Identifying patterns of customer response to price endings

Ralf Wagner
Dialog Marketing Competence Center, University of Kassel, Kassel, Germany, and

Kai-Stefan Beinke
Department of Marketing, University of Osnabrück, Osnabrück, Germany

Abstract

Purpose – The purpose of this paper is to introduce a new approach for the identification of price thresholds, which enables learning true thresholds from previous buying decisions recorded in POS scanner data.

Design/methodology/approach – The methodology presented herein combines spline regression with generalized cross-validation. Classical Chi-square testing confirms the separation of regimes of the price response function by this methodology. Five propositions concerning the consumers' response to odd pricing in a Western-type market are evaluated.

Findings – Despite the widespread retail practice odd prices are unlikely to flag the actual threshold in consumer response. The term odd price refers to prices with a non-zero ending in the cent digit, e.g. .95, .98 or .99, which are commonly used in Western-type markets. Moreover, the simple odd price effects are distinguished from odd-ending prices with the first number left of the decimal point set to an odd number. The results show that even these prices not always flag a threshold in consumer response.

Research limitations/implications – The discussion of the odd-price effect is confused by conflicting empirical results and related interpretations of the underlying mechanisms. In contrast to many previous investigations – which are restricted to the consideration of very few price endings – this study covers all reasonable prices. Statistically significant odd-price effects are found for some brands, but not for all within the same category.

Practical implications – One must argue for checking the thresholds for each brand individually rather than generalizing by applying misleading rules of thumb.

Originality/value – The paper provides researchers as well as practitioners with a methodology to evaluate price thresholds and outlines the shortcoming of contemporary retailers pricing practices in a detailed manner.

Keywords Pricing policy, Price positioning, Consumer behaviour

Paper type Research paper

1. Introduction

Successful price setting is one of the most crucial challenges for retailers. Despite the substantial body of academic research and all models related to pricing decisions, rules of thumb are still predominant in contemporary retail practice (Subrahmanyan, 2000; Montgomery, 2005). Therefore, odd prices prevail for products of various categories in Western economies' retailing (e.g. Schindler, 2001; Folkertsma *et al.*, 2002; Guéguen and Legoherel, 2004). Moreover, Bergen *et al.* (2004) provide evidence of a considerable share of 9-ending prices in internet-based selling. In this paper the term odd price refers to prices with a non-zero ending in the cent digit, e.g. .95, .98 or .99. While favoring odd prices – in particular charging 9-endings – is not limited to specific products or

services, and appears to be valid across many industries, recent research suggests that an adjustment to cultural contexts is advantageous. For instance, Suri *et al.* (2004) found the 9-endings to be less common and less accepted as a fair price in Poland's transition economy than in the USA. Simmons and Schindler (2003) show that the 8-endings, which are associated with prosperity and luck, are highly over-represented in Chinese advertising. Thus, simple and efficient methods to judge whether or not a price flags a psychological threshold in consumer response are needed, especially given the increasing opportunities to be found in South America, Eastern Europe and Asia's transitional economies (Dawar and Chattopadhyay, 2002).

Overrepresentations of specific numbers are not restricted to the digits right of the decimal point. However, the impact of the first digit left of the decimal point is less frequently discussed in the literature. Regardless of the uncertainty concerning price-ending effects, vendors do not risk decreasing their revenue by charging these prices for their product or service, unless the price ending has some negative connotation, such as poor quality (Gedenk and Sattler, 1999; Schindler and Kibarian, 2001). This fact may justify the contemporary managerial price setting behavior, but it offers

no advice as to which of several suitable odd prices is the one to choose. On the one hand, Subrahmanyan (2000) describes retailers as being frustrated with their traditional qualitative methods and Montgomery (2005) argues that they are ready for pricing decision support systems. On the other hand, simple but effective methods are rarely proposed. Overall, the academic discussion of odd pricing focuses mainly on the verification of odd-price effects rather than offering effective decision-making support.

Market researchers are facing a problem similar to the managerial price setting task when calibrating marketing-response models, e.g. in market share analysis. Kalyanam and Shively (1998) as well as Wedel and Leeflang (1998) emphasize the non-smooth shape of an empirical price-response function due to irregularities, such as price-ending effects. From a methodological point of view, identifying such kinks in the response function is not a trivial challenge. Additionally, sparse regimes of the data space, skewness, and multimodality of the data distribution hamper the identification of structural changes in the particular application of price-response analysis. This paper addresses the methodological challenge of grasping these irregularities. Its main objectives are to:

- propose a methodology to assess odd prices that can easily be applied to ordinary point-of-sale (POS) scanner data;
- investigate whether or not prices with the first digit left of the decimal point set equal to 9 are more likely to flag a threshold in customer response in a Western-type market; and
- revise the validity of previously considered hypotheses concerning the price-ending effects on market shares.

The paper is organized as follows. In the next section, we briefly summarize explanations and related impacts of price endings and develop our research propositions. We continue by introducing the generalized cross-validation criterion proposed by Craven and Wahba (1979), its modification by Friedman (1991), and its usage in price-response modeling. Subsequently, we present the results of applying the methodology to data from the German detergent market. Finally, we conclude by discussing the study's theoretical and managerial implications as well as its limitations.

2. Occurrences and impacts of price endings

Investigations of the price-endings impact have yielded conflicting results. Experimental switching from even price to odd-price endings led to dramatic gains in a women's mail-order clothing catalogue (Schindler and Kibarian, 1996), while odd prices have also been found to have no effect on stated preferences (Dodds and Monroe, 1985). Stiving and Winer (1997) even found a negative impact on the sales of canned tuna, but positive effects for yogurt. Table I provides an overview of the previous studies of the price ending's occurrences and impacts.

The Table clearly shows the necessity for developing methods that are applicable to individual markets in order to meet the needs of practitioners, stay abreast of growing opportunities in non-Western markets, and avoid artificially narrowing academic knowledge by restricting research efforts to the odd-pricing phenomena. The conflicting results concerning the impact of price endings depicted in the table may be attributed to different mechanisms that become operative in the markets. Complementing the second part of the Table, Gedenk and Sattler (1999) provide a further compilation of inconsistent results in odd-pricing research. According to the topology of explanations developed by Stiving and Winer (1997), the impacts on customer behavior can be classified in two sets: level effects and image effects. Level effects include buyers' rounding down prices (Coulter, 2001), buyers' left to right comparison (Guéguen and Legoherel, 2004), and the loss of cognitive simplicity of zero-ending prices, which becomes even more prominent in the case of multidimensional prices (Estelami, 1999). Image effects describe the meaning assigned to the numbers, for instance, buyers' interpretation of a 9-ending price signaling a price discount (Quigley and Notarantonio, 1992; Schindler and Kibarian, 2001), a low quality image effect of odd prices (Suri *et al.*, 2004), or the association of 8-endings with luck in the Chinese culture (Simmons and Schindler, 2003).

