

Using daily store-level data to understand price promotion effects in a semiparametric regression model

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Abstract

Though it has been widely reported in the marketing literature that temporary price discounts generate substantial short-term sales increase, the shape of the deal effect curve constitutes a key research topic, for which there are still limited empirical results. To address this issue, a semiparametric regression approach is used to model the complex nature of this phenomenon. Our model is developed at the brand level using daily store-level scanner-data, which allows the study of several nonreported promotional effects, such as the influence of the day of the week both in promotional and nonpromotional periods. The results show that the weekend is the most effective in increasing promotional sales and that asymmetric and neighborhood effects hold. However, 9-ending promotional prices are not impactful.

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1. Introduction

One of the most relevant generalizations in the field of price promotion suggests that retailers' price discounts increase current sales of the promoted brand (Blattberg and Neslin, 1990; Lilien et al., 1992; Blattberg et al., 1995). Not only there exists a wide empirical evidence supporting this belief, but also results obtained across different studies generally confirm the expected inverse relationship between price and quantity sold (e.g., Blattberg and Wisniewski, 1987; Bell et al., 1999; Van Heerde et al., 2001). However, little is still known about the shape of the deal effect curve. Blattberg et al. (1995, p. G127) wonder whether it is linear, concave, convex or S-shaped. The relevance of the shape refers to the optimization of dealing amounts, because it determines the optimal promotional discounts. Therefore,

if the curve is convex-shaped, the firm will return greater discounts than if the curve is concave-shaped.

The promotion literature suggests several phenomena that may contribute to the nature and structure of the relationship between sales and temporary price cuts. All these phenomena may be influenced by the characteristics of temporary price discounts and are related to: the influence of own price deals characteristics, *threshold effects* and *saturation effects* (Gupta and Cooper, 1992); the influence of competing price deals characteristics, *cross-item deal effects* (Sethuraman, 1996; Sethuraman et al., 1999); the influence of own-and-competing-items discounts characteristics, *interaction effects between deals of different items* and the influence of other promotion signals along with price discounts, *interaction effects between price deals and promotion signals* (Inman et al., 1990; Mayhew and Winer, 1992).

Given the relationship between temporary price discounts and sales, it is critical for the retailer to develop an understanding of the characteristics of discounts that most influence sales obtained by the own brand and patterns of substitution among sales in the category to implement better pricing and promotional decisions. In particular,

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assessing the impact of temporary price cuts characteristics on own and competing brand sales will assist managers in making more effective allocations of discounts among brands in the category. Much effort has been done to the date trying to identify the most relevant influences of temporary price discounts on sales, and relevant significance has been found in relation to the magnitude of the discounts (e.g., Blattberg and Wisniewski, 1989), the usage of feature advertising (e.g., Blattberg and Wisniewski, 1987; Wittink et al., 1987; Van Heerde et al., 2001), the usage of displays (e.g., Blattberg and Wisniewski, 1987; Wittink et al., 1987; Van Heerde et al., 2001), and the set of promotional prices ending in the 9 digit (e.g., Blattberg and Wisniewski, 1987; Schindler, 1991; Stiving, 2000; Stiving and Winer, 1997). But the study of promotional effects during each day within the promotional period has not yet been addressed, mainly due to the preponderance of weekly data sets. However, the consideration of the day of the week in promotional periods may be of interest, as it should allow the retailer to set more precise price discounts temporarily. Furthermore, since sales obtained in supermarkets and hypermarkets during the last years have pointed out how sales are much higher during weekends (AcNielsen, 2003) it is important to take into account this pattern to reinforce sales during weekends.

This study is concerned with the shape of the deal effect curve and the nature and structure of daily, tactical competition among brands within a category. The consideration of many relevant phenomena in the deal effect curve can produce complex nonlinearities and interactions, which are better captured with a flexible regression approach. But fully nonparametric regression models suffers from some disadvantages, such as the *curse of dimensionality*, this is, as the number of predictor variables increases, the required number of observations explodes. Some authors (e.g., Kalyanam and Shively, 1998; Van Heerde et al., 2001) propose a semiparametric regression approach, as it has the advantages of power and flexibility of parametric and nonparametric regression models.

We develop a daily store-level scanner-data model at the brand level, aiming to analyze how sales respond to temporary own and cross-item temporary price cuts. We use a semiparametric regression approach similar to that applied by Van Heerde et al. (2001) to model the relationship between sales and own-and cross-item price discounts. This type of modelling was firstly introduced by Robinson (1988) and successfully applied to the deal effect curve analysis by Van Heerde et al. (2001). In our model, daily store-level brand-sales over time are modeled as a nonparametric function of own-and-cross item temporary price deals, together with a parametric function of other indicator predictors. The parametric component captures: (a) the influence of the day of the week (distinguishing promotional from non promotional periods), and (b) promotional prices ending in the 9 digit on sales of the own brand. According to complex relationships that can be expected among variables, the nonparametric component

includes only metric variables (prices indices), whereas the parametric component includes only indicator variables (day of the week on promotional days, day of the week on nonpromotional days, and 9-ending promotional price).

This paper is organized as follows. In the next section, we extend prior research on the phenomena related to the deal effect curve and on the characteristics of deal discounts that have been traditionally considered. We also provide a rationale for the inclusion of the day of the week. In Section 3, the database is described and the semiparametric regression model is presented. In Section 4, we present an application of the semiparametric regression model using daily store-level scanner-data for ground coffee category. Finally, in Section 5, we provide the conclusions and some discussion about general managerial implications.

2. Literature review

The price promotion literature shows that temporary price discounts generate substantial short-term sales increase (Blattberg et al., 1995). Though the relationship between price promotions and sales has been long investigated, little is still known about the shape of the deal effect curve. Many phenomena have been suggested to be relevant, which are influenced by the characteristics of the temporary price deals: threshold effects, saturation effects, cross-item deal effects, interaction effects between deals of different items, and interaction effects between deals and other types of promotions.

While threshold effects refer to the minimum value of a price discount required to change consumers intentions and encourage them to purchase, saturation effects indicate the limit in the amount consumers can stockpile and/or consume in response to a deal (Blattberg et al., 1995).

Since grocery stores typically discount different brands in the same category simultaneously, temporary price discounts can generate cross-brand competitive effects, and it has been observed that price promotion for one brand may have negative effects on sales of other brands in the product category. The importance of such negative cross-effects may vary across product categories. Kumar and Leone (1988) found price deals to be determinant of the promoted brand sales, and to have significant impact on sales of other brands in the category. Blattberg and Wisniewski (1989) found asymmetric patterns in the promotional cross-price elasticities. Sethuraman (1996) and Sethuraman et al. (1999) considered also how relative brand prices affect the cross-item price cut effects.

