Int. Rev. of Retail, Distribution and Consumer Research
Vol. 16, No. 2, 181–197, May 2006

Routledge
Taylor & Francis Group

Assessing the Impact of Temporary Retail Price Discounts Intervals Using SVM Semiparametric Regression

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ABSTRACT *Although the marketing literature has found that temporary retail price discounts cause a significant sales increase, little is known about the specific characteristics of deals that influence the magnitude of the sales spike. In this paper, we analyse the impact of the length of temporary retail price discounts periods on the sales increase using scanner-store daily-sales data for two frequently purchased product categories: ground coffee (a storable category) and yogurt (a perishable category). We develop a robust semiparametric regression model based on support vector statistical theory with several previously proposed predictors along with a daily time description. This model also makes it possible to investigate the impact of temporary retail price reductions on own-and-competing brand sales, observing brand substitution patterns. The results evidence: (1) which days of the promotional period present a higher contribution to the sales spike; (2) the existence of threshold and saturation effects; and (3) that asymmetric cross price effects apply in both categories.*

KEY WORDS: Sales spike, temporary price discounts intervals, SVM semiparametric regression, prices, discounts

Introduction

Nowadays, promotional instruments are of great relevance in retailing. Sales promotion constitutes a very important part of the promotional budget of many retailers, and sometimes they have to use these promotional instruments because of the high level of competition existing in the markets. In grocery retailing, promotion plays a significant role and retailers make increasing use of a variety of promotional tools. In particular, price promotion has become one of the most powerful tools in grocery retailing. Besides, the availability of scanner data to retail chains has provided retailers with a valuable source of information, and it allows them to research how price promotion works and to identify its main effects. Technological developments in data collection such as scanner equipment, along with the intensive growth in promotional expenditures, have

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ISSN 0959-3969 Print/1466-4402 Online/06/020181-17
DOI: 10.1080/09593960600572209

contributed to the recent progress in the modeling of promotional effects. For this reason, different types of models have been developed in order to measure the effects of price promotions (Foekens *et al.*, 1999; Abraham and Lodish, 1993).

Blattberg, Briesch and Fox (1995) report the short-term sales spike produced by temporary retail price reductions, considering it as an empirical generalization. Besides, general concern among practitioners and researchers suggests that temporary retail price discounts increase current period sales of the promoted brand. There is a wide empirical evidence supporting this belief (e.g., Woodside and Waddle, 1975; Moriarty, 1985; Blattberg and Wisniewski, 1988; Blattberg and Neslin, 1990; Blattberg *et al.*, 1995; Walters, 1991; Bell *et al.*, 1999) and results generally confirm the expected inverse relationship between price and quantity sold (though the size of the observed effects varies across studies).

The purpose of this research is to analyse the impact of the length of temporary retail price discount intervals on the sales of the own brand, considering also brand substitution patterns within the category. The investigation will be done in terms of brands, which makes it feasible to observe also the influence of the price-quality tier of the brands. We will build up a semiparametric regression model using store-level daily-sales data. To capture expected flexible interactions among variables, a semiparametric regression analysis based on Support Vector Machines will be developed. This methodology is similar to that proposed by Van Heerde *et al.* (2001), but fits better the data used in this investigation. Then, a model of the type previously mentioned will be formulated for each brand of the categories chosen. In each model, the brand sales of the brand to be explained will be the dependent variable, whereas the price index of that brand, the price indices of competitive brands and the position that each promotional day takes in the promotion period, will be used as explanatory variables.

The paper is organised as follows. First, we describe the database used in this work. Then, the methodology is presented. In particular, a semiparametric support vector formulation is developed. Finally, after results are reported, some limitations and future implications are outlined. Our conclusions are important for retailers because developing a better understanding about the effectiveness of temporary price discounts is critical for the retailer to implement better pricing and promotional practices.

Data Description

The database used in this paper was obtained from a Spanish grocery retail chain. The full database contains scanner information of one supermarket of the chain. The raw data consist of information on daily sales collected with in-store EAN scanning equipment during one year (304 days of sales information). Basically, from the database we can draw information about regular prices, promotional prices and characteristics of promotional periods for all product categories sold by the retailer.

As we note above, we have a complete database with different product categories, so we are not limited in terms of information for product selection. For a preliminary analysis, we focused on two product categories: a storable category, *ground coffee* (with a packaged size of 250 grams) and a perishable category, *yogurt* (with a packaged size of 125 grams). We considered both categories on the basis of the following criteria: the different nature of both categories in terms of perishability and the existence of daily sales records and frequent promotions for all brands (Tables 1 and 2).

