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Arnd Huchzermeier, Ananth Iyer, Julia Freiheit,

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Arnd Huchzermeier • Ananth. Iyer • Julia Freiheit
WHU, Otto-Beisheim Graduate School of Management, Burgplatz 2, 56179 Vallendar, Germany
Krannert Graduate School of Management, Purdue University, 1310 Krannert Building, West Lafayette, Indiana 47907-1310
WHU, Otto-Beisheim Graduate School of Management, Burgplatz 2, 56179 Vallendar, Germany
ah@whu.edu • aiyer@mgmt.purdue.edu • jstolle@whu.edu

Increasing product variety through the use of alternate package sizes is a commonly observed mechanism in the grocery industry. Under such a scheme, however, the response to pricing decisions for each of the different package sizes is affected by how customers make demand choices. We build a demand model in which customers react *smart* to retail promotions through stockpiling and package size switching. The demand model combines a customer choice model with a model in which customers differ in their stockpiling and reservation price levels. We utilize data from the German grocery industry for an empirical fitting of the model. We then develop a store-level inventory model for each SKU and optimize price promotions to maximize expected profit. We show the benefit of capturing the *smart* customer response to price promotions by demonstrating its impact on the reduced inventory costs. We use the model to generate a number of managerial implications of the model for the German grocery environment.

(*Retail Promotions; Price Transparency; Supply Chain Management; Grocery Industry*)

1. Introduction

Consider a retail environment where entering customers are presented the same product in different package sizes with different per-unit prices. Suppose the prices varied temporally. Customers would then be faced with package sizes whose price difference varies across time. We then expect to see an environment in which customers switch their preference for package sizes at different periods, withhold purchases until prices are low enough, stockpile inventory, and continue to observe price, etc. Such an environment would provide a challenging inventory-and-pricing problem for individual package sizes (stock keeping units, termed SKUs). Our goal is to provide a model for such an environment and examine its performance using an empirical data set.

We focus on a data set from the German grocery environment because of the current level of rapid change occurring in the retailing environment in Germany. The German grocery retailing industry has historically consisted of a large number of small stores with limited competition. However, recently, the entry of the US retail chain Wal-Mart, and the growth of Internet-based shopping possibilities have led to increased competition. In addition, changes in German retailing laws now permit a more dynamic retail environment. The introduction of the Euro and the associated price transparency has also generated a discussion of convergence in prices across Europe and thus more pressure on the historically high retail prices in Germany. In this environment, retailers have realized that temporal price changes offer a mechanism to exploit customer heterogeneity and to generate store traffic. Retailers also offer increased product variety through the use of alternate package sizes for the same product. These different package sizes

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have different associated per-unit prices and are also used to segment customers. In such a selling environment, a retailer with a model of his store's customer segments could optimize the choice of promotion price levels and promotion frequencies to maximize expected profit.

Specifically, our goal is to: (a) develop an SKU-level demand model, (b) use the demand model and associated forecast error to model inventory costs, (c) use the inventory model and the demand response to optimize retail prices, (d) fit the models to a data set and evaluate model performance, and (e) use the resulting model to suggest managerial implications. Note that, in principle, the model may be extended to different brands of the same product, different complementary products, etc.

Our demand model consists of two parts: (a) a customer-choice model that estimates the proportion of customers who choose a particular SKU in a period given prices of all SKUs, and (b) a stockpiling model of the total demand for the product across SKUs based on the average price across products and customer-segment inventories across SKUs. We use the term *smart* customer to denote a customer's use of stockpiling and package-size switching in response to retail promotions. We focus on a data set where the same product, diapers in our case, has a selling environment as described above. Our data set consists of weekly prices and sales data for one year for seven sets of products, each with two different package sizes, from five separate store locations. Overall, we utilized 24 data sets for our model and 48 SKU-location combinations.[1] The fitted model is then evaluated using a holdout sample of six months of data for one such data set. We then develop a store-level inventory model for each SKU. We show the benefit of capturing the *smart* customer response to price promotions by demonstrating its impact on the reduced inventory costs. Finally, we use the model to generate a number of managerial implications of the model for the German grocery environment.

This paper is organized as follows: In §2, we discuss our data set. In §3, we provide a forecast model of the demand and present empirical results. In §4, we provide a supply chain inventory model that links the demand structure to expected costs. Section 5 provides managerial implications. In §6, we provide a brief overview of the relevant literature. Section 7 concludes with a summary of our findings.

[1]Note that not all products were being offered at the stores.