Though previous research does not address how the shape of the deal curve depends on the simultaneous presence and amount of other items discounts, the effect of display and feature advertising was analyzed by Woodside and Waddle (1975), Blattberg and Wisniewski (1989), Kumar and Leone (1988) and Bemmaor and Mouchoux (1991).

Regarding all of these phenomena, many characteristics of temporary price discounts have been suggested to have a positive impact on the sales spike, influencing the shape of the deal effect curve. For this reason, researchers have commonly included the impact of relative discounts, 9-ending promotional prices, and the presence of feature advertising and/or displays, as relevant determinants of the sales spike and the shape of the deal effect curve.

2.1. The magnitude of discounts

Many researchers have assumed that perceptions of deal prices and discounts determine consumer purchase decisions. The important role of deal and nondeal price perceptions is illustrated in many marketing models (Blattberg and Neslin, 1990). The economic rationale underlying this issue is clear: temporary price reductions increase the value of the product to the consumer and require immediate action. The marketing literature reveals different consumer behaviors that contribute to the immediate sales boost (Blattberg and Neslin, 1990). Consumers may buy more quantity of the brand (quantity acceleration) and/or earlier (time acceleration). Consumers may buy the promoted brand, which is not the usual one (brand switching). Finally, consumers may also buy the promoted brand in a different store (store switching). These behaviors may also benefit stockpiling behavior (when consumers can stockpile the product), or they may also increase the normal consumption rate (when it is not possible to stockpile the product, i.e., the product is perishable).

It is important to determine whether consumers perceive deals and promotional prices, and to determine the accuracy of those perceptions. The influence of these perceptions has been differently incorporated in the marketing models. It has sometimes been operationalized as regular prices (Blattberg and Wisniewski, 1989; Wittink et al., 1987; Gupta, 1988; Bronnenberg and Wathieu, 1996; Christen et al., 1997; Foekens et al., 1999), as actual prices (Kumar and Leone, 1988; Blattberg and Wisniewski, 1989; Krishnamurthi et al., 1992; Sethuraman, 1996; Foekens et al., 1999), as net prices (Papatla and Krishnamurthi, 1996), relative deal discounts (Blattberg and Wisniewski, 1989), as absolute deal discounts (Gupta, 1988) or as price indices (Van Heerde et al., 2001).

In our model, we do not include regular, actual, or net prices as separate predictors, in order to avoid collinearity with other indicator variables. As Van Heerde et al. (2001), we introduce price indices as metric variables, and we model them in the nonparametric component of the model.

2.2. Promotional prices ending in the 9 digit

There is a clear dominance of retail prices with 9-ending digits in comparison to other ending digits (Schindler and Kirby, 1997; Stiving and Winer, 1997; Wedel and Leeflang, 1998; Gedenk and Sattler, 1999) because retail managers

tend to set prices under the consideration of the last digit of a price having a significant impact on sales. Since Bader and Weinland (1932) initiated the discussion, several approaches have been proposed to explain the preponderance of price endings of 9 (e.g., Schindler, 1991; Schindler and Kirby, 1997; Stiving, 2000), especially in grocery retailing (Stiving and Winer, 1997). Many theories have been proposed both from the consumer behavior and from the operations perspectives, aiming to gain insight on this issue (Stiving and Winer, 1997). Stiving and Winer (1997) summarize them in a comprehensive classification of the effects of price endings that distinguish the operation theories from the consumer behavior theories. Whereas operation theories refer to internal issues of the firm—typically related to cost reductions—consumer behavior theories recommend the use of certain price endings to firms because right-hand digits interpretations by consumers contribute to increase demand.

In this study, we want to account for the importance of 9-ending price effects only during promotional periods because our interest focuses on the effects of promotional prices. As Blattberg and Wisniewski (1987) did, in order to test the importance of this effect we include a dummy variable that takes the value of 1 only when the price promotion ends in the digit 9. These authors observed that using 9-ending promotional prices provides an extra sales increase.

2.3. Feature advertising and displays

The effect of feature advertising and displays was found by Woodside and Waddle (1975), Blattberg and Wisniewski (1987), Kumar and Leone (1988), Bemmaor and Mouchoux (1991), Bolton (1989), and also, feature advertising and displays were shown to increase sales and possibly interact with price promotional discounts (Blattberg and Neslin, 1990). However, few empirical results have been generated regarding the synergies among feature advertising, displays, and price discounts (Blattberg et al., 1995, p. G125).

Although both types of promotional signals were used by the retailer during the period considered, we do not have data available on their usage. Therefore, no relevant variable relative to test these effects could be included.

2.4. Rationale for the inclusion of the day of the week

To our knowledge, the previously described characteristics of temporary price discounts have not been related to any temporal dimension, to the date. Given that sales show a growing pattern during weekends in grocery retailing, it is important to analyze whether this growing pattern is different during promotional periods, and in this case, to quantify the magnitude of the sales increase during weekend promotional periods. Then, the explicit consideration of the day of the week within promotional periods can be highly informative. Specifically, it allows retailers to

observe whether a price deal may reinforce sales obtained during weekends. The development of studies including the day of the week among the characteristics of price discounts may allow researchers to gain a better understanding about which days of the week deal discounts have the biggest impact on the sales spike.

To test this effect, we include 6 dichotomic variables for each day of the week in promotional period, and 6 dichotomic variables for each day of the week in nonpromotional period. The use of different sets of variables will allow us to model different daily patterns for promotional and for non promotional periods.

2.5. Aim of the study

The purpose of the present study is to analyze and explain the promotional effects during promotional days. Our primary focus is both on the shape of the deal effect curve and on the influence of price deal characteristics. To test this effect, we build a model of promotional sales as a possibly complex function of a number of predictor

variables. We propose the use of a semiparametric regression model similar to the one used by Van Heerde et al. (2001), on the basis of the advantages of non parametric regression (flexibility) for the deal variables, and of the advantages of parametric regression (efficiency) for indicator variables. We use daily sales data at the brand unit level with a high variety of price discounts, and we estimate the deal effect curve separately for each brand in the product category.

