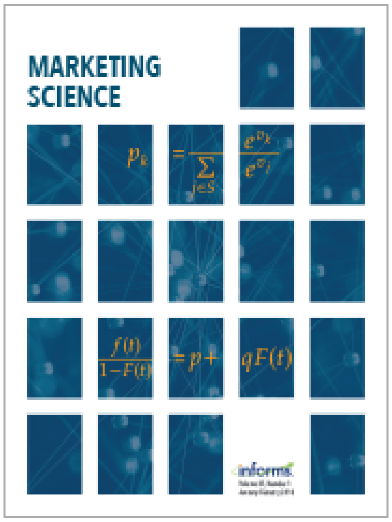

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Practice Prize Report

An Assortmentwide Decision-Support System for Dynamic Pricing and Promotion Planning in DIY Retailing

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The main objective of this report is to describe a decision-support system for dynamic retail pricing and promotion planning. Our weekly demand model incorporates price, reference price effects, seasonality, article availability information, features, and discounts. Building on previous research, we quantify demand interdependencies and integrate the resulting profit-lifting effects into the optimal pricing model. The methodology was developed and implemented at bauMax, an Austrian do-it-yourself retailer. Along with the practical requirements, an objective function was employed that can be used as a vehicle for implementing a retailer's strategy. Eight pricing rounds with thousands of different stock-keeping units have each served as a testing ground for our approach. Based on various benchmarking methods, a positive impact on profit was reported. The currently implemented marketing decision-support system increased gross profit on average by 8.1 and sales by 2.1%.

Key words: reference price; demand interdependency; revenue management; retail strategy; pricing research; dynamic pricing
History: This paper was received August 1, 2005, and was with the authors 3 months for 2 revisions; processed by Gary Lilien.

1. Company Background and Management Problem

bauMax was founded in 1976 and today operates 121 retail stores in six Central and Eastern European countries. The company currently realizes yearly revenues of approximately 1 billion euro, which makes it the largest competitor in the Austrian do-it-yourself (DIY) retail industry. The company has a market share of 25%.

Over the last few years, the Austrian DIY industry has experienced stagnation in sales. Most retailers have extended their assortment to compensate for the sales decrease in their traditional range and now—besides tools and building materials—also sell articles such as furniture and gardening products. bauMax currently has an assortment of around 60,000 stock-keeping units (SKUs). Facing fierce price competition and low profit margins in its home market, bauMax management has successfully initiated an expansion strategy into new Eastern European markets.

To successfully handle the managerial and operational complexity provoked by the excessively large assortment, only a subset of articles was subject to extensive pricing and promotion-planning activities. Based on its own experience, bauMax has practiced tactics such as high-low-pulsing, multiple placements of products in stores, and out-of-store advertisements via flyers or trade magazines. For the large majority of articles, no individual pricing process took place. Instead, prices were determined by simple markup rules and a static price grid. Hence, reengineering of the bauMax pricing process via implementation of an assortmentwide decision-support system based on state-of-the-art marketing decision models was considered. The prospective system was intended to help purchasing, merchandising, and marketing managers in their decision making regarding dynamic price adjustments and promotion-planning activities, as well as to facilitate coordination of interrelated decision tasks such as inventory replenishment.

The companywide data warehouse solution provided fast access to article-specific demand data; it also offered the possibility to condition prices on demand histories (cf. Acquisti and Varian 2005). In brief, the following major functional requirements were expected from the fully implemented pricing decision-support model: (i) it should automatically process article-specific pricing and promotion recommendations, (ii) it should respect inventory considerations to avoid out-of-stock situations, (iii) it should account for indirect profit contributions due to observed purchase interdependencies (lift effects), and (iv) it should be applicable in several countries with different currencies and sales taxes.

