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Abstract

This paper is argues that increasing the number of private labels products in grocery stores is not always an efficient strategy for a retailer wishing to enhance her unit sales. Although private labels can be effective for providing higher margins or developing customer loyalty program, their increased number of Stock Keeping Unit (SKU) assumes item deletions for other types of brand – especially national brands. For this study, we choose to focus on the composition of the whole brand assortment rather than the competitive advantage of this or that brand type. This paper proposes an econometric approach to this assortment reshaping issue. Using data drawn from a retailer panel (provided by IRI Inc), we construct a Multiple Adaptive Regression Spline (MARS) model to investigate the relation between both private label's and national brand's SKU and store-level unit sales. Results are given with respect to store size. We find that only in biggest stores higher levels of private labels leads to enhanced sales.

Keywords Retailing, Private Labels, Assortment, panel, MARS model

For the past fifteen years, private label (PL) market share has been growing constantly in supermarkets throughout Europe and North America (Dobson, 1999; PLMA, 2006). This growth carried out in two ways: first, PL share has known a steady rise in those categories where they were first introduced, second, the number of categories where they are present also increased (Géradon de Véra, 2006). The question we address in this paper is: may the PL share rise endlessly in all categories and take over new ones? Or does a limit exist to what seems their 'irresistible rise'?

For the past decades, European retailers have build up strategies to promote their own brand. Their motivations were threefold. First, own brands strengthen retailer's position for bargaining with manufacturers. Second, own brands are exclusive; as such they serve as a differentiation tool between store chains. Third, own brands play an important role in loyalty programs (Corstjens & Lal, 2000). Thus, private labels have become a central issue for retailers to increase their store patronage.

In today's competitive retail industry, store patronage is a major preoccupation for retailers. As noted by Corstjens and Corstjens (1995), store patronage results from a subtle equilibrium between brand switching and store switching behaviours. Brand assortment, specifically the relative presence of private labels (PL) and national brands (NB), is likely to affect both those behaviours. Thus, it may be a key factor of retail success. However, given the ever higher share of PL, the question may arise: if PL share rises and pushes NB out of the shelves, would NB consumers switch for PL items, or for another store with deeper NB assortment? If PL are a powerful instrument to foster customer loyalty, they may not be effective enough for a retailer to build a clientele on their sole presence. As Dhar and Hoch (1997) pointed out, retailers have to stock NB in order to draw customers to their stores.

Then, competition arises between PL and NB as a way to draw ad retain customers and eventually increase store sales.

The aim of this paper is to address the issue of PL versus NB equilibrium focusing on its effect on total assortment sales; that is, we analyse brand assortment as a whole rather than the competition between brand types.

The rest of the paper is organised as follows. First, we review some relevant literature on PL's and NB's relative ability to promote store sales. Second, we present available data (store panel data provided by IRI). Third, we turn to methodological issues of MARS modeling. Fourth, we present the results and discuss the existence of a limit for PL rise. To conclude, we provide managerial implications and limitations of our research.

PL positioning, brand assortment, and impact on total sales

As stressed earlier, two reasons can be proposed to explain PL rise. The first reason is "organic" growth (within a category where PL are already present); and the second one can be called "spin-off" growth (PL investigating new categories). Those growths may both have an impact on store sales. As far as we know, no paper deals directly with this issue. However, some researches show that PL sales depend on their positioning within brand assortment. Furthermore, literature on assortment management can give some insights into PL issue.

PL's bounded attractiveness

Literature on optimal PL positioning shows their attractiveness is only relative to other brands in the assortment. In terms of quality, price (Sayman and al., 2002) or promotion (Bonnenberg and Wathieu, 1996), PL performance is always relative to other brand's

positioning and marketing strategies. If PL are overpriced, they may not succeed (a minimum price differential is often required with NB), and if they are under-priced, they may suffer from a bad image. This leads to the conclusion that PL attractiveness depends on the very existence of other brands, to which they are compared. Thus, PL may not be able to enhance store sales on their own.