3. Methodology and data analysis

3.1. Description of the database

Our empirical analysis was conducted on a daily store-level scanner-data set for the ground coffee caffeinated category. We chose this product category because it was sold on promotion very frequently, presented daily sales observations and was used in several previous studies (e.g., Guadagni and Little, 1983; Gupta, 1988; Narasimhan et al., 1996). The database was constructed from the receipts

Table 1
Characteristics of the brands selected in the category

Brand	Type of brand	Length of promotional periods	Min–max prices (in pesetas)	Promotional prices (in pesetas)	Relative discount (%)	Day of the week when promotion begins	Day of the week when promotion ends
154	Low-priced brand	4 (beg. of year)	159–225	159	16	Friday	Tuesday
		12		175	7	Thursday	Wednesday
		10		159	14	Saturday	Wednesday
Bahía	Low-priced brand	10	157–195	165	15	Friday	Wednesday
		8		157	17	Saturday	Tuesday
		11		199	23	Saturday	Thursday
		10		199	19	Thursday	Monday
Marcilla	High-priced brand	11	189–259	199	10	Friday	Wednesday
		10		195	9	Thursday	Monday
		12		195	9	Thursday	Wednesday
		12		189	12	Wednesday	Tuesday
		14		189	9	Saturday	Monday
		12		195	17	Monday	Saturday
		14		195	17	Friday	Saturday
		12		195	13	Friday	Thursday
Bonka	High-priced brand	12	185–240	195	9	Thursday	Wednesday
		12		195	9	Thursday	Wednesday
		13		189	12	Wednesday	Wednesday
		12		187	6	Friday	Thursday
		12		189	5	Thursday	Wednesday
		4 (end of year)		185	7	Wednesday	Saturday
		9		195	21	Friday	Tuesday
Saimaza	High-priced brand	9	189–249	199	20	Monday	Wednesday
		13		195	13	Wednesday	Wednesday
		12		189	16	Thursday	Wednesday
		11		189	16	Thursday	Tuesday
		15		199	11	Monday	Thursday
Soley	High-priced brand	6	187–235	195	2	Tuesday	Tuesday
		15		187	1	Saturday	Wednesday

of a Spanish supermarket, since January 2, 1999 until December 31, 1999, with a total of 304 daily observations. Each record in the data set contains information of the purchased product, the identification of the purchased product through the EAN code, the paid price, the quantity purchased, and the date when the purchase took place. Prices are expressed in pesetas, the Spanish currency during 1999. There is no information available about feature advertising nor display activity used by the retailer during the consideration period. The category includes only one package size, 250 g. There are six brands sold in this supermarket: four high-priced (high-quality) premium national brands (Marcilla, Bonka, Saimaza, and Soley) and two low-priced national brands (154 and Bahía). As shown in Table 1, brands 154, Marcilla, Bonka, Saimaza, Soley, and Bahía, are sold on promotion several times. Among these brands, Bahía has no 9-ending promotional prices.

3.2. Model description and parameter estimation

The response variable is the sales units sold of a brand in the category, and a separate model is built for each brand (see Fig. 1). In order to account for the impact of temporary price discounts characteristics on the shape of the deal effect curve, the model specification should contain the most relevant variables involved in the promotional and nonpromotional periods. Price index for each brand in the category will allow to include complex interaction effects among brands in terms of relative discounts. Also, the consideration of the weekly nature of oscillations will introduce temporal information in the model. When observing Fig. 1, weekly oscillation patterns seem to be present both in promotional and nonpromotional periods, but they appear as markedly different in amplitude and in average level. Therefore, two different exogenous (indicator) sets of variables are introduced in order to capture: (1) the day of the week during price discount of the modeled brand, and (2) the day of the week during nonpromotional prices of the modeled brand.

For each given brand (k), the following semiparametric model is specified:

$$y_t^{(k)} = m(\mathbf{X}_t^M) + \alpha^T \mathbf{X}_t^D + e_t, \tag{1}$$

where:

- $y_t^{(k)}$: unit sales of brand (k), $k = 1, \dots, 6$ in day t , $t = 1, \dots, 304$;
- $m(\cdot)$: nonparametric function;
- \mathbf{X}_t^M : vector of M metric variables (day t), $x_{t,m}^M$ is price index of brand m , $m = 1, \dots, 6$. Each price index is calculated as the ratio of current to regular price of brand m in day t .
- \mathbf{X}_t^D : vector of D dichotomic variables (day t) consisting of:
 - $x_{t,1}^D, \dots, x_{t,6}^D$: indicators of the day of week—Monday (1) to Saturday (6)—during promotional periods in brand (k);

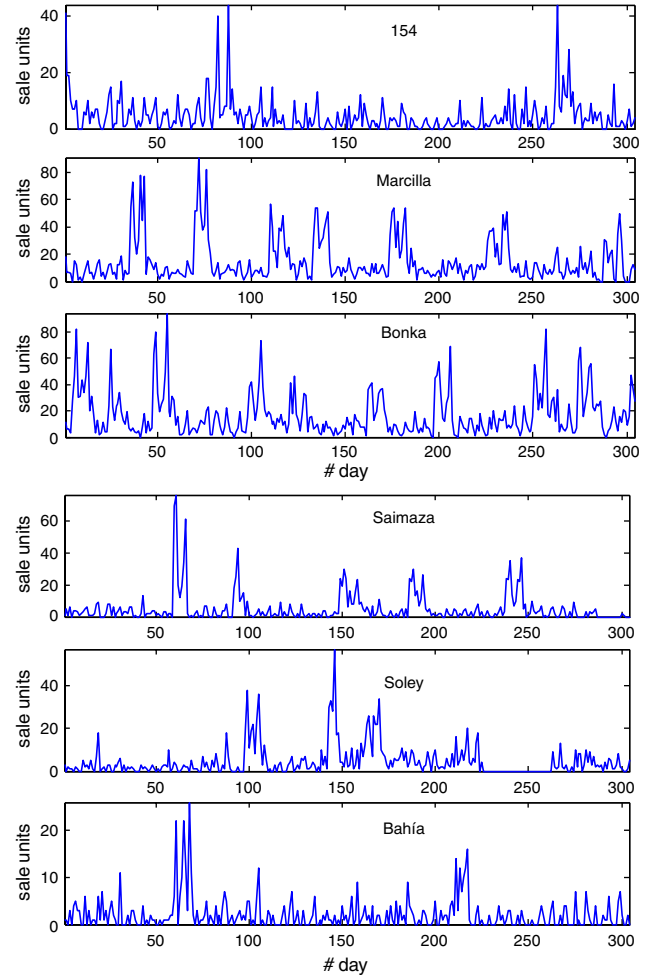


Fig. 1. Sale units during the observed period for all the brands. Promotional spikes and weekly oscillations can be clearly observed in all the brands.

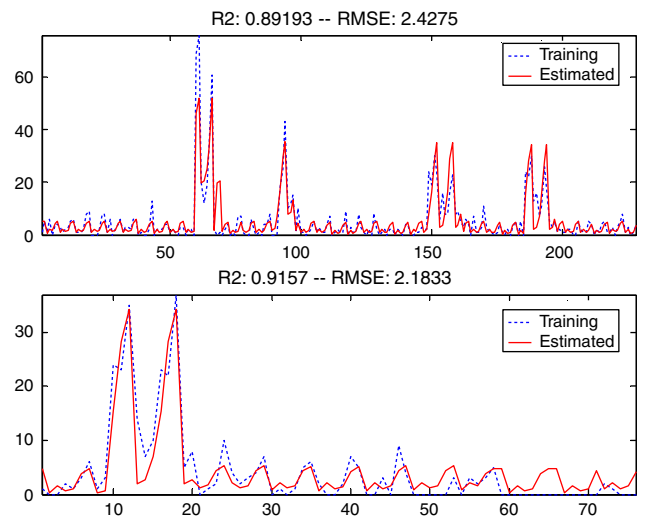


Fig. 2. Example of sales for brand Saimaza that are predicted from our semiparametric regression model: training (up) and test (down) observations.