There are six different brands within the ground coffee category: four premium national brands (Saimaza, Soley, Marcilla and Bonka) and two national brands (Bahía and 154). There is no distributor brand.

In the yogurt category, there are five different brands: three premium national brands (Danone, Sveltesse and Yoplait) and two national brands (Chamburcy and Clesa). Again, there is no distributor brand.

Tables 1 and 2 provide statistical descriptives of brand's sales, prices and temporary price discounts for the storable category and the perishable category respectively.

Table 1. Category data description for the non-perishable category (ground coffee)

Brand	Type of brand	Min-max quantities (in units)	Min-max prices (in pesetas)*	Relative discount (%)	Length of promotional periods
Bahía	Low-priced brand	0–26	157–195	15	10
				17	8
				16	4 (beg. of year)
154	Low-priced brand	0–44	159–225	7	12
				14	10
				21	9
				20	9
Saimaza	High-priced brand	0–76	189–249	13	13
				16	12
				16	11
				11	15
Soley	High-priced brand	0–57	187–235	2	6
				1	15
				23	11
				19	10
				10	11
Marcilla	High-priced brand	0–91	189–259	9	10
				9	12
				12	12
				9	14
Bonka	High-priced brand	0–94	185–240	17	12
				17	14
				13	12
				11	12
				9	12
				9	12
				12	13
				6	12
				5	12
				7	4 (end of year)

*Prices expressed in pesetas, the Spanish currency till December 2001; 1€ = 166.386 pesetas.

Table 2. Category data description for the perishable category (yoghurt)

Brand	Type of brand	Min-max quantities (in units)	Min-max prices (in pesetas)*	Relative discount (%)	Length of promotional periods
				32	4 (beg. of year)
				25	7
				20	12
Chamburcy	Low-priced brand	0–2,226	21–31	20	10
				20	11
				20	12
				20	12
				17	15
				5	12
Clesa	Low-priced brand	0–554	19–24	14	15
				14	5
				26	12
				17	12
Danone	High-priced brand	0–1,168	25–34	16	13
				16	12
				16	12
				13	11
				22	11
Sveltesse	High-priced brand	0–576	29–43	15	12
				19	15
Yoplait	High-priced brand	0–248	23–28	22	12
				15	12

*Prices expressed in pesetas, the Spanish currency till December 2001; 1€ = 166.386 pesetas.

Methodology

Support Vector Machines Semiparametric Regression Model

Blattberg *et al.* (1995) report the short-term sales increase induced by temporary retail price discounts. In this paper, we will focus on the impact of the length of temporary price discounts periods on the sales of the promoted brand, considering also sales substitution patterns. Regarding the quantification of this short-term effect, few studies consider the influence of the specific characteristics of price promotions that influence the magnitude of the sales increase. As we have scanner data records available on a daily basis, we are able to analyse the influence of the order of the promotional day within the promotional period (i.e., the first day within the promotional period, the second day, etc.) on this phenomenon. Therefore, we can determine which days of the promotional period sales increase more.

Given the characteristics of our data base, we develop a regression-type approach. Van Heerde *et al.* (2001) propose a semiparametric approach to estimate the deal effect curve on the basis of the advantage of non-parametric (flexibility) for the metric variables and the advantage of parametric regression (efficiency) for categorical variables. Whilst semiparametric approaches have been shown to be superior both to parametric and non-parametric models, they still exhibit some degree of overfitting in the estimation sample when compared to the validation sample. In this paper, we analyse several previously proposed predictors together with a daily temporal description. This formulation becomes unfeasible in terms of number of features supported either by parametric or by recently proposed semiparametric methods, so that we propose a new and robust semiparametric method based on the support vector statistical methodology.

The known robustness of the nonparametric support vector method, when formulated as a semiparametric procedure, makes it feasible to analyse an increased number of exogenous variables, thus allowing a more detailed time description in the daily time series available. Therefore, we develop a semiparametric model, but based on the alternative model estimation method *Support Vector Machines (SVM)*. In this SVM-SR model, we express brand sales as the sum of nonparametric function of metric variables (price indices of the own-and-competitive brands) and a parametric function of other dichotomic predictors (order of the promotional day within the promotional period). We do not include regular prices as separate predictors in order to avoid collinearity with price indices.

The representation of the model SVM-SR is given by the following specifications. For item k, k = 1, ..., J, the model is expressed by two different sets of weights, one for dichotomic and another for metric variables:

$$y_n = \sum_{m=1}^{M} w^m x_n^m + \sum_{d=1}^{D} v^d x_n^d + e_n \tag{1}$$

where,

y_{nt} is unit sales of brand k in day t, $t = 1, \ldots, \mathrm{T}$,
x_n^m is a vector of metric variables, that contains the price indices of all the brands in the category,
x_n^d is a vector of dummy variables, that contains dummy variables indicators of the existence of price promotion on a certain day of the promotional period, this is the first, second, third, ..., and fifteenth days of promotional period.