2. Model Development

Personalized transaction histories and a representative survey conducted among shoppers in the Austrian DIY retail industry have shown evidence of a relatively high level of store visit frequency. This supports the assumption that typical DIY customers may be characterized by a considerable degree of price consciousness. In addition, it justifies the adoption of reference-price models for deriving pricing and promotional recommendations. Reference price models (Winer 1986) have experienced broad empirical support (Kalyanaram and Winer 1995), and researchers have proposed many methods to infer the unobserved reference price (r). The operationalization applied at bauMax is based on an exponentially smoothed function of the item's own price history (cf. Lattin and Bucklin 1989, Greenleaf 1995, Briesch et al. 1997, Kopalle et al. 1996, Seetharaman 2004). A generalization of our model implemented at bauMax is that customers are permitted to faster adapt their reference prices ($\mu \leq \eta$) to price reductions than to price increases:

$$r^t = r^{t-1} + \mu \max(0, p^{t-1} - r^{t-1}) + \eta \min(0, p^{t-1} - r^{t-1}), \quad 0 \leq \mu, \eta \leq 1. \quad (1)$$

For the case of $\mu = \eta$, this model reduces to the basic adaptive reference price model. This generalization seems more intuitive than others because retailers tend to communicate price reductions, whereas price increases, for obvious reasons, are not advertised. One would also expect customers to more strongly update their reference price when they buy a brand, compared with the case where they buy an alternative brand or postpone their purchase. If an item is actually purchased, price contacts are not only given at the shelf, but may also occur at checkout, when checking the bill, at home when purchased items are put in their storage place, or when the item is consumed or used.

This model also emphasizes the perils of price promotions that are too frequent, as the reference price drifts faster toward the lower (promotion) price. This is especially the case for excessive promotional activities. In this model, the differences between optimal high and low prices in pulsing strategies are decreasing with larger differences between μ and η. Besides price and reference price effects, several other factors can have a significant demand effect (Divakar et al. 2005): Seasonality plays an important role in many categories, such as gardening or building materials.

In an expanding company, the number of outlets changes over time (number of outlets, O), an effect that needs to be considered in the model. In addition, average stock levels per outlet (S/O) can drive demand figures. Features (dummy variable F) and discounts (metric variable H) can also lead to considerable peaks in demand. The overall demand model for each item (SKU) considers the impact of price, reference price, trend, seasonality, features, average stock levels, the number of outlets, and discounts:

$$\begin{aligned} D^t = \beta_0 &+ \underbrace{\beta_1 p^t}_{\text{price}} + \underbrace{\beta_2 PRG^t + \beta_3 NRG^t}_{\text{reference-price}} + \underbrace{\beta_4 t}_{\text{trend}} \\ &+ \underbrace{\beta_5 \sin(2t\pi/z) + \beta_6 \cos(2t\pi/z)}_{\text{seasonality}} + \underbrace{\beta_7 O^t}_{\text{nr.outlets}} \\ &+ \underbrace{\beta_8 \frac{S^t}{O^t}}_{\text{avg. stock level}} + \underbrace{\beta_9 F^t}_{\text{feature}} + \underbrace{\beta_{10} H^t}_{\text{discounts}} + \gamma^t, \end{aligned} \quad (2)$$

with

$$NRG^t = \min(0, p^t - r^t) \quad \text{and} \quad PRG^t = \max(0, p^t - r^t).$$

The error term, γ, is minimized in a LS sense. z denotes the number of seasonal periods. However, to guarantee logical consistency, parameters $\beta_{1\text{–}3}$ and $\beta_{7\text{–}10}$ are restricted in terms of their signs ($\beta_1, \beta_2, \beta_3 \leq 0$, $\beta_7, \beta_8, \beta_9, \beta_{10} \geq 0$, $0 \leq \mu, \eta \leq 1$, $\mu \leq \eta$). Based on evaluation of the data, our opinion is that a linear relationship was sufficient. Note that Equation (2) describes demand at the SKU level, ignoring demand interdependencies between items. Including cross-item effects directly in our demand function seemed prohibitive for such a large assortment. Instead, we separately calculate item-specific profit lift effects, L, based on shopping basket data and incorporate them into the profit function.[1] The direct and indirect discounted item gross profits π over all periods ($t = 1, \ldots, T$) can be calculated as:

$$\pi = \sum_{t=1}^{T} D^t (np^t - cv + L)(1 + \rho)^{-t/z}, \quad (3)$$

[1] Albeit in a different context, the scalability problem associated with models at the SKU level as well as the idea to combine diverse data sources is addressed by Sinha et al. (2005) in an elegant way.

where D^t is the forecasted demand for a path of prices over the planning horizon of $T = 52$ weeks; np denotes the net price after discounts (H^t) and sales tax ψ (which is 20% for most products in Austria, 19% in the Czech Republic, etc.). The merchandise cost per unit is designated by cv and $(1+\rho)^{-t/z}$ is the discount factor, with ρ as the exogenously specified discount rate.

