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Sources and Implications of Asymmetric Competition: An Empirical Study

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***Abstract*:**

There has been a growing interest in the analysis of the asymmetries in competition in literature. Empirical evidence of its existence in the Spanish diaper market suggests us to study the source of these asymmetries and implications for the brand price decisions and more specifically, in the analysis of the brand's competitive position. Literature suggests that aggregation process of heterogeneous consumers in brand preferences or characteristics of the utility function can explain asymmetric competition. The results do not allow the rejection of any of these causes in the analyzed market. The paper also makes methodological contributions suggesting a different approach to aggregate consumers on the basis of their homogeneity on brand preferences.

Keywords: brand competition, consumer choice model, market segmentation, brand quality

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INTRODUCTION*

An accurate and complete understanding of the competitive environment in which a brand operates is essential in order to formulate an effective marketing strategy. The analysis of the competitive environment is a complex task due to the multiplicity of factors that influence it (Deshpande and Gatignon, 1994). Our work focuses on one of these factors: asymmetry in competition. The term "*asymmetry in competition*" describes situations where, for whichever two brands competing in a market, the same competitive actions have different effects on the rival depending on who has taken the action.

Previous studies have offered important insights for understanding the sources of the asymmetries in brand competition. Some authors (Blattberg and Wisniewski, 1989; Russell and Kamakura, 1994; Mela, Gupta and Jedidi, 1998) suggest the aggregation of consumers with different brand preferences as a cause of the asymmetry in competition. Other authors (Allenby and Rossi, 1991; Hardie, Johnson and Fader, 1993; Bronnenberg and Wathieu, 1996; Sivakumar and Raj, 1997 or recently, Sethuraman, Srinivasan and Kim, 1999) suggest that asymmetry proceeds from the characteristics of the consumer choice. This paper presents an empirical test of these two alternative explanations suggested in the literature.

This study examines asymmetries in interbrand competition through the analysis of demand. The choice model methodology has been widely used for this purpose (Guadagni and Little, 1983; Chintagunta, 1994; Gupta, 1988; Kannan and Wright, 1991). The choice models generate a great deal of information that it is necessary to summarize. Cooper (1988) and Kamakura and Russell (1989) suggest different indexes that synthesize the basic characteristics of the brand's demand,

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its vulnerability and competitive clout, through the cross choice elasticities. Brand vulnerability refers to the capacity of a brand not to be affected by competitors, and competitive clout refers to the ability of a brand to take share away from competitors. In the case of symmetric competition, these indexes capture the most relevant information about the brand demand. However, these indexes are not sufficient in the case of asymmetric competition.

In asymmetric competition, the consequences of the competitive actions on demand of one brand for a rival brand differ from the consequences of the competitive actions of the rival brand on the focal brand. Therefore, the relative variation in brand share is not equal to the relative variation that brand price have shown. It is therefore important to distinguish and know the effects of the brand's competitive action on each rival brand and its reaction capacity to each rival's actions. This study proposes to break down the own and cross elasticities matrix into a matrix that shows variation in brand shares and another that shows variation in brand price in order to improve the brand demand analysis under asymmetry in competition.

Methodologically, the work also suggests a new approach to identify consumer segments based on the revealed brand preference. The methodology presents some advantages over other segmentation methods based on brand shares, or models with random effects. With regard to the former, the proposed methodology allows control by the differences in the set of prices that each consumer has faced in their decisions. Concerning the later, our methodology does not assume the independent distribution of consumer preferences among brands and allows the classification of each consumer into the different segments proposed.

The paper is structured in four sections. The first develops the theoretical implications of the existence of asymmetries in the analysis of competitive structure. The second section presents the data base and the methodological aspects. Finally, we report the results in the third section and the main conclusions in the last one.

ASYMMETRIC COMPETITION: DEFINITION AND SOURCES.

Brand competitiveness refers to its capacity to achieve superior performance in terms of profits or profitability (Barney, 1991; Bharadwaj, Varadarajan and Fahy, 1993). One of the major determinants of brand competitiveness is the market structure in which a brand operates (Cooper, 1988).

