ANALYSIS OF SALES OF PRICE PROMOTED CONSUMER GOODS USING SCANNER DATA *)

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SUMMARY

The data under study are weekly recorded scanner data concerning several product lines offered in various German supermarkets. The analysis concentrates on non-perishable branded products for which short-term price promotions were carried out. Within the observation period of about one year the products were characterized by almost constant sales in weeks with unchanged prices and by an abrupt increase of sales when offered at a reduced price. Beside other short-term price cut effects the investigation of the price-demand relationship in such price promoting situations is of greatest importance for the evaluation of appropriate marketing strategies. In order to improve the forecast performance with respect to the determination of the effects of these price promotions on sales different Kalman filter approaches are applied. The yielded results are compared with estimates obtained by linear regression in terms of customary measures of forecast errors. It is shown that the Kalman filter is superior to the conventional regression analysis approaches in almost all cases. Therefore Kalman filtering which is also suited for the incorporation of the effects of various additional marketing activities either via the set of explanatory variables or via a set of control variables can be recommended at least as a supplement to the instruments of analysis commonly applied to price promoting situations. The conclusion is that the possibilities of data collection provided by

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scanner technology will allow the application of more efficient marketing methods and models for which the Kalman filter is just one example whose data requirements have prohibited their use up to now.

1. INTRODUCTION

A field of all-important interest in marketing has been and, still, is the modeling of price-demand relationships despite the increasing and sometimes changing importance of other marketing research areas. With respect to the investigation of short-term price cut effects a lot of empirical and theoretical work can be mentioned (see e.g. Raffée, Rieder and Deutsch (1981) for a recent survey) which can be divided into two categories according to the fact whether emphasis is laid on the manufacturers' or retailers' view of the problem.

Problem formulations devised for manufacturers are given in e.g. Frank and Massy (1971), Cowey and Green (1975), Moriarty (1975) and Prasad and Ring (1976). Frank and Massy (1971) developed a multiple econometric equation model that relates sales to advertised and unadvertised price promotions and special offers. The competitive marketing model proposed by Cowey and Green (1975) is based on regression analysis of historical data such as consumer sales, prices charged, advertising expenditures and distribution levels, and can be used to assess price policies over a prespecified number of periods or to evaluate alternative prices under different competitive conditions. Moriarty (1975) used a generalized least squares model which accounts for market shares in disaggregated sales districts on the basis of cross-sectional time-series data.

Problem formulations devised for retailers are given in e.g. Chevalier (1975), Eckhardt (1978), Blattberg, Eppen and Lieberman (1981) and Wilkinson,Mason and Paksoy (1982). In the study conducted by Chevalier (1975) the impact of display was measured with regard to several product characteristics including prices by means of a factorial experiment. Eckhardt (1978) described strategies for price promotions on the basis of a comprehensive experiment in a supermarket where several products were tested regarding their suitability for price deals. The inventory control model of Blattberg, Eppen and Lieberman (1981) which is based on the assumption that retailers transfer inventory carrying costs to the consumers allows to derive strategic implications concerning the deal price, the frequency of dealing and the quantity bought on deal. Wilkinson, Mason and Paksoy (1982) examined the relative importance of temporary price reductions, display alternatives and advertising for supermarket products by means of an in-store pricing experiment which showed the strong impact that display and price level had on sales.

As can be seen from the above and, of course, not exhaustive discussion how marketing activities, in particular price promotions, influence sales, a well-founded knowledge about price-demand relationships is of great importance. Traditionally, these relationships have been estimated by regression-based models applied to either cross-sectional or longitudinal data. More recently laboratory studies and in-store experiments (see e.g. Kaas (1977) who used the method of paired comparisons as data collecting procedure) have been employed to measure the influence of price on demand.

Mahajan, Green and Goldberg (1982) proposed a model for measuring price-demand relationships via conjoint analysis where respondents must trade off the desire to obtain certain product benefits with the higher prices which they have to pay for these benefits.

In this paper the following problem is tackled: Assumed, a pattern of individual item sales and corresponding prices by week is known for a certain period of the past. What sales can be expected if planned price strategies including price cuts are undertaken for a prespecified number of weeks in the future?

Answers are given with the help of different Kalman filter applications which are shown to be superior to the conventional regression analysis approaches. After a short description of the data basis in section 2, in section 3 needed notations and properties of the Kalman filter technique are described while section 4 gives a collection of the most important results. Section 5 contains our conclusions, especially, some hints for the incorporation of additional marketing activities the needed model modifications of which are pointed out in the appendix together with some exemplary specifications of the Kalman filter approaches.