Similar results can be found in the behavioural decision theory (Huber and al., 1982, Tversky and Simonson, 1993). Considering consumer choice between a PL and a branded product, we can refer to it as a contextual choice. Briefly, PL strongly dominates NB in terms of price, and NB dominates PL in terms of quality but to a lesser extent (Bultez and Guerra, 2005). Choice theory indicates that PL products can benefit from such a situation. Moreover, in the case retailer also offers lower-priced products, PL share may rise significantly due to the 'compromise effect' (Simonson, 1999). This convenient position may explain an important part of PL rise, but it also emphasizes that PL performance is bounded to the existence and positioning of other brands.

Finally, some authors show PL can not succeed in all categories of products. This limitation comes from the role of the category (Dahr and al., 2001) and the perceived risk of the category (Batra and Sinha, 2000). PL "spin-off" growth (by investing new categories) seems to be limited also by technological barriers and consumers' perception of PL ability to overcome those barriers.

To sum up, previous research indicates that PL progression depends on their relationships with other brands in the assortment, and that PL share can not rise endlessly.

Assortment management

The rise of PL in terms of their number of Stock-Keeping Units (SKU) has a mechanical impact on assortment composition. To our knowledge, no authors have directly investigated the effect of this reshaping issue on assortment perception and performance. However, some elements can be found in more general works on assortments.

To begin with, PL introduction has an impact on assortment variety, which is a well documented issue in retailing management. Assortment variety is usually known to have a positive effect on total sales (Kahn and Lehmann, 1991, Oppewahl and Koelemeijer, 2005). But in some cases it may not (Gourville and Sonan, 2005). Consumers' reaction to assortment variety depends on perceived variety rather than actual variety (Kahn and Wansink, 2004), and also on the perceived complexity of choice task (Shugan, 1980). Thus, in order to enhance total sales, PL introduction should take customers' perceptions into account. Moreover, PL introduction (or their share rise) reduces shelf-space allocated to other brands and possibly leads to SKU deletion among other brands. In the case deleted SKUs are among the most preferred items, these item reductions can have a negative impact on store choice (Broniarczyk and al., 1998). Thus, even if PL introduction (and rise) may enhance inter-brand variety, it certainly harms intra-brand variety of branded products, and the net effect on total sales depends eventually on consumers' preferences and perception of the assortment. Thus, retailers should take into account assortment management when thinking of promoting their own brands.

Then, PL price positioning, especially lower priced PL, can also affects global assortment image. Low prices attract price sensitive consumers, and PL introduction may be a way for a retailer to gain market share on this segment. But the presence of low price items may also diminish external reference price and let a more important part of the assortment being considered as too expensive. Moreover, a risk exists for those low prices to fall below consumers' price range acceptability, which may in turn negatively affect willingness to buy

(Petroshius and Monroe, 1987). Thus, the rise of low priced PL seems to be also limited by assortment pricing management and price image issues.

The literature we reviewed converges to the idea that PL share progression depends on retailers ability to properly manage and position their own brands relative to the other brands in the assortment in terms of quality, price, variety, and consumer demand. Several explanations can be found to support this idea that PL can not rise endlessly; and yet they do, for several years in every retail chains and across categories. This strategy can certainly be explained by the higher margins PL provide compared to NB (Mills 1995, Hoch and Banerji 1993). But retailers should wonder whether this strategy in efficient for drawing customers to their stores. In other words, does the rise of PL affect the total number of items a store can sell on average during one week? This paper is a step forward in answering that question.

A first look at the data and some preliminary results

Presentation of available data

Available data for this study consist in average SKU sales, price, promotion and shelf space of twenty-four categories in 496 French retail stores aggregated over one year (September 2004 to September 2005). Stores are grouped in terms of size (into four groups: small supermarkets: SSM, large supermarkets: LSM, small hypermarkets: SHM and large hypermarkets: LHM) and retail chains (18 anonymous chains). The categories (reported in Table 1) are representative of the assortment one can find in any grocery store: catering,

beverage, health and beauty care. Therefore, the pooling of those categories gives a reduced image of the average total assortment.

