variance. Again, the average purchase-amount model was the model explaining the smallest part of the variance in its dependent variable.

This pattern was repeated for Item D, whose average purchase amount model accounted for 9 percent of the variance while the basket-ratio model accounted for 43 percent and the sales-ratio model for 42 percent of the variance in their respective dependent variables (see Table 9.11).

The regression results for Item D, presented in Table 9.11, show that the day of the week had little effect in any of the three models. Only the parameter for the Thursday dummy variable was significant in the two ratio models.

Item D's price deal had a strong impact on the basket and sales ratios and a small positive impact on the average purchase amount of the item. Item D's sales ratio was negatively influenced by price deals for Item A, Item B, and Item C. In addition to these three items' price deals, the basket ratio was also negatively influenced by Item E's price deals.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.63 | 0.07 | -2.54 | 0.06 | 3.32 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | -2.49 | 0.58 | -2.39 | 0.57 | | |
| Item B | | | | | | |
| Item C | 4.84 | 0.85 | 4.96 | 0.84 | 0.13 | 0.07 |
| Item D | -1.89 | 0.91 | -1.91 | 0.90 | 0.20 | 0.07 |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | | | | | 0.03 | 0.01 |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 29% | | 29% | | 15% | |
| n | 144 | | 144 | | 144 | |

*Table 9.10. Item C: Item-level response to sales promotion in the cereal category.*

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -1.78 | 0.07 | -1.69 | 0.07 | 3.32 | 0.00 |
| ***Price Deal*** | | | | | | |
| Item A | -1.80 | 0.55 | -2.19 | 0.50 | | |
| Item B | -1.90 | 0.81 | -2.22 | 0.82 | | |
| Item C | -2.90 | 0.74 | -3.04 | 0.75 | | |
| Item D | 6.88 | 0.79 | 7.02 | 0.80 | 0.17 | 0.04 |
| Item E | -1.28 | 0.66 | | | | |
| Item F | | | | | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | 0.25 | 0.13 | 0.22 | 0.13 | | |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 43% | | 42% | | 9% | |
| n | 148 | | 148 | | 148 | |

*Table 9.11. Item D: Item-level response to sales promotion in the cereal category.*

The regression results for Item E are presented in Table 9.12. Item E's basket-ratio and sales-ratio models are the ratio models explaining the smallest share of variance of the six items' models. The basket-share model accounts for 23 percent of the variance while the share of explained variance in the sales share model is 27 percent. The average purchase item purchase model is again the model explaining the smallest share of the variance with 12 percent. This is, however, better than the model for Item C.

The Friday dummy variable was the only day-of-the-week dummy variable having significant impact in any of the three models for Item E. The sales ratio was on average somewhat higher on Fridays than the rest of the week.

Item E's price deal had significant positive impact in all three models. Its impact on the ratios was fairly strong. Item A's and Item D's price deals had significant impact on Item E's sales ratio. Item A's sales price deal also had a significant negative impact on Item E's basket ratio as well as on the average item purchase of Item E. The average item purchase was positively affected by Item F's price deal.

The average item purchase of Item F, on the other hand, was not affected by any items' price deal, as shown in Table 9.13, presenting the regression results for Item F. The only variable having a significant impact on average item purchase of Item F was the Thursday dummy variable. The model accounts for only 2 percent of the variance, making it the worst performing model in the cereal category. The ratio models explain 45 percent of the variance.

None of the day-of-the-week dummy variables had any significant impact on the basket ratio or the sales ratio.

Item F's price deal had very strong impact on the basket and sales ratios. These ratios were negatively affected by sales promotion for Item A and Item D. The sales ratio was also affected by Item C's price deals.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.45 | 0.03 | -2.99 | 0.08 | 2.75 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | -1.88 | 0.72 | -2.12 | 0.73 | -0.24 | 0.11 |
| Item B | | | | | | |
| Item C | | | | | | |
| Item D | | | -1.81 | 1.03 | | |
| Item E | 6.07 | 0.91 | 6.50 | 0.91 | 0.45 | 0.10 |
| Item F | | | | | 0.33 | 0.16 |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | 0.29 | 0.17 | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 23% | | 27% | | 12% | |
| n | 144 | | 144 | | 144 | |

*Table 9.12. Item E: Item-level response to sales promotion in the cereal category.*

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.87 | 0.06 | -2.71 | 0.06 | 3.35 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | -3.83 | 0.70 | -3.74 | 0.70 | | |
| Item B | | | | | | |
| Item C | | | -1.35 | 0.76 | | |
| Item D | -1.94 | 0.76 | -1.63 | 0.85 | | |
| Item E | | | | | | |
| Item F | 10.23 | 1.07 | 9.72 | 1.08 | | |
| ***Day-of-the-Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | 0.04 | 0.02 |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.Rsq. | 45% | | 45% | | 2% | |
| n | 137 | | 137 | | 137 | |

*Table 9.13. Item F: Item-level response to sales promotion in the cereal category.*

### 9.3.6. Overview of the Regression Results

This section summarizes the regression results in terms of how successful the models are in explaining the variance and the number and type of variables that were retained in the final models.

The explanatory power of a regression model can be expressed as the share of the variance of the dependent variable the model explains. Table 9.14 presents the amount of variance explained by the 23 regression models.

| | Baskets | Sales | Quantity |
|---|---|---|---|
| ***Store Level*** | 33% | 59% | 71% |
| ***Category Level*** | 48% | 52% | n.a. |
| ***Item Level Average*** | 38% | 39% | 11% |
| Item A | 53% | 55% | 22% |
| Item B | 36% | 36% | 4% |
| Item C | 29% | 29% | 15% |
| Item D | 43% | 42% | 9% |
| Item E | 23% | 27% | 12% |
| Item F | 45% | 45% | 2% |

*Table 9.14. Adjusted R-squares.*

We recognize that the store-level average purchase quantity (or purchase amount) model is the model with the highest adjusted R-square, i.e., it is the most successful model in terms of variance explained. The store-traffic model explains less variance than the store sales model.

The two category-level models explain about fifty percent of the variance. The sales ratio model is slightly better than the basket-ratio model.

The item-level models show a consistent pattern in that the purchase-quantity models perform considerably worse than the basket and sales ratio models. On average, the purchase-quantity models explain 11 percent of the variance. The average for the basket ratio models is 38 percent and the average for the sales-ratio models is 39 percent.

The results suggest that the models concerned with the number of shoppers perform approximately equally well at all three hierarchical levels. The sales-related models perform better at the store- and category-levels than at the item level. The purchase-quantity models, on the other hand, perform badly at the item level while performing very well at the store level.

Table 9.15 presents the number of significant model parameters of the regression models. Only one sales promotion parameter was significant in the store-level models of store traffic and store sales. The average basket value was not affected by sales promotion in the cereals category. Sales promotion thus had little impact on the store-level measures.

The day-of-the-week dummy variables, on the other hand, were important for explaining variance of the store-level measures.

| | Sales Promotion | | | Day-of-the-Week | | |
|---|---|---|---|---|---|---|
| | Baskets | Sales | Quantity | Baskets | Sales | Quantity |
| ***Store Level*** | 1 | 1 | 0 | 4 | 4 | 5 |
| ***Category Level*** | 4 | 5 | n.a. | 4 | 6 | n.a. |
| ***Item Level Average*** | 3.0 | 3.2 | 1.5 | 0.2 | 0.3 | 0.8 |
| Item A | 3 | 3 | 2 | 0 | 0 | 2 |
| Item B | 2 | 2 | 0 | 0 | 0 | 1 |
| Item C | 3 | 3 | 2 | 0 | 0 | 1 |
| Item D | 5 | 4 | 1 | 1 | 1 | 0 |
| Item E | 2 | 3 | 3 | 0 | 1 | 0 |
| Item F | 3 | 4 | 1 | 0 | 0 | 1 |

*Table 9.15. Number of significant model parameters.*

The opposite pattern is observed for the item-level models. Few day-of-the-week dummy variables were significant in the item-level models. On average, the item-level models contain less than one of the day-of-the-week dummy variables. At the same time, three sales promotion variables were retained in the item-level models of the basket ratio and the sales ratio. The average number of sales promotion variables in the item-level purchase-quantity model was 1.5.

It can be concluded that these observations are encouraging and strengthen our confidence in the modeling framework.

## 9.4. Deal Discount, Sales Response, and Profit Impact

In this section we investigate the promotion effects on sales of the focal item, other items in the focal category, category sales, and sales of other categories than the focal one, as well as store sales. Recall that the item- and category-level response models developed in Section 9.3 model relative-responses, i.e., they model changes in ratios rather than changes in absolute levels.

Nevertheless, profits do not come from relative sales but from absolute sales. In order to get absolute item sales, we need to integrate the results of the relative models. This is also necessary in order to get absolute category sales and sales of other items in the focal category. Table 9.16 presents the model parameters for each item.

One item at a time is selected as the focal item. The model parameters found in Table 9.16 are inserted into the relative-sales response models. The size of the deal discount is increased in steps of 2 percentage points from 0 to 30 percent of the regular price. For each deal discount, the sales responses are evaluated.

| Focal Item | Store Traffic Constant | Deal | Basket Value Constant | Deal | Category Constant | Deal | Item Constant | Deal |
|---|---|---|---|---|---|---|---|---|
| Item A | 7.92 | 0.00 | 4.47 | 0.00 | -5.44 | 1.38 | -2.60 | 6.13 |
| Item B | 7.92 | 0.00 | 4.47 | 0.00 | -5.44 | 0.69 | -2.34 | 8.66 |
| Item C | 7.92 | 0.62 | 4.47 | 0.00 | -5.44 | 0.96 | -2.54 | 4.96 |
| Item D | 7.92 | 0.00 | 4.47 | 0.00 | -5.44 | 0.69 | -1.69 | 7.02 |
| Item E | 7.92 | 0.00 | 4.47 | 0.00 | -5.44 | 0.47 | -2.99 | 6.50 |
| Item F | 7.92 | 0.00 | 4.47 | 0.00 | -5.44 | 0.00 | -2.71 | 9.72 |

*Table 9.16. Summary of model parameters.*

In addition to the sales-response model parameters presented above, the following assumptions were used when evaluating promotion profits. The profit margin of the focal item, other items in the category, and other categories were assumed to be 20 percent of the regular prices. The manufacturer was assumed to offer the retailer a 20 percent trade deal, measured in percent of the regular retail price of the focal item. There was no requirement from the manufacturer that the retailer should pass anything of the trade deal through to the consumers. The retailer received the trade deal for merchandise sold only.

### 9.4.1. Item A

We shall now investigate how a price deal for Item A affects sales at the three hierarchical levels. Figure 9.3 shows that sales of Item A increase as a result of the price deal. The price deal for Item A also causes sales of other items in the focal category to increase. This means that category sales increase more than the sales of the focal item. Thus, Item A's price deal causes no intra-category cannibalization. All incremental sales of Item A are also incremental sales to the category. In contrast, the inter-category cannibalization is complete. All incremental category sales come from other categories in the store. Store sales are not affected by the price deal for Item A.

The promotion profits seen from the item-, category-, and store-perspective of different deal discounts are presented in Figure 9.4. The item-level promotion profits rise with the size of the deal discount and peak at a deal discount of 24 percent. The category-level promotion profits are larger than the item-level promotion profits for all deal discounts investigated. For deal discounts between 0 and 24 percent, the category-level promotion profits rise with the size of the deal discount. Thereafter, larger deal discounts decrease the category-level promotion profits.

The store-level promotion profits are close to zero for deal discounts smaller than 10 percent. Larger deal discounts lead to negative promotion profits, with the size of the loss rapidly increasing with the size of the deal discount.

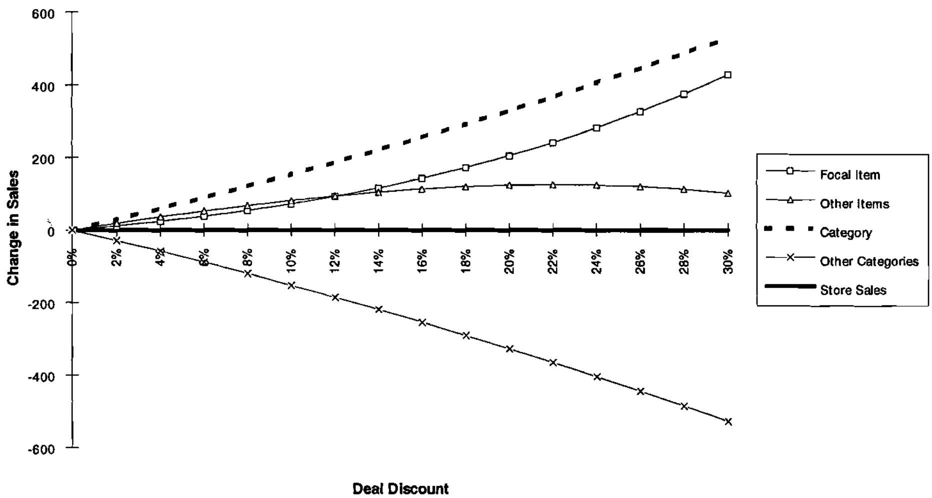


*Figure 9.3. Sales changes caused by Item A's price deal.*

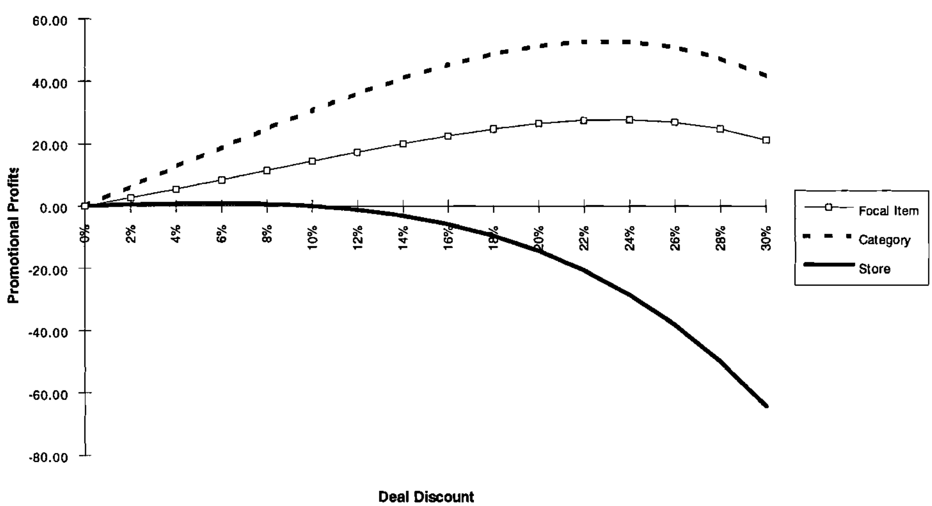


*Figure 9.4. Promotion profits of Item A's price deal.*

### 9.4.2. Item B

The sales changes resulting from a price deal for Item B are presented in Figure 9.5. Item B's price deal has stronger impact on sales of Item B than on the category sales, although category sales also increase due to Item B's price deal. There is some, but not complete, intra-category cannibalization. Inter-category cannibalization, on the other hand, is complete. In other words, the incremental category sales come from other categories. Store-sales are therefore not affected by Item B's price deal.

The changes in sales of Item B, sales of other items in the category, and other categories' sales result in the promotion profits depicted in Figure 9.6.

The item-level promotion profits are higher than the category-level promotion profits, and the category-level promotion profits are higher than the store-level profits for all deal discounts. Small deal discounts lead to small promotion profits irrespective of the level of analysis. Large deal discounts, on the other hand, appear fairly profitable at the item-level, but are negative when measured at the category- or store-level.

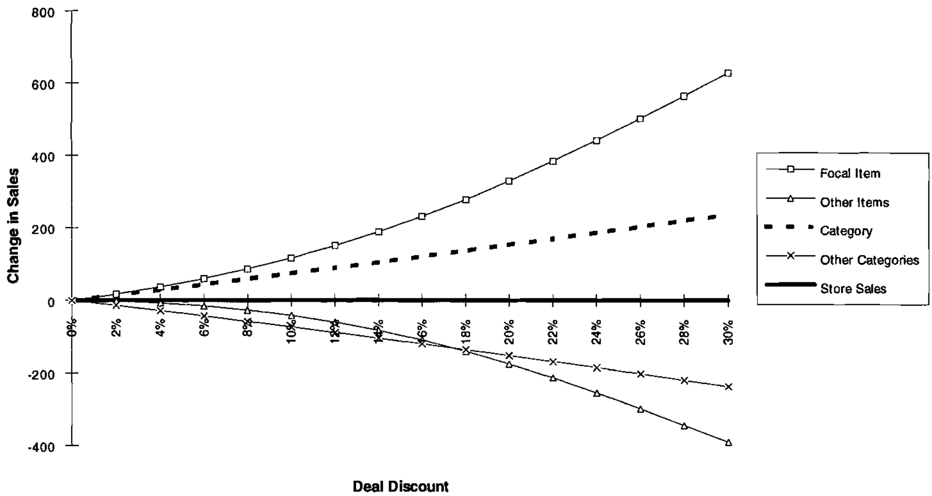


*Figure 9.5. Sales changes caused by Item B's price deal.*

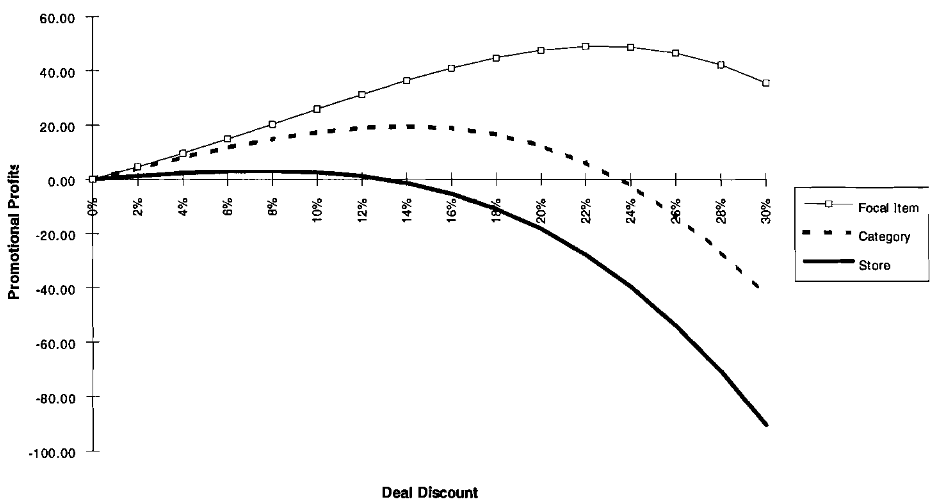


*Figure 9.6. Promotion profits of Item B's price deal.*

### 9.4.3. Item C

Figure 9.7 presents changes in sales for Item C's price deals. The effect on sales of other categories and on store sales are very large compared to the effect on sales of the focal item and the focal category. Separate scales were therefore applied to make the item and category effects visible in Figure 9.7.