Although these effects could be superimposed, compensate for, or enforce each other in real markets, the majority of investigations – in particular in experimental research designs – aim to isolate the effects. Moreover, with some exceptions (e.g. Schindler and Kibarian, 1996; Stiving and Winer, 1997; Kalyanam and Shively, 1998), the studies of price-ending impacts on buyer decisions are limited to considering only a very few odd prices and how they contrast with related even endings. This shortcoming is relevant when image effects are addressed, as exemplified by the meanings assigned to different ages and birthdays. For instance, the 50th birthday is perceived differently from the 49th, and we would expect to find a 0-ending effect. But this effect is less likely to be observed when considering the 20th birthday, since turning 21 in the USA (or 18 in many European countries) means reaching the age of majority and being permitted to buy alcohol, enter clubs, etc. Hence, it is important to include the whole range of relevant numbers when investigating impacts due to the assignation of meanings to numbers. This claim should generally hold for ages as well as for price endings[1]. To summarize the discussion of Table I, we postulate that price-ending impacts depend on:

- the markets under consideration; and
- the range of considered prices.

A systematic investigation of which price ending is the one to choose, for example odd prices, still appears to be a gap in the literature.

Despite all academic skepticism (e.g. Stiving and Winer, 1997; Gedenk and Sattler, 1999), Western managers rely strongly on odd pricing (Folkertsma *et al.*, 2002; Bergen *et al.*, 2004; Guéguen and Legoherel, 2004). One major limitation on the transfer of academic results to managerial practice is the lack of a scheme in which purchase situations are related to a pertinent set of impacts that are operative in these situations. Of course, modern retailing textbooks already provide an overview of buying situations and corresponding pricing advice (e.g. Dunne *et al.*, 2002, Chapter 10), but we are not aware of any scheme that links buying situations to the theoretical concepts in price-ending research such as that of Reed and Ewing (2004) that ties situational aspects to attitudinal explanations in advertising research. Thus, we choose a behavioristic perspective similar to Gedenk and Sattler (1999) to pass over the various explanations and focus on the managerial decision situation for formulating our research propositions.

Table I Overview of recent studies of price endings

Occurrences of price endings	Description	Examples
Western economies retailing	Overrepresentation of odd prices (9-, 8- and 5-endings) as well as even-prices (0-endings)	Stiving and Winer (1997); Schindler (2001); Folkertsma et al. (2002); Guéguen and Legoherel (2004)
Eastern economies retailing	Underrepresentation of 9 endings in Poland	Suri et al. (2004)
	Overrepresentation of 8 endings in China	Simmons and Schindler (2003)
	Overrepresentation of 0 endings for packed meat products in former Hungarian retailing	Ratfai (2003)
Internet-based selling	Overrepresentation of 9 endings	Bergen et al. (2004)
Customer response to odd prices/9 endings		
Positive	Increasing sales/increasing demand	Holdershaw et al. (1997); Gendall et al. (1998); Kalyanam and Shively (1998)
	Increasing number of purchases	Schindler and Kibarian (1996)
	Impression of discount	Guéguen and Legoherel (2004)
Negative	Computational difficulties	Estelami (1999)
	Not accepted as a fair price	Suri et al. (2004)
	Low quality image	Bergen et al. (2004)
No effect	No impact on stated preferences	Dodds and Monroe (1985)
	Changing from odd to the next higher even prices did not reduce the sales	Diller and Brielmaier (1995)
Conflicting results	Positive as well as negative effects	Stiving and Winer (1997)

If a price-ending effect becomes operative, it is expected to cause a change in consumer response. Therefore, the price-response function should be kinked rather than smooth and well behaved, as is assumed in microeconomic theory (e.g. Wedel and Leeflang, 1998; Guido and Peluso, 2004):

P1. If an odd price effect becomes operative, then kinks of the price response function should be located at the odd prices in Western-type markets.

The first proposition is particularly in line with an empirical examination by Kalyanam and Shively (1998), who outline several irregularities in price-response functions for margarine brands, which the authors attribute to odd-price effects. Similarly Coulter (2002) assumes that the odd prices produce kinks in the demand curve just below the related even price.

Let us consider prices consisting of two digits left and two digits right of the decimal point. In the discussion of the symbolic meanings of prices, Schindler (1991) highlights the importance of the first digit left of the decimal point by arguing that prices which are just below a round number (e.g. $49.88, $49.95, and $49.99 are just below $50.00) are encoded by the consumer into a form which represents a lower price. Guido and Peluso (2004) provide a brief compilation of various terms in marketing literature that refer to charging $49.99 instead of $50.00, but the phenomenon still appears to be challenging to marketing researchers. Stiving and Winer (1997) as well as Xia (2003) found that the "place-value" model, which implies a digit-by-digit left-to-right assessment, describes the actual assessment of prices better than the holistic model of processing multi-digit numbers. Schindler and Kirby (1997) investigate the suitability of retailers' price settings for simplification by truncation. This encoding strategy implies stopping the left-to-right processing before all digits of a price are recognized. Of course the retailers benefit from the highest potential underestimation by changing a price with 0 endings in the dollar as well as in the cent digits into the next lower price with 9 endings in the cents as well as the dollar digits, e.g. $40.00 to $39.99. If consumers restrict themselves to process the first digit only, the difference of internally represented magnitudes might be as high as 25 percent. The study by Schindler and Kirby (1997) provides evidence for the relevance of this type of price points in US retailing. To grasp the differences of dollar and cent endings, we will refer to prices with the first digit left of the decimal point equal to 9 and the ending equal to an odd price as odd-odd prices in order to distinguish them from simple odd prices. Thus, $49.99 or $49.95 are odd-odd prices because they are just below the line of $50.00, while $50.99 is a simple odd price. To be more comprehensive, we do not distinguish between simple odd prices with only the last digit equal to 5 or 9 from those prices with the last two digits set to these numbers. This means that we consider all prices such as $50.99, $50.89, or $50.98 as simple odd prices.

In an experimental manipulation of prices consisting of one dollar and two cent digits Thomas and Morwitz (2005) find a positive and significant impact on the price perception of changing the dollar digit by reducing an even dollar price by a cent, e.g. from $3.00 to $2.99. Targeting the price recall in an experimental manipulation of prices with two digits left to the decimal point, Coulter (2001) reports a significant interaction effect between setting the cent digits and the dollar digits equal to 9, but this does not cause higher than expected demand. Moreover, Bergen et al. (2004) actually report a significant negative relation between setting the first digit left of the decimal point equal to 9 and the store quality, which may superimpose a price-image effect:

P2a. If an odd price effect becomes operative, then odd-odd prices are as likely as or even less likely than simple odd prices to flag a threshold in consumers' price response in Western-type markets.

