Chapter 5

Summary and Discussion

5.1 Introduction

In this thesis we focus on some critical questions in sales promotion research, as formulated in Chapter 1 (see also Table 1.5). Chapter 2 deals with the deal effect curve, Chapter 3 with pre- and postpromotion dips, and Chapter 4 integrates both aspects to obtain a decomposition of promotion effects. To study these issues, we have developed econometric models based on store-level scanner data. We describe in Table 5.1 the main characteristics of the research conducted in Chapters 2-4.

Table 5.1: Main characteristics of the research in this thesis

<table>
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<tr>
<th>Subject</th>
<th>Chapter 2</th>
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<tr>
<td>Description</td>
<td>Deal effect curve</td>
<td>Pre- and postpromotion dips</td>
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<td>Description</td>
<td>Nonlinear response of sales to price discounts</td>
<td>Estimation of dynamic promotion effects</td>
<td>Decomposing promotional spike into cross-brand effects, dynamic effects, and category expansion effects</td>
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<td>Model</td>
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<td>Distributed lead- and lag models</td>
<td>Structured semiparametric model</td>
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<td>Product categories</td>
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<td>American beverage product</td>
<td>Tissue</td>
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<td>Dutch food product</td>
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In section 5.2 we present the main conclusions from Chapters 2-4. We then discuss the managerial implications in section 5.3. We also identify some limitations of the research in this thesis which can be addressed through additional studies (section 5.4).
5.2 Summary

Deal effect curve (Chapter 2)

The marketing literature suggests several phenomena that may contribute to the shape of the relationship between sales and price discounts, defined as the deal effect curve. These phenomena can produce severe nonlinearities in the curves, and interactions with other variables. We argue that such complexities are best captured with a flexible approach. Since a fully nonparametric regression model suffers from the “curse of dimensionality,” we propose a semiparametric regression model. Store-level sales over time is modeled as a nonparametric function of own- and cross-item price discounts, and a parametric function of other predictors (all indicator variables except in one data set).

We compare the predictive validity of the semiparametric model with that of two parametric benchmark models and obtain superior performance. The results for three product categories indicate a.o. threshold- and saturation effects for both own- and cross-item temporary price cuts (nonlinear effects). We also show how the own-item deal curve depends on other items’ price discounts (flexible interaction effects). In a separate analysis, we show how the shape of the deal effect curve depends on own-item promotion signals. Our results indicate that prevailing methods for the estimation of deal effects on sales are inadequate.

Pre- and postpromotion dips (Chapter 3)

One of the mysteries of store-level scanner data modeling is the lack of a dip in sales in the week(s) following a promotion. Researchers expect to find a postpromotion dip because analyses of household scanner panel data indicate that consumers tend to accelerate their purchases in response to a promotion – that is, they buy earlier and/or purchase larger quantities than they would in the absence of a promotion. Thus, one should also find a pronounced dip in store-level sales in the week(s) following a promotion. However, researchers find such dips usually neither at the category nor at the brand level.

Several arguments have been proposed for the lack of a postpromotion dip in store-level sales data. These arguments explain why dips may be hidden. Given that dips are difficult to detect by traditional models (and by a visual inspection of the data), we propose models that can account for a multitude of factors which together cause complex pre- and postpromotion dips.

We use three alternative distributed lead- and lag structures: an Almon model, an Unrestricted dynamic effects model, and an Exponential decay
model. In each model, we include four types of price discounts: without any support, with display-only support, with feature-only support, and with feature and display support. The models are calibrated on store-level scanner data for two product categories: tuna and toilet tissue. We estimate the dip to be between 4 and 25 percent of the current sales effect, which is consistent with household-level studies. Overall, the Unrestricted model is the closest to the “best model” results. It is also the model that is easiest to implement.