Item C's price deal has a strong impact on store sales by increasing sales of other categories considerably. Promotion for Item C causes neither intra- nor inter-category cannibalization, leading to the promotion profits presented by Figure 9.8.

As with the store-sales response, the store-level promotion profits are of a greater order of magnitude than the item- and category-level profits. Again, separate scales were used.

The store-level profits are higher than the category-level profits for all sizes of the deal discount. All three levels of analysis report positive promotion profits. While item- and category-level promotion profits peak at deal discounts smaller than 30 percent (the maximum deal discount investigated here), the store-level promotion profits rise with the deal size and show no sign of leveling out. The implication is that the retailer could make larger profits by very large deal discounts for Item C. Some caution is called for, however. The store traffic and store-sales responses to Item C's price deal are too large to be realistic, and may be statistical artifacts. A retailer could test this by running some price deals of, for example, 20 percent deal discount and re-estimating the response models.

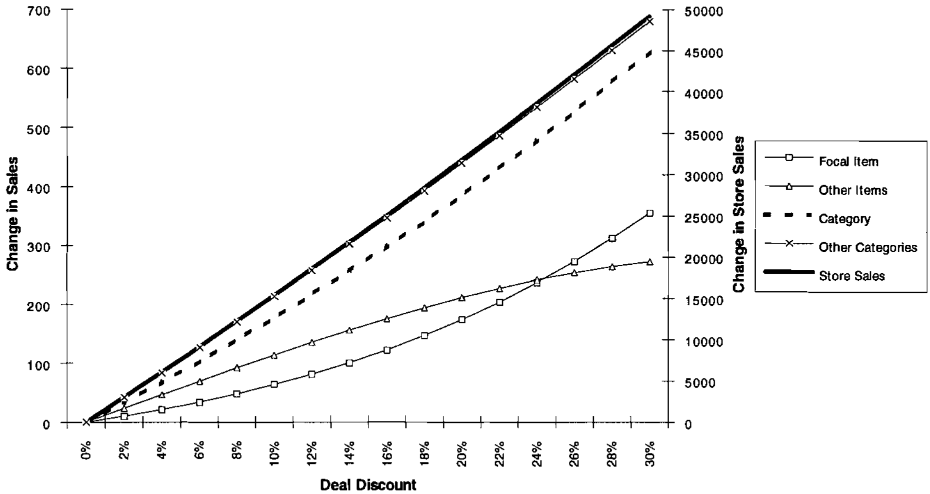


*Figure 9.7. Sales changes caused by Item C's price deal.*

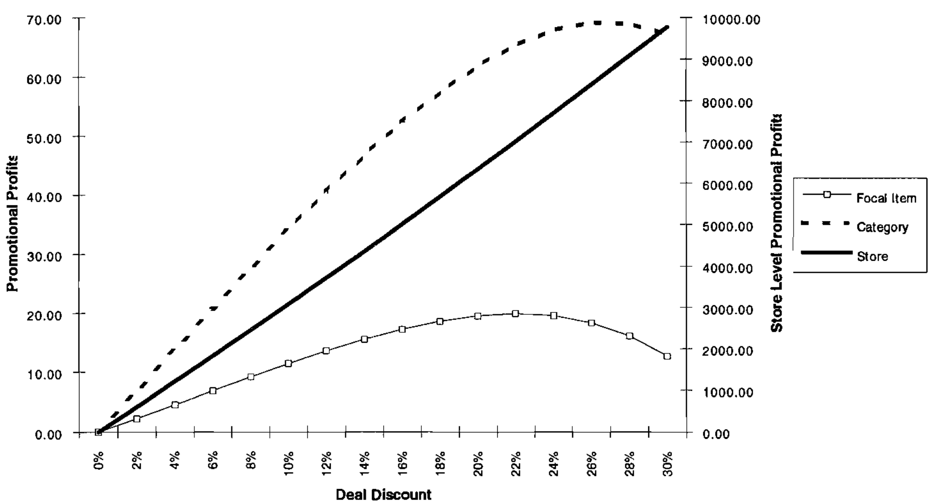


*Figure 9.8. Promotion profits of Item C's price deal.*

### 9.4.4. Item D

Sales responses for Item D's price deals are depicted by Figure 9.9. Store sales are unaffected by Item D's price deal while the promotion does affect category sales, implying that the inter-category cannibalization is complete. Cannibalization within the category is moderate; between one third and half of the incremental sales of the focal item represent incremental category sales.

The promotion profits due to deal discounts on Item D are illustrated in Figure 9.10. Small deal discounts have almost no effect on the store-level promotion profit, while lager discounts are unprofitable.

The category-level promotion profits are positive (but small) for deal discounts up to 20 percent. Larger deal discounts are unprofitable at the category level. The promotion profits measured at the item-level are positive for all price deals examined, with a peak at deal discounts of 20 percent.

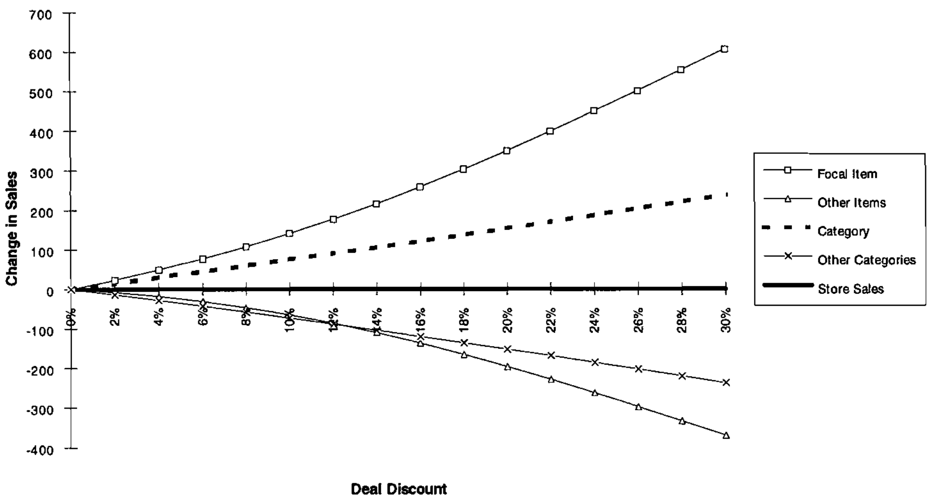


*Figure 9.9. Sales changes caused by Item D's price deal.*

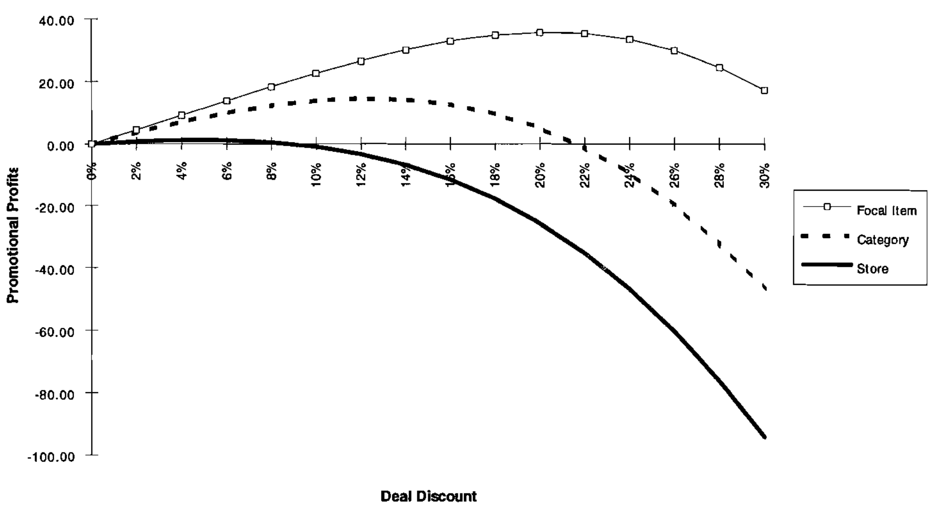


*Figure 9.10. Promotion profits of Item D's price deal.*

### 9.4.5. Item E

The inter-category cannibalization is complete also for price deals for Item E (Figure 9.11). Item E's price deal has a large impact on Item E's sales and some impact on category sales as well, resulting in the profit impact shown in Figure 9.12.

The store-level promotion profits are close to zero when the deal discount for Item E is below 10 percent. Larger deal discounts imply negative store-level promotion profits. Deal discounts smaller than 26 percent generate small profits at the category level. At the item level, all deal discounts examined appear profitable.

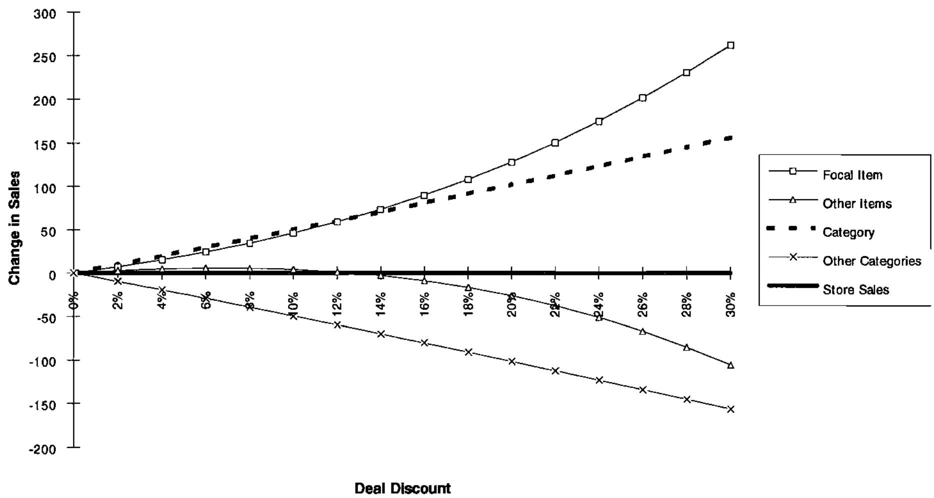


*Figure 9.11. Sales changes caused by Item E's price deal.*

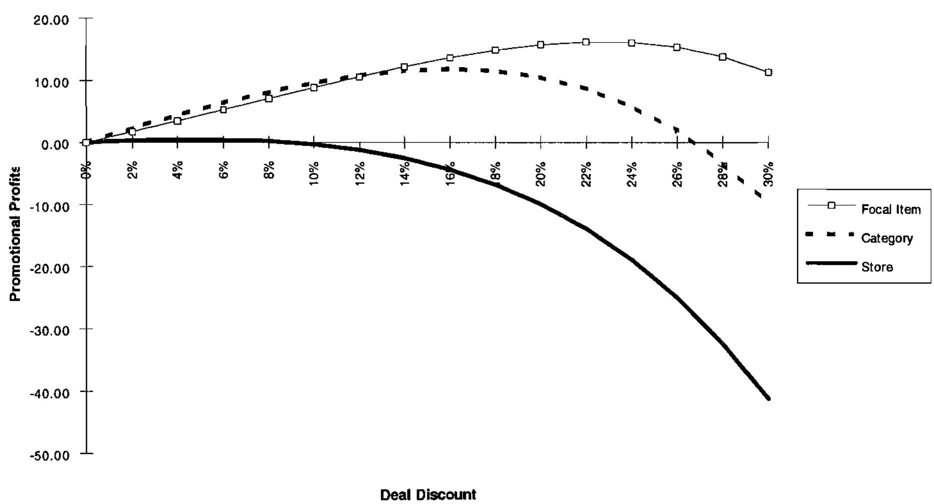


*Figure 9.12. Promotion profits of Item E's price deal.*

### 9.4.6. Item F

Item F's price deals lead to complete intra-category cannibalization. All incremental sales of the focal item come from other items in the category. Category sales are therefore not affected by price deals for Item F. The price deal for Item F has no effect on store sales either.

The promotion profits are presented in Figure 9.14.

The category- and the store-level promotion profits coincide for Item F's price deal, because the price deal has no effect on sales of other categories. The store-level promotion profits of small deal discounts are close to zero because the item-level promotion profits outweigh the reduced gross profits of other items in the focal category. Larger deal discounts are profitable only at the item level.

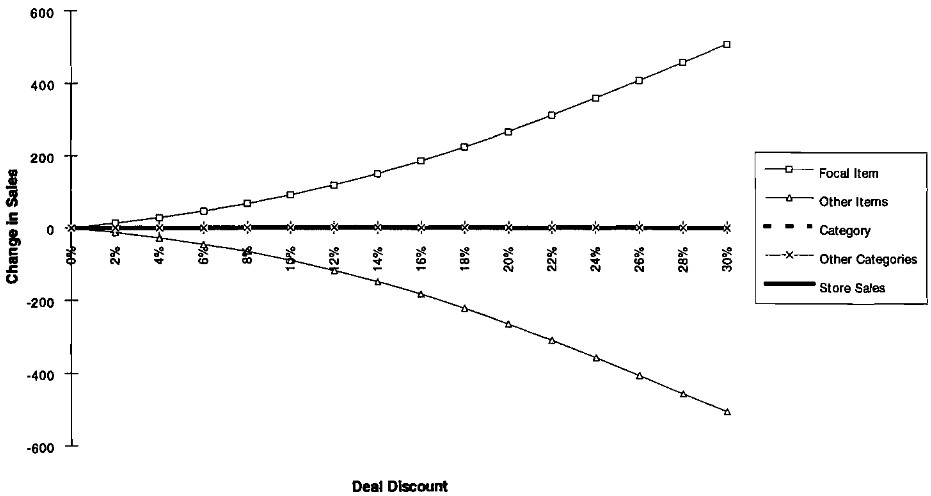


*Figure 9.13. Sales changes caused by Item F's price deal.*

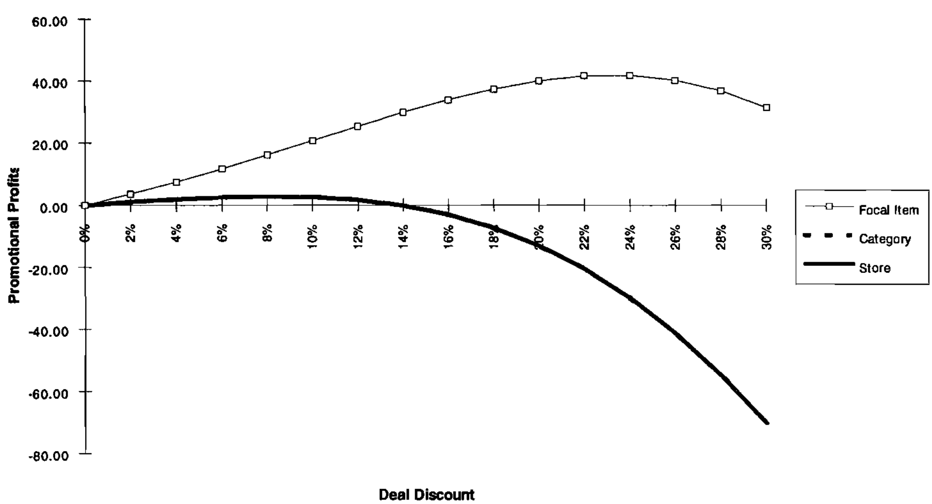


*Figure 9.14. Promotion profits of Item F's price deal. Note that the category- and store-level promotion profits coincide.*

### 9.4.7. Summing Up

To summarize, we have studied the impact of price deals on sales for six items. In all six cases, the price deal had a positive impact on sales of the promoted item. In one of the cases (Item F), intra-category cannibalization due to the price deal was complete. Moderate intra-category cannibalization was observed in three cases (B, D, and E), while the remaining two items (A and C) did not cannibalize on sales of other items in the category. Thus, sales promotion had a positive impact on category sales for five out of six items. Only one of the items' price deal (C), had a positive impact on store sales. Inter-category cannibalization was in that case non-existent while the remaining five cases showed complete inter-category cannibalization.

The item-level profits were larger than the store-level profits for five out of six items (for all deal discounts). For one item (C), the store-level promotion profits were larger than the item-level profits, irrespective of the size of the deal discount. The category-level profits were larger than the store-level profits for four items (A, B, D, E) and equal to the store-level profits for one item (F). In one case, Item C, the store-level promotion profits were larger than the category-level profits. The category-level profits exceeded the item-level profits for two items (A and C). In one case (Item E) the category-level profits were equal to the item-level profits for deals smaller than 10 percent. For deals larger than 10 percent, the item-level promotion profits were larger than the category-level profits for Item E. For three items (B, D, and F), the item-level promotion profits were larger than the category-level profits for all deal discounts.

## 9.5. Determinants of the Size of the Deal Discount

### 9.5.1. Level of Analysis

In this section we examine how the deal discount set by the profit-maximizing retailer depends on the level of analysis, i.e., whether the retailer maximizes item-, category-, or store-level promotion profits. The store-level promotion profits are regarded the as most relevant function for the retailer (see Chapter 5). Thus, deals determined to maximize item- or category-level promotion profits are regarded as sub-optimal. The cost of such sub-optimization is then the difference in store-level promotion profitsof the optimal and the sub-optimal deal. This cost is important for the retailer as it indicates the value of analyzing the promotion profits at the store level.