It should be noted that this proposition is developed from conflicting results in previous research and it appears to contrast the actual price-setting behavior in a broad range of Western-type markets. Retailers in these markets frequently assume or expect thresholds at odd-odd prices. Charging prices just above odd-odd prices is uncommon. Blinder *et al.* (1998, p. 175) show that prices get stuck "at numbers like $9.99 or $29.95, rather then move up to, say, $10.32 or $31.43." This leads to sparse regimes of the data space. This range of possible prices is of particular interest, because the retailers assume a higher sensitivity to price increases when exceeding the lower bound of this regime. They appear somewhat cramped in their perception of common deterministic thresholds at odd-odd prices. Contrarily, the study of Han *et al.* (2001) implicates that the real thresholds are probabilistic rather than deterministic. The managerial relevance of detecting the actual thresholds is emphasized by Levy *et al.* (2004), who argue the most fundamental weakness of retailers' contemporary rule-based pricing practices is that these rules ignore the elasticity of demand and therefore none of them have anything to do with what represents the optimal price.

P2b. If an odd price effect becomes operative, then odd-odd prices are as likely as or even less likely than simple odd prices to flag the thresholds encompassing the sparse regime of the data space in Western-type markets.

In their evaluation of the odd-price effect, Gendall *et al.* (1998) present an experiment whereby they consider the particular price levels of different brands within a certain category. Depending on the price level, they find that either the .95-ending has a significant impact whereas the .99-ending has none, or vice versa. Moreover, Aalto-Setälä and Raijas (2003) provide evidence for the influence of brands' strength on consumers' price knowledge. Holdershaw *et al.* (1997) argue that the impact of odd pricing is related to the price level. In addition, the product prices are found to have significant influence on buyers' formation of consideration sets (Mehta *et al.*, 2003), which holds for internet-based selling as well (Wu and Rangaswamy, 2003). Thus, we expect competing products of the categories' premium segments to have common odd prices, flagging the kinks on the demand curve.

P3a. If competing products are elements of the same consideration set, e.g. a quality segment, then they have similar odd prices in common, which flag a threshold of consumer response in Western-type markets.

The term "similar" allows for marginal discrepancies; prices of $49.99 and $49.95 for two different brands could be judged as the same prices with respect to the consideration set.

From a methodological point of view, these differences appear to be interesting with respect to the complexity of the response pattern. We quantify the complexity of the price-response pattern using the number of thresholds in the price-response function. For instance, Kalyanam and Shively (1998) found two knots in their regression spline approach, one at $.71 and one at $.79, to be consistent with segmentation effects in the market for canned tuna. More generally speaking, Mazumdar and Papatla (2000) argue that calibrating one model with a common operationalization for all segments can lead to biased parameter estimates and incorrect substantive conclusions. Depending on the market segments, they report different sets of variables to have a significant impact on utility offered to the households in their study of reference prices. Extending this argument, we expect the response to have at least the same complexity which is measured by the number of price thresholds:

P3b. If products are elements of the same consideration set, then the customer-response functions are characterized by the same complexity, that is to say, the same number of thresholds flagged by similar price endings.

These propositions are drawn from different previous investigations. Proposition *P2a* and *P2b*, in particular, conflict with retailers' actual behavior. In the next section, we will introduce a methodology with which to reconsider the validity of these propositions. This methodology is not restricted to applications in Western-type markets and the odd-price phenomena, but rather it identifies thresholds at any price ending. Therefore, it should also be useful for evaluating price endings in other cultural contexts.

3. Methodology

3.1 Regression splines

Using regression splines to estimate response functions including irregularities has already been established in marketing literature (Kalyanam and Shively, 1998; Wedel and Leeflang, 1998; Vakratsas, 2001). The basic principle of spline regression is the subdivision of the data space into areas according to the influence of the predictor variables. Each spline covers a sub-region of the predictor data space. Within each regime (defined as such a sub-region of the predictor space marked by knots), the response is expressed by one regression coefficient. Adjacent regimes are characterized by distinct responses that are captured by different regression coefficients. Moreover, in the multivariate case, even the predicting dimension v may change. The model grasps the response $f(\boldsymbol{x}_{mn})$ for brand m to the nth observation of a V dimensional vector $\mathbf{x}_{mn}$ of prices and other marketing mix instruments.

$$\hat{f}(\boldsymbol{x}_{mn}) = \sum_{r=1}^{R_m} \alpha_{mr} B_{mr}(\boldsymbol{x}_{mn}) \ \forall \ m, n \qquad (1)$$

with:

$B_{mr}(\cdot)$ basis function for regime r and brand m

m index of brands

n index of observations

r index of regimes

$\mathbf{x}_{mn}$ vector of predictor variables for brand m and observation n

α_{mr} regression coefficient for brand m and regime r

In line with Wedel and Leeflang (1998), we expect the response function to be non-smooth if any odd-price effects are included. By using recursive partitioning regression, such irregularities could be taken into account, but the approximation suffers from its lack of continuity. A remedy for this problem is introduced by Friedman (1991), who proposes using truncated power basis functions for the representation of splines left and right from a knot k. Choosing a linear interpolation between the knots, each basis function B_{mr} in equation 1 is represented by:

$$B_{mr}(\boldsymbol{x}_{mn}) = \prod_{k=1}^{K_{mr}} [\pm 1 \cdot (x_{v(kmnr)} - s_{kmr})]_+ \quad (2)$$

with

$$[(x_{v(knmr)} - s_{kmr})]_+ = \begin{cases} x_{v(knmr)} - s_{kmr}, & \text{if } x_{v(knmr)} > s_{kmr} \\ 0, & \text{otherwise} \end{cases}$$

and

$$[(s_{kmr} - x_{v(knmr)})]_+ = \begin{cases} s_{kmr} - x_{v(knmr)}, & \text{if } x_{v(knmr)} < s_{kmr} \\ 0, & \text{otherwise} \end{cases}$$

with

k index of knots
s_{kmr} split point for knot k, brand m, and regime r
v index of predictor variables
$x_{v(kmnr)}$ contributing predictor variable for knot k, brand m, observation n, and regime r in dimension v of the data space.

Each knot defines a reflected pair of piecewise linear functions, covering the entire data space in dimension v. This spline approximation constructs tensor products of $K_{mr} + 1$ intervals defined by K_{mr} knots. The knots are neither necessary located at the peaks nor at the valleys of the higher-dimensional response surface, but flag a point of structural change. The resulting response surface is continuous and includes arbitrary irregularities. Hence, the data analytic challenge is twofold:

1 Fixing the number of knots, i.e. learning the number of price thresholds from the data.
2 Locating the knots, i.e. learning the location of thresholds from the data.

3.2 Adaptive knot placing

We tackle both problems – fixing the number of knots and locating the knots – by utilizing the multivariate adaptive spline regression (MARS) algorithm proposed by Friedman (1991). One basic element of this algorithm is the generalized cross-validation (GCV) criterion of Craven and Wahba (1979).

$$\text{GCV}(\lambda_m) = \frac{\frac{1}{N_m} \sum_{n=1}^{N_m} \left[y_{mn} - \hat{f}_{\lambda_m}(\boldsymbol{x}_{mn}) \right]^2}{\left[1 - \frac{c(R_m)}{N_m} \right]} \quad \forall m \quad (3)$$

with

$c(R_m)$ degrees of freedom granted by the model specification
N_m number of observations for brand m
y_{mn} observed market share of brand m in observation n

The total number of observations for brand m is denoted by N_m and y_{mn} is the observed response for brand m and observation n. The term $c(R_m)$ refers to the degrees of freedom granted by a model specification, which accounts for the number as well as the degrees of freedom associated with knot placement (Friedman, 1991).