For the purpose of this analysis, SKUs are combined into brand types (PL, NB…). SKUs are grouped using information provided by IRI on PL type, and a computed index of diffusion. Within PL items a difference is made by IRI between *classical* PL and *premium* PL. *Premium* PL are high-quality products, or niche-products, that have been developed by retailers for a couple of years. For non-PL brands, we compute a diffusion index which is the percentage of stores stocking the brand (this percentage is calculated over the 496 stores available from the panel). *National brands* are those brands whose diffusion is superior to seventy percent. Brands with a diffusion inferior to seventy percent are grouped into the *other brands*.

This grouping leads to four types of brands: classical private labels (PL), premium private labels (PPL), national brands (NB), and other brands (OB). Each of them plays a specific role in assortment management. PL are part of the positioning of the store chain and are use to enhance consumer loyalty, they are usually allocated more shelf space. PPL are a collection of heterogeneous products retailers develop to convey their image. They are not yet strongly developed and are quite different from one retail chain to another and from one category to another. NB are present in nearly all outlets, they are pushed through the distribution channel by the strongest manufacturers. Most retailers do stock them in order to attract and retain consumers, but they sometimes suffer from lack of shelf space due to its allocation to PL. Eventually, OB is quite a heterogeneous brand type, sometimes very low priced, sometimes of high quality. OB are often stocked by retailers for the sake of assortment variety, or in order to serve local specific demand. Each type of brand has a certain amount of shelf space and SKU share (number of brand type's SKU divided by total

number of SKUs in the assortment). We should note that any change in the allocation of space and SKU affects the whole brand assortment in return.

From now, we will focus on the two main types of brand in terms of shelf space and SKU share: NB and PL. Table 1 presents the SKU shares for the two main types of brand in the 24 categories; we can see that those two brand types account for at least 79 percent of the SKU for each category. We can also notice some differences between categories in terms of PL-NB equilibrium. In the Health & Beauty care (except diapers) and liquid categories, NB have a strong position (more than 75 percent of the SKUs). But in most of the catering categories, their share falls under 70 percent, down to 24 percent for the frozen vegetables. Those differences are quite well documented in the literature (Dahr and al., 2001). But the focus of our research is rather on store level than category level shares and sales. In order to have a better insight of store-level strategies in terms of brand assortment management, we choose to pool the categories at the store level. This pooling is done by normalization of the data around the category-mean:

$$X^*_{i,j,c} = \frac{X_{i,j,c}}{X_{i,\cdot,c}} \times 100 \quad ,$$

where X is a variable of interest (price, SKU share, promotion...), i denotes the brand type (i=PL, NB), j the store (j=1...496), c the category (c=1...24). Thus, every store's strategy (reflected in variables $X_{i,j,c}$'s levels) is compared to the average strategy of all the stores from the panel. For the sake of readability, these relative values are then multiplied by 100. Thus, a value below 100 for $X^*_{i,j,c}$ indicates that this variable is below the average of all stores. This transformation emphasizes the differences in allocation strategies adopted by the stores. Moreover, the normalisation being done separately for each category, each variable is compared to the category mean across stores. Thus it is easier to compare across categories and allows the pooling.

	NB	PL		NB	PL
beverages			**catering**		
beer	0.77	0.14	cereals	0.74	0.16
coffee	0.54	0.25	fresh dessert	0.70	0.25
colas	0.80	0.16	frozen starters	0.58	0.31
water	0.79	0.10	cheese	0.62	0.28
whiskies	0.88	0.08	ham	0.58	0.31
H&B care / household products			frozen vegetables	0.24	0.59
hair gel	0.75	0.12	pastas	0.52	0.28
shampoo	0.84	0.07	soups	0.87	0.08
face care	0.76	0.07	chocolate block	0.66	0.21
deodorant	0.86	0.06	yoghurts	0.84	0.13
diapers	0.57	0.27	rice	0.50	0.35
softener	0.85	0.13	wet cat food	0.58	0.30
detergent	0.87	0.07	**TOTAL**	**0.7**	**0.2**

Table 1 : SKU share by brand type and category

Data normalization clearly points out those stores who most promote their PL across all categories. Table 2 shows the means of normalized SKU shares of PL and NB for each store size. These means illustrate for example the decline of PL share with store size. This decline can be seen from two different points of view. On the first hand, one can argue PL are not developed enough to fill up the shelves of bigger stores, whereas on the other hand, one could say PL items are plentiful in smaller stores. One of the aim of our analysis is to determine which point of view is the most accurate for enhancing the store sales.