For each level of analysis, the optimal deal was found by evaluating, for each full percentage point between zero and 100, the promotion profits resulting from a deal of that size. These are called *Deal1*, *Deal2*, and *Deal3*, depending on whether the item-, category-, or store-level promotion profits were used. The promotion profits of *Deal3* are called *Profit3*, while the sub-optimization cost of setting *Deal1* or *Deal2* are called *Loss1* and *Loss2*. Table 9.17 presents the results for the six items analyzed.

| Item | DealReq | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|
| Item A | 0% | 23% | 23% | 6% | -25.27 | -25.27 | 0.94 |
| Item B | 0% | 23% | 14% | 7% | -36.37 | -4.48 | 3.01 |
| Item C | 0% | 22% | 27% | 100% | -30595.38 | -28880.57 | 37600.61 |
| Item D | 0% | 19% | 11% | 4% | -28.67 | -4.77 | 1.18 |
| Item E | 0% | 23% | 16% | 5% | -16.73 | -4.80 | 0.43 |
| Item F | 0% | 23% | 8% | 8% | -27.72 | 0.00 | 2.81 |
| | | | | | | | |
| Item A | 1% | 23% | 23% | 6% | -25.27 | -25.27 | 15.30 |
| Item B | 1% | 23% | 14% | 7% | -36.37 | -4.48 | 21.27 |
| Item C | 1% | 22% | 27% | 100% | -30595.38 | -28880.57 | 37615.79 |
| Item D | 1% | 19% | 11% | 4% | -28.67 | -4.77 | 33.54 |
| Item E | 1% | 23% | 16% | 5% | -16.73 | -4.80 | 10.38 |
| Item F | 1% | 23% | 8% | 8% | -27.72 | 0.00 | 15.76 |
| | | | | | | | |
| Item A | 10% | 23% | 23% | 10% | -24.33 | -24.33 | 14.37 |
| Item B | 10% | 23% | 14% | 10% | -35.83 | -3.95 | 20.73 |
| Item C | 10% | 22% | 27% | 100% | -30595.38 | -28880.57 | 37615.79 |
| Item D | 10% | 19% | 11% | 10% | -25.31 | -1.41 | 30.18 |
| Item E | 10% | 23% | 16% | 10% | -15.92 | -3.99 | 9.56 |
| Item F | 10% | 23% | 10% | 10% | -27.49 | 0.00 | 15.53 |

*Table 9.17. Deal sizes set using item-level (Deal1), category-level (Deal2), and store-level (Deal3) analysis. Profit3 is the profits of the optimal deal evaluated at the store-level. Loss1 and Loss2 are losses due to sub-optimization by setting the deal size to Deal1 or Deal2.*

We first analyze the results presented in the upper section of Table 9.17, i.e., when there is no deal requirement imposed by the manufacturer.

In five out of six cases, item-level deal optimization leads to larger deal discounts than what category- or store-level deal optimization would suggest. In the sixth case (Item C), category-level deal optimization suggests a somewhat larger deal discount than the item-level analysis. Store-level analysis suggests that the retailer should give the customers the item for free. The retailer should however not take this suggestion too literally for two reasons. First, the parameter estimates of the response model may exaggerate the store sales response. Second, since the suggested deal discount of 100 percent is far larger than the largest observed deal discount for Item C, it falls outside the scope of the model. It cannot be regarded as a valid estimate of the optimal size of the deal discount. It may, however, be interpreted as an indication that large deal discounts may be profitable.

Disregarding the results for Item C, the maximum store-level profits are small, with a maximum of SEK 3.01 per day (Item B). Again, it should be noted that these promotion profits are incremental profits to the store compared to the profits reached by a deal of size zero, where the retailer is assumed to absorb all of the trade deal offered. If the manufacturer required the retailer to pass through at least a part of the trade deal, the promotion profits would also include the trade deal money that the retailer would pocket without any deal discount, had the manufacturer not required any deal. A deal requirement of one percent would not change the optimal deal discounts but would increase the promotion profit, as can be seen in the middle section of Table 9.17. Note that the opportunity losses due to myopic decision-making remain the same as with a zero deal requirement.

The lower section of Table 9.17 shows the effects of a deal requirement of 10 percent. Such a deal requirement has no effect on the deal size determined using item-level promotion profits as the function to maximize since *Deal1* is greater than 10 percent for all six items. For one out of six items, the deal requirement increased *Deal2*, the optimal deal discount when the category-level promotion profits are maximized. The deal discount chosen by retailers maximizing store-level promotion profits increased for five out of six items. For each of these five items, the optimal deal discount equals the deal requirement.

A comparison between the store-level promotion profits (*Profit3*) with the one percent deal requirement and the profitswith the 10 percent deal requirement shows that the retailer's promotion profits are hurt by the higher deal requirement. The loss due to myopic optimization of the deal size decreases as a consequence of the higher deal requirement.

### 9.5.2. Trade Deal and Margin

This section examines how the size of the trade deal affects the optimal deal discount. Only results from store-level analyses are presented because these, and not the item-level or category-level analyses, represent optimal deal sizes seen from a retailer perspective.

In order to investigate how sensitive the pass-through of trade promotions is to the profit margin and of the cereals category, the optimal deal size was determined for four levels of the profit margin. The 20 percent profit margin is regarded as the base case and has been marked by a thick line in the figures.

Figure 9.15 presents results for Item A. At a profit margin of 20 percent, the retailer will optimally absorb all trade money for trade deals below 15 percent (of retail price). Larger trade deals will be partially passed through. Examination of Figure 9.15 reveals that the retailer should pass through all of the trade money exceeding 15 percent of the retail price. If the profit margins were 10 percent, the retailer would find it advantageous to absorb all of the trade deal.

At gross margins higher than 20 percent, the retailer would pass through a larger share of the trade deal to the consumers. It can be seen that the relative pass-through is more dependent on the profit margin for small trade deals than for large trade deals.

The pass-through of large trade deals is found to be less sensitive to profit margins than the pass-through of small trade deals Item B. Figure 9.16 shows that a trade deal of 40 percent of retail price of Item B leads to deal discounts between 21 and 26 percent, depending on the profit margin. The corresponding range for a trade deal of 25 percent is 7 to 17 percent. The range for trade deals of five percent is again smaller, because a 5 percent trade deal only induces a deal discount if the retailer's profit margin is 30 percent or higher.

The results for Item C, presented in Figure 9.17, are fairly uninteresting because the model suggests that the deal discount should always be 100 percent. Deal discounts of 100 percent are not very realistic and, as noted above, fall outside the range of the model.

The relative pass-through for Item D (Figure 9.18) ranges between zero, for trade deals lower than 15 percent, and close to 50 percent for trade deals of 40 percent in the base case. The relative pass-through increases with the size of the trade deal for all profit margins examined. The pass-through and the relative pass-through are both more sensitive to the profit margin for small trade deals than for large trade deals.

For Item E, the pass-through and the relative pass-through are very sensitive to the retailer's profit margin (see Figure 9.19).

The pass-through is also more sensitive to the size of the trade deal when the retailer's profit margins are thin than when the margins are fat. In the base case, i.e., when the profit margins are 20 percent, the retailer will pocket all trade money for trade deals smaller than

15 percent. The optimal deal discount then rises with about one percentage point for each percentage point increase of the trade deal.

The results for Item F differs from the previous results in that the deal discount is totally insensitive to the profit margin (Figure 9.20). This is because price deals for Item F leads to complete intra-category cannibalization and the profit margin of all items (including Item F) are assumed to be equal.

The retailer will not initiate any price deal if the trade deal offered is lower than 11 percent. Above 11 percent, the deal discount is an approximately linear function of the size of the trade deal discount. The relative pass-through is consequently higher the larger the trade deal.

In summary, it has been found that the size of the trade deal is important for the size of the optimal deal discount. The larger the trade deal, the larger the deal discount in the store. Small trade deals often fail to induce the retailer to deal the item. In such cases, the relative pass-through of the trade deal to the consumers is larger if the trade deal is larger. Generally, the size of the deal discount is also dependent on the profit margin of the category, with higher profit margins leading to larger deal discounts. The sensitivity of the deal discount is higher for small than for large trade deals.

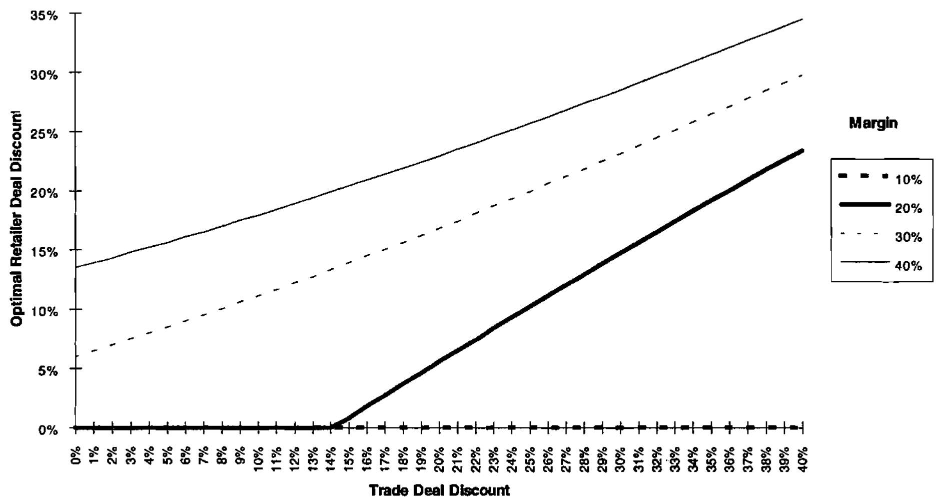


*Figure 9.15. Item A: Optimal deal size by profit margin as a function of the trade deal.*

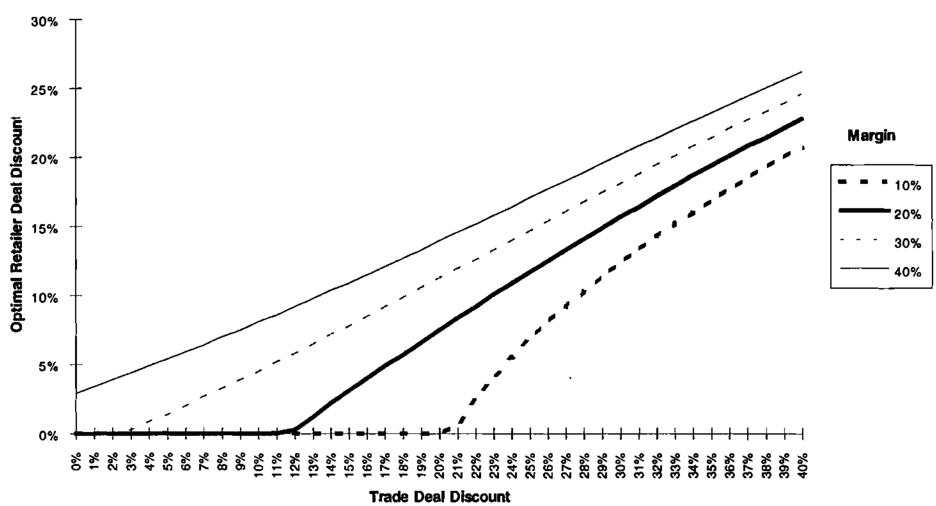


*Figure 9.16. Item B: Optimal deal size by profit margin as a function of the trade deal.*

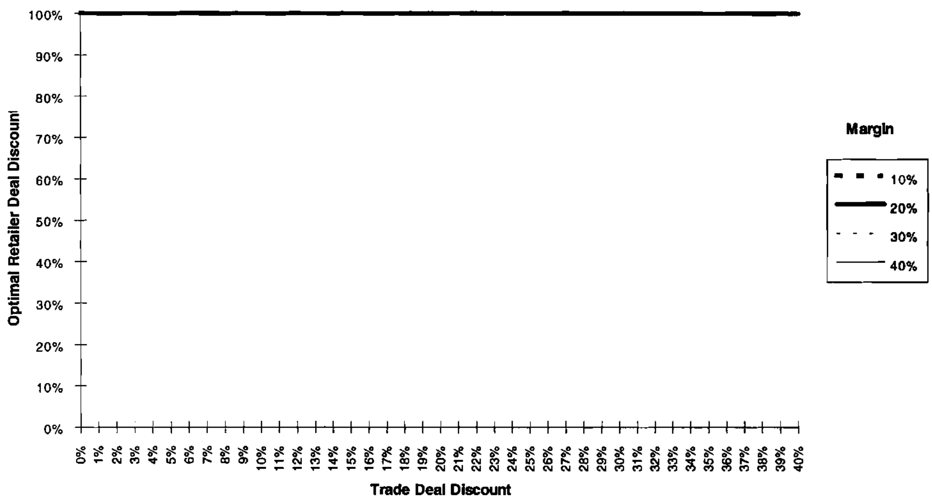


*Figure 9.17. Item C: Optimal deal size by profit margin as a function of the trade deal.*

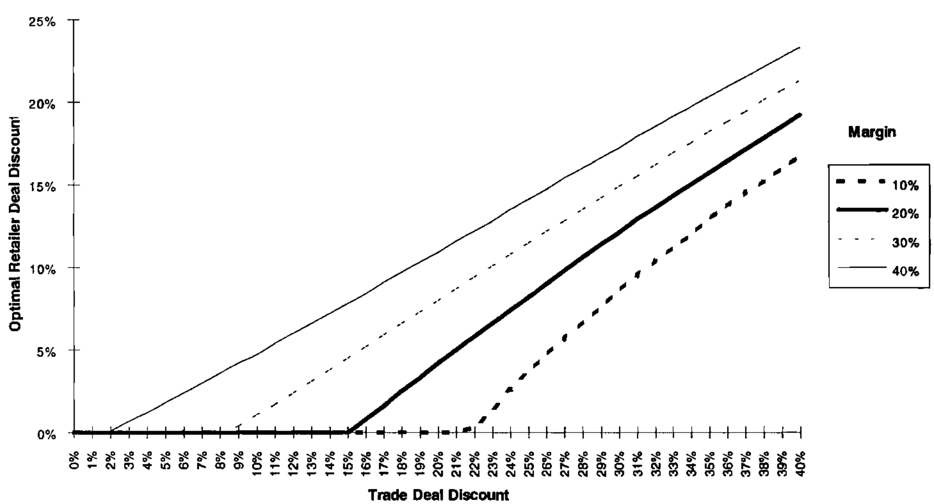


*Figure 9.18. Item D: Optimal deal size by profit margin as a function of the trade deal.*

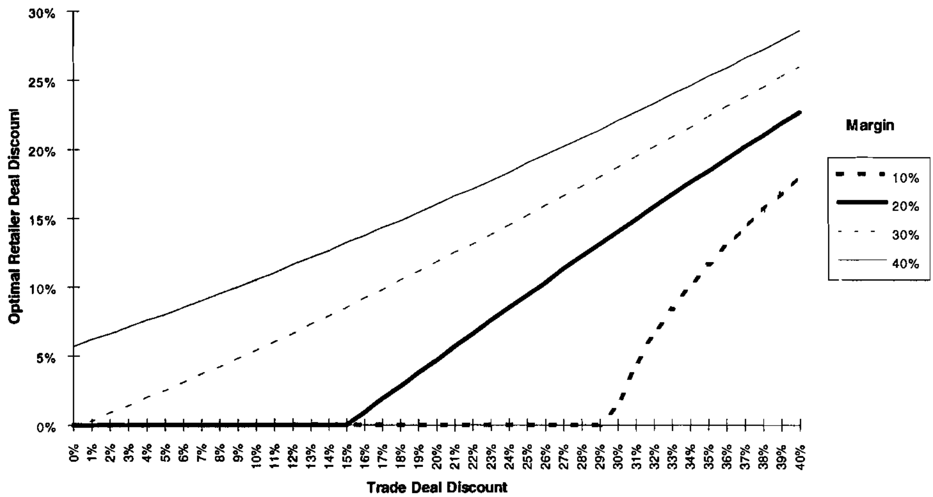


*Figure 9.19. Item E: Optimal deal size by profit margin as a function of the trade deal.*

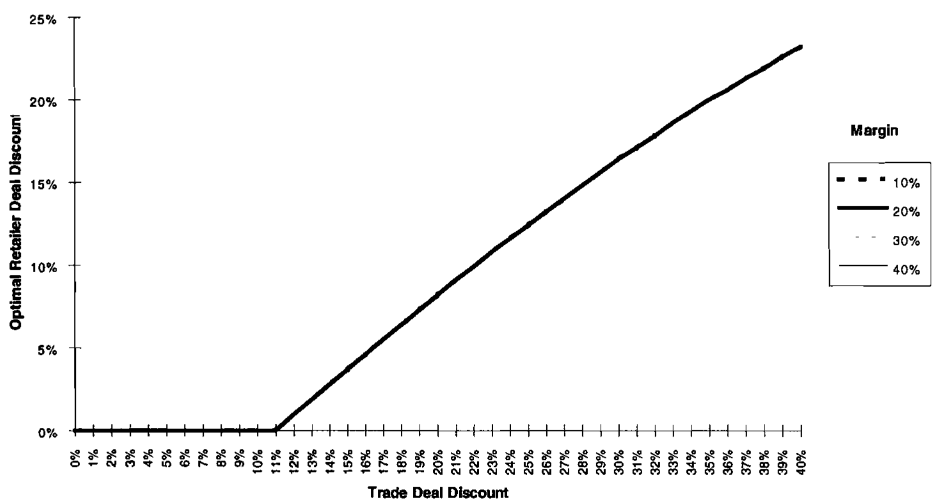


*Figure 9.20. Item F: Optimal deal size by profit margin as a function of the trade deal.*

## 9.5. Conclusions

This chapter started with the development of sales response models for six items in the Corn Flakes & Co sub-category of the breakfast cereals category. It was found that price deals for the six items had little impact on store traffic and store sales for five of the six items, implying complete inter-category cannibalization. The store-level response for the sixth item's price deal was very strong according to the model parameter estimates. However, it is likely that the store-level response was overestimated. On the other hand, as noted in Chapter 7, the choice of the null hypothesis favors the finding of no effect.

The price deal for the focal item had a positive effect on category sales for five out of six items while sales of the focal item was always positively influenced by the price deal. Complete intra-category cannibalization was found in only one case. Three of the items' price deals caused moderate intra-category cannibalization (i.e., item sales rise more than category sales), while two items' price deals caused no intra-category cannibalization.