In a market with several brands and where product decisions have already been taken (i.e. mature markets -see Hauser and Shugan (1983) or Mc.Gahan and Ghemawat (1994)-), market structure is defined by its demands and production costs. Since this market structure is difficult to change, firms or brands develop their competitive strategies inside the boundaries of this marketplace looking for opportunities that allow them to increase their market shares. In this context, price is the main strategic variable that affects the brand demand. Therefore, brands will basically compete on prices (see, for example, Narasimhan, 1988).

The formulation of price strategy requires, among other things, information about the influence of price changes on brand demand (Guadagni and Little, 1983; Grover and Srinivasan, 1992). The analysis of the competitive market structure is an approach for studying this question (see, for example, Urban et al., 1984; Cooper, 1988; Kannan and Wright, 1991; Russell and Kamakura, 1989; Elrod and Keane, 1995; Sivakumar and Raj, 1997; Mela et al., 1998). The random utility theory allows us to raise this analysis of price sensitivity through choice models. Consumer choice models have an economic and behavioral theoretical foundations that make them especially useful to analyze market structure.[1] This discrete perspective assumes that the consumer chooses between several alternatives which are mutually excluded. The usual assumption in these models is that consumers assign random utilities to each brand considered when they are facing a purchase decision, and then select the one with the highest derived utility. These models decompose this utility into a deterministic component, which depends on the intrinsic characteristics of the brand and its price (sometimes and/or other marketing-mix variables), and a random component. Hence, the random utility assigned to a brand j is (see, for details, Ben-Akiva and Lerman, 1985):

$$V_{jt} = \alpha_j + \beta_j X_{jt} + \varepsilon_{jt} \qquad [1]$$

where α_j is the intrinsic utility or value of brand *j*, β_j is a vector of estimated parameters, X_{jt} is the vector of the variables associated with brand *j* (i.e. price, display), and ε_{jt} is a random error.

It is habitually assumed that the error terms ε_{jt} are independent and identically distributed as a double exponential.[2] Therefore, the conditional probability of choosing brand *j* is given by a multinomial logit model as

$$Prob_t\left[Y = j \middle| X_{i1}, X_{i2}, \ldots X_{ik}\right] = \frac{exp(\alpha_j + \beta_j X_{ijt})}{\sum_{k=1}^{J} exp(\alpha_k + \beta_k X_{ikt})} \qquad [2]$$

where there are J alternatives and the value of *Y* indicates the brand choice. To simplify the exposition $Prob_t\left[Y = j \middle| X_{i1}, X_{i2}, \ldots X_{ik}\right]$ will be $Prob_t[Y = j]$ from now on.

In a market with a relatively constant purchase frequency, the probability of choosing a brand could be assimilated as its market share s_{jt} (Cooper and Nakanishi, 1988; Grover and Srinivasan, 1987; Bucklin et al., 1998).

$$s_{jt} = Prob_t[Y = j]$$

Throughout the literature (see for example Cooper and Nakanishi, 1988; Krishnamurthi and Raj, 1991; Russell and Kamakura, 1994; Mela et al., 1998) the analysis of competition among brands in a market has been frequently based on market share analysis through own and cross price

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[1] See Kannan and Wright (1991) or Anderson, De Palma and Thisse (1992) for more details.

[2] See Maddala 1994, p. 60 for more details.

elasticities, $\eta_{mj} = \frac{\partial s_m}{\partial p_j} \cdot \frac{p_j}{s_m}$, where p_j is the brand j's price.

However, using cross-elasticity as a measure of interbrand competition has been sometimes inappropriate as pointed out by Elrod and Keane (1995), Sivakumar and Raj (1997), Mela et al. (1998) or recently Sethuraman, Srinivasan and Kim (1999). They argued that asymmetric price effects may be due by their market shares and prices. Therefore, differences in cross-elasticities can result from differences in market share rather than responsiveness. Therefore, we also analyze competitive structures through the own and cross price response matrix, *R(j, m)*:

Own and Cross Price Response Matrix

$$\begin{array}{ccc} & & \textit{Columns} \\ & & j \;.\;.\;.\; m \\ \textit{rows} & \begin{array}{c} j \\ \cdot \\ \cdot \\ m \end{array} & \begin{pmatrix} \zeta_{jj} & \cdots & \zeta_{jm} \\ .. & . & .. \\ \zeta_{mj} & \cdots & \zeta_{mm} \end{pmatrix} \end{array} \qquad [3]$$

where $\zeta_{jm} = \frac{\partial s_j}{\partial p_m}$ is the partial derivative of brand j's market share with respect to brand m's price.