	NB	PL
SSM	99.00 (24.68)	100.15 (91.55)
LSM	101.19 (17.91)	96.73 (54.29)
SHM	99.08 (14.03)	92.58 (38.73)
LHM	98.04 (13.20)	87.60 (29.83)

Table 2 : SKU share by brand type and store sizes

We must remind here that our point is not to conduct a market share and elasticity analysis of PL versus NB. Such an analysis would certainly provide significant results of PL being more sensitive to shelf space or SKU share. Those results would induce retailers to allocate more of those scarce resources to PL. But this analysis would be biased, as pointed out by Sethuraman and al. (1999) as the market shares of PL and NB are not of comparable magnitude. Moreover, a market share analysis implicitly considers PL and NB as competitors while retailers should think of them as parts of the whole brand assortment whose total sales should be maximised. Pursuing this idea, our analysis next focuses on brand assortment composition and its impact on total store sales using a MARS modeling approach.

The Multivariate Adaptive Regression Spline (MARS) approach

MARS models are part of the greater class of General Additive Models (GAMs). GAMs were introduced by Stone (1985) as a simplification of non-parametric analysis of a large number of variables. They assume an additive relationship between response variable (Y) and non-parametric functions of predictors ($f_j(x)$). This assumption allows to quickly find solutions while remaining more flexible than the usual linear model. The functions of predictors (Basis functions) are computed from the available data making these methods rather 'data-driven'. Spline and Loewess regressions are two well-known examples of GAMs.

Multivariate Adaptive Regression Splines were first introduced by Friedman (1999) as a generalization of the spline approach to the case of multiple predictors. The key aspect Friedman developed is the possibility for the Basis functions to be formed of several predictors. For example, suppose we have one response variable Y and three predictors X_1, X_2 and X_3. A spline analysis would give a result in the form of:

$$Y = \sum_{j=1}^{k} c_j B_j(x)$$

where c's are coefficients, B's the Basis functions indexed from j=1 to k. For example, we could obtain:

$$Y = 4.61 + 0.76 \, Max\left[0, X_1 - 12\right] + 1.19 \, Max\left[0, 12 - X_1\right]$$
$$+ 1.27 \, Max\left[0, X_2 - 4\right] + 2.51 \, Max\left[0, X_3 - 7\right]$$

That would mean X_1 always has an impact on Y, but this impact changes when X_1 becomes greater than 12; whereas X_2 and X_3 have an impact on Y but only when they reach the value of 4 and 7 respectively.

A MARS analysis could lead to a more interesting result in the form of:

$$Y = \sum_{j=1}^{k} c_j B_j(x)$$

$$Y = 3.27 + 1.68 \, Max\left[0, X_1 - 12\right]$$
$$+ 0.94 \, Max\left[0, 12 - X_1\right] Max\left[0, 6 - X_2\right]$$
$$+ 1.86 \, Max\left[0, X_2 - 4\right]$$
$$+ 2.11 \, Max\left[0, X_3 - 7\right] Max\left[0, 2 - X_2\right] Max\left[0, X_1 - 9\right]$$

Interaction between variables are now possible within each Basis function. For example, the second line shows an interaction between X_1 and X_2 when X1 is greater than 12 and X_2 greater than 6. That is, for low values, those variables do not interact, but they do for higher values. Note that MARS algorithm does not require the user to specify which predictors may interact in the same Basis function but rather select these interactions by itself using goodness-of-fit statistics (Note: the type of statistics being used at this step depends on the software. For this article, we used 'mda' R-package that uses Generalized Cross Validation (GCV) which is basically a Residual Sum of Squares (RSS) that takes into account the number of parameters of the model).