Myopic optimization of the deal size usually leads to larger price deal discounts than what would be optimal from a store-level perspective. If store traffic and store sales are responsive to promotion for an item, then the myopically determined deal discount may be smaller than optimal. Category-level optimization generally leads to smaller deal discounts than item-level optimization. As these are often closer to the optimal deal, the sub-optimization cost is smaller when using category-level optimization than when using item-level optimization.

The size of the optimal deal discount is positively related to the size of the trade deal discount and to the profit margin of the category. As small trade deals may fail to induce a retail promotion, the relative pass-through is in general higher for larger trade deals (assuming that the retailer optimizes the deal size at the store level). Another way the manufacturer can use to influence the relative (and absolute) pass-through is by imposing a deal requirement, that the retailer only receives the trade deal if a price deal is executed in the store. Such a deal requirement changes the economic profits of the price deal, because the promotion profits are measured on an incremental basis.

# 10. EMPIRICAL ILLUSTRATION 3: PASTA

## 10.1. Introduction

This chapter contains the third empirical illustration of the proposed model. The model is here applied to six items in the pasta category. Analysis and presentation of results follow the format of the previous chapter. First, the pasta category is described. Then, sales-response models are built at the store-, category-, and item-levels. The sales-response models are then integrated to one sales-response model per item. These models are used to study the profit impact of sales promotion and the optimal deal discount. The retailer pass-through of trade deals is also examined.

## 10.2. Description of the Pasta Category

The test store sells six brands of pasta, two of which dominate the category. Sales of the third largest brand are less than half of the second largest, but almost three times the sales of the fourth brand (see Figure 10.1).

Some descriptive measures for the pasta category are given in Table 10.1. Although pasta only accounts for 0.4 percent of store sales, 2.6 percent of the shoppers buy from the category. The average category purchase was SEK 17.09. Sales promotion is rather infrequent in the category, leading to a low average deal cost (3.0 percent of category sales valued at regular prices).

| Description | Symbol | Value |
|---|---|---|
| Average Basket Value | *St/Bt* | 103.46 |
| Pasta's share of sales | *sjt/St* | 0.4% |
| Pasta baskets to store traffic | *bjt/Bt* | 2.6% |
| Average purchase amount | *sjt/bjt* | 17.09 |
| Deal cost in percent of sales | *dcjt/sjt* | 3.0% |

*Table 10.1. Descriptive measures for the pasta category.*

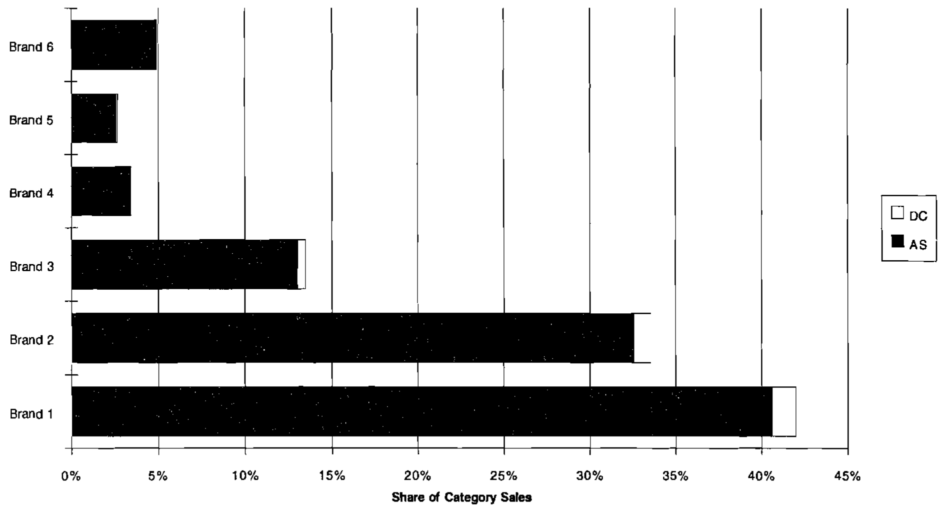


*Figure 10.1. Brand sales in the pasta category. The bars represent sales valued at regular prices divided into actual sales (AS) and deal cost (DC).*

Breaking category sales down by variety and brand, the results are presented in Table 10.2. Macaroni is the largest variety or sub-category with approximately one-third of category sales. Spaghetti is second largest with 28.5 percent followed by tagliatelle etc. (e.g., farfalle, penne, rigate) with 18.9 percent. The tortellini and the lasagne sub-categories are fairly small.

| Brand | Spaghetti | Tagliatelle etc. | Tortellini | Lasagne | Macaroni | TOTAL |
|---|---|---|---|---|---|---|
| Brand 1 | 9.5% | | | | 32.5% | 42.0% |
| Brand 2 | 9.9% | 11.4% | 6.5% | 5.8% | | 33.5% |
| Brand 3 | 5.6% | 4.9% | 3.1% | | | 13.5% |
| Brand 4 | | | 0.9% | 2.5% | | 3.4% |
| Brand 5 | 1.7% | 1.0% | | | | 2.7% |
| Brand 6 | 2.0% | 1.7% | | | 1.2% | 4.9% |
| TOTAL | 28.5% | 18.9% | 10.5% | 8.3% | 33.7% | 100.0% |

*Table 10.2. Market shares of brands and sub-categories.*

The macaroni sub-category is totally dominated by the largest brand with 96 percent of the sub-category's sales. Brand 1 has a strong position in the spaghetti sub-category as well with sales close to that of the sub-category leader, Brand 2. The third largest brand in the pasta category, Brand 3, holds position three in the spaghetti sub-category with close to 20 percent of the sub-category's sales.

Brand 2 holds large shares of the tagliatelle etc. sub-category as well as the tortellini and lasagne sub-categories. In fact, the tortellini etc. sub-category is Brand 2's most important sub-category in terms of sales. Lasagne is the sub-category where Brand 2 has its largest sub-category market share but, as this sub-category is the smallest, its importance for Brand 2's total sales is not very large.

Brand 3's most important sub-category in terms of sales is the spaghetti sub-category, while tortellini is the sub-category where Brand 3 has its largest market share with almost 30 percent of sub-category sales.

### 10.2.1. Selection of Items for Analysis

Two items from each of the three dominating brands were selected for the further analysis. In addition to large sales, these items have been promoted more than other items with similar sales volumes. The six items are presented in Table 10.3.

| Item | Brand | Variety | Size | Relative Deal Cost | Market Share | Rank |
|---|---|---|---|---|---|---|
| Item A | Brand 1 | Macaroni | 1000g | 10.8% | 8.2% | 1 |
| Item B | Brand 1 | Macaroni | 4.5kg | 4.6% | 6.1% | 3 |
| Item C | Brand 2 | Tagliatelle | 500g | 4.5% | 4.6% | 6 |
| Item D | Brand 2 | Spaghetti | 500g | 9.3% | 3.8% | 9 |
| Item E | Brand 3 | Tortellini | 500g | 7.6% | 3.1% | 11 |
| Item F | Brand 3 | Spaghetti | 1000g | 3.1% | 2.6% | 12 |
| Total | | | | | 28.4% | |

*Table 10.3. Description of the six items selected for further analysis. Market shares in percent of category sales.*

Item A is the best-selling item in the pasta category with 8.2 percent of category sales. It is also the item having the highest relative deal cost, i.e., the item with the largest percentage of total sales (valued at regular price) that is given to the consumers in the form of as price deals. Item B, ranking third in terms of sales, is the same product as Item A but in a larger package. Item C and Item D are number six and number nine in the overall market share rating in the category. Item E ranks eleventh while Item F has rank 12. In total, the test store sells 55 different items in the pasta category.

## 10.3. Building the Response Models

### 10.3.1. Data Manipulations

Store sales valued at regular prices were approximated using the same procedure as in the previous chapters, i.e., the actual sales of other categories were increased by five percent and added to the exactly calculated category sales valued at regular prices. The approxmiated store sales valued at regular prices were then used in the calculations of average basket value and the pasta category's share of store sales. The average basket value estimated in this chapter is the same as in Chapter 9, i.e., SEK 103.46.

As described in chapter 9, a period of store traffic and store sales due to a reconstruction of the store's layout led to biased estimates of the importance of store traffic for store sales. These observations were consequently discarded before the models were estimated.

### 10.3.2. Initial Tests of the Model

Before starting the model building, we will examine the correlations between store traffic and the category-level variables and between store traffic and the category-to store ratios. Table 10.4 presents the first set of correlations, those between store-level and category-level variables.

| | Bt | St | bjt | sjt |
|---|---|---|---|---|
| Bt | 1.00 | | | |
| St | 0.87 | 1.00 | | |
| bjt | 0.52 | 0.46 | 1.00 | |
| sjt | 0.54 | 0.52 | 0.91 | 1.00 |

*Table 10.4. Pearson correlations between store traffic (Bt), store sales (St), number of pasta baskets (bjt), and pasta sales (sjt).*

Store traffic and store sales are, as noted before, strongly correlated. The correlations between store traffic and category baskets and between store sales and category sales are also high. We can also observe that the number of category baskets is highly correlated with category sales. All these correlations indicate that the indirect modeling approach may be useful when modeling category sales.

| | Bt | St/Bt | bjt/Bt | sjt/St |
|---|---|---|---|---|
| Bt | 1.00 | | | |
| St/Bt | 0.64 | 1.00 | | |
| bjt/Bt | -0.13 | -0.08 | 1.00 | |
| sjt/St | -0.41 | -0.58 | 0.76 | 1.00 |

*Table 10.5. Pearson correlations between store traffic (Bt), average basket value (St/Bt), category-to-store baskets (bjt/Bt), and category-to-store sales (sjt/St).*

Table 10.5 provides further support for the modeling approach. The correlation between store traffic and the ratio of category-to-store baskets (store traffic) is low. Somewhat disturbing however is the fairly strong negative correlations that appear for the category-to-store sales ratio. Still, what is more important is how successful the regression models are in explaining the variance in the dependent variables.

### 10.3.3. Store-Level Response Models

The exponential model structure was used for the store-level models. The linearized form of the model was described in Chapter 8 (equation 8.1). The variables also follow the definition in Chapter 8.

The estimation procedure follows the pattern described in the Chapter 7. For each dependent variable, a maximum model including price deal variables for all six items and six dummy variables indicating the day-of-the-week was specified. Variables not significant at the 20 percent level in the initial estimation were dropped and the models were re-estimated. Variables were dropped and the models re-estimated until all remaining variables were significant at the 10 percent level. Recall that a variable with the wrong sign was regarded as insignificant. Table 10.6 presents the final regression results.

| | *Store Traffic* | | *Store Sales* | | *Basket Size* | |
|---|---|---|---|---|---|---|
| | *coefficient* | *s.e.* | *coefficient* | *s.e.* | *coefficient* | *s.e.* |
| Constant | 7.94 | 0.01 | 12.44 | 0.02 | 4.46 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | 0.40 | 0.11 | 0.55 | 0.16 | 0.15 | 0.08 |
| Item B | | | | | | |
| Item C | | | | | | |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | 0.06 | 0.02 |
| Wednesday | | | | | 0.10 | 0.02 |
| Thursday | | | 0.24 | 0.04 | 0.22 | 0.02 |
| Friday | 0.11 | 0.03 | 0.49 | 0.04 | 0.41 | 0.02 |
| Saturday | 0.06 | 0.03 | 0.28 | 0.04 | 0.26 | 0.02 |
| Sunday | -0.13 | 0.03 | -0.16 | 0.04 | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 28% | | 58% | | 72% | |
| n | 161 | | 161 | | 161 | |

*Table 10.6. Results of store-level response models.*

Only Item A's price deal has a significant impact on store traffic, store sales and average basket value. Price deal for Item A increases store traffic and the average basket value. This means that its effect on store sales is larger than the effect on store traffic.

Day-of-the-week effects are found significant for all three store-level measures. Consistent with the findings in the previous chapters, the basket-value model is the most successful of the three store-level models in explaining the variance of the dependent variable. The store sales model also has a high coefficient of determination while the amount of variance explained in the store-traffic model is less than 30 percent.

### 10.3.4. Category-Level Response Models

Relative category-level responses to sales promotion are examined in this section. Figure 10.2 depicts the development over time of these variables. The two category-level ratios were modeled using the logistic function. The estimation equation was described in Chapter 8 by equation (8.2).

Table 10.7 presents the final regression models obtained after application of the same procedure which was used in Section 10.3.3. None of the independent variables of the maximum model were retained in the final category-to-store baskets model. The model obviously did not explain any of the variance in the baskets ratio.

The sales ratio is more predictable than the basket ratio for the pasta category. The sales-ratio model explained 34 percent of the variance in the dependent variable. Item E was the only item having a significant impact on the category sales-ratio. Other variables that affected the sales-ratio were the day-of-the-week dummy variables. These show that pasta takes a larger share of Sunday, Monday, and Tuesday baskets' value than of other days' baskets.

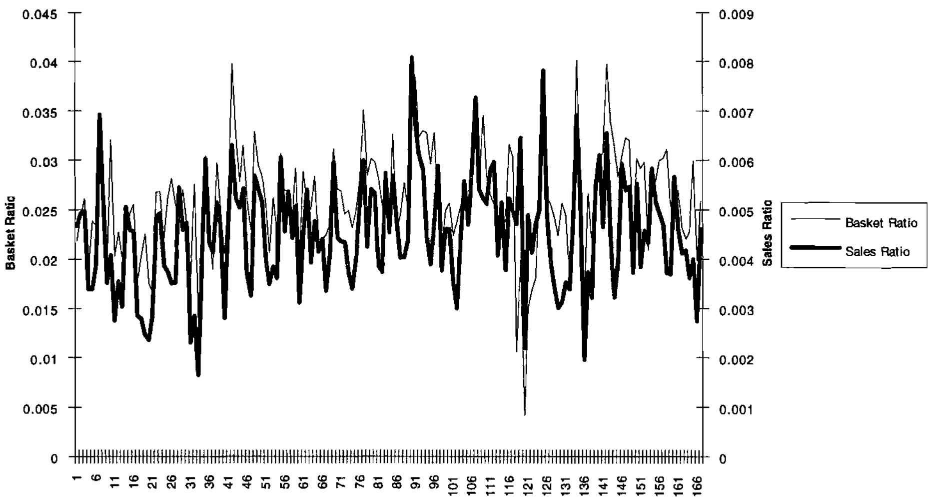


*Figure 10.2. Category ratios' development over time.*

| | Category/Store Baskets coefficient | s.e. | Category/Store Sales coefficient | s.e. |
|---|---|---|---|---|
| Constant | -3.62 | 0.02 | -5.30 | 0.03 |
| ***Price Deal*** | | | | |
| Item A | | | | |
| Item B | | | | |
| Item C | | | | |
| Item D | | | | |
| Item E | | | 1.38 | 0.41 |
| Item F | | | | |
| ***Day of Week*** | | | | |
| Tuesday | | | | |
| Wednesday | | | -0.12 | 0.05 |
| Thursday | | | -0.26 | 0.05 |
| Friday | | | -0.37 | 0.05 |
| Saturday | | | -0.29 | 0.05 |
| Sunday | | | | |
| ***Regression Statistics*** | | | | |
| adj.R.sq. | 0% | | 34% | |
| n | 161 | | 161 | |

*Table 10.7. Category-level response to sales promotion in the pasta category.*

### 10.3.5. Item-Level Response Models

Three item-level models were built for each item. The basket-ratio and sales-ratio models both assumed the logit model structure, while the exponential model was used for the average item-purchase model (see Section 8.3.5).

The maximum models included all variables found in Table 10.8, and were identical across all six items. The final models were found using the procedure described above, with the only difference the formal null hypotheses for other items sales promotion for other than the focal item; promotion would have a positive or zero effect on the ratios. A difference between the models in this chapter and those built for the breakfast cereals is that special display for the focal item was included in the maximum model.

Table 10.8 presents the regression results for Item A. Contrary to the category and store-level models, the basket-ratio model explains the most variance. This was also found in the cereals and coffee categories. All three models explain approximately 50 percent of the variance in the dependent variable.

None of the day-of-the-week dummy variables was retained in the final models for Item A. Item A's own price deal and special display had significant impact on the basket-ratio and the sales-ratio. The average item purchase was only effected by the price deal, which increased the average purchase quantity.

Item B's price deal had significant negative impact on Item A's basket ratio and sales ratio.

Item B's response models are presented in Table 10.9. Price deal and special display for Item B had significant positive effect on all three dependent variables. Item A's price deal affected Item B's basket and sales ratios negatively while Item C's price deal had positive effect on the average purchase of B.

Three of the day-of-the-week dummy variables were significant in the sales-ratio model, while only one was significant in the basket-ratio and average item-purchase models. The models for Item B differ from Item A's models in that the average purchase model accounts for more variance than does the basket-ratio model.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.89 | 0.05 | -2.78 | 0.05 | 2.93 | 0.00 |
| ***Price Deal*** | | | | | | |
| Item A | 3.95 | 0.69 | 4.04 | 0.72 | 0.19 | 0.02 |
| Item B | -2.36 | 0.81 | -2.03 | 0.84 | | |
| Item C | | | | | | |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Display Focal Item*** | 1.18 | 0.30 | 1.17 | 0.31 | | |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 52% | | 50% | | 47% | |
| n | 153 | | 153 | | 153 | |

*Table 10.8. Promotional sales-response, Item A.*

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -2.03 | | -2.63 | 0.08 | 2.17 | 0.00 |
| ***Price Deal*** | | | | | | |
| Item A | -1.66 | 0.63 | -1.77 | 0.62 | | |
| Item B | 2.53 | 1.30 | 2.88 | 1.29 | 0.23 | 0.08 |
| Item C | | | | | 0.11 | 0.05 |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Display Focal Item*** | 0.96 | 0.37 | 0.97 | 0.37 | 0.07 | 0.02 |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | 0.02 | 0.01 |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | -0.42 | 0.17 | | |
| Saturday | | | -0.35 | 0.17 | | |
| Sunday | -0.32 | 0.17 | -0.49 | 0.17 | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 24% | | 29% | | 32% | |
| n | 139 | | 139 | | 139 | |

*Table 10.9. Promotional sales-response, Item B.*

Turning to the item-level models for Item C, we recognize the more normal pattern of more variance explained by the basket-ratio model than by the sales-ratio model, which in turn explains more of the variance than the average purchase model. None of the independent variables of the maximum model was retained in the final average purchase model (Figure 10.13).