The problem can be stated (Vapnik, 1995) as the minimization of:

$$L_p = \frac{1}{2}\sum_{m=1}^{M}(w^m)^2 + \frac{1}{2}\sum_{d=1}^{D}(v^d)^2 + C\sum_{n=1}^{N}(\xi_n + \xi_n^*) \tag{2}$$

constrained to

$$y_n - \sum_{m=1}^{M} w^m x_n^m - \sum_{d=1}^{D} v^d x_n^d \le \varepsilon + \xi_n \tag{3}$$

$$\begin{gathered} -y_n + \sum_{m=1}^{M} w^m x_n^m + \sum_{d=1}^{D} v^d x_n^d \le \varepsilon + \xi_n^* \\ \xi_n, \xi_n^* \ge 0 \end{gathered} \tag{4}$$

By stating the Lagrange functional for this problem, and then obtaining the gradient with respect to the weight variables, we have:

$$w_m = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) x_n^m \tag{5}$$

$$v_c = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) x_n^c \tag{6}$$

where α_n, α_n^* are the Lagrange multipliers corresponding to (3), (4), and hence, the weights are expressed as a linear combination of the observations. Only a subset of the observations have a nonzeros coefficient in (5), (6), so that they are called the Support Vectors, and the solution is expressed in terms of them. Dual functional can be stated as the maximization of:

$$L_D = -\frac{1}{2} \sum_{n,k} (\alpha_n - \alpha_n^*)(\alpha_k - \alpha_k^*) \left(\sum_{m=1}^{M} x_n^m x_k^m + \sum_{d=1}^{D} x_n^d x_k^d \right) - \varepsilon \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) + \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) y_n \tag{7}$$

and the regression function can be expressed as

$$\hat{y}_r = \sum_{m=1}^{M} w^m x_r^m + \sum_{d=1}^{D} v^d x_r^d \tag{8}$$

This represents a parametric (linear) model for both metric and dichotomic variables. However, it is possible to use Mercer kernels in order to introduce a nonparametric (nonlinear) relationship for the metric variables, and finally the regression function can be more conveniently expressed as:

$$\hat{y}_r = \sum_{n=1}^{N} (\alpha_n - \alpha_n^*) K(x_n^m, x_r^m) + \sum_{d=1}^{D} v^d x_r^d \tag{9}$$

Confidence intervals (CI) for the parametric part of the models were calculated for linear coefficients (95% level) using bootstrap resampling.

Estimation Results

Comparison to Other Methodologies

For comparative purposes, we show the estimation results of the SVM-SR model as well as other types of models: a standard semiparametric model (Van Heerde *et al.* (2001) formulation) and a fully parametric (linear) model.[1] Additionally, both additive and multiplicative effects are considered for each brand in parametric and SVM-SR models by taking the natural logarithm of the sale units as well as the natural logarithm of the price indices. Therefore, different parametric and SVM-SR models were adjusted to each brand data, being either additive or multiplicative.

Each time series was split into training (75%) and test (25%) samples. The R^2 and the conventional root mean squared error (RMSE) were obtained in each model for both training and test subsets, in order to be able to detect the presence of overfitting. The models were estimated using Matlab, version 6.5. Tables 3, 4, 5 and 6 provide a summary of the values obtained in both categories.

In general higher values of R^2 can be detected in training observations for all types of models (additive parametric, multiplicative parametric, standard semiparametric and SVM-SR). As it can be noted, the values of R^2 obtained for the SVM-SR additive model are greater than the ones observed in the rest of models for all the brands included in both categories. While in the coffee category the SVM-SR models have captured around 50%–60% of the variability, in the yogurt category the captured variabiliy varies between 45%–55%. As previously mentioned, R^2 values fall at test observations in both categories. With this model we also obtain reductions in RMSE values, which mostly hold at test observations. From these results, it is clear that the SVM-SR additive model outperforms both parametric and standard semiparametric models, having a superior performance (see Tables 3, 4, 5 and 6).

Bootstrap Resampling Results

Figures 1 and 2 show some bootstrap resampling results. The values of the parameter estimates indicate the magnitude of the sales increase for each day of the promotional period. Those estimations with confidence intervals not including 0 values and above 0 indicate that sales increase a certain magnitude (the value of the estimation) that particular day of the promotional period. On the contrary, estimations with values below 0 mean sales decreases.