Although theoretically the number of possible price strategies is huge, business restrictions may considerably reduce the computational effort. In the first implementations, we have applied a simulated annealing approach (cf. Natter and Hruschka 1998, Silva-Risso et al. 1999) and tested a dynamic program. Only after adding the business restrictions did we realize the possibility of calculating all relevant alternatives. bauMax uses a price grid for each country (or currency), reducing the number of different strategies to be investigated to a tractable number. The price grid defined by bauMax also considers any psychological effects such as 9-endings (cf. Gedenk and Sattler 1999). In contrast to the analysis of individual brands, where the researcher can visually inspect the models, automatic use of such models requires additional business rules. Our price recommendations, for instance, are restricted to a maximum of 15% price increases in each pricing round.

The starting point of our calculation of profit lift effects, L_i, is based on observed cross-item correlations (see, e.g., Russell et al. 1997, Russell and Petersen 2000, Mild and Reutterer 2003). The number of purchase occasions f_{ij} when two items i and j are jointly demanded are accommodated in a symmetric matrix $\mathbf{F}$; diagonal elements f_{ii} represent item i's choice frequencies s_i in N purchase transactions. Positive or negative deviations of f_{ij} from the case of stochastic independence, which for two item-sets is given by $(s_i \cdot s_j)/N$, can serve as indications of complementary or substitutional cross-item relationships (see, e.g., Brin et al. 1998, Van den Poel et al. 2003). The various measures inspired by this notion, however, follow a symmetric concept and thus are not suitable for detecting asymmetric cross-item purchase effects. Because our modeling framework aims to detect asymmetric (lift) effects, we employ the proportion of the two conditional probabilities $P(j \mid i) = f_{ij}/s_i$ and $P(j \mid \neg i) = (s_j - f_{ij})/(N - s_i)$. The former denotes the probability of choosing item j given that item i is in the basket, while the latter stands for the probability of observing item j in shopping baskets that do not contain item i.

This serves as a benchmark to test for the existence of asymmetric cross-item effects. Since $P(j \mid i) - P(j \mid \neg i)$ is equivalent to the difference in sample proportions for two-way contingency tables of binary variables and accessible for significance testing (cf. Agresti 1996, p. 19), compliance with the inequalities $(P(j \mid i) - P(j \mid \neg i)) > \xi_{ji}^{\text{lower}}$ or $(P(j \mid i) - P(j \mid \neg i)) < \xi_{ji}^{\text{upper}}$ can be used to determine the presence of a complementary or substitutional purchase effect respectively (where ξ_{ji} is the critical value for a positive lower or negative upper bound of an $\alpha/2$ confidence interval and warrants that only significant effects are taken into account).

To evaluate the monetary impact of significant cross-item effects, purchase quantities in terms of units sold and profit contributions $pc_j^t = np_j^t - cv_j$ are introduced into the procedure. For this purpose, a conditional $I \times I$ copurchase quantity matrix $\mathbf{X}$ is calculated. Similar to $\mathbf{F}$, elements x_{ii} represent item i's overall purchase quantities. The off-diagonal elements $x_{ij(j\neq i)}$, however, capture the quantity of item j conditional on item i's choice and are corrected for significant differences in proportions or are otherwise set to zero:

$$x_{ij}^c = \begin{cases} \dfrac{x_{ij}}{f_{ij}} P(j \mid i) - \dfrac{x_{jj} - x_{ij}}{f_{jj} - f_{ij}} P(j \mid \neg i) \\ \qquad \text{if } (P(j \mid i) - P(j \mid \neg i)) > \xi_{ji}^{\text{lower}} \quad (\forall\, \xi_{ji}^{\text{lower}} > 0) \\ 0 \quad \text{otherwise}, \end{cases} \tag{4}$$