Item C's price deal was the single sales promotion variable found to have significant impact on the basket and sales ratios. Three day-of-the-week dummy variable were retained in the final ratio models, indicating some variation over the week.

Table 10.10 presents the final models for Item D. Price deal for Item D had significant impact on all three item-level measures, while other items' price deals and Item D's special display failed to influence any of the three measures. One of the day-of-the-week dummy variables had significant impact on the sales ratio. The basket ratio, on the other hand, did not show any significant day-of-the-week effects. In contrast, the average item purchase of Item D varied over the week with four of the dummy variables significant.

The average item purchase model accounted for a larger share of the variance than did the sales-ratio model. The worst performance in terms of variance explained was shown by the basket-ratio model. This is the same pattern as was found for Item B.

| | *Item/Category Baskets* coefficient | s.e. | *Item/Category Sales* coefficient | s.e. | *Average Item Purchase* coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -3.42 | 0.07 | -3.23 | 0.07 | 3.00 | 0.01 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | | |
| Item C | 3.79 | 0.68 | 3.89 | 0.69 | | |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Display Focal Item*** | | | | | | |
| ***Day of Week*** | | | | | | |
| Tuesday | -0.36 | 0.15 | -0.36 | 0.16 | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | 0.31 | 0.14 | 0.27 | 0.14 | | |
| Sunday | 0.34 | 0.14 | 0.27 | 0.14 | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 24% | | 23% | | 0% | |
| n | 143 | | 143 | | 143 | |

*Table 10.10. Promotional sales-response, Item C.*

| | *Item/Category Baskets* coefficient | s.e. | *Item/Category Sales* coefficient | s.e. | *Average Item Purchase* coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -3.09 | 0.06 | -3.52 | 0.06 | 2.32 | 0.02 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | | |
| Item B | | | | | | |
| Item C | | | | | | |
| Item D | 3.02 | 0.56 | 3.85 | 0.59 | 0.92 | 0.12 |
| Item E | | | | | | |
| Item F | | | | | | |
| ***Display Focal Item*** | | | | | | |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | 0.09 | 0.03 |
| Wednesday | | | -0.30 | 0.16 | | |
| Thursday | | | | | 0.08 | 0.03 |
| Friday | | | | | | |
| Saturday | | | | | 0.06 | 0.03 |
| Sunday | | | | | 0.07 | 0.03 |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 16% | | 23% | | 31% | |
| n | 151 | | 151 | | 151 | |

*Table 10.11. Promotional sales-response, Item D.*

Item E follows the more common pattern with more of the variance in the basket-ratio and the sales-ratio explained by the model than did the average item purchase model. The two ratio models explain close to 50 percent of the variance while the average item purchase model explained 9 percent (Table 10.12).

None of Item E's final models contain day-of-the-week dummy variables. The item's own price deal had a large positive effect on the basket- and sales-ratios. However, it failed to influence the average item purchase. Item C's price deal influenced the average item purchase positively while Item B's promotion had a negative impact on the sales ratio. The basket- and sales-ratios were both influenced negatively by Item F's price deal.

The results for Item F appear in Table 10.13. The item's own price deal had significant impact on the sales- and basket-ratios while its effect on the average item purchase was insignificant. Item A's price deal had a small positive impact on the average item purchase. No other promotional variables were retained in the final item-level models.

The Friday dummy variable was found significant in the sales model. Other day-of-the-week dummy variables were insignificant in all three models.

Item F's models were not very successful in terms of variance explained. The best fitting model was the basket-ratio model with a coefficient of determination of 13 percent. The sales-ratio model explained 11 percent of the variance while the average item purchase model only reached five percent.

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -4.07 | 0.06 | -3.23 | 0.07 | 3.63 | 0.02 |
| ***Price Deal*** | | | | | | |
| Item A | | | -2.10 | 1.01 | | |
| Item B | | | | | 0.72 | 0.26 |
| Item C | | | | | | |
| Item D | | | | | | |
| Item E | 11.77 | 1.51 | 11.57 | 1.59 | | |
| Item F | -7.05 | 1.77 | -5.41 | 2.09 | | |
| ***Display Focal Item*** | | | | | | |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | | | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 47% | | 46% | | 9% | |
| n | 71 | | 71 | | 71 | |

*Table 10.12. Promotional sales-response, Item E.*

| | Item/Category Baskets coefficient | s.e. | Item/Category Sales coefficient | s.e. | Average Item Purchase coefficient | s.e. |
|---|---|---|---|---|---|---|
| Constant | -3.69 | 0.06 | -3.59 | 0.07 | 2.87 | 0.00 |
| ***Price Deal*** | | | | | | |
| Item A | | | | | 0.08 | 0.03 |
| Item B | | | | | | |
| Item C | | | | | | |
| Item D | | | | | | |
| Item E | | | | | | |
| Item F | 5.84 | 1.37 | 4.99 | 1.39 | | |
| ***Display Focal Item*** | | | | | | |
| ***Day of Week*** | | | | | | |
| Tuesday | | | | | | |
| Wednesday | | | | | | |
| Thursday | | | | | | |
| Friday | | | -0.29 | 0.16 | | |
| Saturday | | | | | | |
| Sunday | | | | | | |
| ***Regression Statistics*** | | | | | | |
| adj.R.sq. | 13% | | 11% | | 5% | |
| n | 121 | | 121 | | 121 | |

*Table 10.13. Promotional sales-response, Item F.*

### 10.3.6. Overview of the Regression Results

We shall now summarize the results of the regression models in order to get a better overview of the important results and to get an indication of the validity of the indirect modeling approach. First, we discuss the models' explanatory power. Then, the types of variables significant in the models are discussed.

The explanatory power of a regression model can be expressed as the share of the variance of the dependent variable the model explains. Table 10.14 presents the amount of variance each of the 23 regression models explained.

| | Baskets | Sales | Quantity |
|---|---|---|---|
| ***Store Level*** | 28% | 58% | 72% |
| ***Category Level*** | 0% | 34% | n.a. |
| ***Item Level Average*** | 29% | 30% | 21% |
| Item A | 52% | 50% | 47% |
| Item B | 24% | 29% | 32% |
| Item C | 24% | 23% | 0% |
| Item D | 16% | 23% | 31% |
| Item E | 47% | 46% | 9% |
| Item F | 13% | 11% | 5% |

*Table 10.14. Adjusted R-squares.*

The store-level model of average purchase amount is the model with the largest share of explained variance. This is important support for the indirect modeling approach because it indicates that the-ratio (i.e., store sales divided by store traffic) is a relevant measure. The store-level regressions show that store sales can be broken down into store traffic and average purchase amount, where variations in store traffic are less deterministic than variations in the average purchase quantity.

The second ratio in the sales decomposition model is the category-to-store-sales ratio. The model explained about one-third of the variance in this ratio. Variations in the ratio of category-to-store baskets could not be explained by the model.

In comparison with the store-level models, the item-level models explain less of the variance in the dependent variables (i.e., the ratios). A further difference between the store-level models and the item-level models is that while the store-level model of basket value (average purchase amount) explained more of the variance than the models of store traffic and store sales, the opposite was found at the item-level; the models of average item-purchase amount item per buyer generally explained less variance than the models of item-to-category baskets and item-to- category sales.

| | Sales Promotion | | | Day-of-the-Week | | |
|---|---|---|---|---|---|---|
| | Baskets | Sales | Quantity | Baskets | Sales | Quantity |
| ***Store Level*** | 1 | 1 | 1 | 3 | 4 | 5 |
| ***Category Level*** | 0 | 1 | n.a. | 0 | 4 | n.a. |
| ***Item Level Average*** | 1.8 | 2.0 | 1.2 | 0.7 | 1.3 | 0.8 |
| Item A | 3 | 3 | 1 | 0 | 0 | 0 |
| Item B | 3 | 3 | 3 | 1 | 3 | 1 |
| Item C | 1 | 1 | 0 | 3 | 3 | 0 |
| Item D | 1 | 1 | 1 | 0 | 1 | 4 |
| Item E | 2 | 3 | 1 | 0 | 0 | 0 |
| Item F | 1 | 1 | 1 | 0 | 1 | 0 |

*Table 10.15. Number of significant model parameters.*

Table 10.15 presents the number of significant model parameters of the regression models. It can be seen that more day-of-the-week dummy variables entered the store-level models than on average entered the item-level models. The opposite pattern was found for the promotion variable. More promotion variables entered the average item-level model than entered the store-level models. This lends support for the modeling approach in that variations over the week are caught mainly by the store-level variables while sales promotion mainly affect the item-level ratios.

## 10.4. Deal Discount, Sales Response, and Profit Impact

This section takes the sales-response models of the previous section and investigates the resulting promotion-profits for the retailer, assuming that the retailer's margins are 20 percent for the focal item, other items in the category, and other categories. It is also assumed that the retailer is offered a trade deal worth 20 percent of regular retail price for items sold, with no requirement that the item should be dealt.

The item- and category-level models developed above are relative to the category, the store sales and traffic. In order to get the absolute sales and basket response we need to integrate the relative models. The integrated sales-response models are then used to study the absolute sales-response to different levels of price deals for the six items (A through F). Table 10.16 summarizes the model parameters for the six items.

| | Store Traffic | | Basket Value | | Cetagory | | Item | | |
|---|---|---|---|---|---|---|---|---|---|
| Focal Item | Constant | Deal | Constant | Deal | Constant | Deal | Constant | Deal | Display |
| Item A | 7.94 | 0.40 | 4.46 | 0.15 | -5.30 | 0.00 | -2.78 | 4.04 | 1.17 |
| Item B | 7.94 | 0.00 | 4.46 | 0.00 | -5.30 | 0.00 | -2.63 | 2.88 | 0.97 |
| Item C | 7.94 | 0.00 | 4.46 | 0.00 | -5.30 | 0.00 | -3.23 | 3.89 | 0.00 |
| Item D | 7.94 | 0.00 | 4.46 | 0.00 | -5.30 | 0.00 | -3.52 | 3.85 | 0.00 |
| Item E | 7.94 | 0.00 | 4.46 | 0.00 | -5.30 | 1.38 | -3.23 | 11.57 | 0.00 |
| Item F | 7.94 | 0.00 | 4.46 | 0.00 | -5.30 | 0.00 | -3.59 | 4.99 | 0.00 |

*Table 10.16. Summary of model parameters by focal item.*

The table entries should be interpreted as follows. Setting Item A as the focal item we are interested in the sales responses caused by Item A's sales promotion. The first row in Table 10.16 gives all the model parameters needed, assuming that the responses are evaluated for a Monday and that the other five items are not promoted.

### 10.4.1. Item A

Evaluating the sales changes due to price deals for Item A from zero percent to 30 percent of the regular retail price for Item A results in Figure 10.3.

The store-level sales effects are of a greater magnitude than the category and item-level sales responses. Therefore, separate scales were used for the store-level effects and the category- and item-level effects in Figure 10.3. In fact, item- and category-level effects are fairly unimportant for Item A compared with the store-level effects. This is because Item A's price deal had a large effect on store traffic and basket value. However, this result should be interpreted with some care because the effect appears to be overestimated. A retail manager would be wise to obtain more data to validate the extreme traffic building effect of Item A's price deal.

The profit impact of Item A's price deal is depicted in Figure 10.4. The store-level profit impact was so much larger that it was drawn on another scale than item- and category-level promotion-profits. Category-level profits are larger than item-level profits for all evaluated deal discounts. Thus, item-level profit evaluation underestimates the profitability of a price deal for Item A. The item-level profit maximum occurs at a smaller deal discount than the category-level maximum. Store-level promotion-profits are still increasing at the deal discount 30 percent indicating that deals greater than 30 percent are even more profitable.

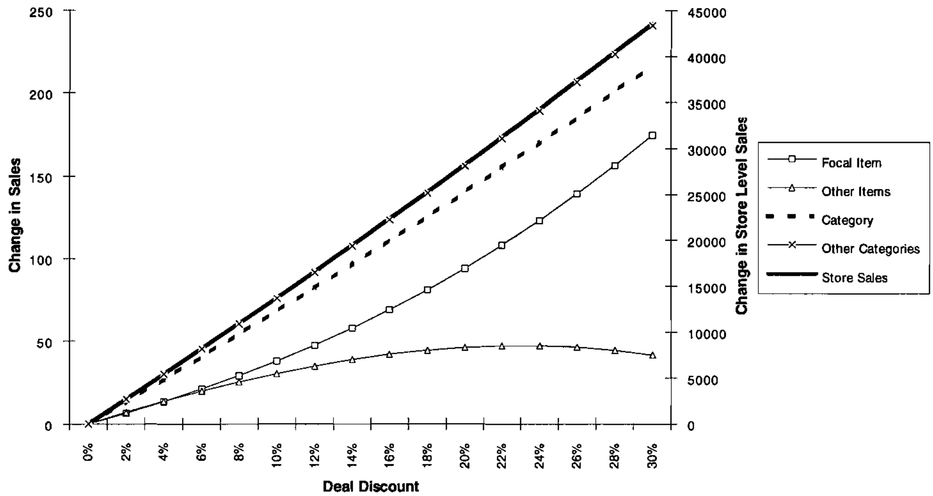


*Figure 10.3. Sales changes caused by Item A's price deal.*

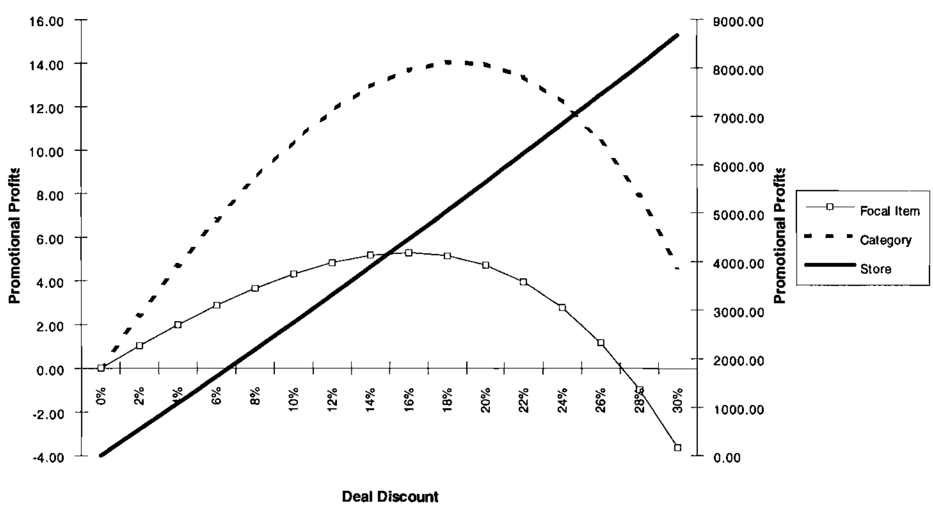


*Figure 10.4. Promotion-profits of Item A's price deal.*

### 10.4.2. Item B

In contrast to Item A, none of the other five items' price deals had any effect on store sales. This may be an overly negative view of the price deal effects, but is more likely to be correct than the large positive effects of Item A's promotion.

Figure 10.5 shows the changes in sales due to Item B's price deal. Category and store sales are not affected by the price deal. The only effect is that Item B cannibalizes on the other items' sales in the category.

The profit impact of price deals for Item B is, according to Figure 10.6, a sad story for the retailer, with negative promotion-profits for all deal discounts at all levels.

Although item-level promotion-profits are negative, item-level evaluation of the profit impact gives an overly positive estimate. The category and store-level promotion-profits are more negative than item-level promotion-profits. Irrespective of the level of analysis used, the retailer would choose not to price deal Item B. Note that category- and store-level promotion-profits coincide because of complete intra-category cannibalization.

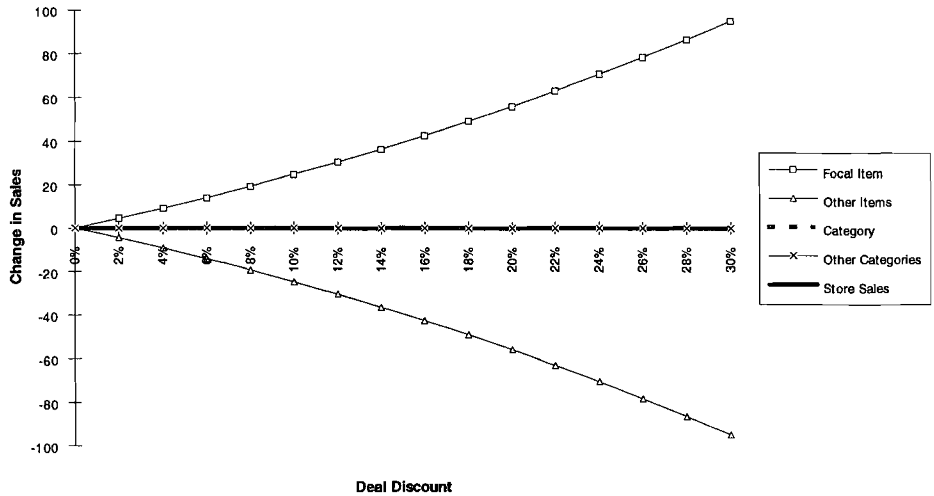


*Figure 10.5. Sales changes casued by Item B's price deal.*

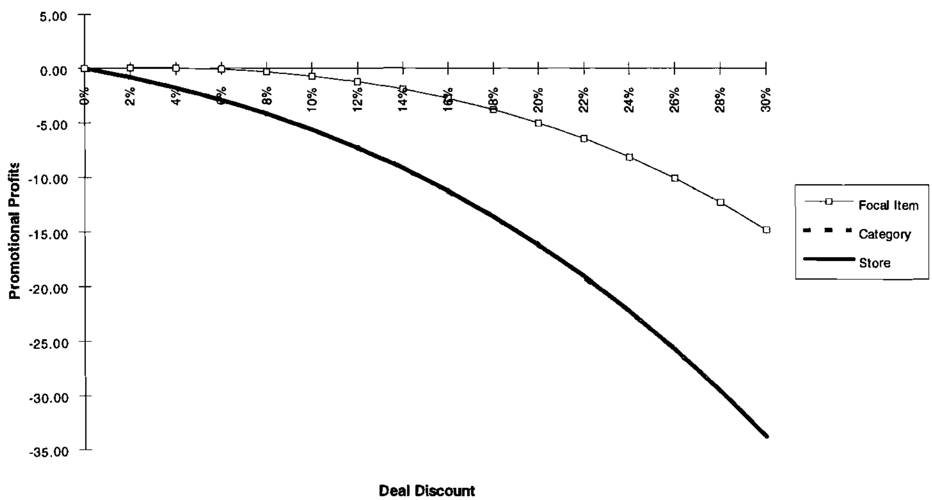


*Figure 10.6. Promotion-profits of Item B's price deal.*

### 10.4.3. Item C

The sales responses due to Item C's price deal are presented in Figure 10.7. Again, store and category sales are unaffected by the promotion. All incremental item sales come from other items in the pasta category. The strength of the response is similar to that of Item B although Item C has a lower base sales as can be seen by comparing the intercepts of the item-level models.