Decomposition of promotion effects (Chapter 4)

Sales promotions play an important role in the marketing mix of European and American firms. A critical condition for the determination of the profitability of promotions is that a model of sales incorporates the sources of sales increases. This is because these sources differ in attractiveness to the manufacturer and retailer. We propose a classification of the different sources of unit sales effects of sales promotions. Based on this framework we develop an extended econometric model calibrated on store-level scanner data. The model allows for a decomposition of the unit sales effect of a sales promotion into cross-brand effects, dynamic (lead and lag) effects, and category expansion effects. We model the relative contributions of these sources as a function of the size of the price discount offered and the type of promotion support (feature and/or display or neither). Our results indicate that it is important to allow for these dependencies. We use the model results to compute the net (incremental) unit sales effect of promotions for manufacturers and retailers. The incremental amounts can be used by managers to implement effective and profitable promotions.

5.3 Managerial implications from this thesis

For managers, the results in this thesis are useful at a conceptual- and at an operational level. At a conceptual level, we provide arguments throughout this thesis that help managers to consider the effects of sales promotions more completely. These arguments include:

- There may be threshold levels in the deal effect curve, causing price promotions to affect sales only beyond some price discount percent (Chapter 2);
• There may be saturation levels in the deal effect curve, causing price promotions to yield no additional sales beyond some price discount percent (Chapter 2);
• The shape of the deal effect curve may depend on the price discount percent offered simultaneously by the retailer for other brands (Chapter 2);
• The response of own-brand sales to price discounts may depend on the type of support offered (feature and/or display or neither) (Chapter 2);
• Although typical sales graphs based on store-level scanner data do not show postpromotion dips (which would reflect stockpiling by households), such dips do exist, as indicated in studies of household data. We discuss reasons why these dips are often hidden in store data (Chapter 3);
• Consumers may adjust their purchase behavior based on the timing and frequency of past promotions, and this causes prepromotion dips (Chapter 3);
• There are substantive advantages to allow the effects of discounts to depend on the (four) different support types we distinguish over the use of traditional variables: prices, feature-only dummies, display-only dummies, and feature-and-display dummies (Chapters 3 and 4);
• The size of the dynamic effect of price promotions may depend on type of support offered (feature and/or display or neither) (Chapter 3);
• Although sales promotions often have large sales effects, the net promotion effects can only be obtained from a decomposition of the sales effects (Chapter 4);
• The amount of price promotion effects attributable to the different sources included in decompositions may depend on: (1) consumer characteristics, (2) category characteristics, (3) brand characteristics, (4) the level of price discount, and (5) the type of support offered (Chapter 4).

At an operational level, managers can use our models to develop more profitable promotion strategies. Since model (4.1) incorporates all relevant factors for a full evaluation of the short-term effects of promotions, it is a good starting point for “what-if” analyses. Once the model is calibrated, managers may use it to estimate sales effects for a price promotion consisting of a specific price discount percent and a specific type of support. The model provides the decomposition of the own-brand sales effect into cross-brand
sales effects, dynamic effects, and category expansion effects. The short-term gain in units from this promotion for the manufacturer is then equal to the sum of the category expansion effect and the absolute cross-brand effect. For the retailer the gain in units equals the category expansion effect. To derive profit implications, the manager needs: (1) the margins of the brand (item) in promotional periods and non-promotional periods, (2) the margins of the other brands (items), (3) the costs of feature advertising and/or displays. With the model results and cost data, the profit for the manufacturer can be computed as follows:

1. Current period profit: the own-brand unit sales under promotion times the margin earned in the promotion period minus the regular unit sales times the regular margin;

2. Pre- and postpromotion period profit: the dynamic effects times the regular margin period (these are expected to be negative);

3. The cost of feature advertising and/or displays.

The profit for the retailer equals the profit for the promoted brand plus the (generally negative) cross-brand effects times the margin earned on these other brands. Based on profit comparisons of various alternative sales promotion designs, the manufacturer and retailer can determine the most attractive design for both parties. Thus, the models developed in this thesis can provide a basis for the development of “effective promotions”, as called for in the Efficient Consumer Response initiative (see Chapter 1).