Those expressions rapidly become quite impractical to read and analyse. But, as for spline regression, the finer part of the outcome is not the exact expression of the Basis

functions, but rather the graphics that helps interpreting the results. The user can easily plot the impact and interaction of pairs of variables on a three dimensional plot. The readability of those graphics combined with the power and flexibility of the MARS approach has led to its growing utilisation over the past few years, especially in Biology and Pharmacology. However, if finance and marketing literature have sometimes used spline regressions (Humphrey and Vale, 2004, Sloot and al., 2006), MARS are not widely used yet despite their interesting results (see for example Deichmann and al., 2002, for an application to Direct Response Modelling).

Store-level sales and brand types: the net impact of PL rise

The model

We have seen, from the literature, that both PL's and NB's effect on store sales is ambiguous. Anyhow, retailer can not stock more items of those two brand types together. An arbitrage has to be done. If we consider the recent development of PL, we could think that this arbitrage did advantage PL.

Thus, the idea is to estimate the effect of PL rise on total sales. Specifically, we want to detect if there is a level beyond which PL rise in terms of SKUs may be harmful for total store sales. An easy way to show that some retailers have gone too far in their PL strategy would be to regress assortment sales on PL number of SKUs using any inverted U-shape function. Yet this approach would in fact suppose that some retailers actually did go too far. If we really want to ask the question without any pre-maid answer, we need to use a flexible specification that does not impose any shape on the relation we are testing; neither U, or S, probit or logit. MARS is therefore an interesting approach. Moreover, we can detect a change

in the effect of PL on total sales with respect to the amount of NB. For example, a high number of PL may be only effective for store sales where there are also a lot of NB (note this results would encourage retailers to rule other brands out of the shelves).

The estimated relation is:

$$Y = \sum_{j=1}^{k} c_j B_j(x)$$

with explained variable $Y = \log\left(\dfrac{unitsales}{numberofSKU}\right)$, and explanatory variables x=[PL_SKUshare; NB_SKUshare; log(price); promotion]. Those variables are computed at the store×category level and centred around 100. "SKU_shares" are the number of SKU for one type of brand divided by the total number of SKU. "Price" refers to the mean of SKU prices. "Promotion" is actually composed of five variables indicating different types of promotions (display, feature, special pack, price reduction, and prospectus), these variables are computed as the number of items on promotion divided by the total number of items. The model is estimated separately for each store size (SSM, LSM, SHM, and LHM). Categories are pooled, but the normalisation of the data is equivalent to the introduction of fixed effects for the categories.

In order to ease the interpretation, results are presented graphically. We present two plots for each model (one two- and one three-dimensional). On the 2D-plots, SKU-shares for NB and PL are represented on the axes, and the level of sales are given by contour lines. On the 3D-plots, SKU-shares are reported on the horizontal axes, and sales on the vertical axis. Those plots represents the estimated log of sales for given values of PL and NB shares. Those shares range from 0 to 200; that is, from no items of a given brand (0), to twice the average retailer is offering (2×100=200).

*Results and managerial implications*

First thing we should note is that clear differences exist in our results with respect to store size. Such a result is important to retailers with stores of different sizes. The PL-NB equilibrium being primarily an allocation problem, this result is not surprising; as bigger stores have more shelf space, they can offer many items without ruling out others. Second, the fit statistics for all the estimated models are rather high. This is not surprising either as the MARS approach is data-driven and the final model is chosen to minimize the residuals sum of squares, leading to high R-square and F statistics. The third statistic (CGV) is based on the RSS and the number of parameters; this is the one MARS algorithm minimizes when choosing the best model.

Let us now consider the results for each store size. In the small supermarkets, the relationship between PL share and sales is overall negative although kinked above the average value of 100. This result indicate PL are usually excessive, but some small stores with a heavy PL program do succeed quite well. These stores may belong to specific retail chains that offer hardly anything but low-priced own brands in their assortments and did actually gained many customers in the past few years (like *Ed*, which is the discount chain from the Carrefour group). Unfortunately, the retail chains in the panel being anonymous, we are not able to give a specific explanation to this phenomena. However, we can clearly see from the graph that, for any level of PL, sales are higher when NB are present in the assortments. Increasing NB share (up to the approximate value of 150) enhances store sales.