The asymmetric competition analysis has recently received more attention by marketing researchers (Russell and Kamakura, 1994; Chintagunta, 1994; Bronnenberg and Wathieu, 1996; Sivakumar and Raj, 1997; Mela, Gupta and Jedidi, 1998; Sethuraman, Srinivasan and Kim, 1999). Asymmetry in competition, in this case, proceeds from the assumption that the own and cross price response matrix is not symmetric (Blattberg and Wisniewski, 1989). The phenomenon is that a price promotion by a brand affects the market share of a rival more than the reverse, $\zeta_{mj} \neq \zeta_{jm}$.

Hypothesis 1: Own and cross price response matrix is not symmetric.

To test the existence of the asymmetric competition described above is interesting for the implications that it has on a brand's price decisions, but also because it seems to contradict the implications of one usual assumption in economic models. In this models, there is no wealth effect in the utility function. Allenby and Rossi (1991) show that under certain assumptions of the utility function (non wealth effect) consumers evaluate two different alternatives by the differences in prices independently from their absolute value.

Some authors have argued that asymmetric competition could be due to the fact that it aggregates consumers where choice decisions hold different preferences (Russell and Kamakura, 1994; Mela, Gupta and Jedidi, 1998). So although the individual preferences do not present wealth effect in their utility functions, the aggregation process could explain the existence of asymmetric competition.

More specifically these authors classified consumers according to their preferences through brand choice frequencies. In this case, they suggested that the cross price response matrix *R(j,m)* is asymmetric when price sensitivity is different across consumer segments. Algebraically, it can be expressed as

$$\begin{pmatrix} \zeta_{jj} & \cdots & \zeta_{jm} \\ \cdot\cdot & \cdot & \cdot\cdot \\ \zeta_{mj} & \cdots & \zeta_{mm} \end{pmatrix} = \left(\beta_s, \ldots, \beta_s\right) \cdot \begin{pmatrix} \sum_s f_s s_{sj}(1 - s_{sj}) & \cdots & \sum_s f_s s_{sj} s_{sm} \\ \cdot\cdot & \cdot & \cdot\cdot \\ \sum_s f_s s_{sj} s_{sm} & \cdots & \sum_s f_s s_{sm}(1 - s_{sm}) \end{pmatrix}$$

where β_s represents the price sensitivity in segment s, f_s is the size of segment s and s_{sj} is the brand j share in segment s.

In this case, interbrand competition will be symmetric when price utility sensitivities are equal across the consumer segments, $\beta_s = \beta \ \forall s$, and asymmetric otherwise. The existence of consumer heterogeneity justifies the asymmetry in interbrand competition.

Hypothesis 2: The existence of consumer segments causes asymmetries in competition.

Another explanation to the existence of asymmetric competition proceeds from assumptions about the way that consumers make choice decisions, the utility function. If the utility function of the consumers presents wealth effect (Allenby and Rossi, 1991) the brand choice does not only depend on the price differences with the rest of the brands in the market but also on the absolute value of their prices. Hardie, Johnson and Fader (1993), Bronnenberg and Wathieu (1996) and Sivakumar (1997) are some examples that have used different utility functions with this characteristic to explain the existence of asymmetry in competition.

Hypothesis 3: Asymmetry in competition is explained by the utility function form.

The existence of wealth effect implies that when the differences between brand prices are the same, but the price level increases, the market shares of higher priced brands decrease. This argument explains the existence of loss aversion in the utility function (Hardie, Johnson and Fader, 1993; Bronnenberg and Wathieu, 1996) or the asymmetric competition between quality tiers (Blattberg and Wisniewski, 1989; Sivakumar and Raj, 1997). High quality brands are usually higher priced. When brand prices increase, although the price differences between brands are the same, some consumers prefer to buy other goods than quality, but these consumers can buy both, other goods and quality, with lower level prices. This explains that variations in consumer utility due to variations in prices is greater for higher quality brands (H) than lower quality brands (L), $\frac{\partial V_H}{\partial p_L} < \frac{\partial V_L}{\partial p_H}$, that is $-\beta_H > -\beta_L$, a well stylized fact in the literature (Sethuraman et al., 1999).