- o $x_{t,7}^D, \dots, x_{t,12}^D$: indicators of the day of week—Monday (7) to Saturday (12)—during nonpromotional periods in brand (k);
- o $x_{t,13}^D$: indicator of 9-ending during promotion in brand (k);
- α^T : (transposed) vector of effects of dichotomic descriptor variables;
- e_t : disturbance term.

This model fulfills the requirement of metric variables allowed to model possibly complex interactions (nonparametric part of the model). The qualitative indicator variables are retained by the linear part of the model, which makes their effect very easy to examine. Also, no interaction effects are to be produced among different days of the week, and hence, they do not need to be modeled nonparametrically. The optimization method is detailed in Van Heerde et al. (2001), and it is briefly included in Appendix A.

Table 2
Fitness measures for parametric/semiparametric, additive-multiplicative models

	R^2		RMSE	
	Train	Test	Train	Test
<i>154</i>				
Par. addit.	0.84	0.81	2.2	2.7
Par. multip.	0.81	0.82	2.2	2.7
Semipar. add.	0.84	0.81	2.2	2.7
Semipar. mul.	0.83	0.82	2.1	2.7
<i>Bahía</i>				
Par. addit.	0.81	0.52	1.6	1.3
Par. multip.	0.77	0.53	1.4	1
Semipar. add.	0.88	0.33	4.5	9.5
Semipar. mul.	0.78	0.52	1.3	1
<i>Marcilla</i>				
Par. addit.	0.87	0.33	4.6	9.5
Par. multip.	0.86	0.84	4.7	9.4
Semipar. add.	0.88	0.33	4.5	9.5
Semipar. mul.	0.87	0.34	4.6	9.1
<i>Bonka</i>				
Par. addit.	0.82	0.83	6.1	7.9
Par. multip.	0.81	0.78	6.3	9.5
Semipar. add.	0.85	0.80	5.8	9.0
Semipar. mul.	0.84	0.82	5.9	11.3
<i>Saimaza</i>				
Par. addit.	0.87	0.91	2.7	2.2
Par. multip.	0.87	0.80	14.4	18.4
Semipar. add.	0.89	0.91	2.4	2.1
Semipar. mul.	0.87	0.94	2.7	1.4
<i>Soley</i>				
Par. addit.	0.69	0.13	3.9	3.7
Par. multip.	0.68	0.17	3.5	2.2
Semipar. add.	0.73	0.11	3.3	3.3
Semipar. mul.	0.71	0.07	3.2	3.1

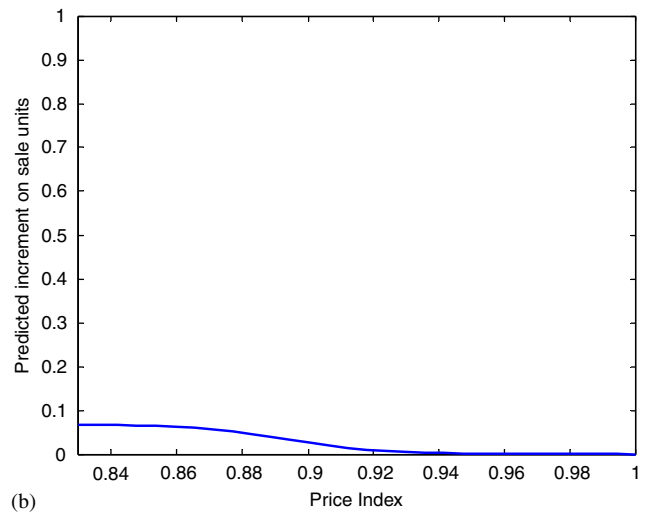
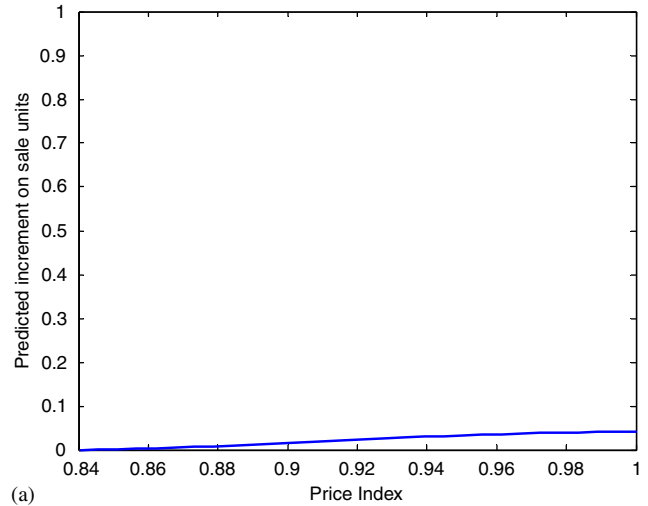


Fig. 3. Own-item deal effect curves for low-priced brands: (a) 154, (b) Bahía.

3.3. Statistical analysis

For comparison purposes, a fully parametric (linear) model using ordinary least squares (OLS) is also adjusted to the data. Additionally, both additive and multiplicative effects are considered for each brand, by taking the natural logarithm of the sale units, as well as the natural logarithm of the price indices.

Therefore, four different models were adjusted to each brand data: parametric (linear) and semiparametric, each of them 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. Confidence intervals (CIs) were calculated for linear coefficients (95% level).