with x_{ij}/f_{ij} and $(x_{jj} - x_{ij})/(f_{jj} - f_{ij})$ denoting the expected conditional purchase quantities of item j given choice or nonchoice of item i, respectively. While Expression (4) tests for complementary cross effects, substitutional effects can be easily incorporated analogously by using an upper bound ξ_{ji}^{upper} $(\forall\, \xi_{ji}^{\text{upper}} < 0)$. In the DIY assortment of bauMax, however, substitutional effects can be observed for a considerably smaller fraction (around 10% of complementary relationships) of item pairs. As a result, matrix $\mathbf{X}^c$ reflects the expected positive and negative contributions to the cross-item quantity "lift" conditional on i's choices. In the final stage of the procedure, the latter is weighted by profit contributions and converted into a per unit base. For complementary items this is accomplished as follows:

$$L_i^{\text{comp}} = \sum_{j=1}^{I} \frac{f_{ij}}{x_{ij}} x_{ij}^c pc_j^t. \tag{5}$$

For the case of substitution, the retailer does not care which item is chosen by the customer unless the profit contribution of the items is different.[2] Hence, in the latter case, the lift-effect is multiplied by the difference in profit contributions:

$$L_i^{\text{subs}} = \sum_{j=1}^{I} \frac{f_{ij}}{x_{ij}} x_{ij}^c (pc_i^t - pc_j^t). \tag{6}$$

[2] Other effects could, for instance, occur because of differences in consumption speed (cf. Sun 2005). However, we do not consider such effects in our model.

The final term $L_i = L_i^{\text{comp}} + L_i^{\text{subs}}$ corresponds to the total profit lift effect per unit of item i and is included in Equation (3).

In our modeling approach, we respect inventory decisions in the following way: For products that the outlets can order from bauMax's distribution centre, delivery times are short. Other products, however, are ordered from the Far East (especially China) and have long delivery times (approximately 2 months). In such cases, we can easily exclude all pricing solutions that yield higher demand forecasts than are available in stock within the following 2 months (cf. Skiera and Spann 1999). Equation (2) is also used to propose article candidates to be included in promotional activities (c.f. Blattberg and Neslin 1993, Zhang and Krishnamurthi 2004). A scoring model utilizing current stock levels, lift effects, price sensitivity, promotional sensitivity, sales, demand, and seasonality serves to rank these articles.

3. Stepwise Implementation and Pricing Process

At the beginning of this project, management was seriously concerned about potential organizational resistance to using the model. To provide evidence that the automated pricing tool can serve as a valuable decision-support tool and to encourage merchandise managers' willingness to pursue price experiments (which indeed is vital for improving future model predictions), a stepwise implementation was favored.

3.1. Step I: Phased Roll-Out of Price Recommendations

Following discussions with management, the decision was made to pursue a phased roll-out as a low-risk strategy of initial model implementation. The first few waves of price adjustments, denoted as pricing rounds, were executed for a limited number of articles in 10 representative Austrian test stores. For an examination period of a couple of weeks, performance of these articles was then benchmarked against a group of reference stores with similar characteristics to the test outlets. After the initial pricing round, model implementation was continuously extended by (i) increasing the number of articles, (ii) including profit-lift effects as outlined in the last section, (iii) imposing the weighted objective function according to Equation (7), and (iv) expanding pricing rounds to other countries.

Evidence of the effectiveness of the implemented system recommendations was always considered as mandatory for the project. The bauMax CFO & CIO, Mr. Werner Neuwirth-Riedl, expressed it the following way: "We were not sure whether we can rely on a computer program that takes over decisions that are in the core of our business. Hence, benchmarking has always been a central issue. We wanted to know exactly what the impact of any change was, and we wanted to interfere if things went wrong."

Figure 1 Cumulated Profit Differences (in Percent) Between Test and Reference Outlets

