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Efficiency Maximization of Retail Campaigns

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ABSTRACT OF THE
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Promotion campaigns are important in the retail business for introducing new products, increasing sales or conducting markdowns. The tradeoff with campaigns lies between increasing demand and maintaining profitable margins. The campaign "investment" needs to be profitable in the long run so that the increased sales outweigh the reduced margin.

In this thesis, the current body of knowledge regarding retail promotion planning and analysis is examined and a log-linear model for estimating the promotional sales based on pricing and use of promotional vehicles is built. The model is applied on sales data from a European grocery chain. The model is mainly based on the SCAN*PRO model developed by Wittink et al. in 1987, but is improved and modified to better fit the analyzed sales data. The model accounts for seasonal effects and dynamic demand effects and is suggested to be used as a decision support tool for promotion planning.

For products with detailed and diversified sales data the model predictions are fairly accurate and can after verification be used, for example, for profit optimization purposes on a product level. The estimated price and promotional vehicle usage elasticities can be used as measures for how effective the products are as promotional products and aid in choosing suitable products for promotion.

Keywords: Promotion, campaign, retail, sales prediction, price optimization, price elasticity

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KANDIDATARBETETS ABSTRAKT

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Försäljningskampanjer spelar en viktig roll i återförsäljningsbranchen då man önskar introducera nya produkter på marknaden, öka på försäljningen eller avyttra produkter. I kampanjplaneringen måste en kompromiss göras mellan att öka efterfrågan och uppehålla lönsamma marginaler. ”Kampanjinvesteringen” bör i det långa loppet vara lönsam så att den ökade försäljningen uppväger de mindre marginalerna.

I denna avhandling undersöks den nuvarande kunskapen gällande planering och analys av promotioner och en log-linjär modell byggs för att estimera kampanjförsäljning på basen av prissättning och användning av marknadsföring. Modellen appliceras på försäljningsdata från en europeisk livsmedelsåterförsäljningskedja. Modellen baserar sig huvudsakligen på den s.k. SCAN*PRO modellen utvecklad av Wittink et al. år 1987, men har vidareutvecklats för att bättre passa den analyserade försäljningsdatan. Modellen beaktar säsongseffekter och dynamiska försäljningseffekter och föreslås kunna användas som ett beslutshjälpverktyg vid planering av kampanjer.

Modellen klarar tämligen väl av att uppskatta kampanjförsäljningen för produkter med detaljrik och varierande försäljningsdata och estimaten kan efter kontroll utnyttjas till exempel i vinstoptimeringssyfte på produktnivå. De estimerade pris- och marknadsföringselasticiteterna kan användas som mått på hur effektiva produkterna är som kampanjprodukter och fungera som hjälpmedel för att välja ut lämpliga kampanjprodukter.

Nyckelord: Promotion, kampanj, försäljning, försäljningsuppskattning, prisoptimering, priselasticitet

Preface

The empirical part of this work was carried out as a part of a project for a client to the consultancy company BearingPoint Finland Oy.

I would like to express my gratitude to my instructor Lauri Kovanen for providing me with an interesting subject and for showing tremendous patience. Additionally I would like to thank prof. Ahti Salo for supervising this thesis. A special thanks goes out to Juhana Rintala for employing me. I also do not want to forget to thank the rest of the team at BearingPoint for providing me with insights and ideas and for showing great team spirit.

Helsinki, 26.9.2011

Jonas Strahl

Contents

1 Introduction

The barcode scanner became affordable and common equipment in grocery stores in the middle of the 1970s, making it easy to register detailed sales data [1]. Since the beginning of the 1980s this data has been utilized to build econometric models of demand and to analyze price response and marketing response effects. Although the research area nowadays is quite mature with hundreds of research papers on theoretical models, quantitative research and qualitative studies, there are still unanswered questions regarding optimal pricing and marketing strategies.

The first objective of this thesis is to analyze a common strategy to boost sales in retailing, that is, promotions. This is done by reviewing the current literature on the topic. The second and main objective is to develop a methodology for making informed and efficient promotion decisions in terms of pricing and product choice, based on sales data. The sales data analyzed in the empirical part of this thesis is provided by a European grocery chain that uses a pricing strategy known in the business as “High-Low”. It is a strategy where products are sold to a higher baseline price, but periodically they are discounted to attract customers and to stimulate sales (in contrast to the also popular “Every Day Low Price” strategy).

The main research question that I try to answer is the following: How should promotion products be priced in order to maximize the promotional impact in terms of short term profit? By modeling the demand of promotional products as a function of the promotional price and the use of promotional vehicles we can predict the promotional demand. This enables us to to calculate a theoretical profit optimizing price when knowing the wholesale cost of the product. As a byproduct of the model, we get a powerful tool for choosing promotional products. The price and promotional vehicle usage elasticities that are estimated for each promoted product can be used as measures for how effective the product is as a promotional product.

To view the promotional pricing as an isolated decision that only affects the profitability of the promoted product in the short-term is a major simplification. There are interaction effects between products making the net profit impact hard to estimate and there are also long-term implications of promotions. Choosing a profit optimizing price may be optimal profit-wise at the product level in the short term, but by completely ignoring the effects promotions may have on the price image of the grocery chain, one can in the worst case ruin the price image, leading to loss of loyal customers to competitors. Additionally there are factors affecting the sales that cannot be modeled reliably. For example, the impact of a new kind of marketing effort cannot be known beforehand and the effect of competitor promotional activities cannot usually be modeled due to lack of data. However, even when ignoring these other effects and looking at pricing as an isolated decision we get valuable insight into planning and evaluating sales promotions.

Although grocery stores mainly focus on retailing of food and therefore do not perfectly represent the whole retailing business, the main principles behind promotions and the price-demand dynamics involved are basically the same or very similar to the rest of the retailing business. The general methodology is thus applicable also to other areas of retailing.

The thesis is structured as follows. Section 2 provides a theoretical background to the topic by giving a short introduction to the retailing industry, defining a sales promotion, discussing the short-term and long-term effects promotions have and finally elaborating on issues and questions raised when modeling promotional response and how they have been solved and answered in the literature. Section 3 presents the research methodology, giving a background to the real-world case behind the thesis and its underlying data, the tools and methods used and the modeling approach. Section 4 presents the results through two product examples followed by a discussion. Section 5 finally concludes the findings of the thesis.

2 Theoretical background

2.1 The retailing industry

Retailing is defined by Merriam-Webster dictionary as “the activities in the selling of goods to ultimate consumers for personal or household consumption”. The retailing industry consists of all the businesses involved in retailing. Retailers can be categorized by their gross margin percent and rate of inventory turnover. There are low-margin/high-turnover retailers, high-margin/low-turnover retailers and even some successful high-margin/high-turnover retailers. Retailers with a low margin and a low rate of inventory turnover will not generate profits needed to remain competitive and survive. [4]

Regardless of the product categories sold all retailers try to differentiate from the competition when choosing their strategies. The retailing strategies differ mainly in terms of choice of assortment breadth and depth, pricing of products, geographical penetration and aim of demographic segments. Common retailer types are department stores, discounters and specialty stores. The department stores compete with assortment, by offering a very wide assortment of goods and services. The discounters compete primarily with price. Specialty stores specialize in a specific product category and may also focus on a particular customer segment. All strategies have their own advantages and disadvantages - some work better during times of economic growth and some work better in tough times. [4]

2.2 Definition of a sales promotion

A sales promotion consists of a collection of incentive tools designed to stimulate quicker or greater purchase of particular products or services by consumers or the trade [15]. Manufacturers use them to increase sales to retailers (trade promotions) and to consumers (consumer promotions). Retailers use them to increase sales to consumers (retail promotions).