The pattern observed along the promotional period in the parameter estimates for all brands in the ground coffee category is very significant, as it indicates different sales responses from low-priced brands with respect to high-priced brands. Whereas it is not possible to observe a clear pattern in sales along the promotional period for low-priced brands, for high-priced brands a visible decreasing pattern in sales has been found from the beginning to the end of the promotional period. Besides, it can be confirmed for high-priced brands that sales increase until the 10th day of the promotion, which indicates that the positive effect of the promotional discount is obtained until that day.

However, the parameter estimates obtained for the yogurt category do not indicate a clear decrease or decreasing pattern in sales along the promotional period. Therefore, it is not possible to confirm the existence of a special pattern in sales along the promotion for the perishable category product selected.

Own-item Deal Effect Curves

The SVM-SR is adequate to capture the complex nature of the relationship between sales and temporary price discounts, and therefore, to investigate how sales respond to temporary retail price cuts.

To illustrate how brand sales respond to own-temporary price discounts, some examples of own-item deal effect curves are shown in Figure 3 (for a low-priced brand of the coffee category and a low-priced brand of the yogurt category) and

Table 3. Estimation results (training and test) for the low-priced brands of the ground coffee category: parametric additive, parametric multiplicative, standard semiparametric formulation (Van Heerde *et al*., 2001) and SVM semiparametric (additive and multiplicative)

	R^2		RMSE			R^2		RMSE	
Bahía	Train	Test	Train	Test	154	Train	Test	Train	Test
Par. addit.	0.60577	$9.3 \cdot 10^{-5}$	1.7287	1.6151	Par. addit.	0.5456	0.1967	2.8919	4.2311
Par. multip.	0.60412	0.00238	1.4612	1.2012	Par. multip.	0.5322	0.1475	2.6945	4.395
Standard semipar.	0.60307	0.0017016	1.4395	1.1957	Standard semipar.	0.5279	0.1583	2.6389	4.3213
SVM add.	0.4743	0.005604	2.0299	1.6525	SVM add.	0.5273	0.1994	2.638	4.1284
SVM mul.	0.61307	0.009410	1.4891	1.1783	SVM mul.	0.4742	0.28049	2.7931	3.8429

Table 4. Estimation results (training and test) for the low-priced brands of the yogurt category: parametric additive, parametric multiplicative, standard semiparametric formulation (Van Heerde *et al*., 2001) and SVM semiparametric (additive and multiplicative)

	R^2		RMSE			R^2		RMSE	
Chamburcy	Train	Test	Train	Test	Clesa	Train	Test	Train	Test
Par. addit.	0.5696	0.1526	69.3807	147.233	Par. addit.	0.5293	0.0190	55.054	65.5801
Par. multip.	0.4793	0.1768	69.0914	122.3733	Par. multip.	0.5176	0.0151	56.6736	45.167
Standard semipar.	0.4695	0.1908	68.2349	123.2152	Standard semipar.	0.5146	0.0102	56.6947	46.7034
SVM add.	0.4894	0.2878	64.4283	102.257	SVM add.	0.4049	0.0353	63.6695	52.7448
SVM mul.	0.4340	0.2938	72.1706	102.9585	SVM mul.	0.4630	0.0272	62.899	38.5546

Table 5. Estimation results (training and test) for the high-priced brands of the ground coffee category: parametric additive, parametric multiplicative, standard semiparametric formulation (Van Heerde *et al.*, 2001) and SVM semiparametric (additive and multiplicative)

	R^2		RMSE			R^2		RMSE	
Saimaza	Train	Test	Train	Test	Soley	Train	Test	Train	Test
Par. addit.	0.5293	0.5577	3.8073	3.2998	Par. addit.	0.4032	$2.9 \cdot 10^{-5}$	4.2129	3.9231
Par. multip.	0.37061	0.4645	3.5992	2.9857	Par. multip.	0.3753	0.000324	3.6529	2.331
Standard semipar.	0.4738	0.4905	3.2643	2.8217	Standard Semipar.	0.43115	0.003066	3.4583	2.4107
SVM add.	0.5198	0.6836	3.5399	3.3945	SVM add.	0.5413	0.005705	3.6387	5.5831
SVM mul.	0.4647	0.6715	3.454	2.7001	SVM mul.	0.5902	0.0002971	3.0503	2.5926
	R^2		RMSE			R^2		RMSE	
Marcilla	Train	Test	Train	Test	Bonka	Train	Test	Train	Test
Par. addit.	0.69105	0.08411	5.943	9.5084	Par. addit.	0.6088	0.4649	6.7229	9.3637
Par. multip.	0.6751	0.08513	5.9262	9.059	Par. multip.	0.59885	0.47771	6.7021	10.637
Standard semipar.	0.69403	0.0866	5.7336	9.03	Standard semipar.	0.62058	0.4069	6.4741	11.6548
SVM add.	0.6451	0.2058	6.4644	8.4474	SVM add.	0.6413	0.3765	6.3274	11.1719
SVM mul.	0.6701	0.08688	5.9009	8.8029	SVM mul.	0.6297	0.3697	7.0519	12.9162