The results for Item C are slightly better than for Item B. Figure 10.8 shows that item-level promotion-profits are small but positive. Category- and store-level promotion-profits are equal and negative for all positive deal discounts. It would thus be optimal not to price deal Item C. Retailers using item-level analysis may decide on a price deal of 12 or 14 percent.

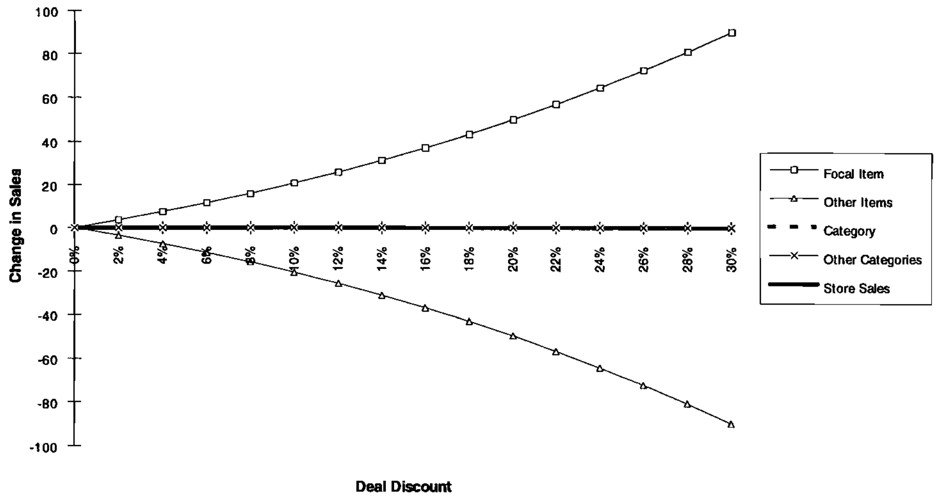


*Figure 10.7. Sales changes caused by Item C's price deal. Note that the category and store-level changes are zero.*

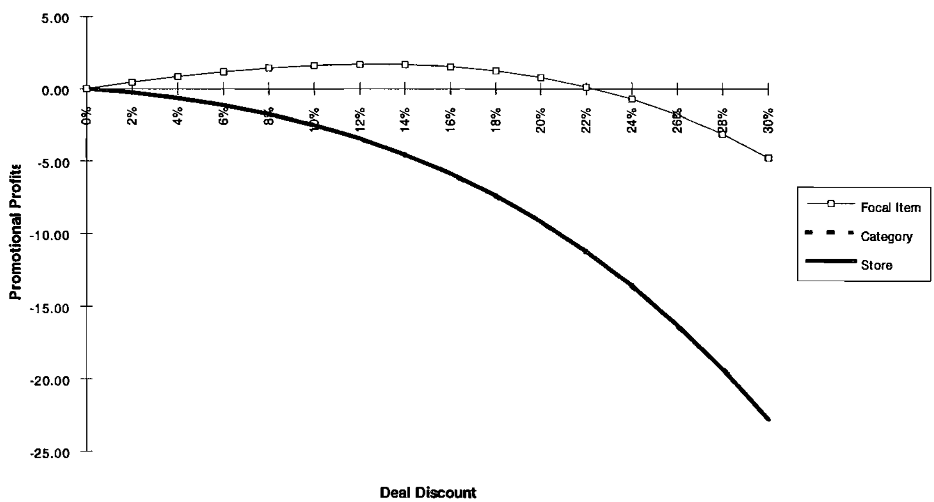


*Figure 10.8. Promotion-profits of Item C's price deal. Note that store and category-level profits coincide.*

### 10.4.4. Item D

The picture for Item D is very much the same as we have seen for Items B and C. The incremental sales of the focal item come entirely from other items in the category, i.e., the intra-category cannibalization is complete. The amount of sales stolen from other items in the category is smaller for Item D than for the two previous items. The sales changes are depicted in Figure 10.9.

The profit impact of price deals for Item D is very small for all deal discounts evaluated. Again, category- and store-level profits are equal while item-level profits are somewhat higher. Item-level analyses would lead the retailer to set price deals which are too large for Item D. However, the promotion-profits are not very sensitive to price deals for Item D.

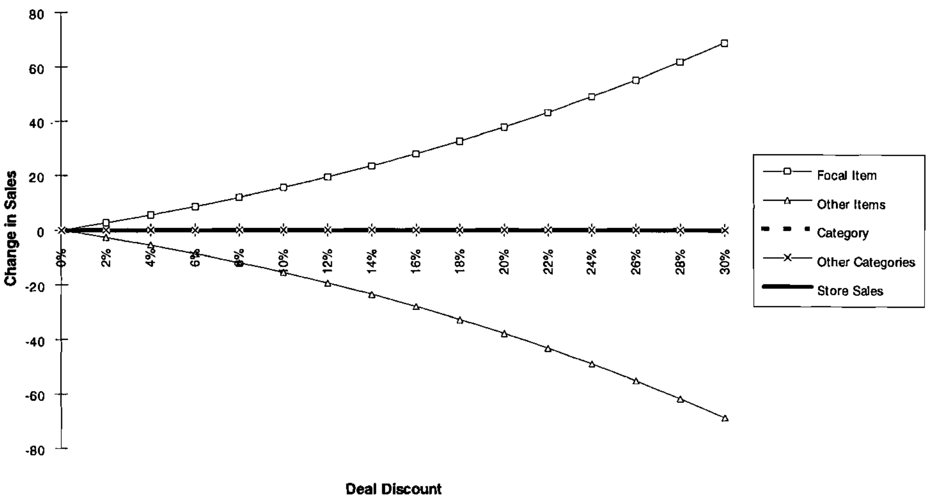


*Figure 10.9. Sales changes caused by Item D's price deal. Note that the category and store-level changes are zero.*

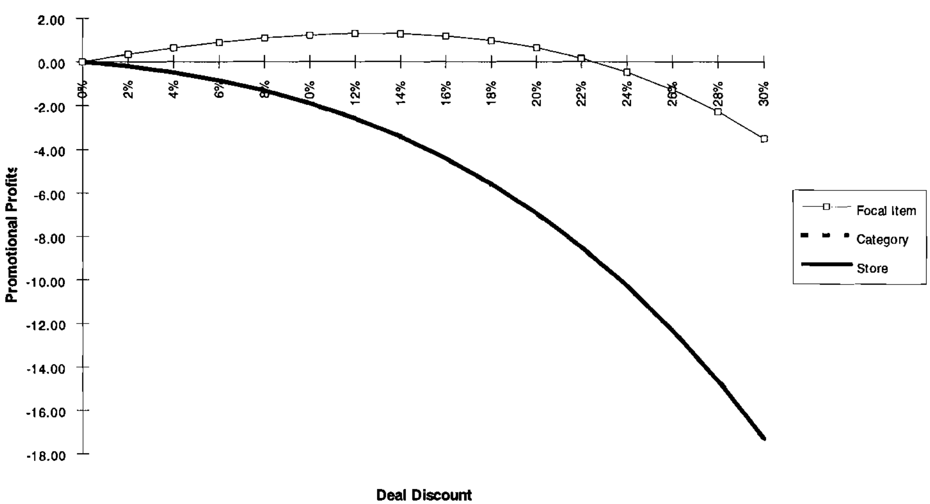


*Figure 10.10. Promotion-profits of Item D's price deal. Note that category- and store-level profits coincide.*

### 10.4.5. Item E

Figure 10.11 shows that the sales changes due to Item E's price deal are more complex than for item's B, C, and D. Item E's price deal has no effect on store sales but does have a positive effect on category sales. The category thus cannibalizes on other categories' sales.

Price deals smaller than 18 percent of regular retail price cause no intra-category cannibalization. Indeed, sales of other items in the category also increase somewhat from the price deal for Item E when the price deal does not exceed 18 percent. Larger price deals lead to moderate intra-category cannibalization.

The promotion-profits of Item E's price deals differ depending on the level of analysis. Store-level promotion-profits are lower than item- and category-level profits for all sizes of the price deal. Small price deals lead to small, but positive, store-level promotion-profits, while larger deals rapidly turn profits negative (see Figure 10.12).

Price deals up to 18 percent are more profitable at the category-level than at the item-level. Thereafter, item-level profits continue to rise while category-level promotion-profits start to decline.

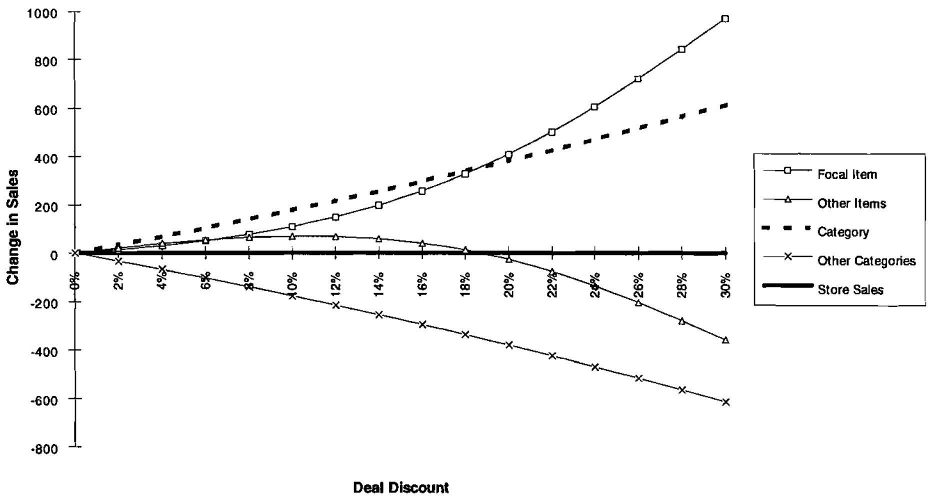


*Figure 10.11. Sales changes caused by Item E's price deal.*

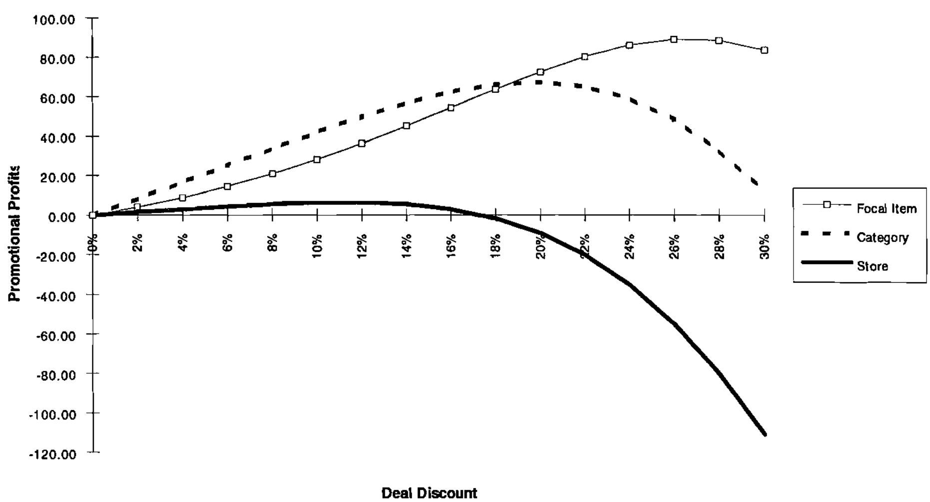


*Figure 10.12. Promotion-profits of Item E's price deal.*

### 10.4.6. Item F

Sales responses to Item F's price deal are, again, like those of Items B, C, and D. Figure 10.13 shows that price deals for Item F lead to complete intra-category cannibalization. Store sales and sales of other categories are unaffected by Item F's price deals.

We have now seen the sales response to the six items' price deals. In the next section we will investigate the profit impact of the promotions.

Figure 10.14 shows the results for Item F's price deals. Due to complete intra-category cannibalization, the category and store-level promotion-profits are identical. Category- and store-level promotion-profits are negative for all deal discounts. Item-level promotion-profits are positive but small for deal discounts up to 30 percent.

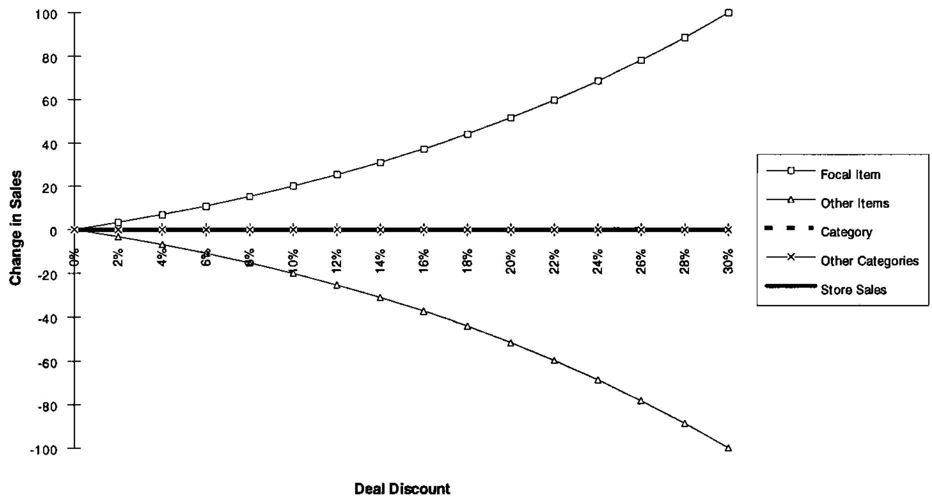


*Figure 10.13. Sales changes caused by Item F's price deal. Note that category and store-level changes are zero.*

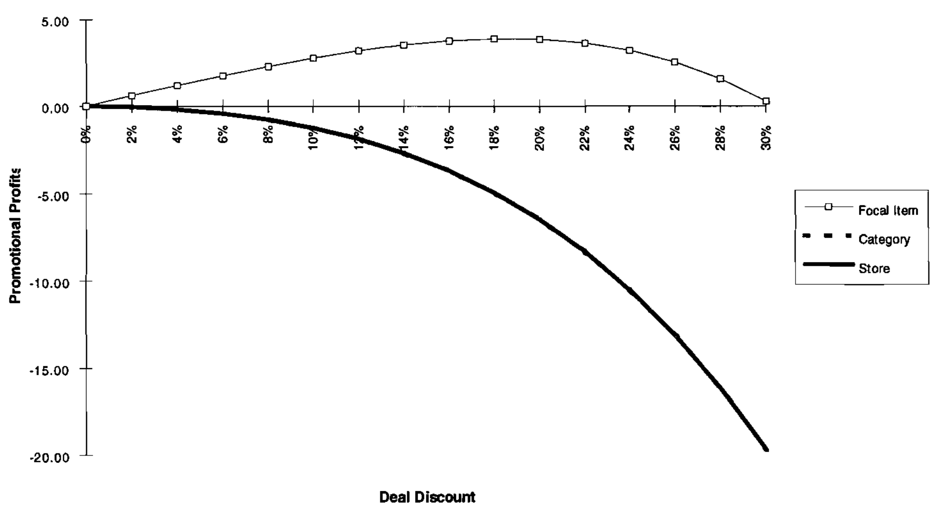


*Figure 10.14. Promotion-profits of Item F's price deal. Note that category- and store-level profits coincide.*

### 10.4.7. Summing Up

In summary, it was seen that the category-level and the store-level promotion-profits coincide in four out of six cases (Items B, C, D, and F) due to complete intra-category cannibalization. The category- and store-level profits were negative in these four cases.

The category-level profits were greater than the store-level profits in one case (Item E) and lower in one case (Item A). The sales promotion had a positive impact on category sales in both cases. For Item E, there was some degree of intra-category cannibalization, while the inter-category cannibalization was complete. This made the category-level profits greater than the store-level profits. Item A's sales promotion, on the other hand, caused neither intra- nor inter-category cannibalization; sales of other items in the focal category as well as sales of items in other categories increased. This made the store-level profitsexceed the item- and category-level profits.

For all other items, the item-level profits were larger than the store-level profits. Due to intra-category cannibalization, the item-level profits were greater than the category-level profitsin all cases but two (Item A and Item E). For Item E, the moderate intra-category cannibalization led to almost equal category- and item-level profits for small deal discounts. Item A's sales promotion caused sales of other items in the focal category to rise. The category-level profits were therefore greater than the item-level profits.

## 10.5. Determinants of the Size of the Deal Discount

### 10.5.1. Level of Analysis

We shall now investigate how the deal discount depends on the level of analysis used by the retailer. The cost of myopic optimization is also examined.

It is assumed that gross margins are 20 percent for the focal item, the focal category, and for other categories. It is also assumed that the manufacturer offers the retailer a trade deal worth 20 percent of the retail price (implying a 25 percent discount on the wholesale price).

Three price deals were determined for each item: the item-level optimized deal (*Deal1*); the category-level optimized deal (*Deal2*); and the store-level optimized deal (*Deal3*). In accordance with the central argument of this thesis, the store-level optimized deal is what we regard as the optimal deal while the item and category-level optimization is myopic. The promotion-profits of the store-level optimized deal are called *Profit3*.

The cost of setting another price deal discount than the optimal deal determined at the store level can be estimated as the difference between *Profit3* and the store-level promotion-profits of such a price deal. The cost of item-level deal optimization is thus the difference between *Profit3* and the store-level promotion-profits of a deal of size *Deal1*. This cost of myopic deal optimization is denoted *Loss1*. In the same way, *Loss2* is the cost of category-level deal optimization. Table 10.17 presents the results for the six items in the pasta category.