2. DATA

The data under study are weekly recorded scanner data concerning several product lines offered in various German supermarkets over a time period of 48 weeks in 1983/1984[1]. Although information about different marketing activities such as special display, retail advertising, shelf-space allocation, compound effects of simultaneously purchased

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[1] Thanks are due to Dr. E. Huppert (A.C. Nielsen Company GmbH, Frankfurt, Fed. Rep. of Germany) who made the data available, see also Huppert (1981) for a discussion of the advantages of scanner data compared to manually recorded store audit and/or consumer panel data.

products, etc., can be recorded with the help of scanner technology, unfortunately, the provided data consist of individual item sales and corresponding prices by store by week, only. Of course, the introduction of scanner technology has already started to revolutionize the possibilities of application of methods and models to the marketing area. The increasing dissemination of this technology was reported e.g. in Huppert (1981) and Simon, Kucher and Sebastian (1983). The application of a multinomial logit model of brand choice to a combination of store and consumer panel scanner generated data was described in Guadagni and Little (1983) whose success concerning their modeling efforts is attributable to the advantages of the scanner data basis.

The analysis of the sales of price promoted consumer goods to be described later on was conducted for non-perishable branded products characterized by a comparatively high turnover and a high deal frequency which were offered during the whole observation period. Two detergents - with brand names Ariel and Sunil - were selected for presentation in this paper. Each of the price promotions for these products lasted for one week, the relative price cuts varied between 10% to 20% in relation to the corresponding regular prices, see Fig. 3 and Fig. 4 presented in section 4 for a graphical illustration of the time-series data comprising prices, actual and forecasted sales. The whole observation period of 48 weeks was divided into two parts: a calibration period of 40 weeks and a forecast period of 8 weeks, so as to compare the actual sales in the forecast period with the forecasts which are based on the estimates made in the calibration period.

3. MODEL

The first assumption is that only prices in the neighbourhood of the regular price p_r are of interest.

For ease of description the next assumption is that the following two types of price response functions are sufficient for modeling the unknown price-demand relationship with respect to price promotions (Of course, the knowledge of better functional relationships between price and demand will increase the forecast performance as can be seen from the results of Tab. 2 where a change from the type 1 price response to the type 2 price response function yields remarkable improvements in terms of customary measures of forecast errors.).

The type 1 approach uses a linear price response function of the form

$$s_t = \beta_{0t} + \beta_{1t}\,(p_r - p_t) \qquad (1)$$

with s_t: sales in period t,

p_t: price in period t,

β_{0t}: average sales at the regular price p_r in period t,

β_{1t}: price response coefficient in period t.

The type 2 approach uses a piecewise linear price response function of the following form

$$s_t = \beta_{0t} + \beta_{1t}p_{1t} + \beta_{2t}p_{2t} + \beta_{3t}p_{3t} \qquad (2)$$

with s_t: sales in period t,

$$p_{1t} = \begin{cases} p_r - p_t & \text{if } p_t \varepsilon I_1 = \{p \mid p_r - p > \alpha\} \\ 0 & \text{otherwise} \end{cases},$$

$$p_{2t} = \begin{cases} p_r - p_t & \text{if } p_t \varepsilon I_2 = \{p \mid 0 \le p_r - p \le \alpha\} \\ 0 & \text{otherwise} \end{cases},$$

$$p_{3t} = \begin{cases} p_r - p_t & \text{if } p_t \varepsilon I_3 = \{p \mid p_r - p < 0\} \\ 0 & \text{otherwise} \end{cases},$$

α: properly chosen value to specify the border between price intervalls,

β_{0t}: average sales at the regular price p_r in period t,

β_{it}: price response coefficient in interval I_i in period t.

The type 1, type 2 price response functions are visualized in Fig. 1, Fig. 2.