The MARS algorithm itself proceeds by taking a forward and a backward step. In the forward step, an initial assignment of knots is placed on the price axis. In order to achieve this, each observation is considered to be a candidate for placing the knot by means of fixing a value for s_{kmr} and

evaluated with respect to GCV criterion in equation 3. Data points minimizing the GCV criterion, as well as the basis functions left and right of this knot, are included in the model sequentially until a maximal number of basis functions R^{max} is reached. Given R^{max} higher than the number of basis functions needed to capture the true response function, the model is likely to be overfitted. To tackle this overfitting and to achieve a balance between the overall model's fit and complexity, the superfluous basis functions are eliminated in the backward step. Again, the selection of basis functions to be excluded from the model is done by minimizing the GCV criterion. Only the first basis function $B_{m1}(.)$ is not eligible, therefore the removal of arbitrary basis functions will not lead to gaps in the response surface or function. Thus, we achieve a continuous and flexible approximation of the true response, consisting of regimes that are most homogeneous with respect to the response. All results presented in section 4 are calculated with $R^{max} = 200$, which is in any case higher than the expected optimal model intricacy.

4. Results

4.1 Regimes of price response

The results outlined in the following are achieved by applying our methodology to a set of POS scanner data that was recorded in 16 German outlets of at least 800 sq.m. covering 144 weeks from January 1995 to October 1997. The sample includes hypermarkets of the major German retail chains, but not discount stores like for instance Aldi, because these outlets were not facilitated with POS scanners. The category under consideration is detergents, and the data include weekly sales for six national brands as well as shelf price per 10 kg stock keeping unit (SKU) for each week in German Mark. Additional promotional activities (price promotion, additional display, and flyers) are consolidated to a dummy variable in order to distinguish usual from promotional sales. Table II provides a brief market structure.

The market share of brand m is defined by dividing the number of sales of this brand in a week by the number of sales of all brands that week. Two of the brands (brand I and brand III with a joint share of about 28 per cent of total sales) constitute a premium level, whereas the other four brands represent the "regular" level.

Notably, except for brand II, all lowest observed prices are even prices, what appears to be in line with the results of Schindler (2001). Table III depicts the results of applying our methodology with the market share as the dependent variable.

The saturated R^2 in the left column of the Table assesses the model's fit when all six prices are used as predictors in the model, whereas the R^2 quantifies the fit of model restricted to brands own price used as predictors. Indeed, its fit appears to

Table II Description of market structure

Brand	Market share (%)	Mean price	Min. price	Max. price
I	8.93	35.10	25.00	43.48
II	22.28	25.54	15.00	37.98
III	19.29	36.88	25.00	41.98
IV	26.17	25.84	14.97	34.99
V	5.36	26.59	15.00	32.99
VI	17.97	28.11	15.00	36.99

Table III Fit measures and knot locations

Brand	R^2	Sat. R^2	F-statistic	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
I	0.472	0.625	647.45	29.00	31.98	-	-	-	-
II	0.582	0.773	389.24	16.99	17.90	19.98	23.23	-	-
III	0.385	0.569	576.61	28.08	35.00	-	-	-	-
IV	0.342	0.508	302.32	16.99	26.98	29.50	-	-	-
V	0.374	0.655	137.31	18.90	22.99	24.00	26.98	-	-
VI	0.652	0.768	466.49	19.85	24.99	25.99	26.90	32.49	32.98

be quite acceptable and concur with results reported from previous market share analysis (Kalyanam and Shively, 1998; Wedel and Leeflang, 1998; Swait and Andrews, 2003).

The Table illustrates a divergence in price-response intricacy as shown in the number of knots and the associated basis functions in the last six columns of the table. In particular, the premium brands I and III are characterized by a comparatively simple price response, consisting only of three regimes separated by two knots. Interestingly, two of these four knots ($k = 1$ for brand I and $k = 2$ for brand III) are assigned to 0-ending prices (29.00 and 35.00), but only one ($k = 2$ for brand I) to an odd price (31.98). This might indicate an image effect related to 0-endings dominating the level effects in this segment. For instance the 29.00 knot tells us that the threshold sales drop starts with any price higher than 29.00. The knot locations delimit regimes with the same price influences and, therefore, show points of structural changes. In the total of 21 knots, only ten are odd prices, one is a price figure (23.23) and the remaining ten are other prices. Thus, the outstanding impact of odd prices has to be scrutinized. Moreover, only two ($k = 3$ for brand II and $k = 1$ for brand VI) of the knots are located at odd-odd prices.

Figure 1 depicts the prices on the horizontal axis and the corresponding market shares on the vertical axis. The reference lines are placed at the knot locations depicted in Table III and separate the response regimes.

Visual inspection of the data reveals two characteristics of the considered market. First, the data are in line with the concept of the downward sloping demand curve. The likelihood of achieving high market shares seems to decrease with increasing prices. But this relation appears to be weak, and a wide spread of market shares is observed with the same price. This results in the pillar structure as illustrated by the figures. Second, the differences in market shares cannot be traced back directly to non-promotion prices (o) and promotion (+) prices. We observed price promotions that resulted in low market shares as well as non-promotion prices in the upper price range level with relatively high market shares. Therefore, the data at hand are considered suitable for the investigation of odd-price effects.

With respect to the pricing behavior, we find retailers heavily favoring odd-odd prices, but as is obvious from the pillar structure of the data-in particular the odd-odd prices just below 30 for the premium brands and just below 20 for the regular brands IV and V – these prices have frequently failed to achieve the expected impact of high market shares. Considering the left border of the sparse regimes of the data space (e.g. from 30 to 32 for brand I and, in particular, from 20 to 23 for brand II) as representatives for the price thresholds presumed by the retailers, the misfit to the real thresholds in consumer response

becomes evident. Only for brand II are the retailer's presumptions congruent to the actual thresholds. From expert interviews (conducted with a product manager of one important manufacturer and three store managers) we learned that the retailers assumed a second threshold at the price of 30 German Mark. This is in line with our data, because none of the observations has a price from the interval (30.00, 32.80). It is likely that retailers relied on other similar rules of thumb for their pricing decisions.

Although the results presented above appear to be plausible in light of visual data inspection, it should be kept in mind that they were achieved by an adaptive technique and therefore are restricted due to their exploratory character. In order to validate the findings, we outline below the results of additional Chi-square tests in the following subsection.