The results show that for all items except Item A, item-level optimization leads to larger deal discounts than category-level optimization. Item A is different because of the store traffic effects noted in the previous section. Also noted earlier is that the size of the store-level effect is exaggerated, which is indicated by the suggested optimal deal of 100 percent for Item A. The store-level profits of giving away Item A for free are estimated to SEK 30,000 per day, which is obviously too optimistic an estimate.

Items B, C, D, and F all failed to affect category and store sales. The retailer's optimal deal for these items is therefore to absorb all of the trade deal and sell the items at their regular prices. The store-level promotion-profits are, according to Table 10.17, zero for these items. It should be noted, however, that this figure does not include the profits the retailer makes by pocketing the trade deal.

Although Item E's price deal does have an impact on category sales, item-level deal optimization leads to larger than optimal deals. Item-level optimization sets the price deal at 27 percent, while category-level optimization sets the deal at 20 percent and store-level optimization leads to a price deal of 11 percent. The 11 percent deal increases gross margins by SEK 6.44 above what the retailer would obtain when absorbing the trade deal.

| Item | DealReq | Deal1 | Deal2 | Deal3 | Loss1 | Loss2 | Profit3 |
|---|---|---|---|---|---|---|---|
| Item A | 0% | 16% | 19% | 100% | 29831.79 | 28953.58 | 34290.25 |
| Item B | 0% | 3% | 0% | 0% | 1.28 | 0.00 | 0.00 |
| Item C | 0% | 13% | 0% | 0% | 3.98 | 0.00 | 0.00 |
| Item D | 0% | 13% | 0% | 0% | 3.00 | 0.00 | 0.00 |
| Item E | 0% | 27% | 20% | 11% | 73.51 | 15.62 | 6.44 |
| Item F | 0% | 19% | 0% | 0% | 5.68 | 0.00 | 0.00 |
| Item A | 1% | 16% | 19% | 100% | 29831.79 | 28953.58 | 34304.34 |
| Item B | 1% | 3% | 1% | 1% | 0.89 | 0.00 | 15.82 |
| Item C | 1% | 13% | 1% | 1% | 3.85 | 0.00 | 9.05 |
| Item D | 1% | 13% | 1% | 1% | 2.91 | 0.00 | 6.84 |
| Item E | 1% | 27% | 20% | 11% | 73.51 | 15.62 | 15.62 |
| Item F | 1% | 19% | 1% | 1% | 5.66 | 0.00 | 6.46 |
| Item A | 10% | 16% | 19% | 100% | 29831.79 | 28953.58 | 34304.34 |
| Item B | 10% | 10% | 10% | 10% | 0.00 | 0.00 | 10.58 |
| Item C | 10% | 13% | 10% | 10% | 1.45 | 0.00 | 6.65 |
| Item D | 10% | 13% | 10% | 10% | 1.10 | 0.00 | 5.03 |
| Item E | 10% | 27% | 20% | 11% | 73.51 | 15.62 | 15.62 |
| Item F | 10% | 19% | 10% | 10% | 4.44 | 0.00 | 5.24 |

*Table 10.17. Optimal deal discount, loss due to myopia, and optimal deal profits.*

If the manufacturer would demand that the retailer passes through some part of the trade deal to the consumers in order to receive the trade money, the promotion-profits, and sometimes the optimal deal, will change. If the optimal deal discount does not change because of the deal requirement, the increase in promotion-profits (compared with the no deal requirement case) reflects the retailer's profits from absorbing all of the trade deal and selling the item at regular price. If the deal requirement alters the optimal deal although the deal requirement is low, the change in promotion-profits can only be regarded as an approximation of the value of the pocketed trade money. The results when the manufacturer requires a one percent or a ten percent price deal are presented in Table 10.17.

The loss due to myopic optimization changes only when the myopically determined deal discount change or when the store-level optimal deal (*Deal3*) changes as a result of the deal requirement, or both. A requirement of a one-percent price deal has no impact on item-level optimal deal, but increases the optimal deal determined at store- or category-level, to one percent in four out of six cases.

The item-level optimal deal (*Deal1*) changes for one item (Item B) as a result of a ten percent deal requirement. The ten percent deal requirement also raises the store- and category-level optimal deal for four out of six items. The change in promotion-profits by increasing the deal requirement from one percent to ten percent is generally small.

### 10.5.2. Trade Deal and Margins

This section investigates how the optimal deal discount and pass-through depend on the gross margin and the trade deals, given that the retailer uses store-level deal optimization. It is assumed that the gross margin of other categories is 20 percent and that the gross margin of the focal item is equal to that of other items in the pasta category.

The results for Item A are presented in Figure 10.15. Due to the strong store-level effect, the model claims that the retailer should give the consumers Item A for free during the promotion period, whatever the trade deal. As already noted, this result should be taken as an indication that a large price deal may be profitable, rather than as a suggestion that the retailer should set the price at zero.

When intra-category cannibalization is complete, as in the case of Item B (Figure 10.16), the retailer will in general find it more profitable to absorb all of the trade deal than to pass it through to the consumers. Only substantial trade deals will lead to price deals in the store, and even then, the pass-through is small. Note that the gross margin of the focal item (and other items in the focal category) has no impact on the optimal deal discount.

Item C is similar to Item B in that the intra-category cannibalization is complete. Figure 10.17 indicates that there is some difference between items B and C since the pass-through is much larger for Item C than for Item B. The difference is that Item C's relative sales response is stronger than Item B's. Although intra-category cannibalization is complete, the incremental sales of Item C mean that higher effective margin sales (i.e., Item C's regular margin and the trade deal) are substituted for the regular margin sales.

The regular gross margin of Item C (and other items in the pasta category) has no effect on the pass-through.

Figure 10.18 presents the results for Item D. The optimal deal for Item D as a function of the trade deal is identical to that for Item C. Going back to the model parameters for items C and D (Table 10.16) we observe that the two items' models are virtually identical.

Item E (Figure 10.19) differs substantially from items B, C, and D. The optimal pass-through is in general large and dependent on the regular gross margin of items in the pasta category. Although price deals for Item E have no impact on store sales, it is profitable for the retailer to let the pasta category cannibalize on other categories' sales when the pasta category has higher gross margin than other categories. When gross margins in the pasta category are equal to other categories' margins (i.e., 20 percent), the trade deal must exceed 8 percent (of retail price) before the retailer will deal Item E. Lower pasta margins obviously lead to smaller pass-through of the manufacturer's trade deal.

The pass-through pattern for Item F resembles that of Item B, C, and D, the difference being that the retailer's pass-through is somewhat higher for Item F. This is due to the stronger relative-sales-response for Item F (see Figure 10.20).

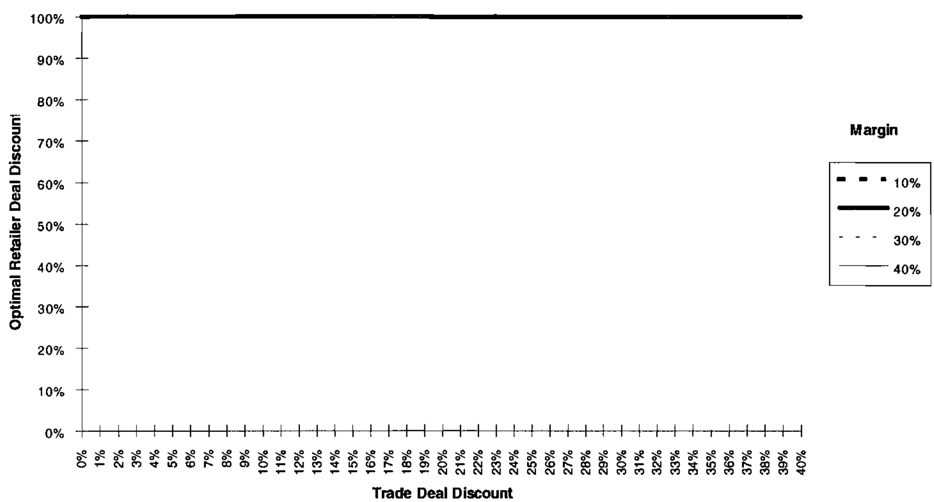


*Figure 10.15. Item A: Optimal deal discount by profit margin as a function of the trade deal.*

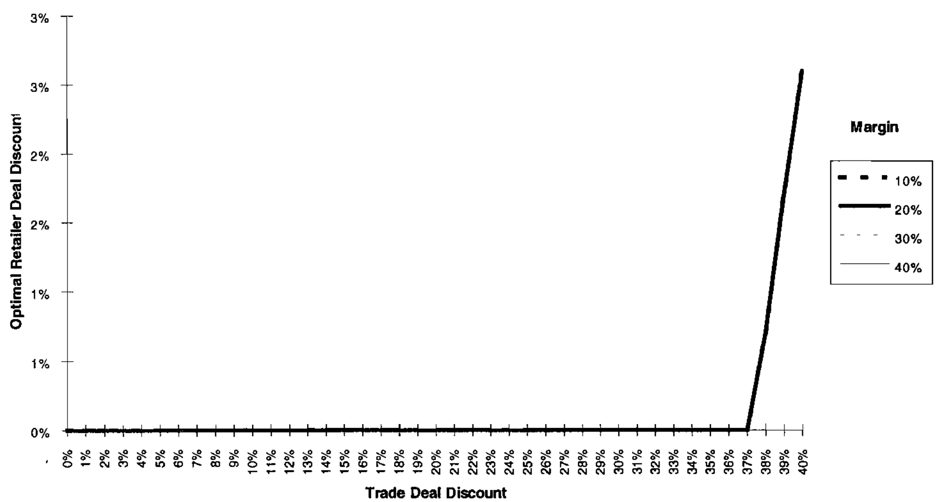


*Figure 10.16. Item B: Optimal deal discount by profit margin as a function of the trade deal.*

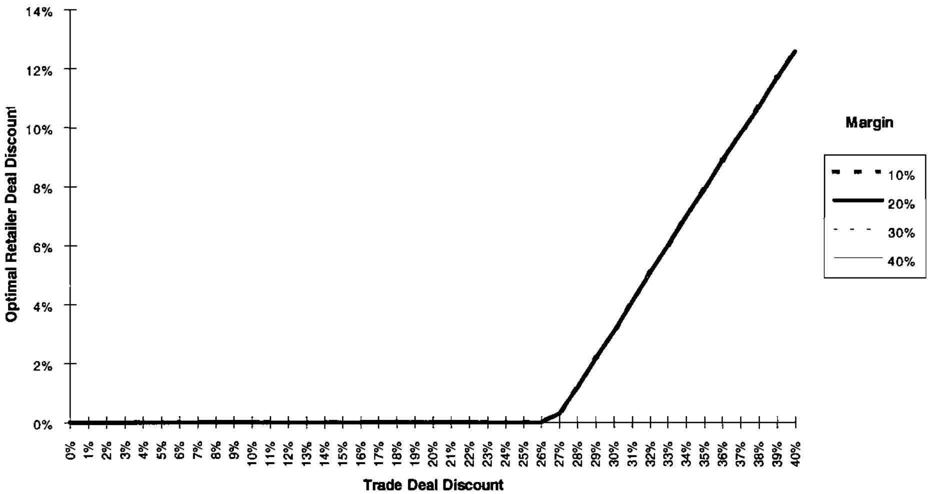


*Figure 10.17. Item C: Optimal deal discount by profit margin as a function of the trade deal.*

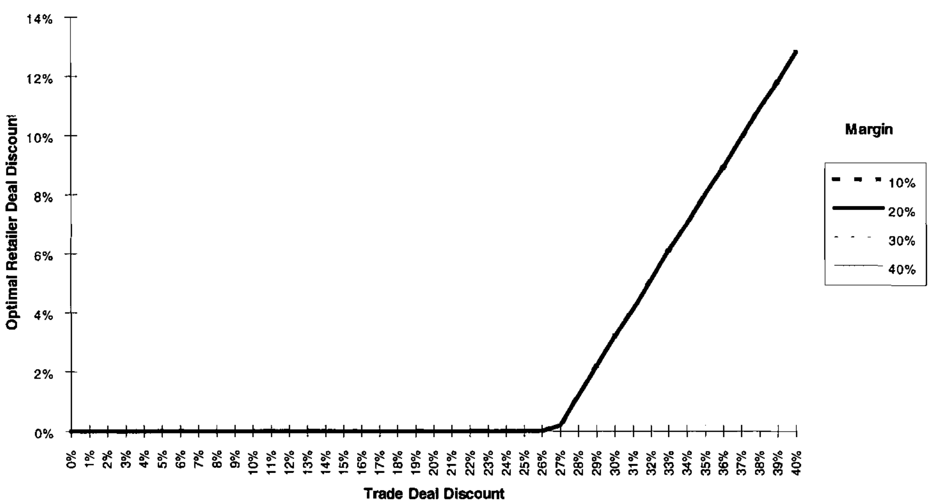


*Figure 10.18. Item D: Optimal deal discount by profit margin as a function of the trade deal.*

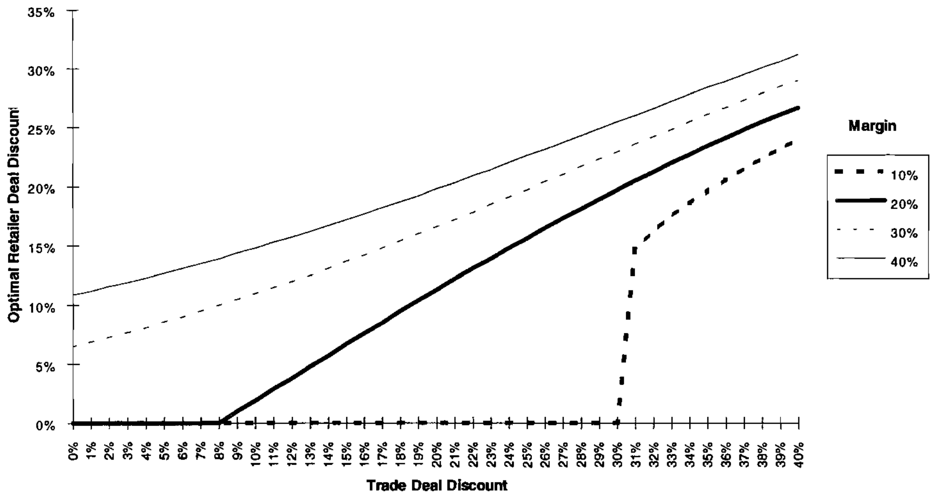


*Figure 10.19. Item E: Optimal deal discount by profit margin as a function of the trade deal.*

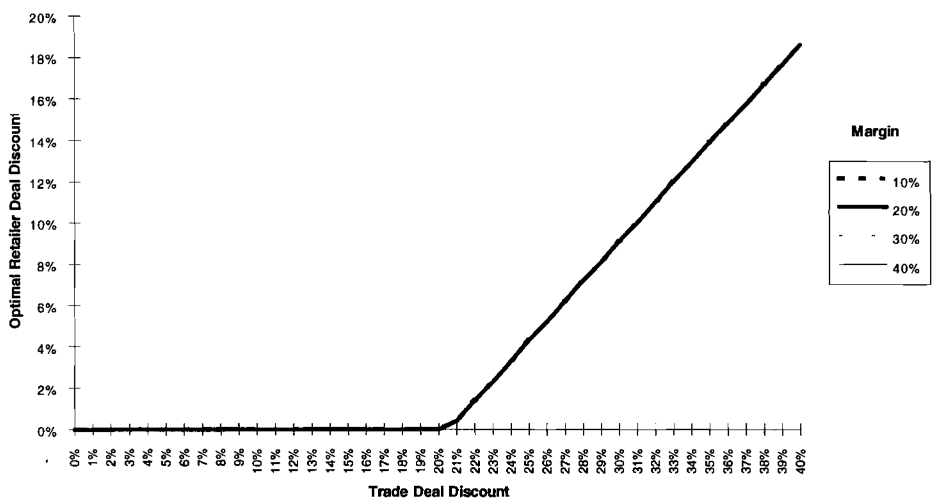


*Figure 10.20. Item F: Optimal deal discount by profit margin as a function of the trade deal.*

## 10.5. Conclusion

It has been seen that price deal in the pasta category has little impact on store traffic and store sales. Only one of the six items' price deals had a significant impact on store sales. This item did not affect the category's share of store sales while one item affected the category's share of store sales without affecting store sales. Four items' sales promotion led to complete intra-category cannibalization.

In these four cases, the retailer would maximize profits by absorbing all of the price deal for most levels of trade deal. Only large price deals would lead to a partial pass-through of the trade deal to the consumers. Retailers using item-level deal optimization would use price deals which are too large.

Item and category-level deal optimization would lead to larger than optimal price deal also for the item whose price deal affected relative category sales. The sub-optimization would, however, be smaller for this item than for the four items whose promotions lead to complete intra-category cannibalization.

Contrary to the other items, the item whose price deal had an impact on store sales would receive a too small price deal if the retailer used item-level analysis when setting the deal discount.

# 11. CONCLUSION

## 11.1. Summary

The purpose of this study was model the profit impact of retailer promotion. The motivation for this study was the observation that the profit impact of sales promotion is poorly understood. In addition, most previous research about sales promotion have assumed a manufacturer's rather than a retailer's perspective. As the retailer's objectives with sales promotion differ from those of the manufacturer, there is a large need for the development of a retailer-oriented, promotion-profit model.

### 11.1.1. Promotion Profit as Change in Gross Profits

It was noted that the economic profit of any action is the change in profits caused by that action. The profit of a sales promotion is thus the difference in the profits that would be obtained if the promotion were launched and the profits that would be obtained in the absence of the promotion. Measuring the profits of a promotion *ex post* thus involves an estimation of what the profit would have been without that promotion. *Ex ante* prognoses of the profit of a promotion require two estimates: the profits with and without the promotion. The difference between these estimates is equal to the difference in gross profits, assuming that fixed costs are not affected by the promotion.

For the firm selling only one item, gross profits change as a consequence of sales promotion in two ways. The profit margin per unit sold may change and the sales volume may change. While the change in per unit profit margin is readily available, the change in sales volume must be estimated.