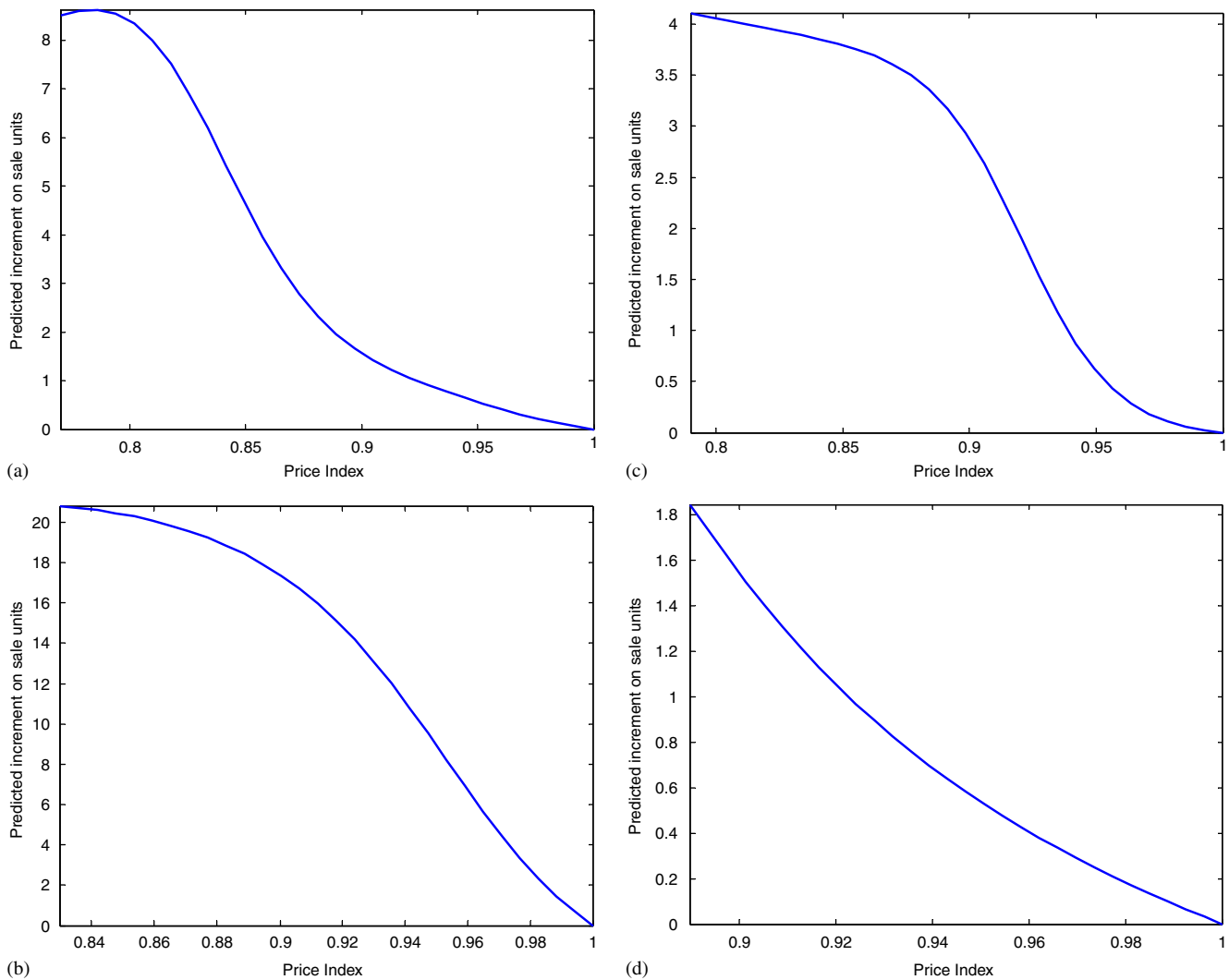


Fig. 4. Own-item deal effect curves for high-priced brands: (a) Marcilla, (b) Bonka, (c) Saimaza, (d) Soley.

Table 3
Evidence of threshold and saturation effects

Own-item deal effect curve	Shape	Threshold level	Saturation level (relative discount)
154	—	None	None
Bahía	—	None	None
Marcilla	L (kink at 10%)	None	20%
Bonka	Concave	None	15%
Saimaza	Reverse S	None	12%
Soley	Convex	None	None

4. Results

Fig. 2 depicts an example of the fitted model when compared to obtained sales data, for a brand of the category (Saimaza). Table 2 shows the fitness and predictive validity statistics for all models.

In general, higher values of R^2 (and lowest of RMSE) can be observed in semiparametric models. Some brands are better modeled by multiplicative effects, some by additive effects, and some are equally modeled by both. In some brands (Bahía, Marcilla, and Soley), R^2 values fall at test observations, but RMSE values at the test observations mostly hold, thus indicating that we can expect low level of overfitting being present, and that the models have in fact captured around 70–90% of the variability.

In the next paragraphs, the main promotional effects obtained with the semiparametric multiplicative model will be presented.

4.1. Own-item deal discount effects

Own-item deal effect curves are shown in Figs. 3 and 4, for low-priced and high-priced brands, respectively. Own-item price indices are at the x -axis and predicted increase in sales units are at the y -axis. The own-item deal effect curves corresponding to high-priced brands show an inverse

relationship between price discounts and sales increases. This finding indicates that the temporary price discounts offered in the high-priced brands of the category generate sales increase. However, since no response to temporary price discounts can be observed in the curves obtained for low-priced brands, price discounts offered in this type of brands do not seem to boost sales.

Regarding the magnitude of the observed sales increase, Bonka appears to be the most sensitive brand to its own discounts and 154 and Bahía the less sensitive brands. In general, price deals used as incentives to increase sales are more effective in the high-priced brands of the category, being the less profitable deals those offered in the low-priced brands. Besides, the shapes obtained in the deal effect curves for high-priced brands indicate the existence of saturation levels. Saturation effects are produced not only by consumer perceptions but also by the possibility of consumers to storage coffee (Blattberg et al., 1995). The results are coherent with the promotion literature, where many researchers have found that perceptions of deal prices and discounts are important determinants of consumer purchase decisions.

Table 3 provides a summary of the shapes found in deal effect curves, as well as threshold levels and saturation levels. Though saturation levels can be observed in most DEC, no threshold levels can be detected. Thus, the existence of saturation levels establishes a limit on the amount that consumers can stockpile.

4.2. Cross-item deal discounts effects

Figs. 5 and 6 present some examples of the three-dimensional deal effect surfaces that are depicted to analyze cross-price promotional effects and interaction effects between price discounts of different items. The vertical axis represents the predicted sales volume of the own-item, and the horizontal axes represent the price indices of the own-brand and of a competing brand. The effect of the remaining brand is cancelled in the model for each of these representations. In order to obtain reliable surfaces, observations with simultaneous price discounts for two or more items are required. Marcilla, Saimaza, and Bonka, are the brands with more simultaneous price cuts observations. Remember that consumer perceptions of simultaneous deal discounts are also important determinants of the results obtained in the three-dimensional surfaces.

We can observe different curves within each 3-D surface:

- *Curve A–B*: it represents the own-brand deal effect curve when the competing brand is not sold on promotion. In general, this curve tends to increase in magnitude with the decreases in own brand price index.
- *Curve B–C*: it shows the changes in sales of the own-brand as a response to the deals offered in the competing brand, being the own-brand not sold on promotion. In general, this curve tends to increase in magnitude with the increases in competing brand price index.