4.2 Re-analysis of price response regimes

For the purpose of statistical testing successful and less successful price points are distinguished with respect to their attained market share. A price is considered to be successful if the market share is higher than the regression parameter estimated for the first basis function B_{m1} (see Table IV). This parameter is comparable to the intercept in conventional regression analysis. Our criterion considers the differences in a brand's strength and describes the mean market share observed for lower prices (in the far left regime).

The most interesting aspect of the previous investigation is the location of the knot next to the price thresholds assumed by the retailers, e.g. 29.00 instead of 29.99 for brand I. This knot placement will be subject to further confirmatory testing before the knot locations are used to evaluate the research propositions *P1-P3b*. The basic idea is to check whether the knot is "correctly" located by means of flagging a point of structural change of price response. Using this method, we test for differences in the balance of success and failure between the regimes to the left and right of the knot location, first left of the gap in the data space, as discussed above. If the knot flags a change, the successful and unsuccessful price points in the two regimes are described by different Bernoulli distributions. Otherwise, the data should be drawn from the same Bernoulli distribution. This is formulated in the following hypothesis for statistical testing:

H_0. Observations with a high market share achieved by a brand under consideration in the two regimes adjacent to the critical knot are drawn from the same distribution.

To check this hypothesis, a Chi-square test for equality of distributions is calculated. The results of this test are depicted in Table V. Since the regime to the right of the critical knot covers the sparse data space, the numbers of observations in both regimes are explicitly considered in the third and fourth column of the Table.

The split points of interest (see column 2 in Table V) as well as the first basis function B_{m1} have been estimated by the analysis of the data under consideration for the test. Consequently, the degrees of freedom for significance testing are corrected by two. However, we can see from Table V that H_0 can be rejected for brands I, III, IV, V, and VI at a level of $\alpha = 0.05$. This results implies that there is a significant difference in the response between the two regimes under consideration.

Brand II, with a knot location in line with retailers' expectation, is simultaneously the only brand for which the

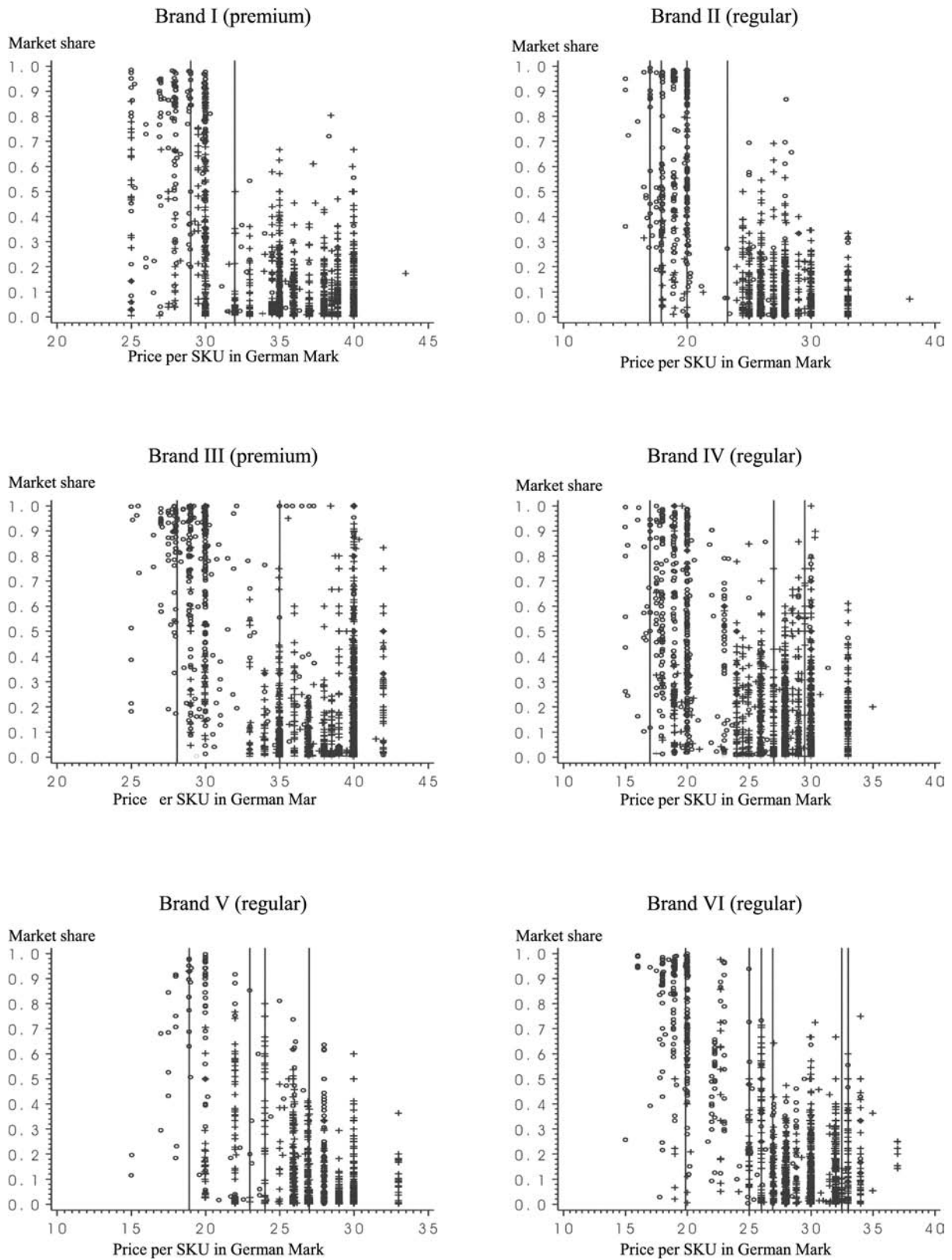**Figure 1** Regimes in the price-response data space