This thesis focuses on retailer promotions aimed at final customers. Many retailer promotions are, however, closely coordinated with the manufacturer and are often partially or fully paid by the manufacturer. [6, 16, 21]

A distinction can be made between price and non-price promotions. The most frequently used form of price promotion is a temporary price reduction. But other forms of price promotions are also possible, such as volume discounts (e.g. "buy three, get one free" or "two for the price of one"), loyalty discounts, coupons and packages with extra content (e.g. "20 % extra"). [16]

Non-price promotions can be divided into "supportive" non-price promotions and "true" non-price promotions. "Supportive" non-price promotions are communication instruments used to inform the customer about a product and are very often used in combination with a price promotion to draw attention to the price. For example, products can be displayed in the store and have a larger price sign or be featured in an advertising leaflet. "True" non-price promotions emphasize the brand of a product or the store and not the price cut. Samplings, tastings and contests are promotion instruments in this category. These promotional events are mostly driven by manufacturers and seldom arranged by retailers on their own. [16]

2.3 Promotional effects

The main short term goal with a sales promotion is to increase sales and profit. Sales increase does not necessarily increase profits. If the margin becomes too small no promotion can stimulate enough sales to offset the small margin. In addition to this fact the promotional profit also depends much on where the sales bump comes from. Is the promotion inducing consumers to switch from competitor stores or is the sales bump just a result of changed purchase timing and product switching? What happens in the long term - are customers becoming more price sensitive due to promotions and less loyal? Or can promotions actually make customers more loyal? Questions like these are important to ask and investigate when trying to estimate the net impact of promotions on profitability.

We can distinguish between short-term effects occurring during the promotion and long-term effects taking place after the promotion. In the following the known short-term effects and the long-term effects of promotions are presented. Some of them have been studied and quantified in detail, others are less clear. See Table 1 for a summary of the effects.

Table 1: *Summary of promotional effects.*

Short-term effects	Long-term effects

• Store switching
• Product switching
  – Brand switching
  – Category switching
• Purchase timing
  – Stock-piling
  – Anticipatory responses
• Increased consumption
• New users
	• Store loyalty
	• Product loyalty
	  – Brand loyalty
	  – Category loyalty

2.3.1 Short-term effects

One of the most desirable promotional effects is to attract customers from competitor stores to buy at least the promoted item and hopefully also the rest of their shopping basket - an effect known as store switching. Store switching increases the market share of the promoting store and always has a positive effect on the profit as long as the promoted items are sold with a positive net margin. The store switching effect has not been studied much, but there is one study from 2004 where the authors show that for peanut butter 34 % of the sales bump came from store switching and for tissues respectively 25 % came from store switching [11].

If the incremental sales originate from current customers switching brand or product we talk about brand switching or product switching and if customers are switching product category we talk about category switching (e.g. customer planning to buy meat but instead buying fish due to a promotion). If customers switch from lower margin products to higher margin products the effect on profit is positive and vice versa if customers switch from higher margin products to lower margin products. Several researchers have studied the magnitude of the switching effects and it was for a long time thought that the majority of the promotional sales volume (about 75 %) came from brand and product switching effects. In a paper by van Heerde, Gupta and Wittink (2003) however it is shown that the commonly used methodology of decomposing the sales promotion bump has often been misinterpreted and that the switching effects account only for 33 % of the incremental sales on average [8].

Promotions can also affect the purchase timing of customers. Customers can either decide to postpone their purchases if they are able to anticipate a coming promotion or they can buy in advance in relation to their original purchase plan. Both effects will enlarge the sales bump during the promotion by moving sales away from preceding and subsequent periods. If the customers stock up by buying large amounts in advance to make the most out of a good deal we talk about the stock-piling effect. The effect on profit is positive if the margin is higher during the promotion compared to the preceding and subsequent periods, and vice versa, if the margin is lower (since sales are just moved in time and not increased in a cumulative manner). The study by van Heerde et al. from 2003 shows that on average about a third of the incremental promotion sales is due to cross period effects.

The cumulative customer purchase quantity can also be affected by a promotion. The promotion can stimulate customers to increase their consumption rate of the promoted product, in which case the profit is always positively affected.

Finally, a promotion can encourage customers to try the product on promotion. Apart from the brand and product switching, there can be new users of the category and the product. In this case the total consumption may increase, which would increase the profits.

2.3.2 Long-term effects

The long-term effects of promotions are generally harder to evaluate than the short-term effects, because the dynamics tends to be much more complex.

The research results on long-term effects are partially conflicting. What is considered almost certain is that very frequent price promotion of a brand decreases the consumers' reference price of the brand, which means that the premium that can be charged for the brand is reduced [2]. A common thought is also that price promotions might decrease the brand image in terms of quality perception and make customers more price sensitive, which would result in deal hunting behavior and reduced brand loyalty [3, 16]. On the other hand, consumers tend to show some inertia in their purchase behavior. Since price promotions encourage consumers to try the product, it is probable that at least some customers will repurchase it after the promotion and the net effect on the market share of the promoted brand would hence be positive. This is confirmed in a study by Ailawadi, Lehmann and Neslin (2001) [16].

The long-term effects of promotions on store loyalty have not been studied much. An important question is whether promotions result in self selection of customers favoring a "High-Low" promotional strategy or whether the promotions actually erode the loyalty of consumers. There is some evidence that consumers who purchase less frequently but more at a time tend to favor stores running an everyday low price strategy and that consumers who purchase more frequently but less at a time favor stores running good promotions, indicating self-selection. The perception of a store's promotions has been found to have a positive correlation with perceived value and store loyalty (Sirohi, McLaughlin and Wittink, 1998). [16]

Finally, an important question regarding long-term effects of promotions is to what extent they affect the overall price image of the store. In non-competitive markets and during economic growth, the price image is necessarily not critical for customer loyalty although important, but in highly competitive markets and during economic downturns a favorable price image is critical for customer loyalty and for keeping market share. Price promotions intuitively affect the price image by communicating price information, but the debate is open whether everyday low price strategies are better at attracting customers than “High-Low” strategies [17].

2.4 Modeling promotional response

The fist step in modeling the promotional response is to evaluate which variables influence sales. The second step is then to decide on a suitable functional form for the model. The goal is to find the relationship between the variables that best explain the variations in the data - in this case the sales variation.

In ideal settings, all possible variables that could explain the variation would be readily available and the quality of the data would be high. This is often not the case. First there is relevant data that is hard or even impossible to get, such as sales and pricing data of competitors. Second there may be relevant variables that we are unaware of. Third, the quality of the data might be low, for example because of missing observations or erroneous data. All these factors make the search for an ideal model much harder and compromises and simplifications in the modeling step must often be made to accommodate for incomplete data.

In Section 2.4.1 I will discuss the advantages and disadvantages of different levels of aggregation of the data. In Section 2.4.2 I will discuss variables that have been found to explain the variation in sales reasonably. Section 2.4.3 covers different functional forms of the model that have been used in the literature. Section 2.4.4 finally presents the influential SCAN*PRO model that the model developed in this thesis mainly is based on.

2.4.1 Choice of aggregation level

We first need to decide whether we want to analyze household-level data, store-level data or higher aggregated data. Household-level data is a term used for describing time-series of the purchases of a product that the individual consumers make, whereas store-level data means time-series of the aggregated sales of a product in a store, i.e. aggregated household-level data. We can also aggregate further into chain-level data where the sales of of a product in all stores of a retailer chain are added together. Finally, we can also analyze market-level data where the sales of a product is aggregated over the whole market, but this kind of data is usually of more interest to manufacturers than to retailers (since manufacturers generally want to know how their product perform in the market and retailers want to know a product perform in their store).

The advantage of household-level data is that one can obtain insights into the underlying consumer responses such as purchase frequency, choice and quantity [11]. The disadvantages are that household-level data is not necessarily representative of all customers and it is hard to get because it is usually acquired by giving volunteers barcode scanning equipment for registering purchases at home or by registering purchases in stores with loyalty cards. Store-level data on the other hand is usually easily available, offers better coverage than household-level data and is computationally easier to handle [11]. For most practical decision support applications in pricing and marketing, store-level data offers adequate resolution. If pricing and marketing decisions are made on chain level we can equally well use chain-level data, since the whole chain can then be treated as one store (given we do not want to analyze the impact of possible demographic differences). This thesis focuses on analyzing store-level and chain-level data and does not discuss modeling with household-level data.