We can expand this profit calculation as follows. Many retailers engage in forward buying behavior due to promotions, i.e., they buy more than they need for the promotion week since they want to take full advantage of decreased purchase costs. If we apply models, such as the ones developed in Chapter 3, to ex-factory data (i.e, the shipment of goods from manufacturers to retailers), we can measure the amount of forward-bought units. We can then multiply these units by the loss in margin for the manufacturer to obtain the loss in profit due to forward buying by retailers. The profit for the manufacturer is then decreased with this loss whereas the profit for retailers is increased with it.

It is possible to expand this exercise further. Since the sales spike caused by sales promotions may involve additional logistic-, holding- and production costs, we should subtract these costs from the profit derived above to the extent that one or both parties bear some of these costs. To accomplish this, both
parties should apply activity-based costing, which allows them to assign costs to specific activities. We might then find that sales promotions are usually not profitable for manufacturers or retailers in the short run (i.e., within a few weeks). However this situation has to be compared with one in which the manufacturer (or retailer) is the only one discontinuing sales promotions. For example, if there exists a large group of consumers who purchase whichever brand is promoted, then this group would be lost to competing brands. This could result in loss of shelf space for the manufacturer and loss of interest in the retailer’s goods, in the long run.

5.4 Limitations and future research

There are several issues within sales promotion effect research that we do not address in this thesis. The following issues deserve attention:

- Long-term effects;
- Endogeneity issues;
- Cross-category effects;
- Store switching effects;
- Promotional price elasticities versus regular price elasticities;
- Price image effects;
- Differences in effects between stores;
- Forecasting of effects.

We elaborate on these issues below.

**Long-term effects of sales promotions**

This thesis focuses on the short-term effects of sales promotions. We assume that all household-level responses that are represented in the promotional sales spike (see also Table 4.1), do not have long term effects. For example, we only consider the possibility of a temporary brand switch due to a promotion, and do not investigate the possibility of a permanent brand switch. A much debated issue in the promotional literature, and one on which the “jury is still out”, is what the long-term effects of promotions are. The long-run effects ultimately determine the profitability of sales promotions. Advocates of (television) advertising (e.g., advertising agencies) often argue that promotions are detrimental to the long-term health of brands. Mela, Gupta, and Lehmann (1997) find that sales promotions do have a (small) negative effect on brand
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equity. On the other hand, Dekimpe, Hanssens, and Silva-Risso (1999) find that the category- and brand sales are generally not affected in the long run by price promotions.

Endogeneity issues

We implicitly assume that all promotion variables are random events. Hence the predictors, including prices, are taken to be exogenous (Wansbeek and Wedel 1999). One can imagine that this is not the case in practice. Sales promotions tend to be the result of joint planning by manufacturers and retailers. Managers can observe sales promotion effects from historical data and attempt to optimize sales promotions in terms of the depth of price discount, type of support, and timing. Hence the distribution of sales promotion activities across stores and over time may be nonrandom. If this is the case, then the disturbance term in the model and the predictor variables are correlated (Wansbeek 1996, pp. 39-42). This means that the promotion variables are endogenous, and it leads to inconsistent estimators of promotion effects. However, our models do not suffer from this endogeneity problem, because they include both store- and weekly indicator variables. In econometric terms, we use a Fixed Effects estimator which is consistent, even if the promotion characteristics are correlated with errors (Wansbeek 1996, p. 40). The application of Random Effects estimation in this case, however, would lead to inconsistent estimators.

Nevertheless, there are potential endogeneity issues in models of sales promotion effects that do not belong to the class of Fixed Effects estimators. Potential endogeneity stems from either (1) correlation between store-specific promotion activities and store characteristics, and/or (2) correlation between time-specific promotion activities and time characteristics. The former case occurs if retailers optimize their activities at the store level based on consumer- and competitor (other retailer) characteristics (Foekens, Leeflang, and Wittink 1999). The latter case occurs if manufacturers and/or retailers optimize the timing of promotion activities based on, e.g., seasonal effects.