2. The Data Set

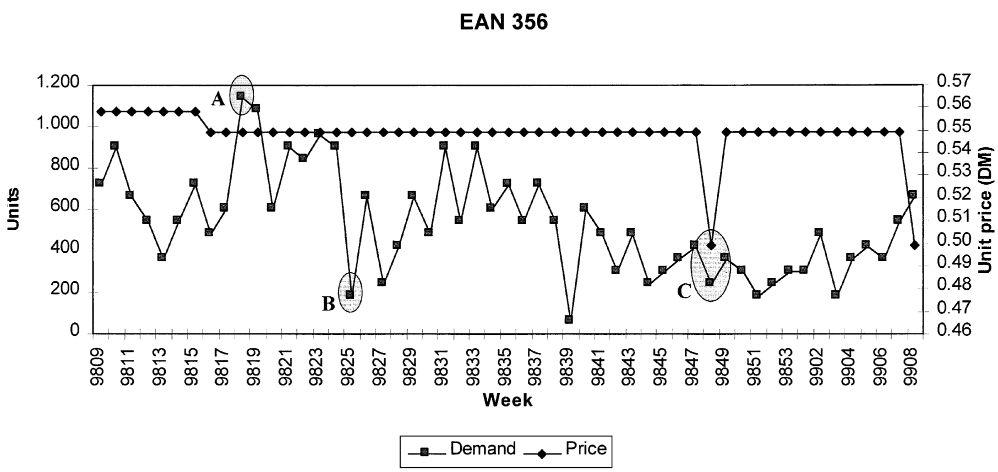
In this section, we describe the data set. We used the actual retail prices, sales data, and costs for one specific product type (diapers). Given that typical retail inventory levels were kept at high levels (and the possibility of quick replenishment from the chain warehouses), store managers claimed low stockouts. We used the sales data as a proxy for demand. We found that switching across brands was not significant in the data set—this was also confirmed by discussions with managers in the stores, who claimed brand switching occurred less frequently for this product type. We focus on diapers produced by Procter and Gamble with the brand name Pampers, with a market share of 81%. There are three reasons for this choice: First, the consumption rate of diapers is steady, and the nature of the product is such that there is no seasonality in its use. Second, diapers are a rather ''expensive'' item, thus we assume it to be promotion sensitive. Third, the retail industry considers Pampers as a *trigger* item, i.e., if it is offered on promotion, store frequency will increase considerably. Our goal is to develop and fit a demand model at the SKU level to this data set.

MADAKOM GmbH[2] provided weekly POS-data from several grocery retailers located throughout Germany. We first plotted price versus demand over a period of one year for one SKU. As can be seen in Figure 1, there does not seem to be a clear relationship between customer demand and price variations for this particular SKU. We point to the following features in this data set:

(1) The points *A* and *B* have the same price level but significantly different demand levels.

[2]A joint-venture of GfK (Gesellschaft für Konsumforschung) Panel Services and CCG (Centrale für Coorganisation), MADAKOM provides a pool of weekly POS-Data from over 150 linked retail chains/stores to retailers and industry.

Figure 1 Price and Demand Time Series for One SKU



(2) Point C shows that when price decreases, the quantity sold decreases.

These features were common throughout the data set. The data thus suggests that focusing on a single SKU may not provide a reasonable model of demand as a function of price. These observations, plus customers' observed loyalty for brand, suggest that the prices of alternative package sizes should be considered in constructing a demand model.

3. An Approach to Modeling SKU-Level Demand

In this section, we will build a model that consists of two components: A first model that estimates how consumer choice across package sizes is affected by the prices for each package; and a second model that estimates how the size of the total purchase is influenced by the pricing used across time. For the first model, we first use a logit model and then consider a simpler model with fewer parameters. For the second model, we use a stockpiling model, at the "brand" level, similar to that in Iyer and Ye (2000).

3.1. A Logit Model

We will describe the procedure for two package sizes—It can be expanded to any number of packages without loss of generality. We collected additional data for different package sizes of the same product and grouped the data according to product types. For example, under the Baby Dry Extra category, there were two package sizes, with 70 units and 136 units respectively for the small and large sizes. We use the index 1 to refer to the 70-unit package size and 2 to refer to the 136-unit package size.

Let the prices p_{1t} and p_{2t} refer to the price per unit for package sizes 1 and 2 at time $t = 1, 2, \ldots, N$. Let the associated observed demand (assumed to be equal to the sales) in period t (in units of product) be d_{1t} and d_{2t}. Generate the proportion of product 1 sold each period as $r_{1t} = d_{1t}/(d_{1t} + d_{2t})$. We will first fit a logit model to this proportion as a function of p_{1t} and p_{2t}.

The logit model expresses the expected proportion of product 1 sold in a period as

$$E(r_{1t}) = \frac{e^{\theta_0+\theta_1 p_{1t}+\theta_2 p_{2t}}}{1 + e^{\theta_0+\theta_1 p_{1t}+\theta_2 p_{2t}}}.$$

Thus, if we define a new variable $r'_{1t} = \ln[r_{1t}/(1 - r_{1t})]$, then

$$E(r'_{1t}) = \theta_0 + \theta_1 p_{1t} + \theta_2 p_{2t}.$$

We then estimated the values of θ_0, θ_1, θ_2 using regression and verified that the errors are normally distributed.

The following is a summary of the steps used to fit the logit parameters to the data set:

(1) Generate the proportion of product 1 sold each period as $r_{1t} = d_{1t}/(d_{1t} + d_{2t})$.

(2) Using r_{1t}, generate r'_{1t} defined as $r'_{1t} = \ln[r_{1t}/(1 - r_{1t})]$.

(3) Do a multiple linear regression of r'_{1t} against p_{1t} and p_{2t}. (We used Microsoft Excel's multiple-regression package to do this step). Record the values of R^2, the fitted values of θ_0, θ_1, θ_2, and check residuals for normality.

(4) Given r'_{1t}, generate the value of $r_{1t} = \exp(r'_{1t})/[1 + \exp(r'_{1t})]$.

Thus, given the fitted parameters θ_0, θ_1, θ_2, our forecast of the proportion of customers who choose package 1 is

$$r_{1t} = \frac{e^{\theta_0+\theta_1 p_{1t}+\theta_2 p_{2t}}}{1 + e^{\theta_0+\theta_1 p_{1t}+\theta_2 p_{2t}}}.$$

The proportion who choose package 2 is estimated as $r_{2t} = 1 - r_{1t}$. This model follows papers in the literature on logit models (see Guadgni and Little 1983, Mahajan and Van Ryzin 1998).