The second data choice decision to be made is the suitable level of temporal aggregation. The decision should be made based on what effects we are interested in measuring. If we are interested in estimating daily effects such as day-of-the-week variations we have to analyze daily sales data (see e.g. Kondo et al. (2000) for an application of day-of-the-week effect estimation using a state space model) [14]. If we do not care about the day-of-the-week variations, the next natural aggregation level is to use weekly data. Pricing and marketing decisions are often made on a weekly basis, so this temporal aggregation level is suitable for most applications. We can also aggregate for example into monthly, quarterly or annual data, but the trade-off is often model exactness since information is lost. Weekly data is the most used temporal aggregation level in the literature, due to the reasons mentioned above.

2.4.2 Choice of explanatory variables

Explanatory variables should selected based on what promotional effects we want to analyze together with the restriction of what variables are available. The minimum requirement for an analysis of price elasticities is two variables, price and unit sales. In a promotion response model we may also want to estimate the effects of marketing effort, such as product featuring and usage of in-store displays for promoted products. In addition to variables of direct interest we might also have to account for other effects, such as seasonal variation in sales and macroeconomic trends, in order to get consistent and reliable price elasticity estimates.

As previously discussed in the section about promotion effects a large share of the promotional sales bump may be attributed to product switching rather than to incremental sales or changed purchase timing. If we want to isolate the cannibalization effect from other incremental effects we need to include pricing and promotion variables of competing products in the model. We can then estimate cross-price elasticities, that is, the effect the prices of competing products have on the sales of the analyzed product. To account for purchase timing effects such as stock-piling propensity we need to include lagged sales or price variables in the model. To estimate possible anticipatory responses we can on the other hand include future sales or price variables.

When adding variables to the model we need to ensure that the data exhibits enough variation. It is impossible to get a price elasticity estimate if the price has been constant during the whole observation interval, and the estimate will not be reliable for a very small variation. Variables may also be linearly related to each other so that it is hard to separate the effects the variables have from each other. This is often a problem with variables describing usage of promotion support since promotion support such as features and displays are often used together [22].

2.4.3 Choice of functional form

We can divide the models that have been used in the literature into three different classes: parametric models, semi-parametric models and non-parametric models.

The majority of the earlier studies have implemented parametric regression models which relate sales to price and promotional instruments [6]. Models with a linear relationship between sales and price have been used as well as semilog functional forms and log-log models. The log-log functional form is currently probably the most commonly used functional form in the retailing industry. This is due to a very popular model known as the SCAN*PRO model that Wittink et al. (1987) formulated for the marketing research company ACNielsen for commercial purposes [10, 22].

Semi-parametric and non-parametric model formulations have lately become more popular. For example, Kalyanam et al. (1998) use a spline regression approach for estimating promotional price effects and van Heerde (1999) proposes a semiparametric model based on the Kernel method [6, 12]. Steiner et al. (2005) continue on this work and suggest a semiparametric model based on penalized B-splines [20]. Semi-parametric and non-parametric models allow for a far more flexible fit of observed data than standard parametric models, since the data is allowed to determine the shape of the fitted curve. On the other hand they require more data points than parametric models for a good fit, since the risk of fitting noise is high. Semiparametric and non-parametric models are also technically harder to estimate than standard parametric regression models. It is also questionable if the detail that semiparametric and non-parametric models possibly add to the deal effect curve would have any impact on managerial pricing and promotion decisions. These are the main reasons why they have not yet won much popularity in the industry and are mainly still only of academic interest [19]. Because this thesis deals with a practical industrial application of price elasticity estimation, the focus is parametric modeling approaches.

2.4.4 The SCAN*PRO model and modifications of it

One of the most influential and used models is the SCAN*PRO model (as mentioned earlier) with over tree thousand commercial applications worldwide [10]. The model can be written in its structural form as follows [5, 10]:

$$Q_{kjt} = \left[\prod_{r=1}^{brands} \left\{ \left(\frac{P_{krt}}{\widetilde{P}_{kr}} \right)^{\beta_{rj}} \prod_{l=1}^{3} \gamma_{lrj}^{D_{lkrt}} \right\} \right] \left[\prod_{t=1}^{51\ weeks} \delta_{jt}^{X_t} \right] \left[\prod_{k=1}^{stores} \lambda_{kj}^{Z_k} \right] e^{u_{kjt}} \tag{1}$$

where

Q_{kjt} = unit sales for brand j in store k, week t

P_{krt} unit price for brand r in store k, week t

$\widetilde{P}_{kr}$ = median regular unit price (in non-promoted weeks) for brand r in store k

D_{1krt} = an indicator variable for feature only: 1 if brand r is featured (but not displayed) by store k in week t, else 0

D_{2krt} = an indicator variable for display only: 1 if brand r is displayed (but not featured) by store k in week t, else 0

D_{3krt} = an indicator variable for simultaneous use of feature and display: 1 if brand r is featured and displayed by store k in week t, else 0

X_t = an indicator variable (proxy for missing variables and seasonal effects): 1 if the observation is from week t, else 0

Z_k = an indicator variable for store k: 1 if observation is from store k, else 0

β_{rj} = the own price elasticity if r=j and cross price elasticity if $r \neq j$

γ_{lrj} = the own promotion vehicle multiplier if r=j and cross promotion vehicle multiplier if $r \neq j$ (l=1: feature, l=2: display, l=3: feature & display)

δ_{jt} = the seasonal multiplier for week t, brand j

λ_{kj} = the store intercept for store k, brand j

u_{kjt} = a disturbance term for brand j in store k, week t

The model is linearized by taking the natural logarithm of both sides whereafter it can be estimated using ordinary least squares. Since the model is multiplicative the β_{rj}:s can be directly interpreted as constant own price and cross price elasticities. Models like these are thus also known as constant elasticity models [5].

The basic SCAN*PRO model has been a starting point for many subsequent enhancements [10]. Van Heerde et al. (2000) include lagged and leading price variables to account for dynamic demand effects [9]. A flexible SCAN*PRO model having a non-parametrical functional part for the discount effect has also been developed by van Heerde [6]. These model modifications have subsequently been combined by van Heerde et al. (2004) to a model both accounting for dynamical effects and using unconstrained estimation of the shape of the deal effect curve [11]. Additionally the methodology proposed is capable of decomposing the sales promotion bump into cross-brand, cross-period and category expansion effects.

Since promotion support variables such as features and displays are often used together (i.e. the D_{lkrt} indicator variables in the SCAN*PRO model) a problem with multicollinearity often arise. Heerde et al. (2004) suggest adding separate price index variables ($P_{krt}/\widetilde{P}_{kr}$ in the SCAN*PRO model) for each combination of promotion support to accommodate for this problem. By doing so we get separate price promotion elasticity estimates for each promotion support combination and this specification also allows for interaction effects between the price discount and the promotion support [22].

The SCAN*PRO model uses price indices ($P_{krt}/\widetilde{P}_{kr}$) instead of the price ($P_{krt}$) to capture the price discount effects better. However, if there is enough variation in the regular price, it can be included as a separate variable [22]. Adding the regular price as a variable also gives us an estimate of the regular price elasticity.

The way the SCAN*PRO model accounts for seasonal variation by using weekly dummy variables has been criticized by Ross Link of Marketing Analytics, Inc. (2004) [18]. He shows that the seasonal dummy variables tend to pick up effects they are not supposed to, such as price and promotions that negatively affects the accuracy of price and promotion coefficients. He therefore proposes using a smoothed category base volume as a seasonality indicator [5]. Additionally one can add holiday dummy variables for holidays such as the Christmas and the Easter.