Table IV Regression parameters

Brand	Response
m = 1	$\hat{y} = 0.589\ (42.29) + 0.162\ BF5\ (20.21) - 0.162\ BF7\ (-25.68)$
	$BF5 = \max\ (0, PRICE1 - 31.98)$
	$BF7 = \max\ (0, PRICE1 - 29.00)$
m = 2	$\hat{y} = 0.645 - 0.250\ BF3 + 0.284\ BF5 + 0.163\ BF7 - 0.199$
	$BF21$
	$BF3 = \max\ (0, PRICE2 - 19.98)$
	$BF5 = \max\ (0, PRICE2 - 17.90)$
	$BF7 = \max\ (0, PRICE2 - 23.23)$
	$BF21 = \max\ (0, PRICE2 - 16.99)$
m = 3	$\hat{y} = 0.797\ (48.71) + 0.127\ (22.06)\ BF1 - 0.101\ BF19\ (-31.01)$
	$BF1 = \max\ (0, PRICE3 - 35.00)$
	$BF19 = \max\ (0, PRICE3 - 28.08)$
m = 4	$\hat{y} = 0.626\ (47.87) - .086\ BF3\ (-6.91) + .118\ BF5\ (14.91) -$
	$.054\ BF19$
	$BF3 = \max\ (0, PRICE4 - 29.50)$
	$BF5 = \max\ (0, PRICE4 - 26.99)$
	$BF19 = \max\ (0, PRICE4 - 16.99)$
m = 5	$\hat{y} = 0.644\ (25.39) - 0.073\ (5.63)\ BF1 + 0.246\ BF7\ (-5.51)$
	$-0.118\ BF9\ (-10.34) + 0.286\ BF23\ (6.14)$
	$BF1 = \max\ (0, PRICE5 - 26.98)$
	$BF7 = \max\ (0, PRICE5 - 24.00)$
	$BF9 = \max\ (0, PRICE5 - 18.90)$
	$BF23 = \max\ (0, PRICE5 - 22.99)$
m = 6	$\hat{y} = 0.751\ (66.01) - 0.096\ BF3\ (-19.39) - 0.232\ BF7$
	$(-4.97) + 0.222\ BF9\ (5.47) - 0.315\ BF13\ (-6.93) + 0.165$
	$BF15\ (5.20) + 0.246\ BF17\ (10.16)$
	$BF3 = \max\ (0, PRICE6 - 19.85)$
	$BF7 = \max\ (0, PRICE6 - 32.98)$
	$BF9 = \max\ (0, PRICE6 - 32.49)$
	$BF13 = \max\ (0, PRICE6 - 25.99)$
	$BF15 = \max\ (0, PRICE6 - 24.99)$
	$BF17 = \max\ (0, PRICE6 - 26.90)$

Table V Test results for the regimes left and right to the critical knot

Brand	Location of knot	Number of obs. Left	Right	Chi-square
I	29.00	159	245	18.73***
II	19.98	227	47	0.05
III	28.08	72	527	74.01***
IV	16.99	29	885	16.22***
V	18.90	25	175	21.88***
VI	19.85	93	317	78.08***

Note: *** $p < 0.005$

knot location is not supported by the Chi-square test. Thus, the results of our explorative investigation using the MARS algorithm for adaptive knot placement are vindicated by this confirmatory analysis. This endorses the use of the knot locations for evaluation of the research propositions *P1-P3b*.

4.3 Examination of research propositions
Table VI summarizes the results of the examination of the research propositions. The first proposition *P1*, assuming that the price-response function is characterized by kinks at odd

Table VI Synopsis of the results concerning propositions *P1-P3b*

	Brands					
	I	II	III	IV	V	VI
P1	+	+	−	ϕ	+	+
P2a	ϕ	+	ϕ	+	ϕ	ϕ
P2b	ϕ	+	ϕ	+	ϕ	ϕ
P3a	−	+	−	ϕ	+	−
P3b	+	ϕ	+	+	ϕ	+

Notes: ϕ = support; + = partial support; − = no support

prices, is evaluated by considering the location of knots depicted in Table III. Although several knots are located at non-odd prices, the general validity of this proposition is not disproved. In detail, it can be seen from Table VI that the proposition is supported by the response for brand IV and receives partial support from the knot locations for the brands I, II, V, and VI.

The proposition *P2a*, assuming that odd-odd prices are not more likely than simple odd prices to flag a threshold in consumer response is supported only by the response for brands with exception of brand II and VI. Even for these brands, only one of four (brand II) and one of six (brand VI) knots are assigned to an odd-odd price. Summarizing the results, this proposition is supported as well.

With respect to the proposition *P2b*, claiming that odd-odd prices are not more likely to flag the thresholds embracing the sparse regime of the data space, our analysis again indicates support. In the regular segment, the relevant knots are placed at 19.98 and 23.23 (brand II), 16.99 and 26.98 (brand IV), 18.90 and 22.99 (brand V), and finally 19.85 and 24.95 (brand VI). For the brands of the premium segment, none of the knots is assigned to an odd-odd price. The identified thresholds for all brands with the exception of $k = 3$ for brand II and $k = 1$ for brand IV support the proposition *P2b*. The brands II, IV, and V have a second sparse regime of the data space just above the price of 30 German Marks. For the premium brands, this second regime is just above 40 Marks. With exception of $k = 3$ brand IV (29.50) there are no thresholds separating or embracing this regime.

According to proposition *P3a*, similar odd prices should flag the thresholds for products of the consideration set, e.g. a quality segment. In order to evaluate this proposition, we consider the two premium brands and four non-premium brands separately. Knots surrounding the sparse part of the data space for brand I are placed at 29.00 and 31.98 and for brand III at 28.08 and 35.00, respectively. Thus, *P3a* is not supported in the premium segment. Interestingly, we find some support for this proposition from the regular segment. The brands II and IV have their lowest thresholds at 16.99. Another common threshold is 26.98 for brands IV and V. Both thresholds are flagging the lower limits of the response regimes covering the sparse sections of the data space.

Targeting the complexity of the response function, the proposition *P3b* postulates that this function should have the same complexity measured by of the number of thresholds, which are flagged by similar price endings. The two premium brands have comparatively simple response patterns consisting of two thresholds only (double kinked shape). Although we do not judge the 98-ending for brand I to be similar to the 08-ending for brand III, the proposition is partly

supported because brands have one threshold at 0-ending prices and both brands have the same number of thresholds.

Overall, the response patterns for the brands in the regular segment are more complex, since a higher number of knots is needed to capture the response. The number of knots needed to describe the response is positively associated with increasing mean prices as well as the range of observed prices for the brands in this segment (see Table II). We attribute the increased number of knots for the brands in this segment to the superposition of different price-ending effects. The proposition *P3b* is supported for brands II and VI, with a response pattern consisting of four knots. For brand II, two knots are located at 98-endings and one knot at a 00-ending price. Similarly, for brand IV, two knots are located at 98 and 99-endings and two knots at 0-endings. Brands III and VI differ with respect to the number of knots, but in turn most of the knots are located at 98 and 99-endings. Therefore, the results for these brands partially support the proposition *P3b*.

To summarize, there is some supporting evidence concerning all research propositions and it should be kept in mind that the propositions were formulated based on the results of previous studies. Particularly, the support for the propositions *P2a* and *P2b* casts doubts on the benefits of retailers favoring odd-odd prices. In general, these prices are not flagging the actual threshold in consumer response.

5. Discussion and limitations

This paper's contribution is threefold. First, we demonstrate the use of a new methodology for the assessment of price endings. This has been found to be easily applicable to POS scanner data. Due to its ability to identify structural changes, such as kinks in the customer response, the methodology may complement experimental investigations (e.g. Gendall *et al.*, 1998) by extracting thresholds relevant for experimental manipulation. In contrast to the previous study by Wedel and Leeflang (1998), the GCV criterion in combination with the forward-backward selection enables a data-driven locating of knots. Therefore, the identified thresholds are independent of any prior assumptions. This enables the investigation of price endings in different cultural contexts. The validity of the knot placing by generalized cross-validation is confirmed by conventional Chi-square testing.