Hypothesis 4: The increase in utility due to price reductions is greater for high-quality brands than low-quality ones.

METHODOLOGY

DATABASE.

The database consists of a consumer data panel collected by a Spanish firm specializing in market research, Dympanel (Sofres Group). This firm has developed a babypanel with information about products consumed by babies aged between 0 and 2 ½ years old. The information is collected through weekly questionnaires filled in by the mothers of 500 babies. The number of panelists is fixed, although their identities can vary over weeks.

The data finally used in the study[3] refers to 16,943 diaper purchases for 479 babies from January 1992 to June 1994, a total of 130 weeks. The diaper market is especially interesting because it fits to the assumptions of the choice models very well. There are no other close substitute products for the range of prices analyzed and the quantity demanded is very stable throughout the time. Consumers purchase an average of 32.4 diapers per week with a standard deviation of 11.2 diapers. The average frequency of purchase is 1.94 weeks (i.e., panelists purchase every 13 days in average) with a standard deviation of 0.87 weeks.

The consumer characteristics used in this study are social class, Spanish region, habitat, age of the baby in weeks and baby gender. The social class is a categorical variable with three categories, high, medium and low, proxies of the household's wealth. Spanish region refers to the household's geographic location -North-East, East, South, Center and North-[4] and habitat refers to the number of citizens in the hometown -less than 30 thousand, between 30 and 200 thousand, greater than 200 thousand, and Madrid or Barcelona (Metropolis)-.

[3] The data used is a part of the original database generated by Dympanel. Due to the specificity of the newborn market, we have rejected the observations referring to babies of less than 10 weeks (14.2% of the original database) and the special format for newborns (10.1%). Competition within pharmacies (5.5%) is also very different from other retailers, so we have rejected those individuals that have purchased diapers in pharmacies and that have bought diapers of a local brand (1.1%), '*junior*' format (2.1%) and '*night*' format (1.4%). To increase managerial relevance (Krishnamurthi and Raj, 1991), we have selected only those individuals who made 20 or more diaper purchases.

[4] North-East is Catalonia-Aragon region, East is Levante, South is Andalucia, Center is Castilla and North is Galicia and the Basque Country.

Table 1 compares the sample available with the Spanish population of babies. Although our sample only covers approximately 13 percent of the population, Table 1 shows that the sample represents quite well the different sectors of the population based on the geographic, economic and demographic variables available.[5]

{Table 1: Sample vs. population}

The information for each observation is the price of the diaper brand purchased, diaper format, types of store and week. The original database offers information about 11 brands. Two of these brands summarize a market share of almost 50% and prices clearly above the rest of the brands that have market shares lower than 13% (see Table 2). To make the analysis feasible, we have selected three choice alternatives, *Brand 1*, *Brand 2* and *Other brands*. For reasons of confidentiality, the name of the two brands with greater market shares can not be revealed. Around 30% of the *Other brand* purchases correspond to private labels. These brands can be ordered by price, and consequently by quality. In this case, *Brand 1* is the most expensive and *Other brand* the cheapest one.

All analyzed brands commercialize the *Large* and *Regular* diaper format. The format refers to the diaper size. Table 2 reports the market shares of the different diaper brands and formats analyzed, and information about the average diaper price, the average age of the consumer and the percentage of males that purchase each one of the categories.

{Table 2: Brand summary}

Table 2 shows that the regular format is the most used, but as the babies grow they begin to use large formats at around 70 weeks old. The format switch seems to be more probable and earlier in the case of boys than girls.

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[5] Dympanel guarantee a maximum sample error of ± 1.58% for whole of Spain.

The data also provides information about the type of store where the diapers are purchased. We have classified it between *hypermarket* and *other stores*.[6] Table 3 reports the brand shares and average price by type of stores.

{Table 3: Brand and stores}

Table 3 shows that the diapers purchased in hypermarkets represent the 26.6% of the total.

EMPIRICAL MODEL AND DESCRIPTION OF THE VARIABLES.