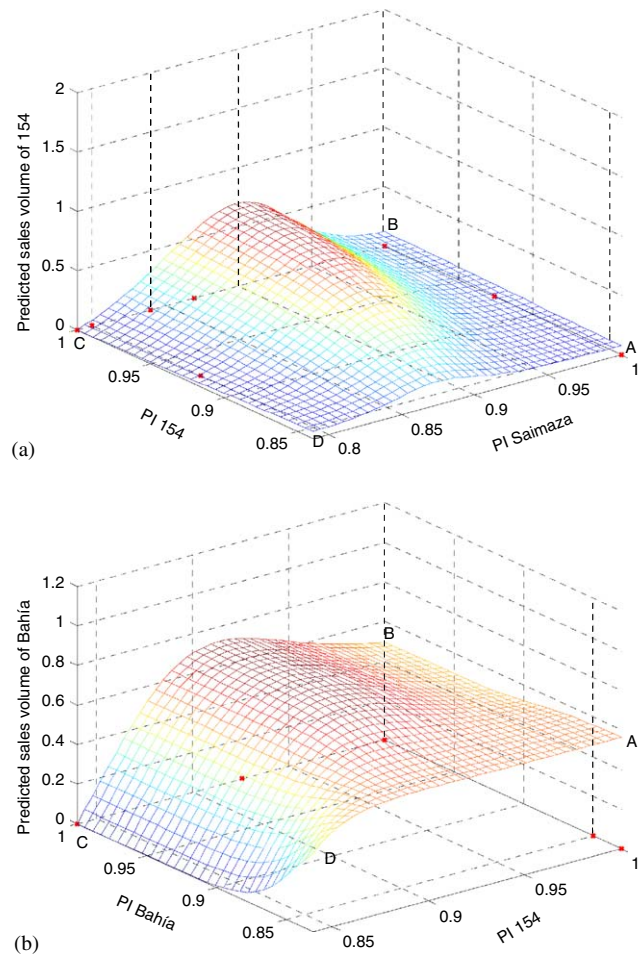


Fig. 5. Three-dimensional deal effect surfaces for low-priced brands: (a) 154, (b) Bahía.

- *Curve C–D*: it represents the own-item deal effect curve when the competing item is sold at the maximum discount. Though in general this curve should increase in magnitude with the decreases in own-brand price index, it also could not, mainly due to consumers perceptions of simultaneous discounts in both brands.
- *Curve D–A*: it shows the changes in sales of the own-item as a response to the deals offered by the competing brand, being the own-item sold with its maximum discount. Though this curve should be increasing in magnitude with the increases in competing brand price index, it also could not, mainly due to consumers perceptions of simultaneous discounts in both brands.

The inspection of the mentioned curves reveals the existence of several cross-promotional price effects. Table 4 summarizes the results obtained for the cross-item promotional effects. The interaction effects are asymmetric, thus supporting an empirical generalization in the sales promotion field: “cross-promotional effects are asymmetric and promoting higher-quality brands impacts weaker brands disproportionately” (Blattberg et al., 1995, p. G124).

In addition to the asymmetric cross-promotional effect, we can also consider the *neighborhood cross-price effect* (Sethuraman et al., 1999), which states that brands that are closer to each other in terms of price, have larger cross-price effects than brands which are priced further apart. This effect applies, as we can observe the largest cross-deal discount effects on brands that are similarly priced.

4.3. The impact of 9-ending promotional prices

For each brand of the category, the impact of 9-ending promotional prices can be detected by considering the value of the corresponding 9-ending indicator and its CI (see Figs. 7 and 8). Those estimates with values higher than 1 and CIs not including 0, indicate that the corresponding 9-ending promotional prices have a significant and differential impact over the sales boost.

Analyzing the value of the estimates and the CIs obtained, it is derived that the parameter estimate is significantly positive in just one brand, 154, that is one of the two low priced-brands of the category. In the other brands of the category, there is not a significant influence of this parameter.

4.4. The impact of the day of the week

The effect of the day of the week in the sales increase is captured by the coefficient estimates of the two first groups of dummy variables and their corresponding CIs, indicating the day of the week in promotional periods and the day of the week in non promotional periods (see Figs. 7 and 8). Those estimates with values higher than 1 and CIs not including 0, indicate that the corresponding promotional days have a significant and differential impact over the sales boost. For all brands, the weekend in promotional periods have a positive and differential impact over sales. The most important influence of the weekend in promotional periods corresponds to Saimaza and Bahía.

5. Conclusions

In this paper, we have focused on the influence that deal discounts characteristics have on the shape of the deal effect curve. We have applied a semiparametric regression model similar to that proposed and validated by Van Heerde et al. (2001). The consideration of daily data can give a more detailed understanding of the phenomena