We implemented this model for each of the 24 data sets. We first report on the multiple-R value for the fitted parameters because it reports on the fraction of the standard deviation explained by the model. Because the cost associated with a given forecast error is proportional to the safety stock, which is proportional to the standard deviation of demand, we suggest that the multiple-R value provides a proxy for the quality of fit of the model. The associated multiple-R value for the fitted-logit model ranged from 35 to 91%. For the particular data set we focus on in the graphs in this paper, the associated multiple-R value was 78%. However, the traditional statistical parameters such as R^2 ranges from 12 to 83%; the R^2 for the particular data set we focus on was 60%, and the adjusted R^2 value for this data set was 57%. All of the associated parameters were significant in the model.

While the logit model permits use of standard regression software to fit parameters, it is based on a zero-order model of the pricing process, i.e., the parameters of the choice process are time independent.[3]

[3]Note that the overall demand model we build is not time independent; the temporal effect of pricing on quantity are modelled in §3.3.

This issue is summarized in Grover and Srinivasan (1989). They state that the zero-order brand-choice process means that the individual consumer's purchase probabilities do not depend on her previous purchases but they can change over time to reflect marketing actions. Other researchers, such as Chintagunta (1998) and Gonul and Srinivasan (1993a), suggest alternative approaches to compensate for this feature of the logit model by including nonstationarity in the choice parameters. Such detailed models require information at the household level. Because we did not have such data, we employ a simpler choice process. We include the temporal effects of price, but at the market-size model in §3.3. We also include the forecast error implied by the fitted model as part of the cost structure of the model in §4. This permits us to account for the cost impact of the simpler model as part of the overall model structure, thereby permitting a representation of the expected cost associated with different pricing policies for the optimizing model in §4.

3.2. The Fit of a Restricted Model

We now examine a simpler, more restricted form of the logit model that we refer to as the a-model. The associated model is expressed as follows:

$$E(r_{1t}) = \frac{e^{\theta_3(p_{1t}-p_{2t})}}{1 + e^{\theta_3(p_{1t}-p_{2t})}}.$$

In this model, we again define $r'_{1t} = \ln[r_{1t}/(1 - r_{1t})]$ and thus generate r'_{1t} as follows:

$$E(r'_{1t}) = \theta_3(p_{1t} - p_{2t}).$$

The parameter θ_3 is estimated by a linear regression of r'_{1t} against $(p_{1t} - p_{2t})$ with the intercept forced to be equal to 0. We record the fitted parameter θ_3, note R^2, and check residuals. Now define a parameter $a = e^{\theta_3}$. This parameter a provides a single parameter to capture the customer's propensity to switch from one package size to the other. Larger a reflects a smaller propensity to switch as the price gap between the package size increases than a smaller value of a.

This fitted model suggests that the probability that a customer chooses package size 1 is estimated as $r_{1t} = (a^{p_{1t}-p_{2t}})/(1 + a^{p_{1t}-p_{2t}})$. As far as the fit within the sample, by decreasing the number of parameters from three in the logit model to one in this model, we should expect the R^2 to decrease. For the same 24 data sets, the corresponding multiple-R value using the a-model ranged from 14 to 85%. For the data set we focus on in this paper, the associated multiple-R value using the a-model was 74%. The R^2 ranges from 2 to 72%; the R^2 for the particular data set we focus on was 54% and the associated adjusted R^2 value was 50.1%. Thus we see a decrease in the fit of the choice model as we decrease the number of parameters. However, the potential benefit of a more parsimonious model is that: (a) It is more robust to the data set and may thus forecast better, and (b) it allows for a simpler characterization of stores, which may provide managerial benefits. We will provide results with both models; i.e., the logit model and the a-model, for the rest of the paper.

3.3. An Aggregate-Stockpiling Model

At this point, we have modelled the consumer choice across packages as affected by the price differences between packages each period. We have not, however, captured the impact of temporal price changes on the total demand in a period. Intuitively, we expect reductions in the average price across package sizes to potentially bring in new customer segments with lower reservation prices and, thus, increase store traffic. We also expect these segments to potentially stockpile to satisfy their future demands. Thus, if one package size is promoted, increases in volume sold of the promoted product may come from both new customer segments, their stockpiling for future periods, and shifts in customer choice across package sizes. We will describe such a stockpiling model.

Suppose the prices in period t are p_{1t} and p_{2t} for package sizes 1 and 2. The average price per unit paid by all consumers who purchase in period t is the weighted price $p_t = r_{1t}p_{1t} + r_{2t}p_{2t}$. The weights used are provided by each of the two models in §§3.1 and 3.2. The total demand (in units) of product is $d_t = d_{1t} + d_{2t}$. We now build a model of demand in each period t that links p_t to d_t. While the general model may consider any number of segments, we describe a model with two segments. Details of the stockpiling model, applied to a single product, are provided in Iyer and Ye (2000). In this paper, the corresponding model is applied to the aggregated (by brand) data.

A quick summary of that model is as follows. We divide customers into two segments—1 and 2. Segment 1 does not stockpile any product, purchases every period, and has a per-period consumption rate of c_1. Segment 2 has a reservation price of r_2 (we assume that r_2 is less than the average regular price for the packages). Segment 2 does not purchase when the prices are at their regular level. However, when the average price drops below r_2, segment 2 purchases a quantity

$$d_{2t} = \max\left[\frac{(r_2 - p_t)c_2}{h_2} - I_{2,t-1},\ 0\right].$$

The inventory $I_{2,t-1}$ is the inventory level of customer segment 2 at the end of the previous period and p_t is the price in period t. Initial inventory is assumed to be zero, i.e., $I_{2,0} = 0$ and in the following periods the inventory level is given by $I_{2,t} = \max(I_{2,t-1} + d_{2t} - c_2, 0)$. We remark that while the response to price is linear within a market segment, the overall link between total demand across segments and price is not linear because of the effect of reservation prices. We refer to Kalyanam (1996) for other approaches to model the link between demand and price that are nonlinear.