Sales time series are very often serially correlated. Basically serial correlation could be considered a norm with economic data. Misra et al. (1997) point out that this can lead to spurious regression and hence inflated elasticity estimates when using standard OLS regression. As a quick solution they suggest testing the time series for non-stationarity and adding lagged variables to correct for non-stationarity. [19]

3 Research methodology and data

3.1 Problem setting

The economic downturn of 2009 made people more aware of prices. This combined with increasing competition had resulted in diminishing margins and lost market share for the client company. One part of an operational excellence initiative launched to regain market share and improve profitability was to analyze and improve promotional activities. The client company had previously been planning their promotions largely based on intuitive decision making and the promotions were mostly manufacturer driven. An analytic approach was now proposed for improving the choice of SKUs (Stock Keeping Units) for promotion and for optimizing the pricing decisions.

3.2 Data

About two and a half years (01/2008 - 07/2010) of daily sales data was provided by the client company for all SKUs in the assortment. The data received was readily aggregated to chain level to decrease the size of the dataset, which was motivated since the pricing and the promotional activities were identical in all stores and pricing and promotion decisions were made on the chain level. The data included sales quantity, sales value and cost of sold goods for each SKU in the assortment and for each day the sales quantity was nonzero. Additionally historical data regarding previous promotions (promoted SKUs and used promotion vehicles) was provided. This data was however missing information about the used promotion vehicles for year 2008 and the overall quality and validity of this data was not guaranteed.

3.3 Tools and methods

The data was imported into an SQL server to make the handling of the data easier and allow for easy data transformation and querying. Since the pricing decisions were made on a weekly basis and the duration of promotions were generally two weeks the daily sales data was aggregated into weekly sales data. The weeks were adjusted to begin on Tuesdays, since this weekday was the standard day for carrying out possible price changes in the stores. Since the weekly price was calculated as the value of sold goods divided by corresponding sold quantity the weekly price estimates could be considered fairly robust also for products having an other price change interval. Matlab was used to implement the demand model and to carry out the calculations.

3.4 Choice of model

When the modeling is restricted to a single product or a product group, plenty of effort can be made by optimizing the model for the characteristics attributed to the demand of that product or product group. In our case the model had to work decently for all products and product groups, and therefore the model formulation had to be fairly robust. Inaccuracies in the data set regarding promotions made modeling an even more challenging task.

The SCAN*PRO model (as described in section 2.4.4) was used as the basis for the model building. Since the regular unit price was not provided in the data it was estimated in the following way:

$$\widetilde{P}_t = \min\left\{\max\left\{P_{t-i}, ..., P_t\right\}, \max\left\{P_t, ..., P_{t+j}\right\}\right\} \tag{2}$$

The choice of $i = 6$ and $j = 6$ was empirically noticed to work well for most products in distinguishing between temporary price discounts and long-term price changes.

Since the promotion support variables displayed a high level of linear dependence the price index variable was split up into separate price index variables for each combination of promotion support as suggested by van Heerde et al. (2004) [11]. Promotion and price variables for the previous period were added to the model to account for dynamic demand effects. Both forward and backward lags were tried with different orders. Forward lagged price variables turned out to be generally insignificant as explanatory variables and backward lagged price variables of higher order than one had low significance. The regular unit price was also added to the model, being generally significant for items showing fluctuations in the regular unit price during the observed time period and insignificant for items with low variability in the regular unit price.

Seasonality effects were accounted for in the model by calculating a smoothed category base volume and using that as the seasonal indicator. The approach using weekly dummy variables utilized in the SCAN*PRO model was also tested, but these variables turned out have a low significance and picked up parts of demand spikes not attributed to seasonal effects. In addition to the seasonality index dummy variables for important holidays and special events were added, such as Christmas week and first week of year.

To account for serial correlation problems the sales quantity for the previous period was added as an explanatory variable. The estimated multiplier for this variable can be interpreted as a measure for the sales inertia effect.

Price interaction effects between substitute products is known to exist for most products and omitting the effect from the model could potentially skew the estimates of other effects. Since information on which products were considered substitutes to each other was not available, the price interactions between substituting products could not be modeled in an automatized manner easily. However, for comparison purposes a price index variable consisting of the best discount of a substitute product for each week was constructed for a sample of products and added to the model. All products from the same product category having a reasonably high market share were considered as substitutes. This approach is not optimal, but it can be expected to at least give an indication of the order of magnitude of the substitute effect.

The final model had the following form:

$$Q_t = e^{\beta_0} \prod_{i=1}^{8} \left\{ PI_{i,t}^{\beta_{i,0}} PI_{i,t-1}^{\beta_{i,-1}} \right\} \prod_{j=1}^{7} \left\{ \gamma_{j,0}^{D_{j,t}} \gamma_{j,-1}^{D_{j,t-1}} \right\} \widetilde{P}_t^{\varepsilon_0} Q_{t-1}^{\theta_{-1}} \zeta_0^{SI_t} SPI_t^{\eta_0} \prod_{k=1}^{2} \left\{ \delta_k^{X_{k,t}} \right\} e^{\alpha_t} \tag{3}$$

where

Q_t = unit sales week t

β_0 = regression constant

$PI_{i,t}$ = price index, week t, promotion vehicle combination i (i=1: discount only, i=2: discount and display, i=3: discount and extra positioning, i=4: discount and leaflet, i=5: discount, display and extra positioning, i=6: discount, display and leaflet, i=7: discount, extra positioning and leaflet, i=8: discount, display, extra positioning and leaflet). Defined as $PI_{i,t} = P_t/\widetilde{P}_t$ if combination i, else $PI_{i,t} = 1$.

P_t = unit price, week t

$\widetilde{P}_t$ = regular unit price (previous non-promoted price), week t

$\beta_{i,0}$ = unit price elasticity of demand for promotion vehicle combination i ($\beta_{i,-1}$ = lagged price elasticity)

$D_{j,t}$ = an indicator variable for usage of promotion vehicle combination j without price discount (j=1: display only, j=2: extra positioning only, j=3: leaflet only j=4: display and extra positioning, j=5: display and leaflet, j=6: extra positioning and leaflet, j=7: display, extra positioning and leaflet). Defined as $D_{j,t} = 1$ if combination j, else $D_{j,t} = 0$.

$\gamma_{j,0}$ = promotion vehicle multiplier for promotion vehicle combination j ($\gamma_{j,-1}$ = lagged promotion vehicle multiplier)

ε_0 = regular unit price elasticity

SI_t = seasonal index, week t (smoothed category base volume)

ζ_0 = multiplier for seasonal index

SPI_t = price index for best discount of a substitute candidate product, week t

η_0 = multiplier for substitute product price index

$X_{k,t}$ = an indicator variable for holiday weeks and other special weeks (k=1: Christmas, k=2: First week of year), week t. $X_{k,t} = 1$ if holiday or special week k is in week t, else $X_{k,t} = 0$.

δ_k = holiday and special week multiplier for holiday or special week k

α_t = a disturbance term, week t

By taking the natural logarithm of both sides of equation 3 we finally get

$$\begin{aligned} \ln Q_t &= \beta_0 + \sum_{i=1}^{8} \{\beta_{i,0} \ln PI_{i,t} + \beta_{i,-1} \ln PI_{i,t-1}\} + \sum_{j=1}^{7} \{\ln \gamma_{j,0} D_{j,t} + \ln \gamma_{j,-1} D_{j,t-1}\} \\ &\quad + \varepsilon_0 \ln \widetilde{P}_t + \theta_{-1} \ln Q_{t-1} + \ln \zeta_0 SI_t + \eta_0 \ln SPI_t + \sum_{k=1}^{2} \{\ln \delta_k X_{k,t}\} + \alpha_t \quad (4) \end{aligned}$$

which can be estimated using OLS.