Small Supermarkets (SSM); Fit Statistics AdjR²:0.986 F:1108 GCV:0.187
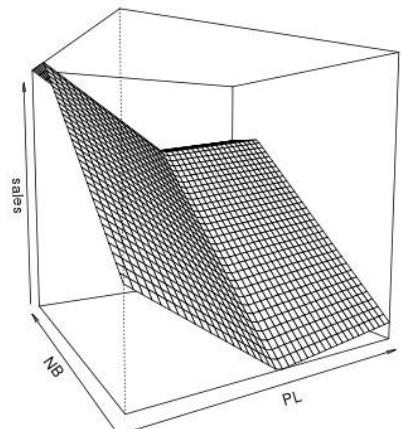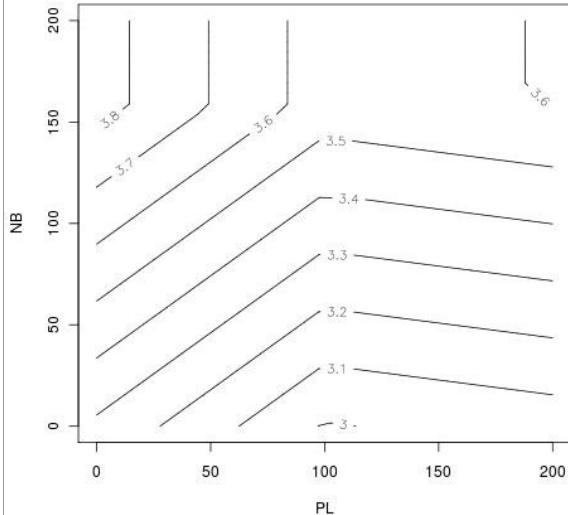
Large Supermakets (LSM); Fit Statistics AdjR²:0.992 F:3525 GCV:0.125
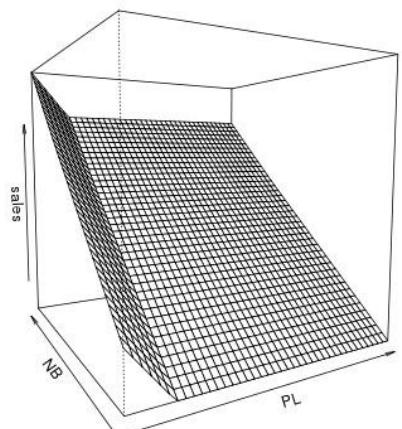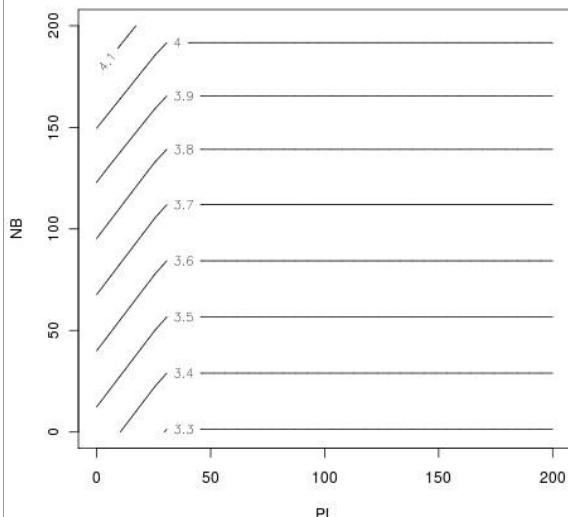
In the large supermarkets, the situation is quite similar. The differences are we don't find any positive effect for highest values of PL share (this tends to confirm the hypothesis about specific retail chains of small supermarkets). Moreover, there is no kink in the relationship between NB share and sales either. This may be explained by the fact that no large supermarket from our panel has reached a point where NB are becoming excessive. Thus, for this store size, the PL-NB equilibrium adopted by retailers could, in any case, be changed in favour of NB in order to enhance store sales.

In the small hypermarkets, we found no significant effect of NB share on sales. However, the relationship between PL share and sales is strictly decreasing. But we should notice that, for small hypermarkets, estimated sales have very low variance (range for SHM: 4.6-4.4=0.2) compared to other store sizes (SSM:0.8, LSM: 0.8, LHM:0.9). Thus, for small hypermarkets, it may be awkward to put to much emphasis on the effect of explanatory variables on assortment sales.