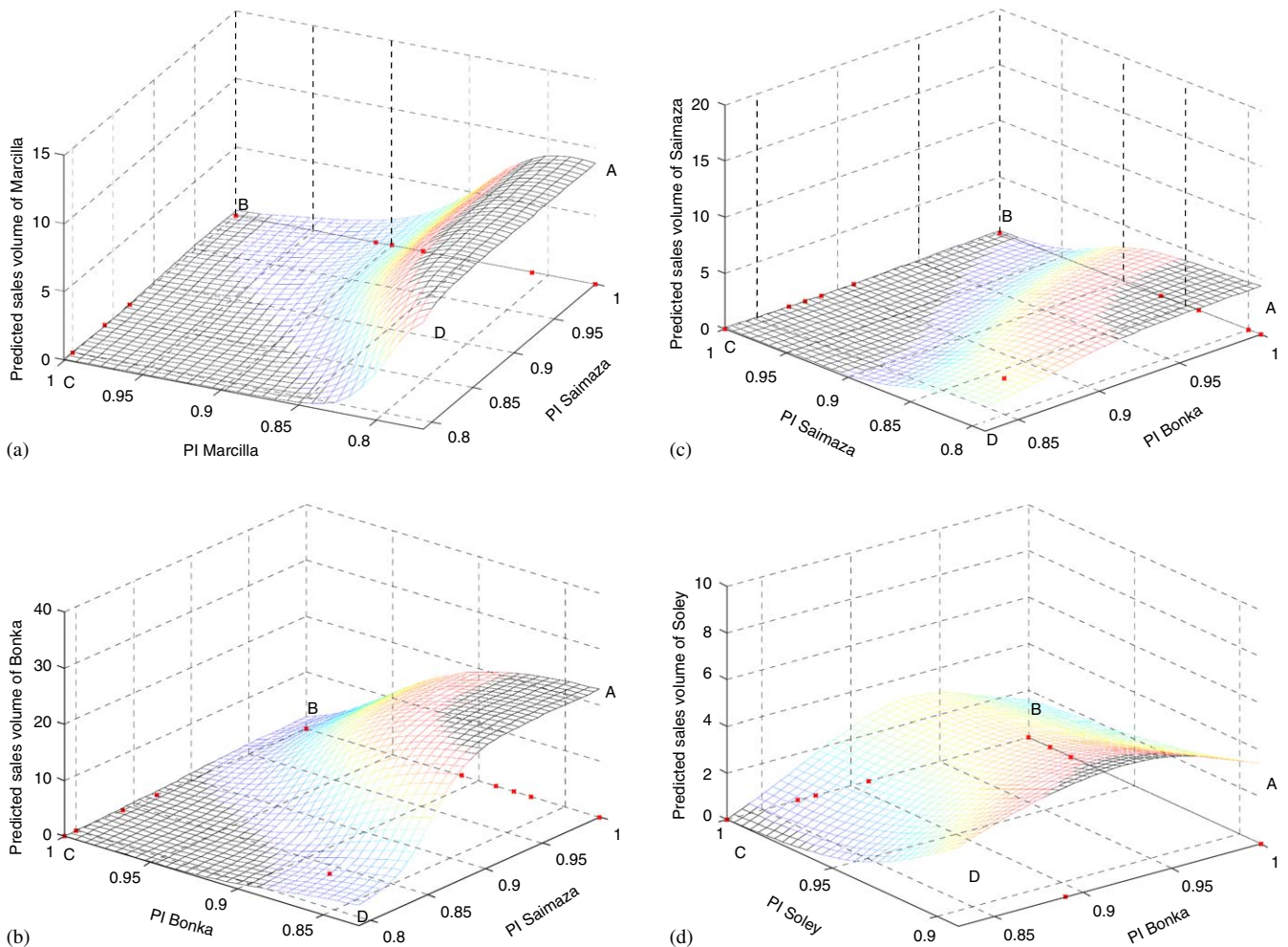


Fig. 6. Three-dimensional deal effect surfaces for high-priced brands: (a) Marcilla, (b) Bonka, (c) Saimaza, (d) Soley.

Table 4
Evidence of asymmetric and neighborhood cross-price effects

Brand	Most influential price deals
154	Marcilla; Bonka
Bahía	Marcilla; Saimaza
Marcilla	Bonka; Saimaza
Saimaza	Bonka; Marcilla
Bonka	Marcilla; Saimaza
Soley	Marcilla; Bonka

involved, and it allows us to measure the influence of the day of the week in brand sales.

The model applied here is easy to use, and it provides a regression analysis that accommodates flexible interaction effects for the price discounts of different brands in the nonparametric component. When compared to standard parametric models, the semiparametric regression exhibits a better fit in our data. The shape of the deal effect curves show how price discounts used as incentives to increase sales are more effective in the high-priced brands of the category. This model also provides empirical support for saturation levels. Though deal effect curves do not indicate the existence of any threshold effect, some curves indicate saturation effects. This means that all minimum values of price deals required to change consumers' purchase decisions are effective in the category, and that there exist certain levels of discounts that produce saturation effects in the curve. The saturation points may be due to consumer perceptions and to the limit on the amount of coffee that consumers can stockpile in response to a price promotion.

Our results also show the existence of asymmetric cross-price effects and neighborhood cross-price effects. Then, it is confirmed that promoting high-priced (high-quality) brands has a stronger impact on sales of low-priced (low-quality) brands than the reverse, and that cross-price effects are stronger on the sales of brands with similar prices.

Promotional price discounts accelerate sales especially during weekends. However, 9-ending promotional prices do not show a relevant influence over the sales spike. One reason for this occurrence might be that when there is a discount, people are more interested in the magnitude of the discount rather than whether the price ends in 9. End-9 could probably be more effective for regular prices.

The availability of data referring to the usage of feature advertising and displays must lead us to the study of additional effects to be included in the model and analyzed in other database in which they are available.

Further research is needed to determine the generalizability of the modeled shape of the deal effect curves. It is also important to determine the generalizability of these results to other category products, as well as to the study of additional promotional effects, such as complementary effects in other categories.

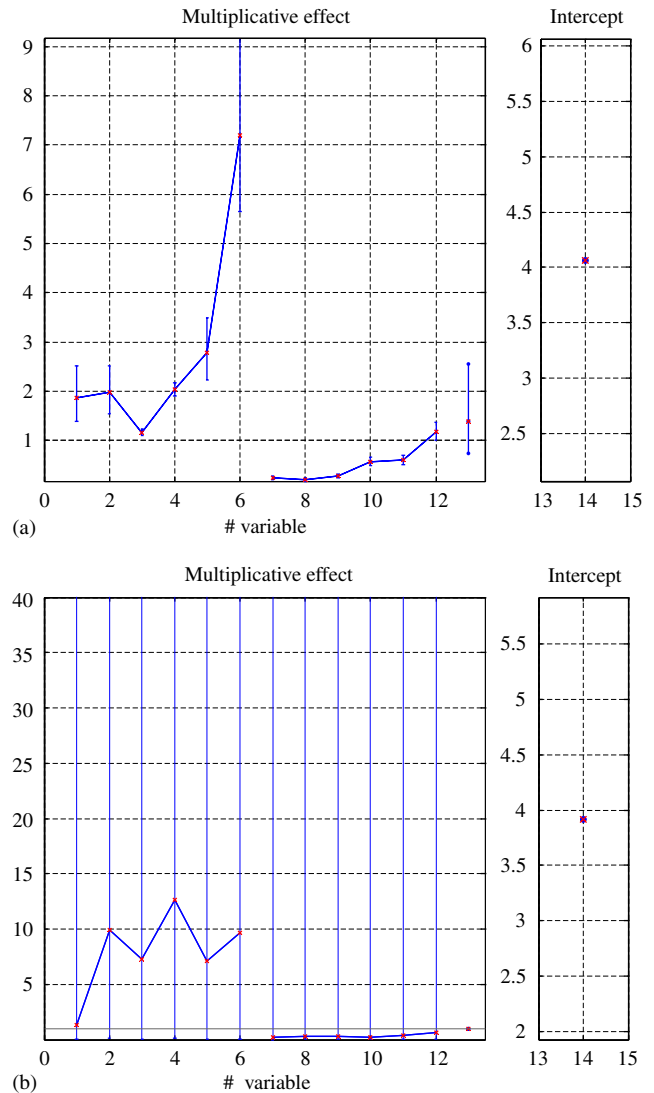


Fig. 7. Confidence intervals for the parametric component of low-priced brands: (a) 154, (b) Bahía.