4 Results

In this section we first validate the model by presenting two examples where the model is applied to sales data. In the first example the model is fitted to sales data for a package of toilet paper (8 rolls) with a large market share and with a price elasticity known to be high. The second example product is a half liter can of an imported beer brand with a lower market share. We then present some general findings of the modeling exercise and discuss the validity of the model as a decision support for promotion planning.

4.1 Example 1: Toilet paper

Since the package of toilet paper was a product with a large market share and a price elasticity known to be high it was a suitable choice for validating the OLS assumptions of the model. The results of the regressions are found in Table 2. First a regression (regression 1 in the table) was conducted using the model described in the previous section (equation 4) but leaving out the substitute price index. All variables were significant at a 1 % significance level except for the regular unit price and the Christmas week that were insignificant. The R-squared value was 0.9172. The residuals were not however normally distributed according to the Shapiro-Wilk test. This was due to some outlier observations with low sales. Further investigation revealed that these outlier observations were attributed to the weeks immediately after the largest annual discount campaign that focuses on multipacks and induces extraordinary sales for toilet paper. The residuals were also serially correlated for all normal significance levels according to the Durbin-Watson test for serially correlated residuals.

To account for the outlier observations a dummy variable was added to the model to account for the low sales volumes after the annual campaigns. The results of the new regression are presented in Table 2 as regression 2. The addition of the dummy variable raised the R-squared value to 0.9579, had some minor effects on the elasticity estimates and made the standard errors smaller. The residuals could now be considered normally distributed according to the Shapiro-Wilk test, but the residuals were still serially correlated.

To estimate the effect of substitute product pricing on the sales the substitute product price index was added as an explanatory variable. The results of the regression can be found in Table 2 (regression 3). The inclusion of the variable had minor effects on the elasticity estimates, made the standard errors slightly smaller and the R-squared value was raised to 0.9656. The serial correlation of the residuals was however still significant (although smaller), possibly making the standard error estimates unreliable. Newey-West robust standard errors were calculated for comparison purposes (regression 4) for the same model as in regression 3. As can be seen in Table 2 the robust standard errors differ slightly from the ordinary standard

Table 2: *Regression results, package of toilet paper (8 rolls). Regressions 1-3 estimated using OLS. Regression 4 same as regression 3, but using Newey-West robust standard errors.*

Dependent Variable: $\ln Q_t$	(1)	(2)	(3)	(4)
ε_0 (Regular unit price)	-0.1962	-0.8616	-0.9358	-0.9358
	(0.9853)	(0.7087)	(0.6440)	(0.7119)
$\beta_{1,0}$ (TPR)	-7.4085*	-6.9187*	-6.7703*	-6.7703*
	(0.5887)	(0.4244)	(0.3868)	(0.4958)
$\beta_{2,0}$ (TPR & Display)	-7.7034*	-7.5914*	-7.686*	-7.686*
	(0.5385)	(0.3858)	(0.3506)	(0.4283)
$\beta_{3,0}$ (TPR & Pallet)	-11.3135*	-11.5423*	-11.9118*	-11.9118*
	(1.2413)	(0.8891)	(0.8115)	(0.3363)
$\beta_{5,0}$ (TPR, Display & Pallet)	-10.1691*	-10.3895*	-10.5848*	-10.5848*
	(0.6905)	(0.4949)	(0.4515)	(0.9362)
$\beta_{1,-1}$ (TPR)	2.6734*	1.6361*	1.4993*	1.4993‡
	(0.7658)	(0.5583)	(0.5080)	(0.7884)
$\beta_{2,-1}$ (TPR & Display)	3.3532*	1.9493*	1.9027*	1.9027*
	(0.8093)	(0.5966)	(0.5421)	(0.4803)
$\beta_{3,-1}$ (TPR & Pallet)	5.1550*	3.2684*	3.4950*	3.4950*
	(1.5037)	(1.0934)	(0.9945)	(0.5846)
$\beta_{5,-1}$ (TPR, Display & Pallet)	4.5780*	2.9421*	2.7627*	2.7627*
	(1.0056)	(0.7387)	(0.6722)	(0.5636)
ϑ_{-1} (Lagged quantity)	0.4066*	0.2285*	0.2060*	0.2060*
	(0.0780)	(0.0587)	(0.0536)	(0.0539)
ζ_0 (Seasonality index)	0.2363*	0.3283*	0.3037*	0.3037*
	(0.0555)	(0.0408)	(0.0374)	(0.0387)
η_0 (Substitute product PI)	-	-	0.5411*	0.5411*
	-	-	(0.1144)	(0.1609)
$\ln \delta_1$ (Christmas week)	0.1051	0.1791‡	0.1733*	0.1733*
	(0.1272)	(0.0914)	(0.0830)	(0.0518)
$\ln \delta_2$ (First week of year)	-0.6757*	-0.6264*	-0.6393*	-0.6393*
	(0.1537)	(0.1102)	(0.1001)	(0.0903)
$\ln \delta_3$ (After big campaign)	-	-1.2254*	-1.2417*	-1.2417*
	-	(0.1238)	(0.1125)	(0.0419)
Observations	116	116	116	116
R^2	0.9172	0.9579	0.9656	0.9656
Durbin-Watson test (p-value)	0.0002	0.0044	0.016	0.016
Shapiro-Wilk test (p-value)	0.0000	0.4184	0.4900	0.4900

Notes: Standard errors are showed in parentheses. * p-value < 0.01, † p-value < 0.05, ‡ p-value < 0.10.

errors, being generally bigger, but are still of the same order of magnitude. See appendix A.1 for a plot of the sales and price data.

4.2 Example 2: Beer

A half liter can of an imported beer brand was chosen as a second example product for validating the model. The results of the regressions are found in Table 3.

The model described in equation (4) (but leaving out the substitute price index) was first estimated (regression 1 in Table 3). The model gave good fit with an R-squared value of 0.9409 and all independent variables significant on a 1 % significance level except for the Christmas week that was insignificant. The residuals were not normally distributed according to the Shapiro-Wilk test, due to some outlier weeks. One of the outlier weeks was the Easter week but the reasons behind the two other outlier weeks were not identified. Some possible reasons could be special events, erroneous promotion data or stock issues. Correcting for these outlier weeks with dummy variables (regression 2) resulted in residuals closer to being normally distributed and also showing a smaller degree of serial correlation.

Finally, a substitute product price index was added as an explanatory variable. Leaving out the modeling of the substitute effect for this product did not have any major implications for the price elasticity estimates, but made them slightly smaller as intuition would suggest. The substitute effect is smaller compared to the toilet paper example, since beer is not as generic and interchangeable for most people as toilet paper. See appendix A.2 for a plot of the sales and price data.

4.3 General findings and discussion

The model fitted fairly well for most SKUs with large sales volumes, long sales history (enough data points) and enough price variation in the data. Multicollinearity problems arose for some products, usually involving at least one of the lagged price index variables, but this problem was avoided by leaving out the problem variables and running the regression again in an automated manner. For products with low sales volumes, short sales history or small price variation, the results were generally poor. Low sales volumes can be a symptom of out-of-stock issues[1] making the model inaccurate. Short sales history (few data points) make the model estimates inaccurate, even if the weekly sales volumes are large and there is enough price variation in the data. Finally small price variations make it impossible to estimate the effect of pricing on sales. Even if the model fit would be good it is questionable if extrapolation far outside the tested price range could yield accurate sales predictions. Generally the modeling approach suggested here is applicable for established products that have been price promoted at least a few times. This ensures that the data variation needed for statistical inference.

The estimates should probably not be used as such for price optimization without further product specific analysis and validation. They can however rather safely be

[1] The manufacturer might have delivery problems or there might be internal logistic issues, leading to empty shelves in the stores.