In the large hypermarkets, we found a positive relationship between PL share and sales. We can also notice a small drop for PL share values between 150 and 170. This drop illustrates a problem one should be aware of when using GAM models like MARS. Being mainly data-driven, this class of models sometimes over-fits the data, leading to small untimely variations in the modeled relationship. However, the broad shape of the graph indicates, for once, a positive effect of PL share on sales. But, once again, this effect is moderated by the presence of NB. For a NB share above the average value of 100, we note a significant rise in sales. That is, the positive effect of PL is higher in the presence of NB. In this situation, retailers should stock higher levels of both PL and NB, and, as a consequence, rule out of the shelves some items from the other brand types.

Small Hypermarkets (SHM); Fit Statistics AdjR²:0.995 F:3569 GCV:0.105
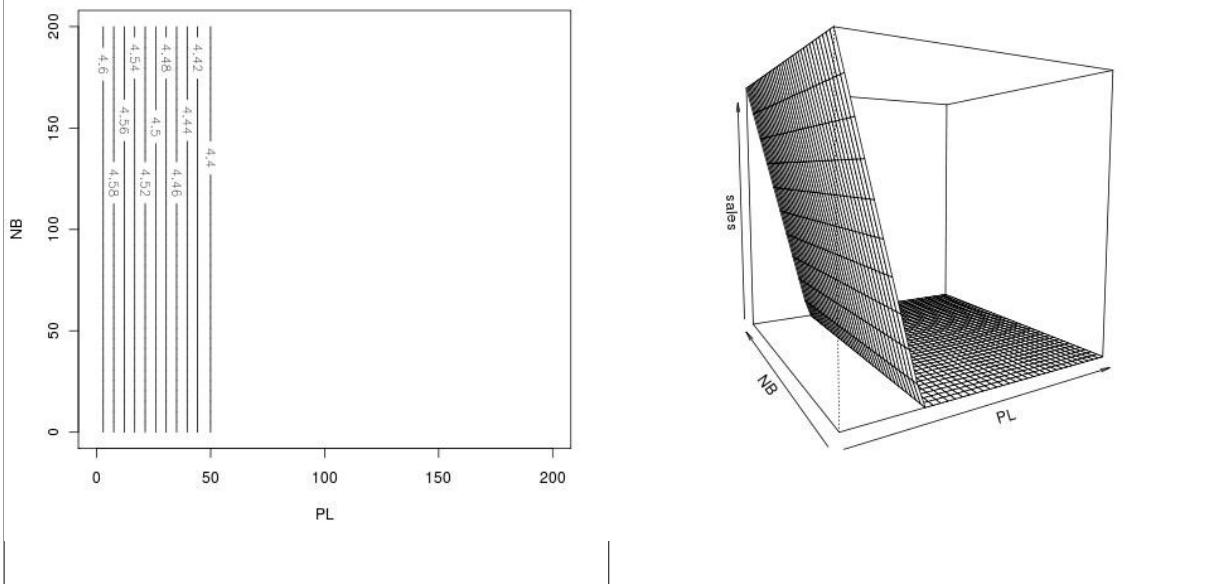
Large Hypermarkets (LHM); Fit Statistics AdjR²:0.997 F:5055 GCV:0.094
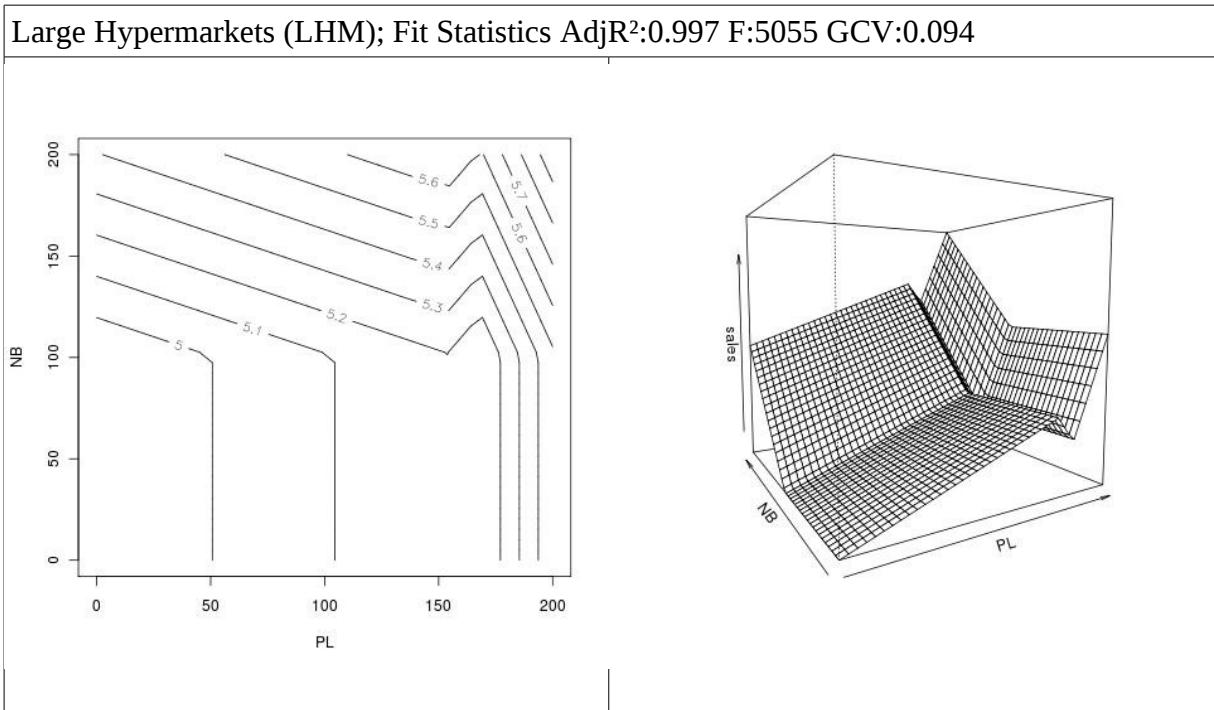
Using those results, we can propose an answer to the question of potential negative effect of PL rise on assortment sales. Clearly, this answer should depend on the store size. We have seen from Table 2 that PL are relatively more present in smaller stores. Question was then to determine if PL were too much present in small stores or too few in bigger ones. The results tell us that those assertions are both valid. The point is that PL strategy does not seem to be well adapted to store size. Retailers offer more or less the same number of PL SKUs in smaller or bigger stores. This leads to PL overabundance in SSM and a lack in LHM where PL are drowned in the crowd of SKUs. For this reason, results show that LHM stores may rise their PL share in order to foster their sales, whereas others (SSM, LSM, SHM) stores should rule some PL items out of their assortment.