We fit this model to the aggregated data set. The model parameters fitted to the aggregated data enable us to generate a forecast for aggregated demand d_t as a function of the weighted average price per unit p_t. In Figure 2 we plotted the estimated demand versus the actual sales data. For the data set we focus on, we see that the fitted model generates a multiple-R value of 85.9% (R^2 of 73.8%) using the logit model to generate weighted prices. The range of multiple-R values using the stockpiling model for the 24 data sets ranged from 33 to 94% (the R^2 values ranged from 11 to 89%) using the logit model for weighted prices. We repeated this procedure using weights derived from the a-model described in §3.2. For the data set we focus on, the associated fitted model using weights derived from §3.2 generated a multiple-R value of 87.0% (the corresponding R^2 value was 75.6%). The range of multiple-R values for the other 24 data sets using weights from §3.2 was from

Figure 2 **Actual Demand Versus Demand Forecast on an Aggregated Level**

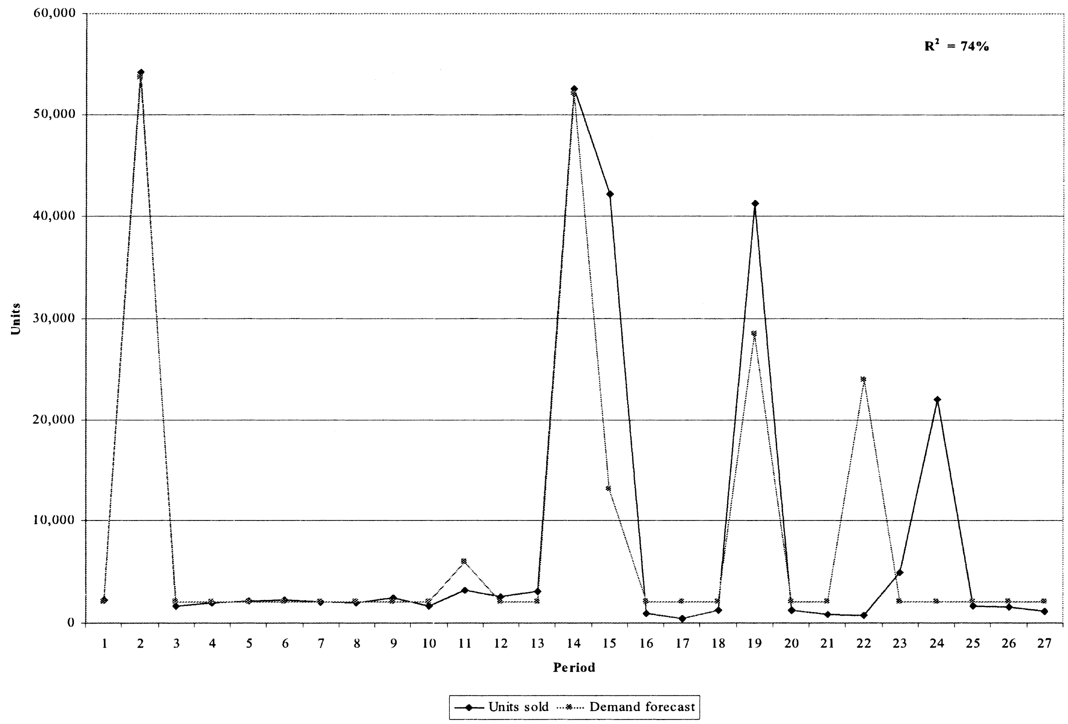
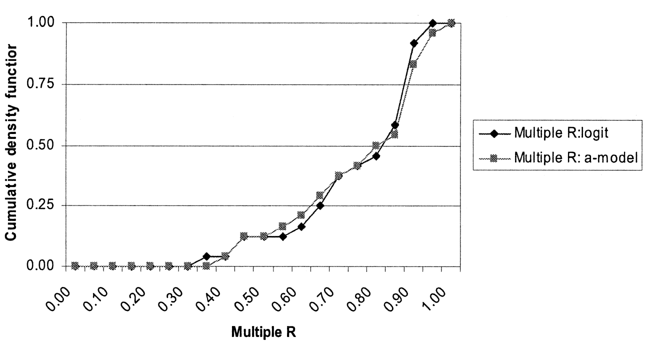


Figure 3 **Multiple *R* Values for the Aggregate Fit Using the Logit and *a*-model**



36 to 96% (the corresponding R^2 values ranged from 13 to 92%).

Once we have the stockpiling model, we disaggregate to generate individual package-level demand as $d_{1t} = d_t r_{1t}$ and $d_{2t} = d_t(1 - r_{1t})$, where d_t is obtained from the stockpiling model. These two steps can be done with our model (using a) and using the logit model (using the three parameters θ_0, θ_1, θ_2). The individual package-level demand predictors were then compared against the actual sales. The value of multiple-R for the large packages was 86.5% (the corresponding R^2 value was 74.8%) for the sample data set when the logit model was used to generate weights in the corresponding stockpiling model. The range of multiple-R over the 24 data sets was from 36 to 97% (the R^2 values ranged from 13 to 95%) for the large packages. The corresponding value of multiple-R using the a-model for the weights and the associated-stockpiling model was 87.5% (R^2 was 76.5%) for the large package. The range of values for the multiple-R was from 38 to 98% (R^2 values ranged from 14 to 95%). We conducted a normality test for the residual variance of the three groups analyzed in the sample store. The p-values suggest that the residual variances are normally distributed; i.e., at a significance level of 1% the null hypothesis of normality could not be rejected. Figure 3 compares the aggregate fit of both the logit and the a-model over the 24 data sets.