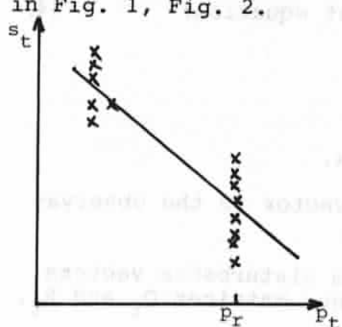

Fig. 1:
Linear price response

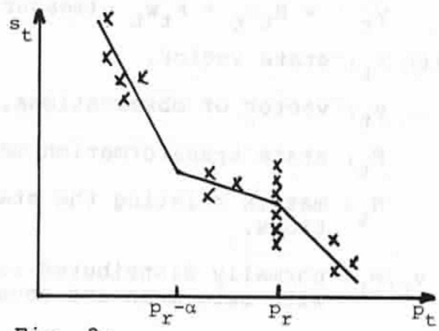

Fig. 2:
Piecewise linear price response

The marked asterisks show possible (price, sale) coordinates. Prices p_t which do not exceed the regular price p_r and price cuts which are all of nearly the same order of magnitude are shown in Fig. 1 in which case a linear price response function can be used. However, empirical results revealed that prices above or below the regular price as well as price cuts of different orders of magnitude need different price response coefficients for proper sales fitting as outlined in Fig. 2.

On the basis of these two types of price response functions the estimation of the sales of the price promoted products is tackled by the recursive Kalman filter forecasting approach. Kalman filtering developed at the end of the fifties (see Kalman (1960)) was soon taken up in the engineering sciences and in the course of time applied to problems in economics and business administration for the purpose of econometric modeling and time-series analysis, see e.g. Otter (1978) for an application of the Kalman filter to a macro-economic model describing relations between investments, profits and capital stocks in the U.S.A. between the world wars, Harvey (1981) for a discussion of how to handle autoregressive moving average models or other approaches for which time-varying parameters, missing observations, unobserved components, etc., are of interest by the Kalman filter and Edel (1980) for comparisons of forecast simulations on the basis of different Kalman filter model modifications. The underlying assumptions of Kalman filtering will not be discussed in detail, for a more thorough description of basic properties see e.g. Mehra (1979) or Harvey (1981).

The state space representation of the Kalman filter in the form used in this paper requires the specification of the following first-order vector difference equations

$$x_{t+1} = F_t x_t + G_t v_t \quad \text{(transition equation)} \qquad (3)$$

$$y_t = H_t x_t + K_t w_t \quad \text{(measurement equation)} \qquad (4)$$

with x_t: state vector,

y_t: vector of observations,

F_t: state transformation matrix,

H_t: matrix relating the state vector to the observations,

v_t, w_t: normally distributed random disturbance vectors with zero mean and covariance matrices Q_t and R_t,

G_t, K_t: weight matrices for the disturbances.

In the state space model (3), (4) attention is concentrated on the state vector x_t which evolves over time t according to the transition equation (3). Generally, the state vector x_t is not directly observable but related to a vector of observations y_t via the measurement equation (4) which allows the estimation of x_t. The disturbances v_t and w_t in both the transition and measurement equation are assumed to be serially uncorrelated and uncorrelated with each other in all time periods and with the initial state vector x_o. This initial state vector x_o is assumed to be normally distributed with mean $\hat{x}_o$ and covariance matrix $\hat{P}_o$. The vectors and matrices $\hat{x}_o$, $\hat{P}_o$, F_t, G_t, H_t, K_t and Q_t, R_t are assumed to be known or to be estimated by appropriate input data. All matrices are deterministic but may be time varying. These data specifications give an impression of the amount of input data needed for Kalman filter applications unless simplifying assumptions can be used. Here, with respect to marketing problems the possibilities of data collection provided by scanner technology will allow to overcome some of the restrictions imposed by the data requirements of such more efficient methods and models.

On the basis of the type 1 and type 2 price response functions the following Kalman filters were used:

<u>Kalman 1:</u> $x_t = \begin{pmatrix} \beta_{ot} \\ \beta_{1t} \end{pmatrix}$, $y_t = s_t$, $F_t = ID_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

$H_t = (1, p_r - p_t)$

yield

$$\begin{pmatrix} \beta_{ot+1} \\ \beta_{1t+1} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \beta_{ot} \\ \beta_{1t} \end{pmatrix} + G_t v_t \qquad (5)$$

$$s_t = (1, p_r - p_t) \begin{pmatrix} \beta_{ot} \\ \beta_{1t} \end{pmatrix} + K_t w_t \qquad (6)$$

where the weight matrices G_t, K_t specify whether random disturbances have to be considered and how these disturbances influence the state vector and the observed sales.

<u>Kalman 2:</u> $x_t = \begin{pmatrix} \beta_{ot} \\ \beta_{1t} \\ \beta_{2t} \\ \beta_{3t} \end{pmatrix}$, $y_t = s_t$, $F_t = ID_4$, $H_t = (1, p_{1t}, p_{2t}, p_{3t})$

yield vector equations similar to (5), (6).