Table 6. Estimation results (training and test) for the high-priced brands of the yogurt category: parametric additive, parametric multiplicative, standard semiparametric formulation (Van Heerde *et al.*, 2001) and SVM semiparametric (additive and multiplicative)

	R^2		RMSE	
Danone	Train	Test	Train	Test
Par. addit.	0.5293	0.0190	55.054	65.5801
Par. multip.	0.5176	0.0151	56.6736	45.167
Standard semipar.	0.5146	0.0102	56.6947	46.7034
SVM add.	0.4649	0.0353	63.6695	52.7448
SVM mul.	0.4630	0.0272	62.899	38.5546

	R^2		RMSE	
Sveltesse	Train	Test	Train	Test
Par. addit.	0.2713	0.0036	59.5206	71.9321
Par. multip.	0.08353	0.00576	61.2343	58.2233
Standard Semipar.	0.0866	0.000298	59.6313	58.779
SVM add.	0.0640	0.108	53.866	53.5195
SVM mul.	0.09860	0.08161	59.2652	49.954

	R^2		RMSE	
Yoplait	Train	Test	Train	Test
Par. addit.	0.7002	0.0309	12.1018	10.8855
Par. multip.	0.5543	0.0222	10.0213	6.5183
Standard semipar.	0.5349	0.02732	11.0367	6.6098
SVM add.	0.7384	0.02198	12.677	10.6383
SVM mul.	0.6176	0.023138	9.9715	6.1388

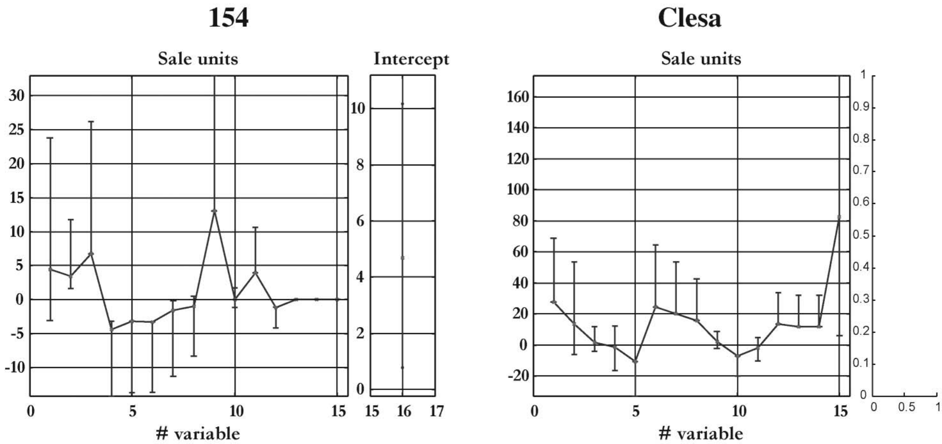

Figure 1. Bootstrap resampling results for: one low-priced brand of the ground coffee category, 154 (left) and one low-priced brand of the yogurt category, Clesa (right)

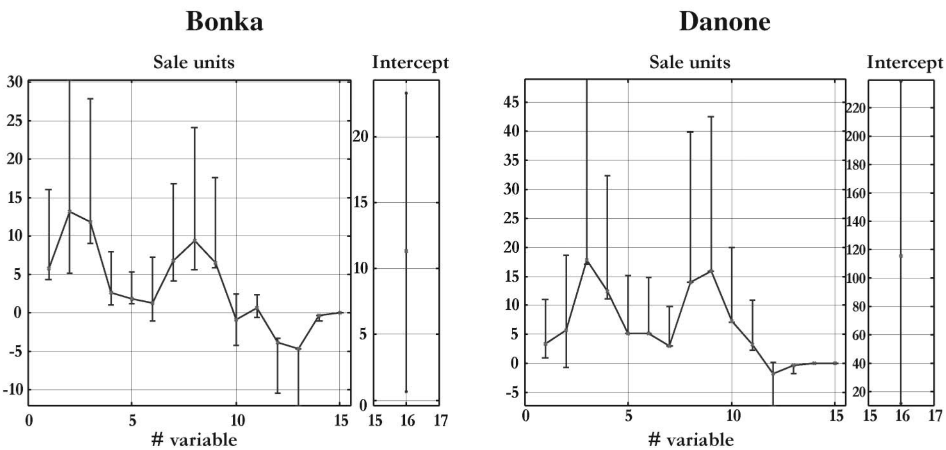

Figure 2. Boostrap resampling results for: one high-priced brand of the ground coffee category, Bonka (left) and one high-priced brand of yogurt category, Danone (right)

in Figure 4 (for a high-priced brand of the coffee category and a high-priced brand of the yogurt category), with own-item price indices on the x-axis and predicted sales increases on the y-axis.