When we fitted the disaggregated model to our data set, we observed the following properties: The fit for the larger packages was always considerably better than the fit for the smaller package. While the R^2 values for the large packages were as reported, and, thus, acceptable, the fit for the smaller packages had parameters that were statistically significant but with low R^2 values—typically less than 10%. However, for most stores and products, with the current pricing scheme, the small packages accounted for less than 10 to 30% of the total units sold. Thus, even though the forecasting model performs poorly for the smaller package, it has a small effect on overall costs. In our interviews, we were warned that during times of promotion, achieving high service levels for the small package sizes was less of a concern to store managers. Because only sales data were recorded, the quality of fit of the model for small package sizes may be affected. This may explain (at least in part) the relative poor fit that we obtained.

3.4. Predictive Impact of the Model—Using a Holdout Sample

We reported results in the previous sections when we fitted the model to data collected from week 9 in 1998 to week 8 in 1999. In this section, we report on use of the fitted parameters to predict sales for weeks 9 through 31 of the 1999 demand season. We examined the performance of both the logit model for consumer choice and an associated-stockpiling model as well as a proposed a-model and the associated-stockpiling model. For the holdout sample, the R^2 value for the aggregate model was 74% and the R^2 value for the larger package was 51% using the logit model of customer choice. The corresponding multiple-R value was 71%. The corresponding R^2 values were 74 and 71% using the a-model and the multiple-R value was 84.2%. What do we conclude? For the data set, this suggests that a more parsimonious model delivered better performance. While this is not a generalizable conclusion, it does suggest a potential role for the use of simpler and perhaps more robust models of data.

A potential reason for this performance is that the objective function that we use while fitting the model, i.e., minimizing squared error, may not reflect the objective when it comes to model forecasting given that the parameters of the stockpiling model are influenced by the fitted parameters of the choice model. It is perhaps more appropriate to choose a likelihood function that better reflects the goals of the model fitting—We leave that to future research. In discussing the theory in the rest of this paper, we will use the a-model. We remark that this is only for convenience of exposition—The same statements could be made with the three parameter logit model too.

We examined other aggregate models such as a linear relationship between demand and price. The linear model generates R^2 values of 5.8 and 59% for the same two package sizes. In contrast, our aggregate model generated an R^2 of 10 and 74%, with the higher R^2 referring to the large package that comprised about 87% of the total demand. Thus, while it is difficult to conclude that we have the best possible model, we surmise that the model fit suggests that we at least have as reasonable a model as any of the others in the literature given the data constraints, i.e., aggregate data rather than panel data.

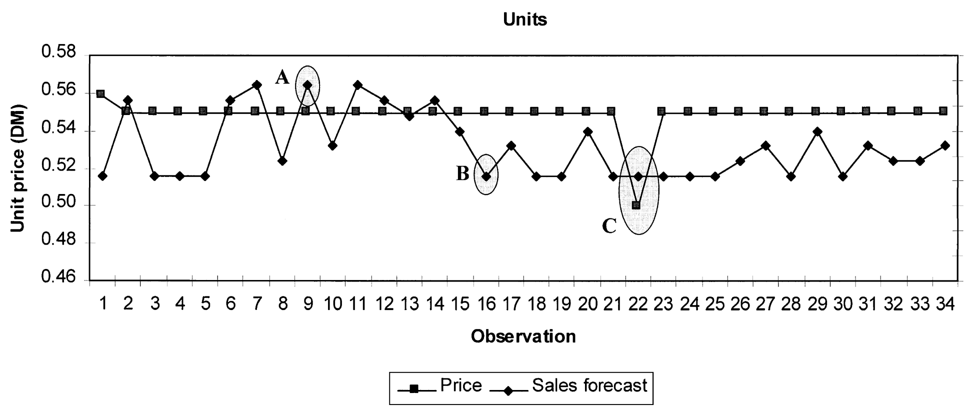
Figure 4 shows that our fitted demand model recreates the idiosyncracies that were observed in our original data (in Figure 1). For example, points A and B show the forecast of very different demand levels at the same price level. Point C shows the effect that sales do not necessarily increase, if there is a price promotion.

4. An Inventory Model with Optimal Promotions

We now focus on using the models generated above to optimize the level and depth of promotions to maximize store profits. This requires us to model the supply costs associated with the demand model. We turn again to the supply-side model in Iyer and Ye (2000). This section will show how the aggregate-stockpiling model describing customer purchases can be used to optimize expected profits using a promotion strategy.