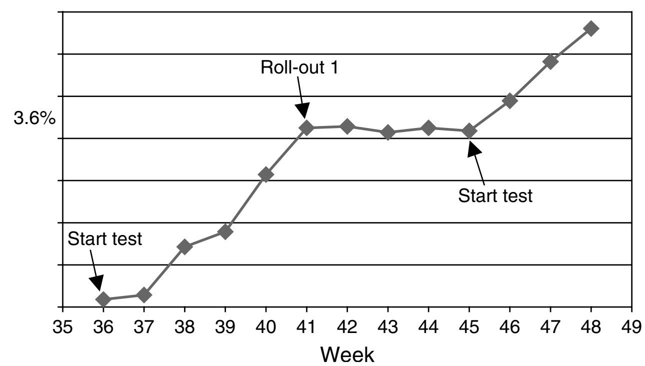


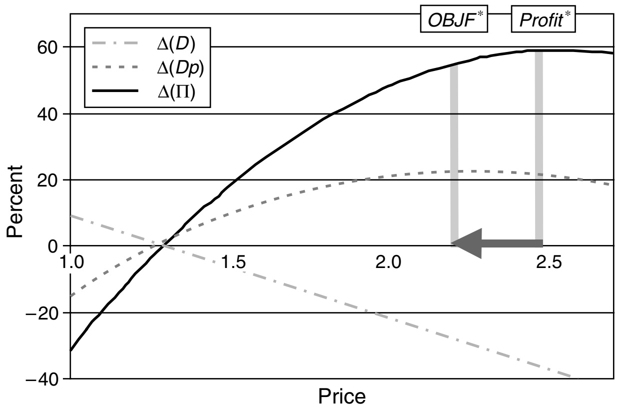
Figure 1 illustrates some key findings for the first two price experiments. For the 1,900 articles being dealt with in this initial pricing round, profit differences between test and reference outlets are computed and cumulated over weeks. Fostered by the observation of a significant increase of 3.6% in relative profits only six weeks after starting the first pricing round, management had rolled out the new prices to all Austrian outlets by week 41. After roll-out, profits also increased in the remaining outlets and differences diminished over the next few weeks until the second price round began. The following price rounds showed similar patterns to the one depicted here.

3.2. Step II: Imposing a Weighted Objective Function

In the first phase of implementation, profit-optimal price recommendations were derived, such as shown in Figure 2, where a price increase was optimal for the specific item, moving the current price from the intersection point toward *Profit**. As reported in the previous subsection, actual profits indeed increased for the articles being dealt with here. However, we soon realized that increased profits were often achieved at the cost of decreasing quantities. This observation entailed emotional discussions with merchandise managers, who were afraid of missing their sales and volume targets and felt the need to defend their market shares. On the other hand, both the bauMax owner and the CFO strongly emphasized profitability. Consequently, we had to find a way of considering the different management perspectives in our modeling framework. To resolve this problem, we incorporated an explicit weighting scheme for relative changes in gross profits (ω_1), sales (ω_2), and demand (ω_3) into the decision-support system:

$$OBJF = \omega_1 \Delta(\pi) + \omega_2 \Delta(pD) + \omega_3 \Delta(D). \tag{7}$$

Figure 2 Trade-Off Between Sales and Profit for Different Prices



This objective function is calculated for all different pricing strategies available, and the pricing strategy that maximizes *OBJF* is chosen. The weights were determined in accordance with bauMax management. As a compromise of the various managerial standpoints, profit received the highest weight ($\omega_1 = 0.7$), whereas sales ($\omega_2 = 0.2$) and demand ($\omega_3 = 0.1$) received lower weights. Notice that a higher weighting of demand would result in more aggressive pricing strategies (cf. Natter and Hruschka 1998).

The arrow in Figure 2 depicts the effect of this new objective function ($OBJF^*$). Based on our own experience, this approach nicely utilizes the relatively flat profit optimum, sometimes leading to significant increases in quantity without being too far from profit optimum. In retrospect, introduction of this weighted objective function was probably one of the most important steps to enhance the general acceptance of the decision-support system.

3.3. Step III: Companywide Implementation

Enthusiastic about the success of the first implementation step and content with the dispelling doubts from the merchandise managers, management decided to terminate the procedure of test versus reference-outlet comparisons and to proceed with the companywide implementation of the system. Since mid-2004 (about one and a half years after the project began), pricing rounds have been scheduled bimonthly and recommendations are passed along to an approval workflow tool (see the pricing process below). Naturally, the benchmarking approach used until then was no longer appropriate. For further evaluation purposes, a new performance measurement tool was developed that compares the actual with forecasted sales and profits at the individual article level. For evaluation of the pricing path recommended by the system, model forecasts for a conservation of initial prices (as if the price remained unchanged during the evaluation period) were used as a baseline.