A reverse S-shape is apparent in all own-item deal effect curves, indicating the existence of different threshold and saturation levels. In the ground coffee category, the threshold effects obtained show that the minimum value of promotional discounts required in the category to change consumers' purchases is below 5%. It means that the smallest promotional reductions offered in the category are effective for increasing sales. An exception to this can be found in the brand Soley, where no threshold effect is detected. Almost all saturation effects obtained in this category vary between 12% and 17% levels of discount. However, in the brand Soley the saturation effect is detected with smaller levels of discounts (5%) see Table 7.

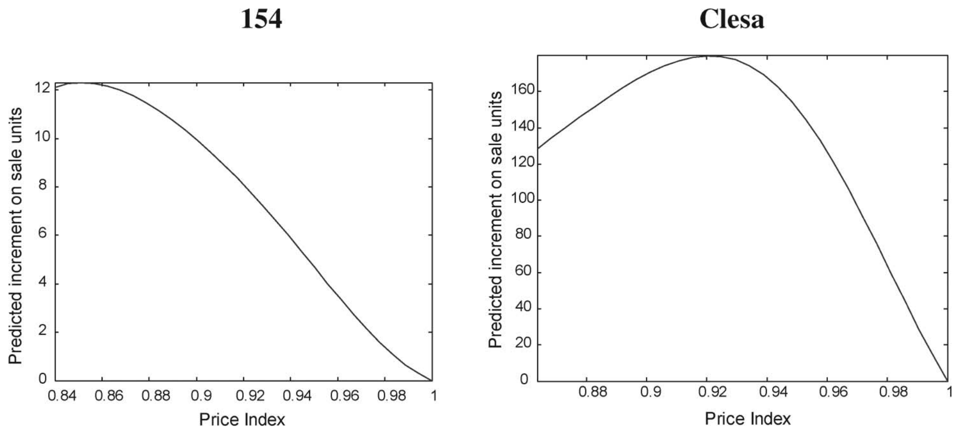

Figure 3. Own-item deal effect curves for: one low-priced brand of the ground coffee category, 154 (left) and one low-priced brand of the yogurt category, Clesa (right)

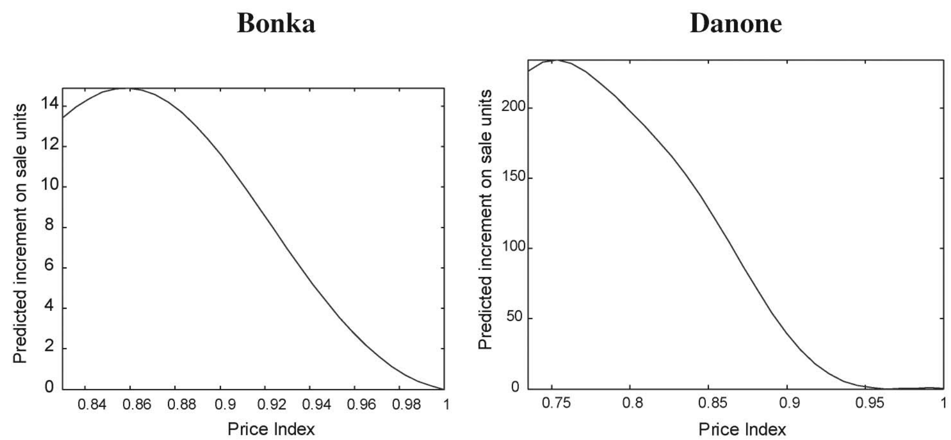

Figure 4. Own-item deal effect curves for: one high-priced brand of the ground coffee category, Bonka (left) and one high-priced brand of the yogurt category, Danone (right)

In general, both the threshold and saturation effects obtained in the yogurt category are higher than in the ground coffee category. The smallest threshold effect is detected at a level of 5% of discount at the brands Chamburcy, Danone and Yoplait. An exception to this is found in the brand Clesa, where no threshold effect is detected. The saturation effects observed in this category vary between 8% and 25% levels of discount see Table 8.