Consider a store that sells two different package sizes of a given product. Assume that prices are at two levels—regular price or a promotion price. Suppose the smaller pack size has a price p_{1n} where n is

Figure 4 Price Versus Demand Forecast of the Disaggregation Model



r during regular price periods and l during promotion periods. Suppose the larger package size has a price of p_{2n} where (as before) n is r during regular price periods and l during promotion periods. Given the SKU-level prices, define variables r_{1n} and r_{2n}, and the weighted price each period $p_n = r_{1n}p_{1n} + r_{2n}p_{2n}$. Now assume that we fix the prices $p_{1r} = p_{1l}$ and keep p_{2r} fixed at a level $\leq p_{1r}$. We now decide to promote the larger package size by dropping the price to p_{2l} with a certain frequency that follows a negative binomial distribution with parameters 2 and $q(p_l)$ where $q(p_l) = 2h_2/(r_2 - p_l)$. (We refer the reader to the paper by Iyer and Ye (2000) for details of this model.) For each of these prices, let d_{1n} and d_{2n} refer to the individual package size demand and $d_n = r_{1n}d_{1n} + r_{2n}d_{2n}$ refer to the total demand.

If we define c to be the cost per unit for each product the retailer orders, h as the holding cost per unit of product that the retailer has to hold throughout the period, and π as the loss of goodwill for each unit of unfulfilled demand, we can write down the expected profits for each of the two SKUs each period. Z provides the service level that we assume to be the same during promotion and nonpromotion periods, $b(Z)$ is the right linear loss function, and σ is the standard deviation of the forecast error. Let G_{ij} ($i = r$ or l and $j = 1, 2$) refer to the expected profit in a period with i referring to a regular or promotion period and j referring to package 1 or 2. Let σ_{ij} refer to the associated forecast error. The corresponding expected profit, following the steps in Iyer and Ye (2000), is

$$G_{ij} = (p_{ij} - c)d_{ij} - (hZ + (p_{ij} + h + \pi - c)b(Z))\sigma_{ij}.$$

Consider the case when the forecast error is σ for regular periods and σ' for the promoted periods. The expected profit G_{tot}, i.e., the total expected profit across both package sizes, is obtained by adding up the expected profit across package sizes each period, and is expressed as follows:

$$G_{\text{tot}} = (p_r - c)c_1 + \frac{(p_l - p_r)c_1}{\dfrac{r_2 - p_l}{h_2}} + (p_l - c)c_2 + \frac{b(Z)(\sigma p_{1r} - \sigma' p_{1l})}{\dfrac{r_2 - p_l}{h_2}} - (hZ + (p_{2r} + h + \pi - c)b(Z))(\sigma_{1r} + \sigma_{2r}). \quad (1)$$

Note that obtaining the optimal p_l^* and thus p_{2l}^* requires numerical search. The figures show the effect of a on the weighted price (see Figure 5) and associated expected profits (see Figure 6). The basic intuition is that a lower value of a may suggest deeper and less frequent promotions than a higher value of a. This reduction in promotion decreases the demands that occur due to switching. We also see that, correspondingly, expected profits rise with a. We have thus linked the demand model and its associated supply costs to generate an optimal promotion plan and associated expected profit.

Under special conditions, however, the model described above can provide a closed-form expression

Figure 5 Effect of *a* on the Weighted Price

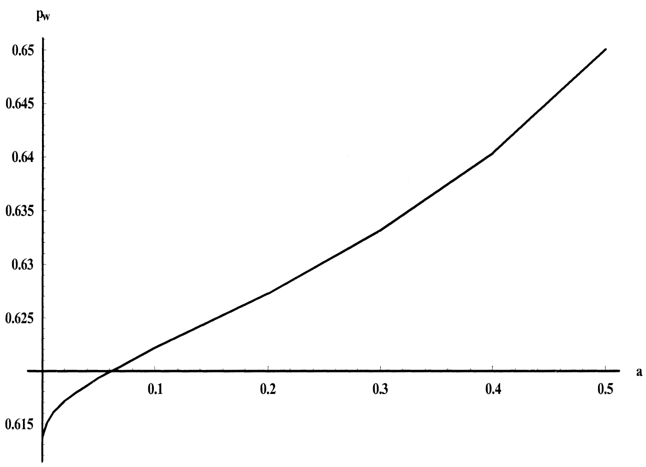
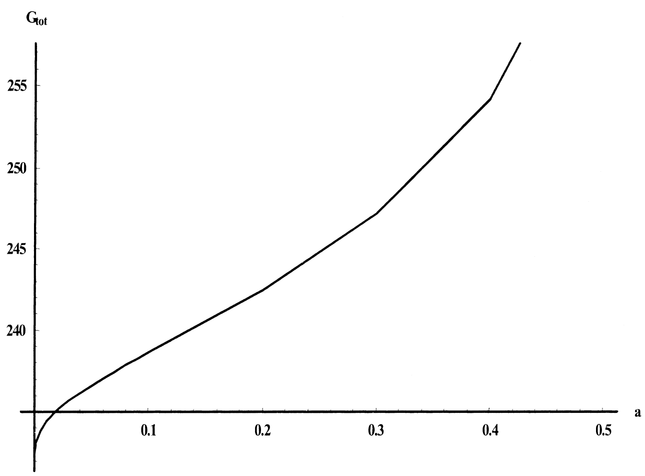


Figure 6 Effect of *a* on the Expected Profit



for the optimal promotion price. This information is provided to permit a quick check of the solutions obtained. For example, consider the case when $\sigma = \sigma' = c_v d_{ij}$, i.e., the coefficient of variation (c_v) of the forecasted demand for each SKU is constant. Under this case, we get the expected profit as

$$G_{\text{tot}} = (p_r - c)c_1 + \frac{(p_l - p_r^w)c_1(1 + c_v b(Z))}{\dfrac{r_2 - p_l}{h_2}} + (p_l(1 + c_v b(Z)) - c)c_2. \tag{2}$$

Note that if we solve for the optimal p_l^*, we get the expression

$$p_l^* = r_2 - \sqrt{\frac{c_1 h_2 (p_r - r_2)}{c_2}}. \tag{3}$$

This condition for the weighted promotion price is independent of the consumer choice process. Given the optimal promotion price, however, the associated price charged for the promoted SKU will depend on the choice process.