The empirical analysis of the demand is conducted by the multinomial logit model described in the first section of the paper (see equation [2]). The general expression of the random utility (equation [1]) used throughout the empirical work will be

$$\begin{aligned} V_{jt} &= \alpha_j + (\beta + \rho_j) Price_{jt} + \delta a_j Age + \delta g_j Male + \sum_{\forall M} \gamma_{Mj} SegmentM_t \\ &+ \sum_{\forall M} \lambda_M (Price_{jt} * SegmentM_t) \end{aligned} \qquad [10]$$

where j represents six choice alternatives, a combination of the three brands and the two formats -*LARGEBRAND1*, *LARGEBRAND2*, *LARGEOTHERS*, *REGULARBRAND1*, *REGULARBRAND2* and *REGULAROTHERS* as omitted alternative-.

Price$_{jt}$ is the diaper price of alternative j at choice occasion t. The consumer data panel available holds only the brand price paid in the purchase occasion t, so we do not know the rest of the rival brand prices per consumer in each purchase occasion t, usually known as faced prices. Krishnamurthi and Raj (1988) suggest an approach that consists of computing the average price matrix by week and store. We extend the approach to the other available variables. As some of them were statistically insignificant, we work only with the variables: brand, format, store and

[6] *Hypermarket* is a store with more than 50 lines and 2,500 square meters. The *Otherstores* category includes supermarkets, department stores, specialized stores, traditional stores and others.

region. We run regressions for the 130 weeks where the dependent variable was the price and the independents were five dummies (*brand 1*, *brand 2*, *regular*, *hypermarket* and *north*).[7] The models' fits were acceptable with an average R^2 equal to 0.541 that fluctuates between 0.39 and 0.631.

Consumer Variables. Babies which are heavier or more corpulent seem to need bigger diapers. The main difference between diaper formats is their size and absorbent capacity. On the other hand, the age and gender of the baby are variables related to the baby's weight and his/her corpulence. Therefore we expect that older and male babies will have higher probabilities of choosing large formats. The statistic description presented above (see Table 2, columns 2 and 3) seems to confirm these assumptions. So we are going to control by age and gender of the baby in all the model estimations. The variable $\boldsymbol{Age_t}$ is a continuous variable measured in weeks. The baby gender variable $\boldsymbol{Male_t}$ is equal to 1 if the baby is male and 0 if the baby is female.

Segment variables. The incorporation of consumer heterogeneity into utility functions has been widely discussed throughout the literature. Although this debate begins in the early eighties (Guadagni and Little, 1983), there is not a clear consensus about the best way to incorporate this heterogeneity into the multinomial logit models (Wedel and Kamakura, 1998). One of the ways used has been the consumer segmentation on the basis of the purchased brand shares (Guadagni and Little, 1983; Krishnamurthi and Raj, 1991; Gupta, 1988). The main criticism of this method is that it does not control by the set of prices and other variables what consumers have faced in their decisions. Chintagunta, Jain and Vilcassim (1991) suggest that the best solution seems to be the estimation of a model with fixed effects. The problem is when there are only a few observations for each household, conventional maximum likelihood estimation will lead to inconsistent estimates of the parameters (Hsiao, 1986). The suggested way by some authors (Chintagunta et al., 1991; Gonul and Srinivasan, 1993; Gupta et al., 1997) to deal with this problem is to estimate a random effect model. The main criticism of these models are that they

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[7] The results are available upon request to the author.

assume independent distributions of consumer preferences among the brands and that they do not allow the classification of individuals into each one of the segments created.

We propose an alternative segmentation approach that integrates the two cited perspectives (for a detailed description see Appendix A). From the information of the purchases of each consumer and the estimated parameters by a model without fixed effects, we can compute the fixed effect parameters under certain assumptions. On the basis of this information, we can classify individuals into different segments in a way that approximates the maximum value of the log-likelihood function given a certain number of segments. We will increase the number of segments until the increase in information is not relevant in accordance with the Akaike Information Criterion (see Judge et al., 1980).

Applying this methodology to our case, we accept the solution with six switcher segments (see Appendix A for details). For each segment, we make dummy variables ***Segment*** $\boldsymbol{M_t}$ where $M = 1,...,6$. This variable is equal to 1 if the consumer belongs to the segment M and 0 otherwise. Then we are going to work only with those consumers that have purchased at least two analyzed brands, an overall of 10997 purchases by 305 consumers. The main characteristics of the segments are reported in Table 4 and Table 5.