Conclusion

Product assortment planning is nowadays a growing issue in retailing research and practice (Mantrala and al. 2009). Important researches have been done on price and variety management, as well as the efficiency of PL programs. Yet, retailers still consider their own products as competitors of branded products whereas PL and NB should be seen as part of the whole assortment. One reason may be that retailers and manufacturers are usually competitors in the vertical relationships. But at the end, consumers make their choice and decide which store to visit and how much products to buy. Thus, in order to enhance their unit sales, retailers should first consider the attractiveness of their whole assortment regardless of the relative performance of their own brand compared to manufacturers'.

In this paper, we developed a MARS modeling approach to investigate the effect of both PL and NB on assortment sales. This data-driven methodology requires very few hypotheses and provides graphical results that are easily understandable. The main result is

that PL strategy needs to be adapted with respect to store size. Specifically, PL presence should be reinforced in biggest stores (LHM), and reduced in others. We are aware these recommendations go against the usual practices and recent findings (Sudhir and Talukdar 2004, Ailawadi and al 2008), but we emphasized our approach is based upon unit sales and not upon margins, profits, or loyalty. We hope our results will contribute to the interesting debate on PL role within assortments and encourage further research. Future analyses could focus for example on the category-level. Indeed, PL are more efficient in some categories compared to others.

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