Having initialized the Kalman filter in an adequate way (see e.g. Kahl and Ledolter (1983) for a discussion of the problems of initialization, estimation of other needed input data and forecast error comparisons) the estimates of the state vector are successively updated by adding new observations and processing them within the recursive filter equations. The state vector varies over time according to the differences between the observations to be added and the one-step-ahead predictions based on the previous state vectors. All influences affecting the state of the modeled system or, to say it in other words, all experiences made in the past, are accumulated and make the filter learn to react with increasing accuracy to new observations.

4. RESULTS

Both Kalman filter versions are applied to the brands selected for the analysis of the price deals. In order to judge the forecast performance of the Kalman filter approaches compared to conventional regression analysis the whole observation period of 48 weeks for which scanner data were available is divided into a calibration period of 40 weeks and a forecast period of 8 weeks. The calibration period is used to determine the estimates within the Kalman or regression approaches needed for forecasting in the forecast period. In this forecast period sales are estimated on the basis of the known prices and compared with the actual sales.

Fig. 3 shows the prices and actual sales of Sunil together with the Kalman 1 estimates. As only two kinds of prices, the regular price and price cuts of the same order of magnitude, occur application of the Kalman 1 version is suitable. Fig. 4 depicts the prices and actual sales of Ariel together with the Kalman 2 estimates. Here, prices above and below the regular price and even price cuts of different orders of magnitude occur, thus, the Kalman 2 version proves to be more appropriate what can be seen from the results of Tab. 2 which indicate that a change from the Kalman 1 to the Kalman 2 version yields remarkable improvements in terms of customary measures of forecast errors.

The goodness of fit of such short-term forecasts of sales is of great importance for assessing the effects of future price deals. Of course, many measures of forecast errors have been developed and discussed. Here, the SSE (sum of squared errors) and TIC (Theil's inequality coefficient, see Theil (1970)) measures are computed and compared where for a forecast period of T weeks from T_o+1 up to T_o+T SSE and TIC are given according to

$$SSE = \sum_{t=1}^{T} (\hat{s}_{T_o+t} - s_{T_o+t})^2$$

$$TIC = \left(\frac{1}{T}\sum_{t=1}^{T} (\hat{s}_{T_o+t} - s_{T_o+t})^2\right)^{\frac{1}{2}} \Big/ \left((\frac{1}{T}\sum_{t=1}^{T} \hat{s}^2_{T_o+t})^{\frac{1}{2}} + (\frac{1}{T}\sum_{t=1}^{T} s^2_{T_o+t})^{\frac{1}{2}} \right)$$

with $\hat{s}_t$: forecasted sales in period t,

T : forecast horizon.

The R^2 measure is inadequate for forecasting because values greater than one can occur with respect to the forecast period.

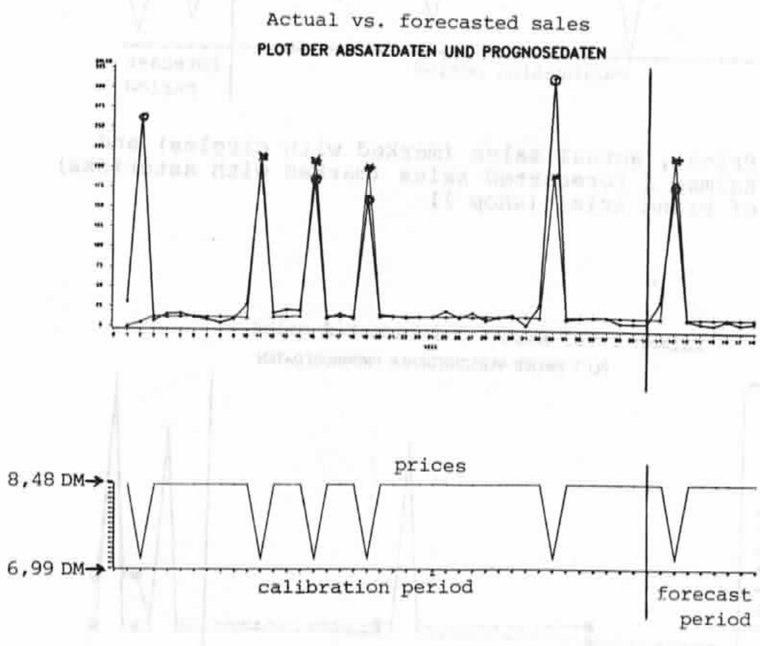

Fig. 3: Prices, actual sales (marked with circles) and Kalman 1 forecasted sales (marked with asterisks) of brand Sunil (shop 4)