We caution that for trigger products, optimal pricing plans may be based on the impact of this product's prices on stimulating store traffic that may increase profits for other (possibly unrelated) product categories. Since our model and our data set focuses only on the diaper category, we may expect the optimal promotion price generated by the model to be higher than that observed in practice.

5. Discussion

5.1. *Smart* Customer Response

Our data indicates that customers are *smart* in that they calculate the per-unit price of the product and adjust consumption across package sizes. We can see that during a price promotion, demand increases by as much as 36 times the mean nonpromotion demand. Our disaggregation model suggests that customers do choose the lower-priced products.[4] This is consistent with a recent survey of the German grocery industry, which states that 59% of German consumers chose items that were on promotion (Rosbach 1999). As evidenced by our data, customer reactions to price differences prevent retailers from achieving the benefits of price discrimination.

In our model, we captured the *smart* customer behavior with the switching factor *a.* A small value for *a* indicates a high willingness to switch between product sizes to take advantage of a lower per unit price. Therefore, if one package size is priced differently from the other one, most customers will switch to the lower-priced package. The *a* values we calcu-

[4]The two different package sizes, if offered on promotion simultaneously, are not offered at the same per-unit price. The smaller package is more expensive than the larger one.

lated for our data set were all very low, supporting the fact that most customers switched over to buying the larger package due to its lower per-unit price during promotions. A high value of a indicates a lower willingness to switch between package sizes. If this is the case, different promotional prices make more sense, since customers will not readily switch from one package size to another.

Our model can serve as a valuable tool to retailers by offering them an indicator (i.e., the factor a) for choosing whether or not to use price differentials for different product packages during promotions. Figure 6 shows that the retailer profits increase with a and most of those benefits stem from the ability to isolate the reactions to price promotions by package size.

5.2. Benefits of Package Variety

In this section, we explore the logistics benefits of price promotions across package sizes. Our data set indicates that about 75 to 85% of the units were sold on promotion. The demand model we generate for the large packages (which were primarily the promoted package) had R^2 values ranging (as stated earlier) from 14 to 95%. The smaller packages were less predictable but accounted for a smaller number of units. This improvement in sales forecasts for the majority of the demand provides a corresponding logistics cost benefit to the system.

It is always assumed that more variety increases demand variability. Since we had data from stores that sold one package size and did not promote product, we examined the logistics costs for those stores. In order to derive some conclusions as to the effect of different package sizes for our particular product, we looked at demand variability at those stores. The coefficients of variation varied between 25 and 47% for the first store, between 39 and 140% for the second store, and between 46 and 113% for the third store. This suggests that isolating the predictable customers (i.e., those who shift to the lower-priced package during promotions) may enable a reduction of forecast error and thus reduction of logistics costs. This highlights a beneficial aspect of package variety.

5.3. Retail Competition

To show the profit implications of this model, we used our data set to generate the profit function for one sample store. The optimal promotion price for the larger package p_{lb} is given by DM 0.517. The actual average promotion price for the larger package was DM 0.434, which is not only below the optimal promotion price given by the model, but is also below our calculated costs. An analysis of the expected profit also shows that profits deteriorate at a very fast rate to the left of the optimal promotion price, thus it is very sensitive to the promotion price. This is true for all stores that we analyzed.

In the current German market, retail formats are changing from small ''Mom and Pop'' stores towards discounters and superstores (i.e., stores with a sales area greater than 1,500 m^2).[5] Our model suggests that in this highly-competitive market, it is essential to pay attention to customer behavior and to understand and evaluate individual micro-market structures. Coordination of pricing and inventory management allows retailers to compete effectively in a more competitive industry. Our data shows that profits could be increased significantly with a potential model of consumer choice and temporal purchases (e.g., a 30% increase of expected profits was observed for our sample store).

However, we caution that the current model does not include the spillover effects of promotion of this trigger item on other product categories. Perhaps promotions of diapers permit expected profit increases for other products. We leave such investigations to future research and data sets.

5.4. Trends

Today prices across Europe still vary considerably for one and the same product. For example, a package of Pampers diapers in the United Kingdom can be obtained for an amount equaling DM 16.88, whereas the same package costs DM 24.98 when purchased in Germany (Handelsblatt 1998). In the future, transactions in Euro will lead to greater price transparency

[5]Discount stores now account for 34% (up 17% over the last 10 years), and superstores account for 32% (up 5% over the last 10 years) of all retail stores (Wolfskeil 1999).

and will eliminate some of these price differences. Prices are expected to converge across countries (Bowley 1998). But rather than having different prices across national boundaries, prices may vary according to regional markets (i.e., rural areas versus urban areas, etc.), thus price discrimination is still possible (Krömer 1998). We believe that the understanding of micro-markets will be essential in defining the corresponding pricing structure that will allow for more rather than less price discrimination. For example, our store data analysis shows that between 10 and 30% of the volume sold consists of small packages. This suggests that retailers can effectively exploit the structure of their local customer base to extract additional value.

6. Literature Review

We first focus on a set of papers that model the consumer choice process. We use the term *smart customers* to refer to customer models where prices across product sizes (in our case) or across product attributes are actively processed by the customer to arrive at purchase choices. Papers on consumer choice typically model either the choice between different products (i.e., brands) or the consumers choosing between stores. Blattberg and Wisniewski (1989) use a model based on utility theory and different preference distributions to model how consumer preference distributions affect interbrand competition. Their focus is especially on price-induced patterns of competitions, i.e., how trade promotions affect the choice of brands. A discussion of ''brand-switching consumer'' behavior is found in Silva-Risso et al. (1999, p. 278).