{Table 4: Parameter estimation for the six-segment solution}

{Table 5: Brand shares by segments}

According to the results presented on Table 5, the size of the segments are similar varying between 11.4% and 22.3% of the overall analyzed sample. Consumers in segments 3, 1 and 6 revealed clear preference for *Brand 1*, *Brand 2* and *Other brands*, respectively. The consumer preferences are shared between *Other brands* and *Brand 1* in segment 5 and with *Brand 2* in segment 4. Finally, consumers in segment 2 share their preferences among all the brands.

HYPOTHESES TEST

Our hypotheses are directly related to the cross price responses, ζ_{jm}. In accordance with the equations [2] and [3], the conditional market share of brand j can be expressed now as,

$$s_{jt} = Prob_t[Y = j] = \frac{exp(V_{jt})}{\sum_{k=1}^{J} exp(V_{it})}$$

where V_{jt} is the equation [10], that is,

$$V_{jt} = \alpha_j + (\beta + \rho_j) Price_{jt} + \delta a_j Age + \delta g_j Male + \sum_{\forall M} \gamma_{Mj} SegmentM_t$$
$$+ \sum_{\forall M} \lambda_M (Price_{jt} * SegmentM_t)$$

The existence of a symmetric own and cross price response matrix, $\zeta_{mj} = \zeta_{jm}$, establishes the next set of restrictions in the parameters of the equation [10], $\rho_j = 0 \;\; \forall j$ and $\lambda_{Mj} = 0 \;\; \forall M$.

So we will reject Hypothesis 1, existence of asymmetries in competition, when we can not reject neither of the above restrictions, that is, $\rho_j = 0 \;\; \forall j$ and $\lambda_M = 0 \;\; \forall M$.

The existence of heterogeneity in consumer preferences will explain the asymmetries in competition when $\lambda_M \neq 0$ for some M, assuming that $\rho_j = 0 \;\; \forall j$. Therefore, we will reject Hypothesis 2, existence of consumer segments causes asymmetries in competition, when the restriction $\lambda_M = 0 \;\; \forall M$ can not be rejected, assuming in the model that $\rho_j = 0 \;\; \forall j$.

Asymmetries in brand competition will be explained by the way that consumers establish their preferences, $\rho_j = 0 \;\; \forall j$ and $\lambda_M \neq 0 \;\; \forall M$. The explanation of asymmetries in competition due to utility function form, Hypothesis 3 will be rejected when the first restriction, $\rho_j = 0 \;\; \forall j$, can not be rejected.

The existence of wealth effect in the utlity function suggests that when high-quality brands decrease their price they have a greater impact on consumer utility than when low-quality brands decrease their price. In our model, it implies that $-\rho_H > -\rho_L$, where H refers to a high-quality brand and L a low-quality brand. In our data, *Brand 1* and *Brand 2* are higher priced or higher quality than *Other brands*. Therefore Hypothesis 4, the increase in utility due to price reductions is greater for high-quality brands than for low-quality, will be rejected when the coefficient ρ for the *Other brands* will be equal to or lower than *Brand 1*'s or *Brand 2*'s ρ coefficient.

RESULTS

To test the above hypothesis, we estimate a set of multinomial logit models where the random utility is expressed by equation [10], imposing different restrictions on their parameters. In Model 3, we constrained equation [10] by the fact that price sensitivity does not change among segments, $\lambda_M = 0 \ \forall M$. Model 4 imposes that utility price sensitivity does not change among brands, $\rho_j = 0 \ \forall j$ and Model 5 corresponds to equation [10] without restrictions. Table 6 reports the parameters of Model 3, Model 4 and Model 5.

{Table 6: Estimation Results for Conditional Logit Models}

Hypothesis 1 states that the own and cross price response matrix is not symmetric. Symmetry in competition implies that $\lambda_M = 0 \ \forall M$ and $\rho_j = 0 \ \forall j$. Comparing the value of the log-likelihood in Model 2 (see Table 4) and Model 5, this hypothesis is rejected at conventional levels of significance (Likelihood ratio test (LRT) = 216.22; $\chi^2_{0.995}(10) = 25.2$).

Hypothesis 2 argues that the existence of heterogeneity in brand preferences is a source of asymmetries in competition. The null hypothesis that consumer segments do not explain asymmetries, $\lambda_M = 0 \ \forall M$, is rejected at conventional levels of significance comparing the log-likelihood values of Model 3 and Model 5 (LRT = 167.8; $\chi^2_{0.995}(5) = 16.7$).