3.4. Structure of the Pricing Process

Besides adequate model building, a well-defined pricing process plays a crucial role in ensuring the translation of model recommendations into actions. Therefore, parallel to the companywide system implementation, a standardized pricing process flow was established. The sequence of tasks for performing a pricing round is depicted in Figure 3.

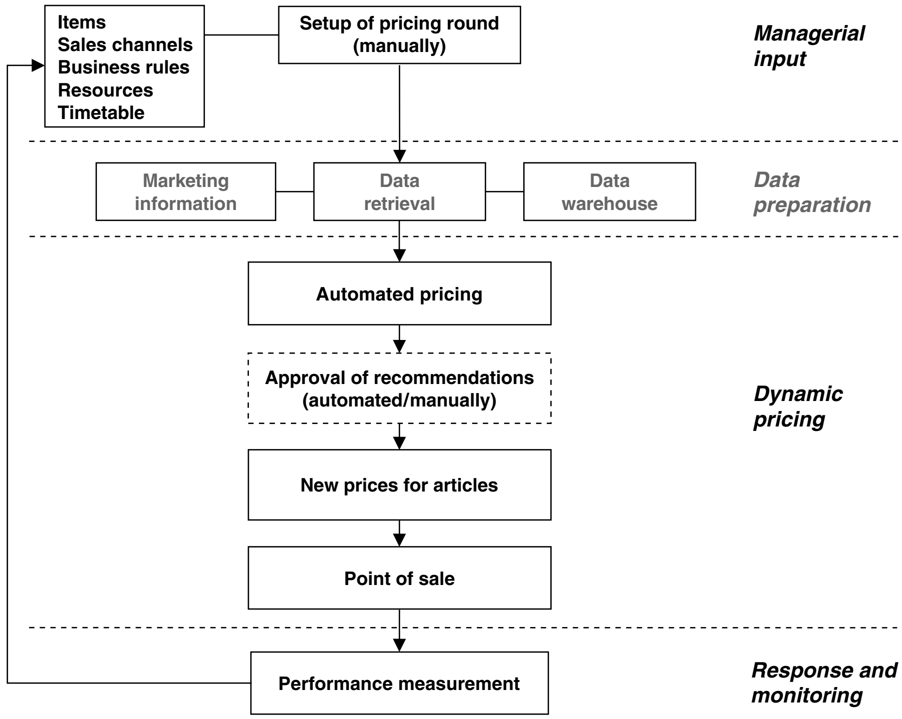
Initially, some managerial input is required. Although the model is designed to assist decision making for the complete range of articles, the list of relevant items and sales channels is restricted. For example, managers might feel like following certain business rules, but limited marketing resources or past experience from previous rounds can also impose constraints. Furthermore, timing issues need to be determined.

The next steps are automated: Input data are retrieved from the data warehouse, and optimal prices are derived by the model. By default, price recommendations are transferred to store managers at the point of sale directly. However, at this point merchandise managers can still interfere manually by means of an interactive approval workflow tool. This tool enables managers to refuse price recommendations for specific articles by indicating a reason for rejection. After collection of response data, the effectiveness of actions taken is evaluated using the extended performance measurement tool.

The information collected by the approval workflow tool provided excellent feedback for both fine-tuning the decision-support system and improving communication between users and the project development group. In the first pricing rounds, most rejections were caused by a deficient consideration of links between items of the same articles but with different levels of attributes, such as colors or packing sizes (e.g., a 20-kilo paint tub is expected to be more expensive than smaller pack sizes of the same product, but two different colors are required to be offered at the same price even if profits and/or sales are lower). Managers insisted on maintaining product line size parities for such product families and—as a consequence—the model had to be adjusted appropriately.

Another important reason for the denial of a proposed price increase was managers' concerns about competitor prices. In such cases, supplementary annotations on the driving forces behind the resulting recommendations (such as price-inelastic demand and/or low price consciousness for the questionable articles) were able to foster mangers' confidence and to further increase the rate of acceptance. Overall, numerous interactions with managers and feedback loops within the framework of successive pricing rounds brought bauMax's management to

Figure 3 Pricing Process



adopt a more formal, disciplined, and thorough pricing process.