A number of papers have focused on the use of scanner panel data and the associated-forecasting model. While these papers start with different levels of detail than our data set, they do provide a number of alternate approaches to model both the choice process as well the demand. Grover and Srinivasan (1989, 1992) assume that consumer brand choice process is zero order but allow brand choice probabilities to vary between periods. All sizes are treated the same for the scanner panel data set of ground coffee. Gonul and Srinivasan (1993a, 1993b) suggest a multinomial logit model with augmented heterogeneity specifications to capture unobserved differences across households. They provide an application to a scanner panel data set of disposable diapers where the price per unit is constant across sizes. Papatla (1996) suggests a model where the deterministic impact of marketing variables such as price, display, and features are multiplied with household specific scale parameters for preference, price sensitivity, and promotion response. The model is applied to a scanner panel data set of liquid detergents. Guadgni and Little (1983) use a logit model of individual customer choice to study the response to market variables using a scanner panel data set. Baltas (1998) studies an integrated model of brand choice and category demand using a two-stage model where customers optimize their use of a budget to choice across product categories. Chintagunta (1998) introduces the concept of state dependence in brand-choice models by including time varying state dependence where brand-switching probabilities depend on interpurchase times. While each of these papers sheds important light on the forecasting component, they all use scanner panel data sets while we have access only to scanner data. A recent paper by Nijs et al. (2001) uses a scanner data set describing national sales in Dutch supermarkets to study the impact of the marketing mix on short-run and long-run promotional effectiveness. Their results suggest that price promotions rarely exhibit persistent effects. Our goal is to develop a model that can then be used for optimizing pricing and minimizing inventory costs. We thus present our model as a contribution to both the forecasting as well as the corresponding associated-expected profit-maximizing pricing model.

In an empirical study, Mela et al. (1997) examine the long-term effects of promotions and advertising on consumers' brand-choice behavior. The smart customer in this context refers to the link between advertising, brand choice, and customer decisions. The impact of pricing decisions on consumers' choice of stores is shown in an empirical study by Walters (1988). Kumar and Leone (1988) measure the effect of retail store promotions on both brand and store substitution. They show that store substitution effects are not only a function of the promotional price, but also a function of the geographic proximity of the stores. Mahajan and Van Ryzin (1998) provide an overview of current research linking retail inventory management and consumer choice models. A survey of the economics of variety appears in Lancaster (1990).

The link between promotions and sales is captured primarily through models of customer heterogeneity. Eppen and Liebermann (1984) propose a model with two customer segments with different inventory holding costs. In their model, retail price promotions are optimal for the retailer because of the difference between the holding cost for the retailer and the customer. A similar approach is presented by Blattberg et al. (1981), where customers differ in holding costs and have the same reservation price. Jeuland and Narasimhan (1985) model customers with different reservation prices and holding costs. We present a model in this paper that is similar to the one by Iyer and Ye (2000). They model differences in holding costs, reservation prices, and consumption rates across customer segments. The resulting demand is modelled as a log-normal distribution around the stockpiling model. Iyer and Ye (2001) provide a mixed-integer programming model linking the model results to optimal pricing decisions for a data set that also incorporates market share constraints and other pricing considerations. The aggregate demand model in this paper is closely linked to the models in Iyer and Ye (2000), who focus on a single product. However, in this paper, by combining a stockpiling model with a consumer choice model, we expand the use of their model to multiple products.

Similarly, there have been several industry publications focused on trade or manufacturer promotions. For a recent industry study, see the ECR Europe report (1999) on promotion tactics. An analysis of trade promotions is provided in Blattberg et al. (1995). The issue of trade promotions will not be considered in our model—we will assume that the manufacturer employs an Every Day Low Purchaser Price (EDLPP) strategy. This assumption is appropriate for the product and manufacturer we consider.

7. Conclusions

We focus on the link between the smart customer reaction to differences in unit prices across package sizes. Our model uses a customer choice model and a stockpiling model to capture the impact of pricing differences between packages on both the total demand as well as the individual package size demand. We fit the associated model to a data set. The resulting model is also evaluated against a holdout sample. The empirical results suggest that a parsimonious model we propose may generate better performance for the holdout sample. This suggests that simpler consumer response models may have a better forecasting performance due to their inherent robustness. The inventory model focuses on optimal choice of a pricing plan to maximize expected profit. The model suggests implications for the German retail grocery environment.

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Appendix. Notation

- t Index of time periods.
- i Index of customer segments, where $i = 1,2$.
- m Index of package sizes, where s = small packages, and b = large packages.
- n Index of pricing periods, where r = regular price and l = promotion price.
- $d_{k,t}$ Demand in period t for each SKU k.
- $p_{k,t}$ Price per SKU k in period t.
- $d_{i,t}$ Demand of customer segment i in period t.
- r_i Reservation price of segment i.
- c_i Consumption rate of segment i.
- h_i Holding cost of segment i.
- $I_{i,t}$ Inventory level of segment i in period t.
- a Weighting parameter.
- p_{nm} Price per unit of package m at price n.
- G Expected profit.
- c Cost per unit of product.
- h Holding cost per unit of product.
- π Cost of goodwill.
- σ Forecast error for small packages and large packages during regular price periods.
- σ' Forecast error for larger packages during promotion price periods.

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