Hypothesis 3 assumes that the asymmetry in competition is explained by the presence of wealth effect in the consumer preferences. The null hypothesis $\rho_j = 0 \ \forall j$ is rejected at conventional levels of significance comparing the log-likelihood values of Model 4 and Model 5 (LRT = 64.6; $\chi^2_{0.995}(5) = 16.7$).

The presence of wealth effect in the utility function imposes that the utility sensitivity to price reductions will be greater for high-quality brands than for low-quality brands, Hypothesis 4. The null hypothesis that $-\rho_H > -\rho_L$, where *H* is a high-quality brand (*Brand 1* and *Brand* 2) and *L* a low-quality (*Other brands*) are rejected at conventional level of significance for the parameters in Model 5.

Above all, the results confirm the existence of asymmetric competition in the Spanish diaper market. It seems that the existence of consumer segments is the main cause of these asymmetries, although utility functional form can also explain a great part of these asymmetries.

The managerial implications of these results are that a suitable analysis of the competitive environment has to emphasize the existence of asymmetries in price effects. The next section adapts the traditional analysis of the brand competitive position to the existence of asymmetric competition.

DEMAND ANALYSIS

In general a simple way to analyze the competitive structure of a market is the brand shares. Under some assumptions, i.e. symmetric competition and equal brand competitiveness, brand shares information is enough to answer two basic questions for a brand manager: i) from which brands proceed the share increases of one brand (Share Increase Sources) ii) what is the decrease on prices needed to counteract the price movements of other brands (Reaction Capacity).

The *equal brand competitiveness* implies that a new customer of one brand has the same probabilities to proceed from each one of the other brands. So the information about market shares is enough to know from which brands proceed its share increases. In our case with the data available in Table 2, the existence of equal brand competitiveness would imply that a share increase of the *LARGEBRAND1* would proceed a 8.5 per cent (8.5 = 7.8 /(100-8.6)) from the *LARGEBRAND2* and 9.6 per cent, 21.8 per cent, 16,8 per cent, 43,3 per cent respectively from the *LARGEOTHERS*, *REGULARBRAND1*, *REGULARBRAND2* and *REGULAROTHERS*.

The existence of symmetric competition makes redundant the two questions above. The decrease on prices necessary to counteract the price movement of a rival brand is equal to the percentage of new consumers captured by the rival that proceeds from the brand managed. So in the example before, *LARGEBRAND2* would has to decrease their price 0.085 pesetas to recover their market share after a price reduction of 1 peseta done by *LARGEBRAND1*.

A main concern for an analyst is the importance of the assumptions above, equal brand competitiveness and symmetric competition, and after that, to develop ways to measure the share increase sources and the capacity reaction of the brands. The information generated by the choice models can help us to answer all of these questions and to know the brand share increase after a certain variation of its price (Attraction power).

Kamakura and Rusell (1989) and Cooper and Nakanishi (1988) suggested measures of the attraction power and competitive position of each brand extracted from the price elasticities matrix. As we have defined asymmetric competition on the basis of the price response matrix, we are going to use it to define the attraction power, the share increase sources and the reaction capacity of the brands. Table 7 shows the price response matrix[8] for Spanish diaper brands.

A*ttraction power* is measured by the capacity of a brand to gain market share with changes in its price when the rest of the brand's prices remain constant, that is, the diagonal elements of the price response matrix with a negative sign, $-\zeta_{jj}$. The diagonal elements in Table 7 show that *REGULARBRAND 1* has the highest attraction power in the market analyzed, approximately three times higher than *REGULAROTHERS*, that almost double the rest of the brands.

The existence of asymmetric competition implies that the *competition in destination*, how the price movements of the managed brand affect the demand of competitors, and the *competition in origin*, how affect the price changes of the other brands on the demand of the managed brand,

[8] The price response matrix is computed from the Model 5 estimation (see Table 6).

will be different.

The analysis of *competition in destination* has usually been synthesized by the Competitive Clout index ($\sum_{m=1}^{J}\zeta_{mj}^{2}\ \forall m \neq j$) and the *competition in origin* by the Vulnerability index ($\sum_{m=1}^{J}\zeta_{jm}^{2},\ \forall m \neq j$) suggested by Kamakura and Russell (1989) or Cooper (1988) and applied here to cross price responses. We report all of these indexes in Table 7.