Second, the distinction of odd-ending prices with respect to the first number left of the decimal has rarely been addressed in previous studies considering Western-type markets. With respect to retailers' actual behavior, this gap should clearly receive more attention in theory development. Our results show that odd-odd prices rarely flag a threshold in consumer response. At least in the market we considered, managers would be well advised to rethink their pricing practices. If practitioners are striving to slightly undercut the thresholds, the proposed methodology facilitates direct decision support through the identification of the relevant thresholds.

With respect to contemporary pricing practices, the evaluation of propositions *P2a* and *P2b* allows a further conclusion. For instance, Blinder *et al.* (1998) describe the vendors to leap upward to the next higher odd-odd price when raising prices. Since odd-odd prices are not more likely to flag thresholds embracing the sparse data regime, favoring odd-odd prices next to these regimes as well as eluding to charge prices from these regimes lacks any rationale.

Akin to the results of Kalyanam and Shively (1998), another pattern has been identified. The higher numbers of knots for the regular segment brands indicate the superposition of different odd-price effects. The two premium brands gave the strongest support for the proposition *P3b*. We attribute this to the quality image effect emerging from the price level of the brands. Two of the four knots in the response for these brands were assigned to even prices. With respect to practitioners, this result emphasizes the need for a consistent marketing mix. For researchers this result underscores the importance of covering the whole range of relevant prices for the investigation of price-ending effects rather than restricting it to very few price points.

Considering the heterogeneity of price thresholds, our study identifies two common thresholds for the brands in the regular segment. These common thresholds might be useful to guide practitioners in improving their pricing practices. The methodology proposed herein exposes the gap between retailers' beliefs and experience and the actual thresholds for individual product categories. It might help to overcome the drawbacks of contemporary pricing practices that rely on general rules of thumb.

Rather retailers could:
- carefully check the true thresholds for each brand individually;
- decide which brand should be priced below the "promotional" threshold and adjust the prices for these brands; and
- raise the prices of all other brands within the category so high that they slightly undercut the next higher threshold.

The rationale is that the promoted brands are expected to achieve a high market share and maintain a fairly good perception of the value-for-money ratio offered by the outlet. The not-promoted brands are provided with a substantial increase in profitability. The choice of products to be promoted by means of the promotion calendar cannot be answered by using our methodology (c.f. Silva-Risso *et al.* (1999) for a detailed discussion), but our methodology might be advantageous in two ways:
1 If the promoted product offers a substantial profit margin or the manufacturers' refunding and trade promotion reimbursements are related to the sales volumes, the identification of the thresholds enables the maximization of retailers' profits.
2 The customers are likely to assess the value-for-money ratio offered by a retailer and make up a price image based on very few promoted products (Burton *et al.*, 1994; Volle, 2001). Thus, the identification of the true thresholds might support the retailers in creation and maintaining an improved price image without losing profitability.

Of course, this study has several limitations. First, adaptive learning from a finite data set, as we did by employing the MARS algorithm, may be sensitive with respect to outliers. Bootstrapping, bagging, and boosting offer a remedy for this. Second, this study is limited to learning from data and neglecting all managerial experiences and insights, which Wedel and Leeflang (1998), for example, used for their knot placing. Employing the Bayesian MARS approach of Holmes and Mallick (2001) might be one direction of further research to extend this research design. Third, our analysis is restricted to the consideration of the price impact. In this study all

variations of additional marketing activities are summarized by a binary variable for the distinction of regular and promotional sales. Clearly, including further explanatory variables introduces multicollinearity, but the MARS algorithm is found to perform comparatively well even in such cases.

Finally, in the course of the ongoing diffusion of modern retail formats in developing transition economies (Alexander and de Lira e Silva, 2002; Colla, 2003), scanner data reflecting the customers' response to price endings in different cultural contexts have become available. Besides the direct support for pricing decisions, new opportunities for marketing scholars to amplify the knowledge on the impact of price endings, currently dominated by the Western-fashioned odd prices, arise from this.

Note

1 The authors thank Robert Schindler for adding this example in the discussion of a previous version of this paper.

References

Aalto-Setälä, V. and Raijas, A. (2003), "Actual market prices and consumer price knowledge", *Journal of Product & Brand Management*, Vol. 12 No. 5, pp. 180-92.

Alexander, N. and de Lira e Silva, M. (2002), "Emerging markets and the internationalization of retailing: the Brazilian experience", *International Journal of Retail & Distribution Management*, Vol. 30 No. 6, pp. 300-14.

Bergen, M., Kauffman, R.J. and Lee, D. (2004), "Store quality image and the rational inattention hypotheses: an empirical study of the drivers of $9 and 9¢ price endings among internet-based sellers", paper presented at the Informs Conference on Information Systems and Technology (CIST-2004), Informs, Denver, CO.

Blinder, A.S., Canetti, E.R.D., Lebow, D.E. and Rudd, J. (1998), *Asking about Prices*, Russell Sage Foundation, New York, NY.

Burton, S., Lichtenstein, D.R., Biswas, A. and Fraccastoro, K. (1994), "The role of attributions in consumer perceptions of retail advertisements promoting price discounts", *Marketing Letters*, Vol. 5 No. 2, pp. 131-40.

Colla, E. (2003), "International expansion and strategies of discount grocery retailers: the winning models", *International Journal of Retail & Distribution Management*, Vol. 31 No. 1, pp. 55-66.

Coulter, K.S. (2001), "Odd-ending price underestimation: an experimental examination of left-to-right processing effects", *Journal of Product & Brand Management*, Vol. 10 No. 5, pp. 276-92.

Coulter, K.S. (2002), "The influence of print advertisement organization on odd-ending price image effects", *Journal of Product & Brand Management*, Vol. 11 No. 5, pp. 319-34.

Craven, P. and Wahba, G. (1979), "Smoothing noisy data with spline functions: estimating the correct degree of smoothing by the method of generalized cross-validation", *Numerische Mathematik*, Vol. 31 No. 4, pp. 377-403.

Dawar, N. and Chattopadhyay, A. (2002), "Rethinking marketing programs for emerging markets", *Long Range Planning*, Vol. 35 No. 5, pp. 457-74.

Diller, H. and Brielmaier, A. (1995), "The impact of rounding-up odd prices: results of a field experiment in German drug stores", *Pricing Strategy and Practice*, Vol. 3 No. 4, pp. 4-13.

Dodds, W.B. and Monroe, K.B. (1985), "The effect of brand and price information on subjective product evaluations", in Hirschmann, E. and Holbrook, M. (Eds), *Advances in Consumer Research*, Vol. 12, ACR, Provo, UT, pp. 85-90.

Dunne, P.M., Lusch, R.F. and Griffith, D.A. (2002), *Retailing*, 4th ed., South-Western, Mason, OH.

Estelami, H. (1999), "The computational effect of price endings in multidimensional price advertising", *Journal of Product & Brand Management*, Vol. 8 No. 3, pp. 244-56.

Folkertsma, C.K., van Renselaar, C. and Stokman, A.C.J. (2002), "Smooth euro changeover, higher prices? Results of a survey among Dutch retailers", WO Research Memorandum Series, No. 682E, Netherlands Central Bank, Amsterdam.