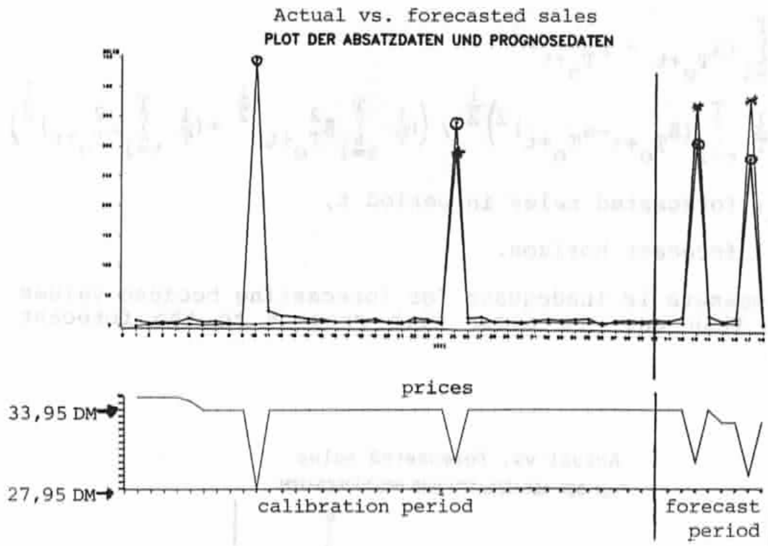

Fig. 4: Prices, actual sales (marked with circles) and Kalman 2 forecasted sales (marked with asterisks) of brand Ariel (shop 1)

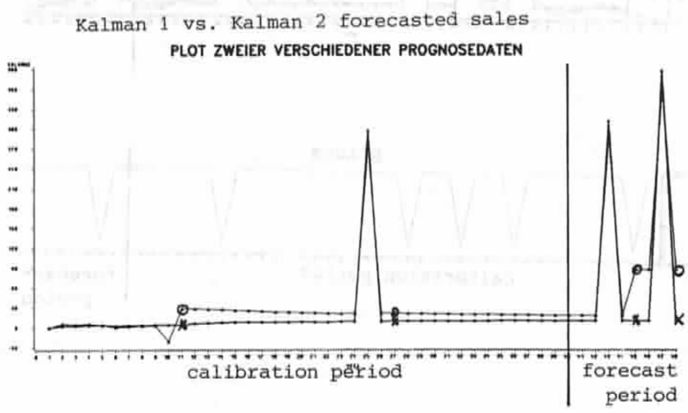

Fig. 5: Kalman 1 forecasted sales (marked with circles) and Kalman 2 forecasted sales (marked with asterisks) of brand Ariel (shop 1)

Forecasting approach / Shop	Regression		Kalman 1	
	SSE	TIC	SSE	TIC
Shop 1	730.02	0.094	721.73	0.096
Shop 3	25.92	0.060	21.55	0.056
Shop 4	337.93	0.126	243.52	0.109

Tab. 1: Measures of forecast errors for Sunil

Forecasting approach / Shop	Regression		Kalman 1		Kalman 2	
	SSE	TIC	SSE	TIC	SSE	TIC
Shop 1	3826.93	0.181	3670.25	0.178	1790.40	0.124
Shop 2	811.79	0.300	774.59	0.295	721.11	0.279
Shop 3	290.04	0.216	281.48	0.214	104.66	0.130
Shop 4	922.76	0.214	911.96	0.214	774.57	0.173

Tab. 2: Measures of forecast errors for Ariel

Tab. 1 and Tab. 2 show two sorts of results: First, Kalman filtering outperforms regression. Second, the knowledge of better functional relationships between price and demand yields remarkably improved forecasts as can be seen on comparison of the Kalman 1 and Kalman 2 versions.

Upon examination of Fig. 3 and Fig. 4 the substantial increases in sales attributable to price cuts are fitted well by the Kalman filter in the forecast period. As no a-priori knowledge existed in both cases the state vector of the initial period was set equal to zero (see appendix 2 for a complete description of the model specifications), thus the first increase in sales cannot be accounted for by the Kalman filter but, subsequently, the estimates more and more adapt to the sales actually realized.