In order to explain saturation effects, two mechanisms can be argued. One refers to the limit on the amount consumers can stockpile (Blattberg *et al.*, 1995) and/or consume in response to a temporary price discount. The other is the *discounting of discounts effect* (Gupta and Cooper, 1992) and is related to the consumers' perception of the information about the discounts. Then, when consumers' perceptions of promotional discounts are less than the real discount, saturation effects are detected in the deal effect curve.

Table 7. Evidence of threshold and saturation effects from the analysis of the own-item deal effect curves (ground coffee category)

	Shape	Threshold Level	Saturation Level
Low-priced brand			
Bahía	Convex. Reverse S	5%	17%
154	Convex. Reverse S	2%	15%
High-priced brand			
Saimaza	Reverse S	4%	17%
Soley	Reverse S	–	5%
Marcilla	Reverse S	2%	12%
Bonka	Reverse S	2%	15%

Table 8. Evidence of threshold and saturation effects from the analysis of the own-item deal effect curves (yogurt category)

	Shape	Threshold Level	Saturation Level
Low-priced brand			
Chamburcy	Kinked L	5%	20%
Clesa	Reverse S	–	8%
High-priced brand			
Danone	Reverse S	5%	25%
Sveltesse	S	10%	22%
Yoplait	Reverse S	5%	25%

Three-dimensional Deal Effect Surfaces

Retailers frequently offer price promotions to increase sales of the promoted brand. However, the impact on competing brands sales can affect the overall category profitability (Moriarty, 1985; Kumar and Leone, 1988; Walters, 1991).

As there were observations of simultaneous temporary price discounts, reliable three-dimensional deal effect surfaces could be constructed. The vertical axis of the surfaces indicates the predicted sales volume of one brand of the category and the other two axes represent the price indices of that brand and another competing brand.

The analysis of different curves of the surfaces is very interesting to gain an insight about substitution patterns in the category:

- The curve A-B is the own-item deal effect curve, obtained when the competing brand has a price index of 1.
- The curve C-D shows how own-brand sales vary, considering that the own-brand offers different levels of discounts and the competing brand offers maximum discounts.
- The curve B-C is the cross-item deal effect curve and shows how own-brand sales vary, considering that the own-brand does not offer any discount and the competing brand offers different levels of discounts.

- The curve D-A shows how own-brand sales vary, considering that the own-brand offers maximum discounts and the competing brand offers different levels of discounts.

In Figure 5 we show two three-dimensional deal effect surfaces, one for a low-priced brand of the ground coffee category, Bahía, and another one for a low-priced brand of the yogurt category, Chamburcy. In Figure 6 two dimensional three-deal effect surfaces are provided for a high-priced brand of the ground coffee category, Saimaza, and another one for a high-priced brand of the yogurt category, Yoplait.

It is noted that the discounts that steal more sales from the rest of brands correspond to the high-priced brands of the category. Then, the interaction effects across competitive brands appear to be asymmetric. This finding is consistent with the literature review (Sethuraman, 1995, 1996; Sethuraman and Srinivasan, 1999; Sethuraman *et al.*, 1999).

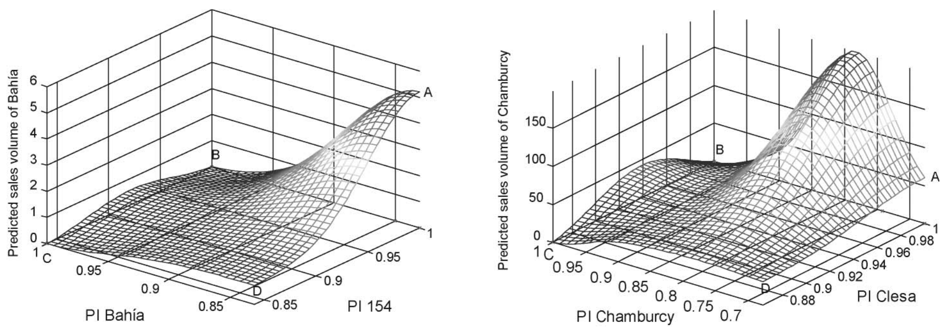

Figure 5. Three-dimensional deal effect surfaces for: one low-priced brand of the ground coffee category, Bahía (left) and one low-priced brand of the yogurt category, Chamburcy (right)