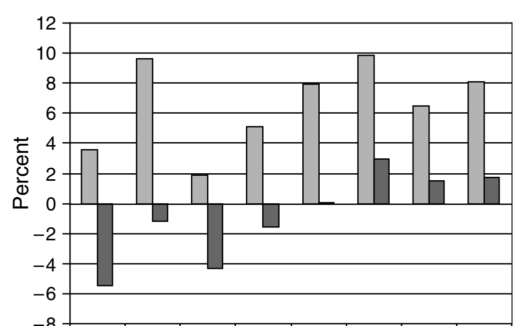
4. Impact on Profit, Sales, and Price Image

By the end of 2004, a total of eight pricing rounds had led to price changes on more than 11,000 different items. The system was responsible for more than 5 million new price tags. Here, we briefly summarize the aggregate outcome of these eight price adjustments by using the extended performance measurement approach as implemented after roll-out of the final system.

For each pricing round, the bar chart shown in Figure 4 visualizes the relative profit and sales differences between actual realizations and respective model baselines, assuming maintenance of initial prices. Throughout, a positive impact on profits can be reported. Sales figures, however, show a negative deviation for the first four rounds and a positive effect for the last three rounds. It is important to note that the above-described weighted objective function, including profits, sales, and quantity effects, was only applied in the later rounds. Furthermore, the model's predictive performance benefited from early experiments. The final implemented system in rounds six to eight showed an average profit increase of 8.1% and a sales increase of 2.1%.

With regard to the possible effects of recent price fluctuations on the overall price image as perceived by customers (cf. Levy et al. 2004), we can refer to a recently conducted image study: While roughly the same fraction of respondents believed that prices had either decreased or increased, the majority of 61% of regular bauMax shoppers stated that they were not aware of any significant price changes over the last year. In addition, compared to the five top competitors, bauMax is still considered to be the DIY retailer with the second most attractive price image. Thus, according to this study, it does not seem to be that such micro strategies have a negative impact on image in the short run. Future studies will shed light on the long-term effects.

Figure 4 Impacts of Pricing Rounds on Aggregate Profits and Sales



	1	2	3	4	5	6	7	8
Profit impact	3.6	9.6	1.9	5.1	7.9	9.8	6.5	8.1
Sales impact	−5.5	−1.2	−4.3	−1.6	0.0	3.0	1.5	1.7

5. Transportability and Generalization to Other Contexts

Currently the decision-support system has been functionally enlarged and user friendliness has been improved. In principle, we see no major obstacles to applying the model to the price and promotion planning of frequently bought consumer goods. Nevertheless, because of data requirements and model structure, important item categories such as slow-moving items cannot be tackled. Furthermore, products such as fashion goods or consumer electronics are not suitable because of their short life-cycles. Because of the lack of data, this implementation does not consider competitive prices. Although the latter are likely affecting optimal prices even if competitors do not directly react on price or demand (cf. Sudhir et al. 2005) changes, the degree of aggressiveness of competitive pricing behavior prevalent in a specific industry can be assumed to exert a significant impact on the resulting optimal pricing strategies. As a consequence, in industries where immediate competitive reactions to price changes can be expected, the model should be adapted accordingly (cf. Shankar and Bolton 2004). At bauMax, the problem of not considering competitive reactions was alleviated by excluding from automated pricing some 100 articles that competitors focus on.

A prerequisite of our model is the availability of previous price changes. In cases where variance in prices was low at bauMax, we started careful price experiments to create an appropriate base to estimate price effects. We are currently intensifying integration efforts with regard to the supply side. This research aims to develop integrated demand-and-supply chain management models through a linkage of reference price and inventory- and production-planning models.

6. Summary

We reported on a large-scale practical implementation of marketing science models to solve problems in the field of retail revenue management. The prices of a subset of articles from a DIY retailer were automatically optimized by the application of reference price models. The consideration of demand interdependencies between products, as well as the specification of a weighted objective function, turned out to be necessary business requirements. A large positive impact on profits was achieved. The models used at a more advanced stage of implementation also led to a considerable increase in sales.

Currently, thousands of separate models for different countries are estimated at the article level every two months and are provided to the store managers using a fully automated workflow. The bauMax CEO, Mr. Martin Essl, highlights the importance of this project as follows: "This implementation is one of our most important strategic projects for the future growth of bauMax, which enables us to sustainable competitive advantage."

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