The two Kalman filter versions are compared in Fig. 5. In the calibration period slightly different estimates are obtained but the extended Kalman 2 version yields obviously better results in the forecast period. This difference is due to the fact that within the Kalman 1 version only one parameter for an overall price response is estimated whereas the more flexible Kalman 2 version allows for different parameters according to various price intervals. The marginal price reductions of about 3% in three weeks of the forecast period can be modeled more appropriately with the Kalman 2 version.

5. CONCLUSIONS

The results presented above indicate that the Kalman filter technique can be properly applied to modeling of price-demand relationships with respect to price promotions. Kalman filtering has proved to be superior to conventional regression approaches because of the flexibility and adaptability of the underlying state space model. Therefore the Kalman filter can be recommended as a suitable instrument in situations when decisions on price deals based on historical data have to be made.

The approaches illustrated above can easily be extended by incorporation of additional marketing activities such as advertising and display which can be represented either within the set of explanatory variables or within a set of control variables as is shown in appendix 1. Further empirical work using comprehensive data bases which can be provided by scanner technology needs to be done in order to ensure that corresponding research efforts will be applied in the marketing area.

APPENDIX 1

A modification of the Kalman filter which allows the incorporation of control variables is outlined and the impact of this modification on the modeled system is discussed.

The transition equation (3) can be extended as follows

$$x_{t+1} = F_t x_t + C_t u_t + G_t v_t \tag{7}$$

with u_t: vector of control variables,

C_t: weight matrix relating the control variables to the state vector.

The measurement equation (4) will not be changed. How the matrix C_t and the control vector u_t can be determined in order to model price-demand relationships by means of the modified Kalman filter (4), (7) is drafted below.

Assumed, the previously used linear price response function (1) appropriately represents the observed purchasing behavior. On the one hand the price elasticity coefficient

$$\varepsilon_t = \frac{ds_t}{dp_t} \cdot \frac{p_t}{s_t} \tag{8}$$

looks like

$$\varepsilon_t = \frac{\beta_{1t}\, p_t}{\beta_{ot} + \beta_{1t}(p_r - p_t)} \tag{9}$$

if (1) is used in (8).

On the other hand, if prices charged in two succeeding periods differ the price elasticity coefficient can be approximated (provided that s_t is unequal to zero) in the following way

$$\varepsilon_t = \frac{s_t - s_{t-1}}{p_t - p_{t-1}} \cdot \frac{p_t}{s_t} \tag{10}$$

The unknown coefficient β_{ot} in (9) can be estimated as the average of the purchases made in those periods when the product was offered at the regular price.

The coefficient β_{1t} can be determined after simple transformations of (9) according to

$$\beta_{1t} = \frac{\varepsilon_t \; \beta_{ot}}{p_t(\varepsilon_t - 1) - \varepsilon_t p_r} \tag{11}$$

utilizing the previously computed values ε_t and β_{ot}.

If the time varying weight matrix C_t consists of the coefficient β_{1t} and if

$$u_t = p_r - p_t \tag{12}$$

is used as a control variable accounting for the corresponding variation of sales the state vector x_t consists of one element by means of which the sales of the current period can be estimated. In this onedimensional approach the matrices F_t and H_t are scalars and set identical to 1.

APPENDIX 2

The input data required for the Kalman filter computations of the examples of Fig. 3 and Fig. 4 are:

Kalman 1

Initial conditions: $\hat{x}_o = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$, $\hat{P}_o = \begin{pmatrix} 20 & 0 \\ 0 & 200 \end{pmatrix}$.

Weight matrices: $G_t = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$, $K_t = 1$.

Covariance matrices: $Q_t = 0$, $R_t = 100.$

Kalman 2

Initial conditions: $\hat{x}_o = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$, $P_o = \begin{pmatrix} 20 & 0 & 0 & 0 \\ 0 & 200 & 0 & 0 \\ 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 20 \end{pmatrix}$.

Weight matrices: $G_t = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}$, $K_t = 1$.

Covariance matrices: $Q_t = 0$, $R_t = 100$.

By setting the covariance matrix Q_t of the random disturbance v_t equal to zero a Kalman filter approach closest to regression results which already shows a better predictive efficacy than regression. Moreover various sensitivity analyses which are not reported here were carried out. The covariances Q_t and R_t as well as the initial conditions and the weight matrices were varied systematically. In summary two conclusions can be drawn: First, the initial conditions have an effect on the estimates only during a short phase of the calibration period. Second, the incorporation of a random disturbance v_t influences the adaptability of the state vector essentially in those periods for which the regular price is charged.

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