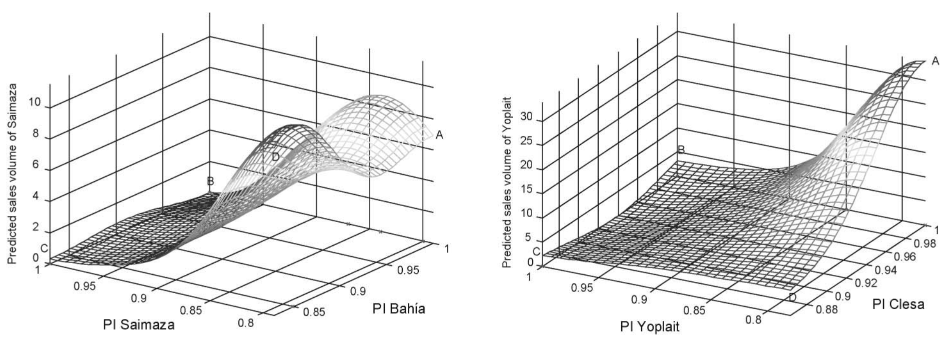

Figure 6. Three-dimensional deal effect surfaces for: one high-priced brand of the ground coffee category, Saimaza (left) and one low-priced brand of the yogurt category, Yoplait (right)

Conclusions, Limitations and Further Research

In this study, we have focused on the influence of the days that comprise the promotional period on the quantity acceleration effect, considering also the impact of the deal discounts on own-and cross-brand sales. To test these effects, we have used scanner data corresponding to two product categories, a storable category, ground coffee, and a perishable category, yogurt.

Once the proposed model has been developed and the results have been obtained, it is confirmed that temporary retail price reductions increase brand sales of the categories studied, which is a consistent finding with the literature review (e.g., Blattberg *et al.*, 1995; Bell *et al.*, 1999). Our semiparametric modeling approach enabled us to determine how promotional sales behaved through the promotional period. In particular, we observed in the high-priced brands of the storable category that promotional discounts had a bigger impact during the first days of the promotional period, whereas no special pattern was detected in the low-priced brands of this category. However, in the perishable category it was not possible to confirm the existence of any special pattern in sales along the promotional period.

We also estimated the own-item deal effect curves for all brands within both categories and observed that almost all curves presented an S-reverse shape, indicating different threshold and saturation levels (Tables 7 and 8). In general, the threshold and saturation levels obtained were slightly higher in the perishable category, the yogurt category.

Besides, our findings show the existence of asymmetric cross-price effects in both product categories. Then, it is confirmed that promoting high-priced brands has a stronger impact on sales of low-priced brands than the reverse.

From these results some guidelines can be suggested for the retailer to set adequate promotional discounts periods. In the first place, promotional periods for the high-priced brands of the storable category should not exceed 10 days, otherwise the promotion profitability could be reduced. In addition to this, discount levels should not exceed a certain magnitude, which depends on the considered brand.

In the perishable category, as no regular pattern in sales has been detected, it is not possible to confirm the existence of an optimum number of promotional days. However, discounts should be set at levels between 5% and 25%, especially in order to induce sales avoiding saturation effects.

Retailers should also consider the existence of asymmetric cross price effects when setting the promotional discounts magnitude as well as the number of promotional days. Since asymmetric cross-price effects can produce complex substitution effects among brand sales within the selected categories, retailers should take into account how brand sales interact with one another before setting the promotional intervals.

We can refer to some limitations that arise in the research. It might be argued that the product categories' special characteristics could limit the generalisability of the findings. In fact, it affords a very specific test of the effects of retail price promotion. For that reason, the price promotional effects investigated may be particular, both in direction and magnitude, to the categories investigated.

Also, the promotional effects might be particular to the specific conditions of the study: the type of the store examined (i.e., supermarket), the promotional strategy employed by the retailers (e.g., heavy emphasis on weekly price discounts) and the competitive environment.

Finally, further research is needed to determine the generalisability of these results to other category products, as well as to the study of additional promotional effects, such as complementary effects in other categories. It would be interesting to include the time period between temporary price discounts. Certainly, as consumers build up domestic inventory when promotions occur, the time since the last promotion can be especially important in non perishable categories such as coffee.

Acknowledgements

This research has been funded by the Research Project of the Ministerio de Economía y Ciencia (Spain) SEJ ECON SEJ2005-06105 *Gestión de las promociones y de las marcas de distribuidor para un desarrollo eficiente de la estrategia de marketing del minorista* and by the Viceconserjería de Universidades, Investigación e Innovacion, Junta de Comunidades de Castilla-La Mancha (Spain). The authors acknowledge the anonymous reviewers for their valuable comments.

Note

1 The estimation procedure for the parametric model is ordinary least squares (OLS) and for the standard semiparametric model, the one described in Van Heerde *et al.* (2001).

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