Friedman, J.H. (1991), "Multivariate adaptive regression splines", *Annals of Statistics*, Vol. 19 No. 1, pp. 1-141.

Gedenk, K. and Sattler, H. (1999), "The impact of price thresholds on profit contribution – should retailers set 9-ending prices?", *Journal of Retailing*, Vol. 75 No. 1, pp. 33-57.

Gendall, P., Fox, M.F. and Wilton, P. (1998), "Estimating the effect of odd pricing", *Journal of Product & Brand Management*, Vol. 7 No. 5, pp. 421-32.

Guéguen, N. and Legoherel, P. (2004), "Numerical encoding and odd-ending prices: the effect of a contrast in discount perception", *European Journal of Marketing*, Vol. 38 Nos 1/2, pp. 194-208.

Guido, G. and Peluso, A. (2004), "Consumers' perception of odd-ending prices with the introduction of the Euro", *Journal of Product & Brand Management*, Vol. 13 No. 3, pp. 200-10.

Han, S., Gupta, S. and Lehman, D.R. (2001), "Consumer price sensitivity and price thresholds", *Journal of Retailing*, Vol. 77 No. 4, pp. 435-56.

Holdershaw, J., Gendall, P. and Garland, R. (1997), "The widespread use of odd pricing in the retail sector", *Marketing Bulletin*, Vol. 8, pp. 53-8.

Holmes, C. and Mallick, B. (2001), "Bayesian regression with multivariate linear splines", *Journal of the Royal Statistical Society, Series B*, Vol. 63 No. 1, pp. 3-17.

Kalyanam, K. and Shively, T.S. (1998), "Estimating irregular pricing effects: a stochastic spline regression approach", *Journal of Marketing Research*, Vol. 35 No. 1, pp. 16-29.

Levy, M., Grewal, D., Kopalle, P.K. and Hess, J.D. (2004), "Emerging trends in retail pricing practice: implications for research", *Journal of Retailing*, Vol. 80 No. 3, pp. xiii-xxxi.

Mazumdar, T. and Papatla, P. (2000), "An investigation of reference price segments", *Journal of Marketing Research*, Vol. 37 No. 2, pp. 246-58.

Mehta, N., Rajiv, J. and Srinivasan, K. (2003), "Price uncertainty and consumer search: a structural model of consideration set formation", *Marketing Science*, Vol. 22 No. 1, pp. 58-84.

Montgomery, A.L. (2005), "The implementation challenge of pricing decision support systems for retail managers", *Applied Stochastic Models in Business and Industry*, Vol. 21 Nos 4/5, pp. 367-78.

Quigley, C.J. and Notarantonio, E.M. (1992), "An exploratory investigation of perceptions of odd and

even pricing", in Crittenden, V.L. (Ed.), *Developments in Marketing Science*, Academy of Marketing Science, Chestnut Hill, MA.

Ratfai, A. (2003), "The dynamics of pricing points", working paper, Central European University, Budapest.

Reed, P.W. and Ewing, M.T. (2004), "How advertising works: alternative situational and attitudinal explanations", *Marketing Theory*, Vol. 4 Nos 1/2, pp. 91-112.

Schindler, R.M. (1991), "Symbolic meanings of a price ending", in Holman, R.H. and Solomon, M.R. (Eds), *Advances in Consumer Research*, Vol. 18, ACR, Provo, UT, pp. 794-801.

Schindler, R.M. (2001), "Relative price level of 99-ending prices: image versus reality", *Marketing Letters*, Vol. 12 No. 3, pp. 239-47.

Schindler, R.M. and Kibarian, T.M. (1996), "Increased consumer sales response through the use of 99-ending prices", *Journal of Retailing*, Vol. 72 No. 2, pp. 187-99.

Schindler, R.M. and Kibarian, T.M. (2001), "Image communicated by the use of 99 endings in advertised prices", *Journal of Advertising*, Vol. 30 No. 4, pp. 95-9.

Schindler, R.M. and Kirby, P.N. (1997), "Patterns of rightmost digits used in advertised prices: implications for nine-ending effects", *Journal of Consumer Research*, Vol. 24 No. 2, pp. 192-201.

Silva-Risso, J.M., Bucklin, R.E. and Morrison, D.G. (1999), "A decision support system for planning manufacturers' sales promotion calendars", *Marketing Science*, Vol. 18 No. 3, pp. 274-300.

Simmons, L.C. and Schindler, R.M. (2003), "Cultural superstitions and the price endings used in Chinese advertising", *Journal of International Marketing*, Vol. 11 No. 2, pp. 101-11.

Stiving, M. and Winer, R.S. (1997), "An empirical analysis of price endings with scanner data", *Journal of Consumer Research*, Vol. 24 No. 1, pp. 57-67.

Subrahmanyan, S. (2000), "Using quantitative models for setting retail prices", *Journal of Product & Brand Management*, Vol. 9 No. 5, pp. 304-15.

Suri, R., Anderson, R.E. and Kotlov, V. (2004), "The use of 9-ending prices: contrasting the USA with Poland", *European Journal of Marketing*, Vol. 38 Nos 1/2, pp. 56-72.

Swait, J. and Andrews, R.L. (2003), "Enriching scanner panel models with choice experiments", *Marketing Science*, Vol. 22 No. 4, pp. 442-60.

Thomas, M. and Morwitz, V. (2005), "Penny wise and pound foolish: the left digit effect in price cognition", *Journal of Consumer Research*, Vol. 32 No. 1, pp. 54-64.

Vakratsas, D. (2001), "A multivariate adaptive regression spline (MARS) approach to modeling market response", in Breivik, E., Falkenberg, A.W. and Groenhaug, K. (Eds), *Rethinking European Marketing: Proceedings from the 30th EMAC Conference*, Norwegian School of Economics Business Administration, Bergen, 8-11 May.

Volle, P. (2001), "The short-term effect of store-level promotions on store choice, and the moderating role of individual variables", *Journal of Business Research*, Vol. 53 No. 2, pp. 63-73.

Wedel, M. and Leeflang, P.S.H. (1998), "A model for the effects of psychological pricing in Gabor-Granger price studies", *Journal of Economic Psychology*, Vol. 19 No. 2, pp. 237-60.

Wu, J. and Rangaswamy, R. (2003), "A fuzzy set model of search and consideration with an application to an online market", *Marketing Science*, Vol. 22 No. 2, pp. 411-34.

Xia, L. (2003), "Consumers' judgments of numerical and price information", *Journal of Product & Brand Management*, Vol. 12 No. 5, pp. 275-92.

About the authors

Ralf Wagner is a Lecturer, Business Administration and Marketing, Faculty of Economics, Bielefeld University, Bielefeld, Germany. He is the corresponding author and can be contacted at: rwagner@wiwi.uni-bielefeld.de

Kai-Stefan Beinke is a Lecturer at the University of Osnabrück, Osnabrück, Germany.