Table 3: *Regression results, can of imported beer (0.5 l). Regressions 1-3 estimated using OLS.*

Dependent Variable: $\ln Q_t$	(1)	(2)	(3)
ε_0 (Regular unit price)	-3.1427*	-3.3321*	-3.2799*
	(0.3934)	(0.3388)	(0.3348)
$\beta_{1,0}$ (TPR)	-7.2874*	-7.1392*	-7.1149*
	(0.3865)	(0.3318)	(0.3272)
$\beta_{2,0}$ (TPR & Display)	-8.3250*	-8.3200*	-8.2856*
	(0.2947)	(0.2512)	(0.2489)
$\beta_{3,0}$ (TPR & Pallet)	-7.3113*	-7.2872*	-7.1944*
	(0.6953)	(0.5923)	(0.5853))
$\beta_{1,-1}$ (TPR)	1.9746*	1.8600*	1.7796*
	(0.6715)	(0.5742)	(0.5672)
$\beta_{2,-1}$ (TPR & Display)	2.6221*	2.4107*	2.2501*
	(0.6699)	(0.5731)	(0.5698)
$\beta_{3,-1}$ (TPR & Pallet)	2.4237*	2.2697*	2.2582*
	(0.8695)	(0.7415)	(0.7308)
ϑ_{-1} (Lagged quantity)	0.2865*	0.2619*	0.2472*
	(0.0729)	(0.0698)	(0.0618)
ζ_0 (Seasonality index)	0.0735*	0.0796*	0.0930*
	(0.0289)	(0.0250)	(0.0254)
η_0 (Substitute product PI)	-	-	0.3224†
	-	-	(0.1512)
$\ln \delta_1$ (Christmas week)	-0.0259	-0.0454	0.0007
	(0.8996)	(0.7954)	(0.1736)
$\ln \delta_2$ (First week of year)	-1.1488*	-1.1708*	-1.1238*
	(0.1659)	(0.1413)	(0.1410)
$\ln \delta_3$ (Easter week)	-	-0.3989*	-0.3929*
	-	(0.1395)	(0.1375)
$\ln \delta_4$ (Outlier week 1)	-	0.9011*	0.8701*
	-	(0.1724)	(0.1705)
$\ln \delta_5$ (Outlier week 2)	-	-0.8418*	-0.8033*
	-	(0.2409)	(0.2381)
Observations	135	135	135
R^2	0.9409	0.9582	0.9597
Durbin-Watson test (p-value)	0.0816	0.3199	0.3363
Shapiro-Wilk test (p-value)	0.0005	0.0854	0.1419

Notes: Standard errors are showed in parentheses. * p-value < 0.01, † p-value < 0.05, ‡ p-value < 0.10.

used for product choice and classification purposes. The most price elastic products can for example be identified as products suitable for price promotion. By taking into account the promotional vehicle usage variables, the products best suitable for featuring or for allocating extra placement for during the promotion can be identified. One has to remember though that only products that have been promoted before can be classified in this way, since historical promotion activity of course is needed for estimating the promotional response. This means that possibly great promotion products might be left unidentified, since they have never been tested. However, since products with similar characteristics and market share usually behave similarly, an educated guess can usually also be made about the promotional efficiency for untested products.

Further analysis on product level and validation of the price elasticity estimates makes it possible to use the elasticity estimates for price optimization. A profit maximizing short-term promotion price for a single product can in theory be calculated. For highly price elastic products the calculated profit maximizing margin might turn out to be uncomfortably low. It may be a good idea to only use prices that lie in or very close to the tested price range, since there is no guarantee that the model gives reliable sales predictions when extrapolating data. One also has to remember that the model presented here does not model cross price elasticities. A profit maximizing short-term promotion price calculated based on this model might thus be profit maximizing for the product, but not necessarily for the product group as a whole. For a more complete analysis substitute product information is needed and cross price elasticities must be calculated and accounted for in the optimization.

External factors not accounted for in the model should also be taken into consideration when pricing products for promotion. The most important external factor is the promotional activity of competitors. If a competitor is promoting the same product to a lower price than you and with high visibility, the sales predicted by the model will most likely be higher than the real outcome. Additionally such bad price publicity might take a toll on the overall price image. Hence, promotional prices with high visibility should be matched with competition or be better than the competition. When pricing much lower than the competition, the risk of starting a price war[2] must also be assessed. History shows us this is a real threat - price wars were for example started in the Dutch grocery retailing market in 2003, leading to lower profits for all involved retailers [7]. A good rule of thumb is simply to try to promote different products than the competition in order to discourage price comparison behavior by the customers and discourage price competition behavior by competitors.

A general rule for using of marketing resources is hard to give since the effects are product specific. Comparing the price and promotion vehicle usage elasticities with each other on the product level reveals the impact of marketing effort. It has however been shown that the usage of promotion vehicles combined with price reductions generally tend to have positive interaction effects, see e.g. Blattberg et al. (1989) or Karolefski et al. (2006) [3, 13]. This effect was also evident in the data set analyzed in this thesis (see appendix B for more details). Combining usage of

[2]A commercial competition characterized by the repeated cutting of prices below those of competitors (Merriam-Webster dictionary)

multiple promotion vehicles with deep discounts might thus often be the the most effective use of limited marketing resources.

The model is a short-term model and does not by any means predict how promotions affect customer behavior in the long-term. As discussed in the theoretical background the long-term effects are hard to study and are thus also not very well studied. However, a general finding is that too frequent price promotion of the same product will deteriorate the brand value and affect the customer's base price expectations. A rule of thumb is thus to avoid frequent price promotion of the same product and instead try to promote different products.

5 Conclusions

In this thesis we have built a model for estimating the promotional sales based on pricing and usage of promotional vehicles. The model is applied on sales data from a European retailer and serves as a decision support tool for promotion planning.

The model accounts for seasonal effects and dynamic demand effects. Due to lacking data the interaction effects between products could not be modeled accurately. The model fitted fairly well for most SKUs in the examined dataset with large sales volumes, long sales history (enough data points) and enough price variation in the data. For SKUs with low sales volumes, short sales history or small price variations the model fit was generally poor.

On a product level the model can be used to forecast the promotional sales as a function of price and usage of promotional vehicles. For products with detailed sales data the model predictions are fairly accurate and can after verification be used for example for profit optimization purposes on a product level. There are however external factors that are not captured by the model, such as competitor pricing, that should be taken into account before the sales prediction accurateness can be considered reliable.

Another useful application of the model is its usage as a decision aid for selecting suitable products for promotion. This is done by estimating the model for all products and using the price and promotional vehicle usage elasticities as measures for how effective the products are as promotional products.

A rather simple parametric log-linear model such as the one presented in this thesis can help generate valuable knowledge about promotions. Semiparametric and nonparametric models could possibly reveal even more information about the shape of the deal effect curves, but they require more data points than parametric models for a good fit and it is also questionable if the extra resolution could be translated into better pricing and promotion decisions. The simple modeling approach suggested in this thesis would probably be useful for most retailers lacking previous experience in sales data based pricing practice. It does not offer a complete solution for promotion planning, but when utilized in an appropriate way, it is a usable decision support tool for making better informed and more efficient promotion decisions.