We believe, however, that both types of optimization strategies are relatively unlikely to occur in practice. For example, we argue in Chapter 1 that there are very few managers who evaluate sales promotion effects. And, as we discuss in this chapter, the determination of profit from sales promotions is a nontrivial task. It is therefore quite unlikely that optimizing behavior, even in its most rudimentary form, actually takes place. The distribution of promotion activities across stores and over time in our data sets seems to confirm this
assumption. Since these stores typically belong to one chain (one exception: tissue data set), they tend to offer the same sales promotion in a given week, and there is little or no opportunity for stores to differ in promotion policies. And, although the distribution of discounts is not uniform across all possible levels, all possible discount sizes tend to occur with some positive frequency. Importantly, the timing of promotions seems to be random in our data sets. This is consistent with economic theories (Varian 1980, Narasimhan 1988, see also section 1.2). If the timing of promotions were systematic, all consumers would be able to predict their occurrences, and this would prevent managers, for example, from having informed households pay less than uninformed households.

Two studies have addressed endogeneity issues in a discrete choice framework, i.e., using household-level panel data. Besanko, Gupta, and Jain (1998) assume that the prices are the equilibrium outcomes of Nash competition among manufacturers and retailers and they also estimate the equilibrium pricing equations. Villas-Boas and Winer (1998) use instrumental variables to account for the endogeneity problem. Both studies find that the estimate of the price response parameter is generally biased to zero when the endogeneity of prices is ignored.

These two studies address endogeneity in regular prices and not in promotional prices. Therefore, it would be useful to study the endogeneity effect in models of sales promotion effects. Specifically, it would be interesting to test models that do not belong to the class of Fixed Effects estimators (our models do). If there is little or no endogeneity, we can use Random Effects estimation which is known to be more efficient than Fixed Effects estimation. Wansbeek (1996, pp. 42-52) proposes tests for endogeneity and also proposes a solution for panel data. It will be beneficial for future research to study this issue, because as our understanding of promotion effects grows, and the allocation of expenditures to stores and weeks improves, Random Effects models in particular may generate very different and better results, if endogeneity is accommodated.

Cross-category effects of sales promotions

This thesis focuses on sales promotion effects within product categories, and it excludes cross-category effects. Although there are some studies that deal
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with cross-category effects of promotions (Walters 1991), these effects have only recently obtained more attention. For example, Chintagunta and Haldar (1998) find, based on household data, that a price cut in one category increases the purchase probabilities of another, for both pasta and pasta sauce (hence we have complementary effects). Bell and Bucklin (1998) show how marketing variables influence the timing of product category purchases:

*Store switching effects of promotions*

This thesis focuses on within-store effects of sales promotions. A key unanswered question is whether deals bring in customers who generate incremental store sales. And: in what categories? Are these customers profitable to the retailers, given their acquisition cost? Some older studies found some cross-store effects: Kumar and Leone (1988) for disposable diapers and Walters (1991) for cake mix, spaghetti, and spaghetti sauce. But we need more detailed research to assess how promotions affect store choice.

*Price image effects of sales promotions*

This thesis does not address the effect of sales promotions on the way consumers perceive the price image of retailers. Along with store switching effects, this is one of the important questions retailers face regarding promotions (Blattberg, Briesch, and Fox 1995). Do promotions affect the price image of a retailer? How? Is an EDLP (everyday low price) strategy superior to a promotional strategy in creating or changing a price image? Which pricing strategy is better for attracting customers? Hoch, Drèze, and Purk (1994) conclude from a large-scale experiment that a Hi-Lo strategy (i.e., having high (Hi) regular prices and low (Lo) promotional prices) is 30 percent more profitable than a EDLP strategy. However, their computations do not include all cost components of sales promotions.