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Appendix A. Semiparametric model estimation procedure

In order to use the kernel estimation in the semiparametric procedure, an adequate kernel function must be chosen. A frequent choice is the normalized Gaussian

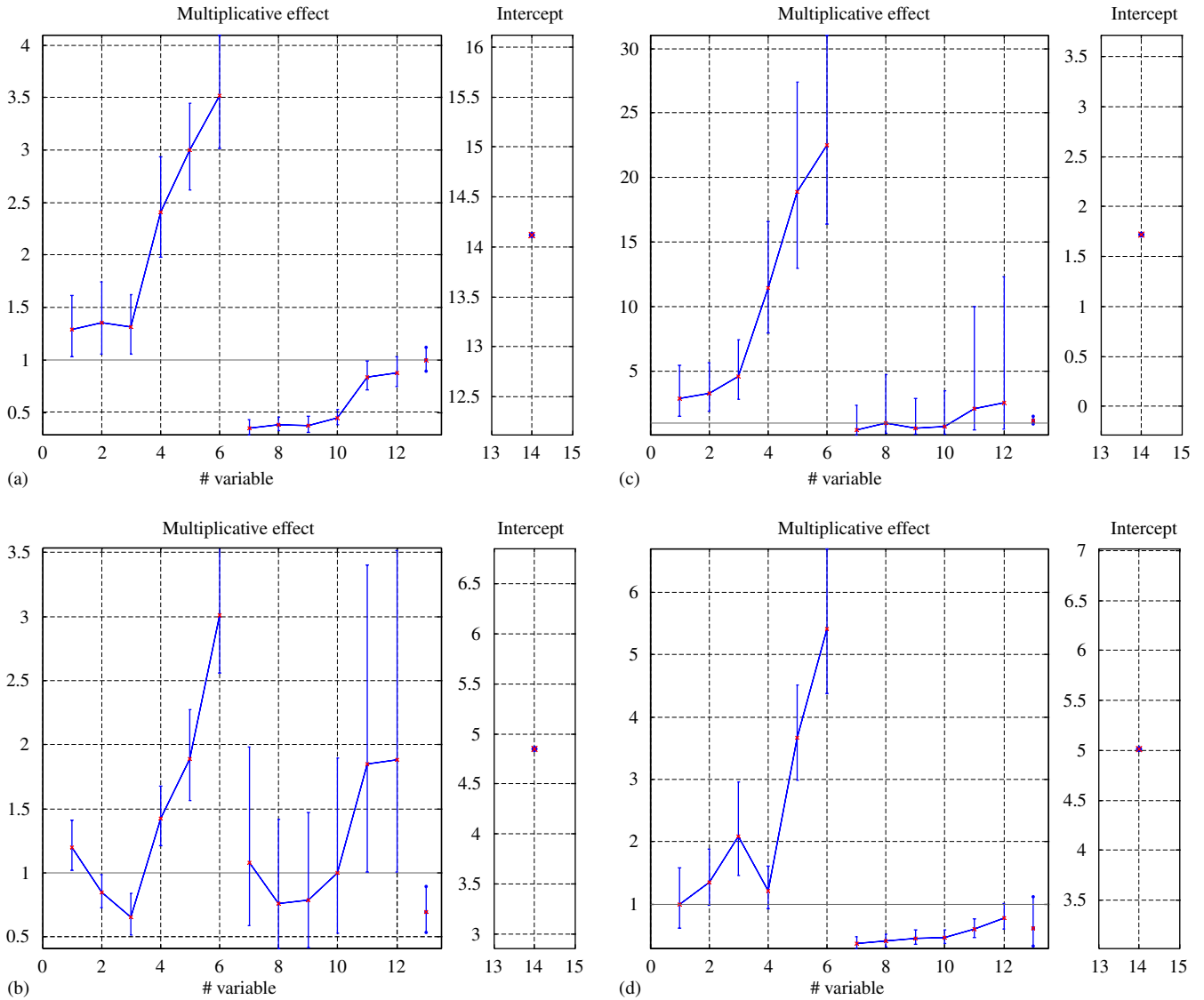


Fig. 8. Confidence intervals for the parametric component of high-priced brands: (a) Marcilla, (b) Bonka, (c) Saimaza, (d) Soley.

kernel:

$$K(\mathbf{X}) = K(x_1, \dots, x_M) = \prod_{m=1}^M \frac{1}{\sqrt{2\pi}} \exp(-x_m^2). \quad (\text{A.1})$$

The estimation procedure used by Van Heerde et al. (2001) has been first described by Lee (1996). Semiparametric model (A.1) can be simplified as follows:

$$y = m(\mathbf{X}^M) + \boldsymbol{\alpha}^T \mathbf{X}^D. \quad (\text{A.2})$$

By taking conditional averages on the metric variables we obtain

$$E(y|\mathbf{X}^M) = m(\mathbf{X}^M) + \boldsymbol{\alpha}^T E(\mathbf{X}^D|\mathbf{X}^M) \quad (\text{A.3})$$

and by substrating (A.2) and (A.3):

$$y = E(y|\mathbf{X}^M) + \boldsymbol{\alpha}^T (\mathbf{X}^D - E(\mathbf{X}^D|\mathbf{X}^M)) + e, \quad (\text{A.4})$$

where e denotes the model mismatch. The procedure consists of three consecutive steps:

- Step 1. Estimate:

$$E(y|x_m^M) \cong \frac{\sum_{j \neq i}^N K((x_i^M - x_j^M)/h) y_j}{\sum_{j \neq i}^N K((x_i^M - x_j^M)/h)}, \quad (\text{A.5})$$

$$E(x_d^D|x_m^M) \cong \frac{\sum_{j \neq i}^N K((x_i^M - x_j^M)/h) x_d^D}{\sum_{j \neq i}^N K((x_i^M - x_j^M)/h)}, \quad (\text{A.6})$$

where h is the bandwidth parameter of the model, and it can be seen as a tradeoff between bias and variance of the estimator.

- Step 2: Define the new criterion variable and the new predictors by removing the effect of the nonparametric

part of the model, and use OLS to calculate linear coefficients \mathbf{a}_N , i.e., solve by pseudoinversion:

$$\tilde{y} = y - E(y|\mathbf{X}^M) \approx \mathbf{a}_N^T(\mathbf{X}^D - E(\mathbf{X}^D|\mathbf{X}^M)). \quad (\text{A.7})$$

This OLS estimator of \mathbf{a}_N is obtained by postulating a Gaussian asymptotic distribution for the coefficients, as described in Van Heerde et al. (2001). Note that the interception is lost during the estimation process, and hence, it cannot be obtained from (A.7) and it is captured by the nonparametric component of the model.

- *Step 3*: The nonparametric component of the model is calculated by standard nonparametric estimation:

$$\widehat{m}(\mathbf{X}^M) = \frac{\sum_{i=1}^N K((x_i^M - x^M)/h)\tilde{y}}{\sum_{i=1}^N K((x_i^M - x^M)/h)}. \quad (\text{A.8})$$

Different bandwidth parameters may be used in Steps 1 and 3. For each model, the bandwidth in Step 1 is set to 0.05, and it is found in Step 3 by the conventional leave-one procedure.

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