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A Sales and price data plots

A.1 Toilet paper

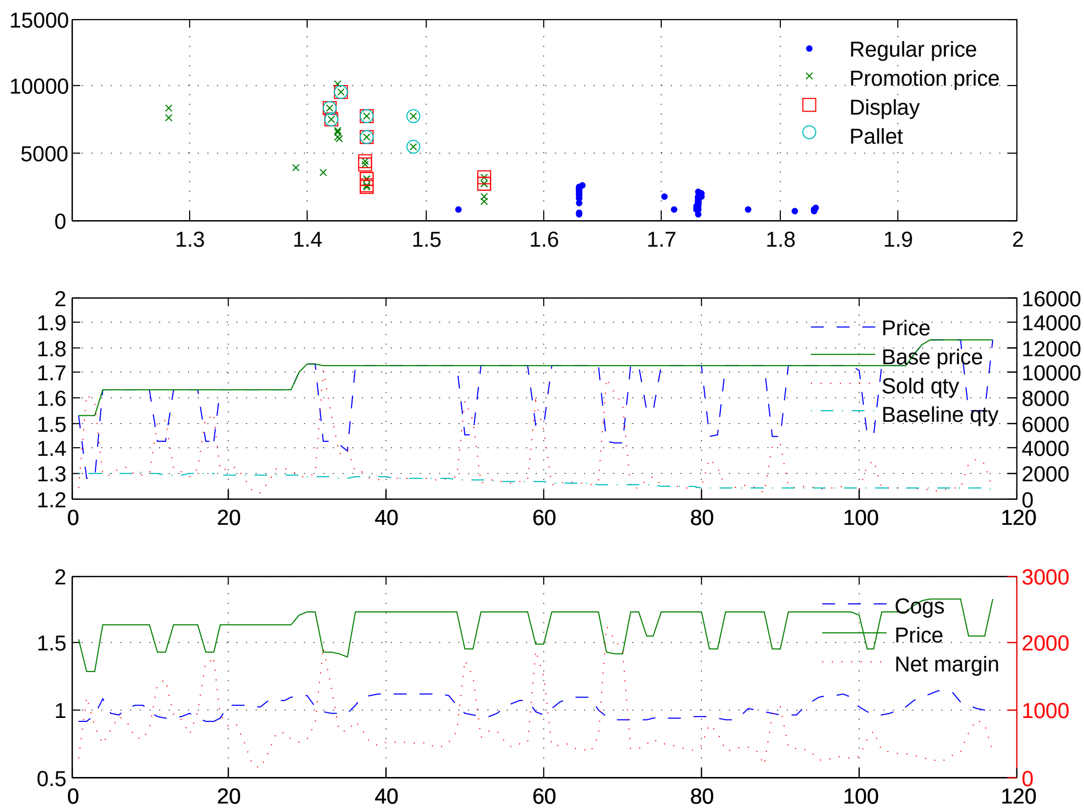

Figure 1: *A visualisation of the price dynamics for the toilet paper analyzed in the results section. The upper graph is a plot having the price on the x-axis and the sold quantity on the y-axis. The legends indicate different promotion support vehicles. The middle graph shows time-series of the price and the sold quantity. The lower graph shows time-series of the cost of goods, the sales price and the total net margin.*

A.2 Beer

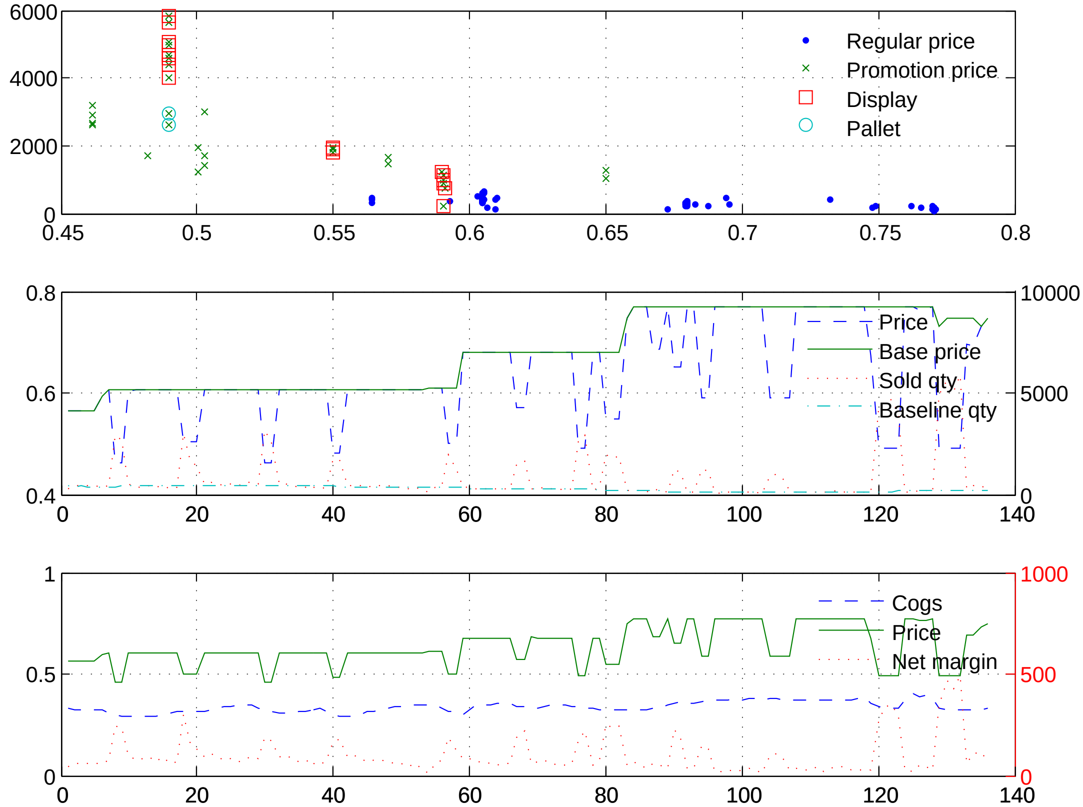

Figure 2: *A visualisation of the price dynamics for the beer brand analyzed in the results section. The upper graph is a plot having the price on the x-axis and the sold quantity on the y-axis. The legends indicate different promotion support vehicles. The middle graph shows time-series of the price and the sold quantity. The lower graph shows time-series of the cost of goods, the sales price and the total net margin.*

B Interaction effects between promotion vehicles

Table 4 the average sales boost effect of different price discount and promotion vehicle combinations. The average was calculated over all products in the analyzed data set for which reliable sales data was available. The numbers in the table are indices defined as the sales count during a promotion week divided by the average sales during a non-promotion week (baseline sales). Some combinations are missing in the table due to no or very few observations in the dataset.

For example, a price discount between 10-20 % would on average increase the sales by 278 % (index value of 378). Combining a display and a pallet in stores together with the price discount would on average increase sales by 482 % (index value of 582).

Table 4: *Average sales boost effect of price discount and promotion vehicle combinations.*

	Discount					
Promotion vehicle	0-10%	10-20%	20-30%	30-40%	40-50%	50-60%
Discount only	292	378	481	571	701	686
Display only	256	401	504	624	823	816
Pallet only	327	483	605	732	684	-
Display & leaflet	256	427	589	719	962	-
Pallet & leaflet	344	486	678	762	952	965
Display & pallet	330	582	730	767	772	-
Display, pallet & leaflet	462	596	766	845	794	1204

C Summary in Swedish

När streckkodsläsaren introducerades i butikerna i mitten av 1970-talet blev det lätt att registrera detaljerad försäljningsdata. Sedan början av 1980-talet har denna data utnyttjats till att konstruera ekonometriska modeller för att förutsäga efterfrågan och bedöma effekten av marknadsföring. Även om forskningsområdet idag kan anses vara noggrant studerat finns det fortfarande mycket att upptäcka på grund av de snabba förändringarna på återförsäljningsmarknaden.

Försäljningskampanjer spelar en viktig roll i återförsäljningsbranschen då man önskar introducera nya produkter på marknaden, öka på försäljningen eller avyttra produkter. I kampanjplaneringen måste en kompromiss göras mellan att öka efterfrågan och uppehålla lönsamma marginaler. "Kampanjinvesteringen" bör i det långa loppet vara lönsam så att den ökade försäljningen uppväger de mindre marginalerna. Denna avvägning görs ofta inom industrin på basen av känsla och erfarenhet, men genom att analysera försäljningsdata kan man erhålla en mer kvantitativ grund för avvägningen.

I detta arbete undersöks den nuvarande kunskapen gällande planering och analys av promotioner och en log-linjär modell byggs för att estimera kampanjförsäljning på basen av prissättning och användning av marknadsföring. Modellen tillämpas på försäljningsdata från en europeisk livsmedelsåterförsäljningskedja.