*Promotional price elasticities versus regular price elasticities*

We estimate only promotional price elasticities in this thesis. Although it is theoretically possible to include regular price effects in the models, it is difficult to do in practice because regular prices tend to be highly collinear with other predictors (see also footnote 6 in Chapter 2). How these two elasticities compare is still unknown. This is an important issue that yields

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2. Several presentations on this topic were held at the Marketing Science Conferences at Insead in 1998 and at Syracuse University in 1999.
no conclusive results in the literature either. Some argue that the price
discount component of promotions works exactly as any price reduction
(price elasticities are equal to promotional elasticities). Others argue that the
temporary nature of promotional price reductions results in a higher sales
spike because the consumer forward buys, purchase accelerates, and increases
category consumption in some situations. This suggests that the promotional
price elasticity net of stockpiling etc. may be close to the regular price
elasticity. Still others argue there is a “transaction” utility to promotions that
does not exist with regular price reductions, and therefore promotions increase
sales more than regular price changes do.

**Differences in promotion effects between stores**

This thesis assumes equal promotion effects in a proportional sense for all
stores. A potentially rewarding research area is to exploit local conditions
for the development of promotional strategies for individual stores. In other
words, we could apply micro-marketing to sales promotions, if local conditions
cause promotional price elasticities to differ widely between stores. We can
imagine three classes of local-condition variables: in-store variables, customer
characteristics, and variables measuring the competition. One example of an
in-store variable that may influence elasticities is shelf space allocation. A
relatively larger shelf space for a brand may make its price elasticity more
negative, since the brand is more apparent to customers. An example of
a customer characteristic is the average number of young children of the
store’s customers, which may affect price elasticities for some food products.
There exists a large body of literature about the characteristics of “deal-prone
consumers”, including Montgomery (1971), Blattberg et al. (1978), Bawa and
Shoemaker (1987), and Bawa, Srinivasan, and Srivastava (1997).\(^3\) Finally, a
competitive variable is the presence of an aggressive price discounter, which
may reduce within-store elasticities.

Several store-level studies have related store-specific price elasticities to
various exogenous variables. Both Bolton (1989) and Hoch et al. (1995)
first estimate these elasticities and next use them as criterion variables in
a second-stage regression model. Montgomery (1997) uses a simultaneous
approach for estimating and explaining elasticities. These studies, however,
lack a theoretical foundation. Kalyanam and Putler (1997) do offer a

\(^3\) Deal-prone consumers are not equivalent to deal-to-deal consumers. Whereas deal-prone
consumers purchase both in promotion- and in nonpromotion weeks, deal-to-deal consumers
purchase only in promotion weeks.
5.4. Limitations and future research

A theory-based model for elasticity differences between stores based on household data. There is an opportunity, however, to construct models from household-level theories which are calibrated with store-level data. We are currently developing such models, to be estimated on a combination of store-level scanner data, household-level survey data, and in-store data.

**Forecasting the effects of promotions**

We mainly focus on descriptive models for sales promotion effects. Although we present a predictive validation exercise in Chapter 2, the emphasis in this thesis lies on the evaluation of past sales promotions based on relevant considerations. To further substantiate the usability of our models for the “what-if” scenarios we mention in section 5.3, we need a thorough understanding of the predictive capabilities. In this respect it is not only important to provide average predictive validation results, but also details about when and why a model predicts well versus not. An illustration of this idea is provided in the differences in forecast accuracy for own-brand price-cut observations and for other observations in Chapter 2. One can obtain more precise information on the predictive performance through the use of models that explain (differences in) forecast errors with descriptive statistics for the data. We can use such a “diagnostic validation approach” for an assessment of what conditions lead to more precise forecasts. Knowing this can provide a basis for future model building. We believe that the marketing literature lacks a full appreciation of the benefit of more detailed predictive validation exercises.