Sales promotion typically reduces the profit margin per unit while increasing the sales volume. It is important to note that the lower margins not only pertain to the incremental sales caused by the promotion, but also to the sales that would have occurred in the absence of the promotion. The promotion profits are thus dependent on sufficient incremental sales to overcome the negative effect caused by lower margins on baseline sales.

For firms selling more than one item, the profit of the promotion for one item (the focal item) is not only dependent on the change in profits from sales of the promoted item, but from the change in gross profits from sales of all other items as well. The change in gross profits from other items is only a consequence of changes in sales volumes, since the per unit gross profits of these items are not affected by the promotion of the focal item. In order to measure the profit of a promotion for the focal item, we need to estimate how sales of other items will change.

Sales of other items than the promoted item may increase, decrease, or be unaffected as a consequence of the promotion. When sales of other items decrease, we have substitution effects, implying that the promoted item steals from the sales of other items. This is also known as sales cannibalization. When sales of other items increase, we have complementarity between the items. If sales of other items are unaffected by the promotion, the profit of the promotion is simply the change in gross profits from the focal item.

If the number of items the firm sells is not too large, the sales effect on each individual item can be estimated. The profit of the promotion can then be calculated as the sum of the change in gross profits from sales of the promoted item and the change in gross profits from sales of each other item. However, this is not feasible when the number of items is large.

Grocery retailers carry large assortments consisting of several thousands of items. It is well known that there are interdependencies among many of these items. The substitution effects are perhaps the most obvious, but the complementarity effects may also be important. The combination of large assortments and the interdependencies among the items makes measurement of promotion profits in grocery retailing difficult, because the total change in gross profits from other items may be large, even if the effect on each item is small and difficult to measure.

### 11.1.2. The Sales Model

The solution suggested in this study is based on the notion that grocery shoppers usually buy more than one item when shopping. Indeed, most grocery shoppers buy baskets of groceries; the reason is probably the fixed cost in the form of the effort to visit the store. This behavior gives rise to a general complementarity among all items that enter the shopping baskets, and highlights the importance of store traffic, i.e., the number of shoppers or shopping baskets.

Positive effects on sales of other items than the promoted item may then come from an increase in store traffic caused by the promotion. The size of the average basket is thereby important to observe because if the incremental shoppers only buy the promoted item, then sales of other items would not be positively affected.

The shopping basket is also important for substitution effects. We can think of the content of the shopping basket as three kinds of items: the focal item, its closest substitutes, and all other items. The focal item's closest substitutes are the other items in the same category as the focal item. This category is cslled the focal category and we can calculate its share of the basket's value. Multiplying by the number of shopping baskets gives the sales of the focal item.

This calculation makes it possible to express the average content of the focal item in the baskets as the product of the four factors: (1) the store traffic, (2) the average basket value, (3) the focal category's share of store sales, and (3) the focal item's share of category's sales. Expressed as an equation, sales of the focal item are:

$$s_{ijt} = B_t \cdot \frac{s_t}{B_t} \cdot \frac{s_{jt}}{s_t} \cdot \frac{s_{ijt}}{s_{jt}} \qquad (11.1)$$

where

| | | |
|---|---|---|
| $s_{ijt}$ | = | sales (valued at regular price) of item $i$, category $j$, period $t$ |
| $s_{jt}$ | = | category sales (valued at regular prices) category $j$, period $t$ |
| $s_t$ | = | store sales (valued at regular prices) period $t$ |
| $B_t$ | = | store traffic, i.e., total number of shopping baskets, in period $t$ |

Sales of other items in the focal category and sales of other categories than the focal category can then also easily be calculated. By building models for each of these four factors, we can estimate the change in sales of the focal item, other items in the focal category, and of other categories caused by sales promotion (or other changes in the marketing mix).

### 11.1.3. The Profit Model

The estimates of the changes in sales for the promoted item, other items in the same category, and other categories can then be used to calculate the promotion profit. The retailer's promotion profit is thus the sum of three terms: (1) the change in the gross profit from the focal item, (2) the change in the gross profits from sales of the other items in the focal category, and (3) the change in the gross profits from sales of items in other categories. This measure of promotion profit is the way to measure promotion profits that is most relevant to retailers, and is called store-level promotion profits or just promotion profits. Expressed as an equation, we have:

$$\Delta\pi_3 = \underbrace{\Delta\pi_1}_{(1)\text{ focal item}} + \underbrace{(\Delta\pi_2 - \Delta\pi_1)}_{(2)\text{ other items in focal category}} + \underbrace{(\Delta\pi_3 - \Delta\pi_2)}_{(3)\text{ other categories}} \qquad (11.2)$$

where

| | | |
|---|---|---|
| $\Delta\pi_1$ | = | change in item-level gross profits |
| $\Delta\pi_2$ | = | change in category-level gross profits |
| $\Delta\pi_3$ | = | change in store-level gross profits |

The first term, the change in gross profits from the focal item, is called item-level promotion profits, while the sum of the two first terms is called category-level promotion profits. Both item- and category-level promotion profits are myopic in that they do not consider the full impact of the promotion.

The store-level promotion profits of a promotion for the focal item can be calculated using the formula:

$$\Delta\pi_3 = \underbrace{\underbrace{\underbrace{\overbrace{\Delta s_1 m_1 + \Delta s_1\left(t^\theta - DEAL\right) + s_1^*\left(t^\theta - t^* - DEAL\right)}^{\text{focal item}}}_{\text{item level promotional profit}} + \overbrace{m_2\left(\Delta s_2 - \Delta s_1\right)}^{\text{other items in focal category}}}_{\text{category level promotional profit}} + \overbrace{m_3\left(\Delta s_3 - \Delta s_2\right)}^{\text{other categories}}}_{\text{store level promotional profitcategories}} \qquad (11.3)$$

where

| | | |
|---|---|---|
| $s_1^*$ | = | baseline sales of focal item valued at regular price |
| $\Delta s_1$ | = | change in sales of focal item caused by promotion |
| $\Delta s_2$ | = | change in sales of focal category caused by promotion |
| $\Delta s_3$ | = | change in store sales caused by promotion |
| $m_1$ | = | gross margin of item (percent of regular retail price) |
| $m_2$ | = | average effective gross margin of other items in the focal category |
| $m_3$ | = | average effective gross margin of products in other categories |
| $DEAL$ | = | deal discount on focal item (percent of regular retail price) |
| $t^*$ | = | trade deal (percent of regular *retail* price) received by the retailer if focal item is *not* promoted by the retailer |
| $t^\theta$ | = | trade deal (percent of regular *retail* price) received by the retailer if the focal item is promoted by the retailer |

The trade deal received by the retailer is a function of the trade deal offered by the manufacturer and the requirements the manufacturer imposes on the retailer. For example, the manufacturer may offer a trade deal of 20 percent (in percent of the retail price) if the retailer displays the item and offers the consumers at least a 10 percent deal. Formally, such requirements can be modeled in the following way:

$$t = \begin{cases} TROFFER \text{ if } (DEAL \geq DEALREQ) \text{ and } (DISPLAY \geq DISPREQ) \\ 0 \text{ otherwise} \end{cases} \tag{11.4}$$

where

| | | |
|---|---|---|
| *TROFFER* | = | trade deal offered on focal item (in percent of regular *retail* price) |
| *DEALREQ* | = | minimum deal required to obtain the trade deal |
| *DISPREQ* | = | indicator of display requirement to obtain the trade deal |

The strength of substitution effects, or cannibalization, were defined formally using the changes in item, category, and store sales. The intra-category cannibalization measure was defined as:

$$\Phi_{12} \cdot \Delta s_1 = \Delta s_2 \tag{11.5}$$

An intra-category cannibalization measure of zero indicates complete intra-category cannibalization, i.e., that all incremental sales of the promoted item came from other items in the same category. If the measure is unity, the promoted item does not cannibalize at all on other items in the same category, and values greater than unity indicate that sales of other items in the category also increase.

Similarly, inter-category cannibalization was defined as:

$$\Phi_{23} \cdot \Delta s_2 = \Delta s_3 \tag{11.6}$$

Similar measures were also defined to describe the relation between changes in the number of buyers of the focal item and the change in the number of buyers of the focal category, as well as the relation between the change in the number of buyers of the category and the change in store traffic.

### 11.1.4. Myopic Measures and Myopic Optimization

The promotion measurement level generally affects the numerical outcome of the profit measurement (see equation 11.3). Due to strong substitution effects within the focal category (intra-category cannibalization), the item-level profit is almost always greater than the category level promotion profit. Whether the category-level promotion profit is smaller or larger than the store-level promotion profit depends on the degree of inter-category cannibalization. If the promotion increases store traffic, it is likely that the category-level measure understate the promotion profit. In such cases, the most myopic measurement level (i.e., the item-level) may actually be closer to the store-level promotion profit.

That myopic measures of promotion profits differ from store-level promotion profits is in itself a reason to measure promotion profits at the store level. Even more important is that the promotion chosen by the profit-maximizing retailer depends on the level of measurement. Store-level deal optimization is, thus, the selection of the deal that maximizes store level promotion profits, while myopic optimization selects the deal maximizing a myopic measure of promotion profits.

Myopic optimization leads to sub-optimization when the myopic optimization leads the retailer to select another promotion than store-level optimization. The cost of the myopic optimization is then the opportunity loss incurred by using a less than optimal promotion. This cost is the difference in store-level promotion profits of the optimal deal and of the myopic deal.

## 11.2. What is New?

The main contribution of this research is the system of models for analyzing retailer profits of sales promotion. This system consists of two types of models: the sales-response models and the profit models. In relation to previous sales-response models, the model developed here can be seen as an extension and adaption of the indirect modeling approach described by Naert and Leeflang (1978) to the grocery retailer's situation. Its most important new feature is that it explicitly includes store traffic. A contribution of this research that is closely related to the sales model is the usage of receipt data for the measurement of the promotion effects. The sales-model framework is conceptually related to the DuPont model used for analyses of accounting data, in that both models decompose the measure of interest into a chain of key ratios. Changes in the measure of interest can then be analyzed in terms of changes in the key ratios.

The profit model developed here is based on the principle that the profit of an action is given by the change in profits that this action causes. This is a basic economic principle, borrowed from economic theory and operations research, that has been used by other researchers studying promotion profits. What is new here is the specification of the retailer's costs and revenues of the promotion. Also new is that the model identifies three levels (item-, category-, and store-level) at which promotion profits can be measured. The store level is the relevant profit measurement level for the retailer, while the item and category levels are regarded as myopic. The observation that the promotion profits at the store level and at the myopic levels are different is new, as is the definition of the cost of myopic promotion optimization.

The formal definition of cannibalization in retailing is a contribution of the present research. Consequently, the illustration of the impact of cannibalization on promotion profits is also new. This research also highlighted the importance of store traffic for promotion profits.

Previous studies have shown that retailer promotion can be seen as a function of trade promotion. This study extended those findings and showed that the deal size and the retailer's pass-through depends on the:

- size of trade deal
- retailer's level of optimization
- gross margins for focal item, other items, and other categories
- cannibalization and store traffic effects
- deal requirements

The pattern of the impact of these factors is fairly complex, and there is important interaction among these factors.

## 11.3. Generalizations

The model and measurement method can be generalized to other types of marketing activities undertaken by retailers. The model is most directly generalizable to frequently occurring marketing events because of the need for data. However, effects of larger changes could be evaluated *ex-post* by using statistical methods, or *ex-ante*, by using the model to calculate the profit impact of the change, given the managers' assumptions.

The model may also be generalized to other settings than grocery retailing. The model should be most relevant for situations where the customer buys a basket of products, such as for example, department stores, fast food restaurants, and banks.

The numerical values of the response functions are not supposed to be generalized. First, the sales response may differ across stores, product categories, and items. Second, the product categories and items were systematically, rather than randomly, chosen. Third, scanner data makes such generalizations unnecessary, as each retailer should use their own data to estimate the models. This should preferably be implemented as an ongoing tracking and experimentation system, re-estimating the models frequently.

## 11.4. Limitations

The research reported here has a number of limitations that should be noted. First, the model and method presented seek to increment profits rather than pursue profit maximization. If there has been little variation in the controllable variables, the model works most reliably when small changes from a reference level are considered when making predictions based on historical data. The model might not cover the global optimum when it is parameterized with historical data. Over time, the model needs to be re-estimated. The path may or may not lead to a global optimum, but the lack of a guarantee that the global optimum will be reached should not prevent us from seeking improvement.

Second, the proposed model does not consider simultaneous optimization of all products' promotions. That would be too difficult a task. The model is in any case an improvement from current pratice, which only regards sales or possibly gross margin of the promoted item. The model focuses the attention on the consequences for the store gross margin of sales promotion for one item or a group of items.

A third limitation of the model is that it is a one-period model, considering only current profits. The general model can easily be generalized to a multi-period setting, but would be rather difficult to estimate empirically. It may be that the indirect modeling approach used here would hamper such multiple-period modeling.

Fourth, it is assumed that the margins of other items in the focal category are homogeneous or that the effect on other items sales are proportional to their sales. Similarly, margins of other categories are assumed to be homogeneous or to have a sales effect on other categories which is proportional to their sales. Although these are reasonable approximations that make the model parsimonious, they constitute limitations. However, as noted in the model development, the model can be extended to accommodate groups of items with different margins or which are differently affected by the promotion, or both. Such groups may be groups of items within the focal category, or groups of other categories. An interesting way to extend the model would be to use the hierarchical attraction models developed by Foekens *et al.* (1992) in order to model sales of all items within the focal category. Their approach could also be used to model asymmetries in the inter-category cannibalization.

## 11.5. Suggestions for Further Research

In addition to the possibilities for improvements of the model that the above-identified limitations of the present research indicate, future research in the following areas would be valuable.

Future research may use the models developed here to study the promotion profits for different types of products. One typology that appears to be useful for such research was suggested by Pellegrini (1989). Pellegrini makes a distinction between type A and type B products, where type A products can have an impact on the store choice while type B products have no impact on the store choice and are simply bought in the store visited.

Such studies would also be important in order to examine whether the effects are homogeneous across categories and stores. If the effects are fairly homogeneous across some dimension, knowledge could be accumulated and generalized to other stores and other products. That would be very useful for theory development and for retail-chain management.

It would also be interesting to investigate the effects of different types of sales promotion, for example, whether the consumers meet the promotion in-store or out-of-store, and whether the promotion gives the consumers a direct incentive to buy or if it only serves to remind the consumers of the product. This may affect the sales response pattern and the profits of sales promotion.

The deterministic-response models used here could be replaced by stochastic-response models to simulate the variance of promotion profits. This may be interesting for the retailer for two reasons. First, a smaller average profit may be preferable to a large average profit when the variance of the latter is high (though the retailer may spread the risks). Second, the profit of the average response is in general different from the average profit from the stochastic response. This is because profit is not a linear function of response. Stochastic simulation of sales makes inventory costs interesting to model.

It would also be interesting to combine the models developed here with panel data. The linkages between individual and aggregate behavior could then be studied. Alternatively, the individual behavior may be simulated and the aggregate outcome of the simulated behavior could be compared with the aggregate outcome as measured with receipt data.

Future research could also adapt the model to better correspond to a chain-store perspective. That would mean better modeling of the store choice and should include cannibalization among stores.

Another way that the models developed here could be used in future research is as input in models of trade deal profits. That may lead to game-theoretic models of manufacturer and retailer behavior.

A further area for future research is the examination of other functional forms of the response models than the logit and exponential models used in this study. Research investigating alternative estimation procedures and techniques would also be of interest.

## 11.6. Managerial Implications

The most important managerial implication of the present research is that retail managers must be aware of the interdependencies among the many items in retail assortments. This means that it should be important to develop and install systems that can collect and process the relevant data.

This research showed the importance of store traffic for sales and profits. It appears that retail managers should preferably install point-of-sales systems that can collect receipt data. If receipt data is not available to the retailer, the item sales data should at least be complemented with the number of receipts produced by the scanner system. This figure would be available from most cash registers.

For tracking and marketing control purposes, it is important that store traffic is explicitly modeled. For example, the responsibility for insufficient sales of a promoted product should not fall on the given category if the reason for the low sales is that store traffic was low. The system of models developed in this report could be the base for such a tracking and control system.

A furthert implication of the present research is that there may be problems associated with the trend towards category management and the store-in-the-store management principle where the store's categories are run as profit centers and employees receive bonuses tied to category performance. Category management is based on the assumption that the sales of different product categories are independent. When this assumption does not hold, category management will be sub-optimal. If the category is important for store traffic, it is likely that the store's category managers will use less promotions than optimal for the store. On the other hand, inter-category cannibalization implies that a store run as a portfolio of category profit centers will over-use sales promotions. The proposed model should help the retailers to measure the profit impact of sales promotion, thus giving them the possibility to improve the design of promotions and a way to determine the sub-optimization cost, if any, of category management.

Measurement of the profit impact of sales promotion should also be important for retailer who has other objectives than maximizing profits from the current period's promotions. Such retailers will find the model useful for estimating the opportunity cost of the chosen promotion, and possibly for avoiding unnecessarily costly sales promotions.

Retailers who do not have access to the necessary data could use the model framework presented in this report as a decision-calculus model. The decision calculus methodology developed by Little (e.g., Little 1975b) starts with a model parameterized using judgmental data. Decision calculus provides a consistent method to calculate the implications of the assumptions managers make. The assumptions are made explicit which makes comparisons between alternative plans easier and more objective. The sensitivity to changes in assumptions and decision variables can be calculated.

Problem understanding and learning may be improved by using decision calculus models and judgment of multiple managers can be integrated. Lodish (1982) reports that the decision-support system for retailers that he developed using decision-calculus methodology led to new marketing research projects to get better estimates of the response functions. For a discussion of decision calculus and managerial judgment, see also Chakravarti, Mitchell, and Staelin (1979, 1981) and Little and Lodish (1981).

The decision-calculus usage of the promotion-profit model may be important for pre-testing sales promotions and other marketing activities that have not been used before. Since historical evidence of the sales response to such activities does not exist, scanner data would not help the retailer. Judgmental data is then the best available alternative. That may also be the situation for the manufacturers, who may not have direct access to retail-level scanner data. However, manufacturers would do better to forge alliances with retailers to gain access to retail level receipt data. Last but not least, this research shows that manufacturers should use retailer-oriented data and models to understand the needs of their immediate customers.

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