Syftet med detta arbete är att erbjuda en överblick av den nuvarande kunskapen gällande planering och analys av promotioner, samt att utveckla modell som kan fungera som hjälpmedel för att göra informerade och effektiva kampanjbeslut gällande prissättning och produktval.

En försäljningskampanj består av en samling av incitamentverktyg designade för att stimulera försäljningen av en viss produkt eller en grupp av produkter. Producenter använder sig av dem för att öka försäljningen av sina produkter till återförsäljare och återförsäljare i sin tur använder sig av dem för att öka på försäljningen till slutkonsumenterna. I detta arbete fokuserar vi oss på kampanjer som riktar sig till slutkonsumenter. Bara fantasin sätter gränser för den slutliga kampanjdesignen, men i regel bygger alla kampanjer på ökad synlighet av produkten genom marknadsföring och/eller någon form av prisrabatt.

Den kortsiktiga målsättningen med en försäljningskampanj är att öka på försäljningen och vinsten, men en ökning av försäljningen är inte nödvändigtvis lika med en vinstökning, ifall marginalen sänks för mycket. Utöver denna självklarhet har det också stor betydelse varifrån försäljningsökningen kommer. Är det fråga om en faktisk ökning av konsumtionen, eller köper konsumenterna på lager vilket betyder att försäljningen kommer att vara mindre efter kampanjen? Lämnar konsumenten bort någon annan produkt ur sin köpkorg i stället? Har kampanjen fått kunder att byta butik från konkurrenten? Vad händer på lång sikt - blir kunderna bara mera priskänsliga på grund av försäljningskampanjer och mindre lojala, eller kan försäljningskampanjer göra kunder mera lojala? Alla dessa frågor är viktiga att undersöka då man försöker estimera en försäljningskampanjs nettoeffekt på lönsamheten.

Vi kan dela in en försäljningskampanjs effekter i kortsiktiga effekter som sker under promotionen och omedelbart efter och i långsiktiga effekter som visar sig först en tid efter kampanjen. I tabell 1 presenteras en sammanfattning av effekterna. I korthet önskar man naturligtvis att försäljningsökningen helst skall komma från ökad konsumtion och butiksbyte. Ifall kunden byter produkt till följd av kampanjen vill man helst att kunden skall byta från en produkt med lägre marginal till en produkt med högre marginal för då ökar vinsten. Ifall kunden köper på lager bör marginalen helst vara högre under kampanjen än vid normalpris för att nettovinsten skall öka (detta är möjligt ifall leverantören subventionerar inköpspriset). På lång sikt är det önskvärt att kampanjerna påverkar konsumenternas allmänna prisuppfattning positivt (d.v.s. att återförsäljarens priser anses förmånliga) och att kunderna blir mera lojala. Det är i sin tur inte önskvärt att kampanjprodukternas varumärkesvärden förstörs genom för frekvent förekommande rabattkampanjer. Det har gjorts en hel del forskning gällande de kortsiktiga effekterna, men de långsiktiga effekterna är svårare att undersöka och det finns därmed betydligt mindre forskning och mindre tillförlitlig forskning gällande dessa. I kapitel 2.3.1 och 2.3.2 presenteras en del av dessa forskningsresultat.

När vi modellerar kampanjförsäljning är det första steget i modellbygget att ta reda på vilka variabler som påverkar försäljningen. Det andra steget är att hitta en lämplig funktionsform för modellen som bäst kan förklara sambandet mellan försäljningen och de förklarande variablerna. En del variabler är lätta att hitta data för medan det för andra variabler är betydligt svårare eller praktiskt taget omöjligt (t.ex. konkurrenters prissättning). Datan kan dessutom vara inexakt och av låg kvalitet vilket försvårar modellbygget. I detta arbete fokuserar vi oss på analys av försäljningsdata på butikskedjenivå per produkt och vecka. Denna aggregationsnivå uppfyller våra behov väl, eftersom prissättningen i vårt fall görs på kedjenivå och inte på butiksnivå och prisförändringar görs inte dagligen utan på veckonivå. Denna aggregationsnivå har ofta använts i litteraturen och är dessutom i allmänhet lätt att få tag på.

I litteraturen har både parametriska, semiparametriska och icke-parametriska modeller undersökts. Majoriteten av studierna har dock implementerat parametriska regressionsmodeller som relaterar försäljning till pris och marknadsföring. Modellen som utvecklas i detta arbete baserar sig huvudsakligen på den så kallade SCAN*PRO modellen utvecklad av Wittink et al. år 1987, som är en log-linjär regressionsmodell. Se ekvation (1) och kapitel 2.4.4 för noggrannare detaljer.

Den slutliga modellen presenteras i kapitel 3.4. Se ekvation (3) för modellen i multiplikativ form och ekvation (4) för samma modell i linjär form efter logaritmering. Modellen beaktar prissättning, användning av marknadsföring, säsongseffekter och dynamiska försäljningseffekter. Säsongseffekten beaktas dels med dummyvariabler för vissa helger såsom jul och med ett index baserat på en utjämning av kategoriförsäljningen. Dynamiska effekter beaktas genom att föregående periods försäljning och prissättning tagits med som förklarande variabler. Prisinteraktionseffekter mellan produkter kunde inte modelleras fullständigt, eftersom information gällande vilka produkter som är substitutprodukter till varandra inte kunde erhållas. Eftersom effekten är känd att existera är det dock inte lämpligt att lämna bort modelleringen av den fullständigt - åtminstone inte före man har kunnat konstatera att dess inverkan är liten. För att kunna estimera storleksordningen på effekten lades det för ett sampel av exempelprodukter till en prisindexvariabel som bestod av den bästa rabatten för varje vecka för de produkter som hörde till samma kategori och hade relativt stor marknadsandel. Även om denna metod för att modellera substitutionseffekten inte är optimal ger den i alla fall en indikation av effektens storleksordning.

Modellen visade sig tämligen väl klara av att uppskatta kampanjförsäljningen för produkter med detaljrik och varierande försäljningsdata med hög försäljning och lång försäljningshistoria. Däremot var såsom väntat anpassningen dålig för produkter med låg försäljning, kort försäljningshistoria och låg prisvariation. I arbetet presenteras regressionsresultaten för två exempelprodukter: WC papper och ett importerat öl. För båda produkterna hade försäljningsdatan stor variation och volym och marknadsandelen var stor respektive medelstor för produkterna. Basmodellen visade sig för båda produkterna ge höga R^2 värden, men vissa problem uppstod med utanförliggande observationer och seriekorrelation. Genom att undersöka orsakerna till de utanförliggande observationerna och korrigera för dem kunde modellens anpassning ytterligare förbättras. Substitutionseffekten var signifikant för båda produkterna, men påverkade inte elasticitetsestimaten påtagligt. Att lämna bort modelleringen av substitutionseffekten torde knappast leda till väldigt stora felaktigheter i estimaten.

Estimaten kan efter kontroll utnyttjas t.ex. i vinstoptimeringssyfte på produktnivå. De estimerade pris- och marknadsföringselasticiteterna kan användas som mått på hur effektiva produkterna är som kampanjprodukter och fungera som hjälpmedel för att välja ut lämpliga kampanjprodukter. Det bör dock poängteras att det finns flera faktorer som inte beaktats i modellen såsom bl.a. konkurrenternas kampanjaktivitet, vilket gör att modellen inte kan användas utan eftertanke och att elasticitetsestimaten inte nödvändigtvis är fullständigt pålitliga. Som hjälpmedel för prissättning och produktval vid kampanjplanering fyller dock modellen helt klart sin funktion och speciellt för återförsäljare utan tidigare erfarenhet av prissättning baserad på försäljningsdata kan modellen erbjuda ett helt nytt perspektiv på kampanjplaneringen.