The existence of asymmetric competition, also implies that the correct reaction on prices needed to counteract the rivals movements can not be deduced from the brand shares variations observed, $\frac{p_j}{p_m} \neq \frac{\partial s_m}{\partial s_j}$. In this sense, it is important for brand managers to distinguish the *Share Increase Sources*, i.e., from which brands does the brand analyzed extract its market share when it decreases its price, and the *Reaction Capacity*, i.e., the increase in prices that a brand has to make in order to counteract the price movements of other brands.

The *Share Increase Sources* (SIS) matrix is obtained by the division of each element (*j,m*) of the price response matrix by the diagonal element (*m,m*), $SIS_{jm} = -\frac{\zeta_{jm}}{\zeta_{mm}} = -\frac{\partial s_j}{\partial s_m}$. Each column *m* of the SIS matrix shows the percentage increase of brand *m* share that proceeds from each one of their competitors.

On the other hand, the *Reaction Capacity* (RC) matrix is obtained by dividing each element (*j,m*) of the price response matrix by the diagonal element (*j,j*), $RC_{jm} = -\frac{\zeta_{jm}}{\zeta_{jj}} = -\frac{\partial p_j}{\partial p_m}$. Each column *j* of the RC matrix shows the increase on prices that brand *j* has to do to counteract an increase of 1 peseta of each one of the other brands.

Table 8 shows for the market analyzed the values of the SIS and RC matrixes obtained. As can be seen in the SIS matrix, when *LARGEBRAND1* reduces its price, captures the 32.6 percent of its market share increase from *REGULARBRAND1* (row 4, column 1). In a market with symmetric competition, the SIS matrix will be the transpose of the RC matrix, so in this case *REGULARBRAND1* would have to reduce its price 0.326 pesetas to maintain their brand share after one peseta reduction in *LARGEBRAND1* price. The value obtained in the element (row 1, column 4) of the RC matrix is 0.902 far away from the 0.326. Due to the existence of asymmetric competition, *REGULARBRAND1* has to reduce its price 0.902 pesetas to maintain their brand share after one peseta reduction in *LARGEBRAND1* price.

The results presented in the SIS matrix and the RC matrix are also synthesized by the Competitive Clout and Vulnerability indexes. The SIS Clout indexes $(\sum_{m=1}^{J}(SIS_{mj})^2 \ \forall m \neq j)$ show that the dispersion in the distribution of percentages captured by each one of the brands is very similar, but the SIS Vulnerability indexes $(\sum_{m=1}^{J}(SIS_{jm})^2 \ \forall m \neq j)$ show that there are some brands, *REGULAROTHERS 1*, *REGULARBRAND 1* and *REGULARBRAND 2,* in this order, from which the other brands extract greater percentages of its share.

The RC Clout indexes $(\sum_{m=1}^{J}(RC_{mj}) \ \forall m \neq j)$ show that four pesetas has to be the sum of the increases of the rest of the firms necessary to counteract an increase of one peseta in the price of *REGULARBRAND 1*. This value is far from the 1.5 pesetas obtained for the *REGULAROTHERS*, more than the double of the values obtained for the rest of the brands. The RC Vulnerability index for brand j $(\sum_{m=1}^{J}(RC_{jm}) \ \forall m \neq j)$ show that *REGULARBRAND 1* is the only brand that, with a reduction of less than one peseta, can counteract the price reductions of one peseta of the rest of the brands.

Since now we have been focusing on the measurement of the share increase sources and the reaction capacity of the firms assuming not equal brand competitiveness and asymmetric competition among brands. Now we are going to develop some measures to evaluate these assumptions, the competitiveness and the asymmetry matrixes.

The values of the SIS matrix obtained above could be explained by differences in brand shares (see Table 2 column 1) or by levels of interbrand competition. The level of competition between brand j and brand m, c_{jm}, could be measured as the ratio between the percentage of new consumers captured by brand m from brand j, SIS_{jm}, and the percentage of consumers that have bought brand j over the consumers population that have bought other brands different from m, $\frac{s_j}{1-s_m}$. This coefficient depends on the brand that has changed the prices, $c_{jm} \neq c_{mj}$. So we can construct the Competitiveness matrix where the element (row j, column m) is

$$c_{jm} = \frac{(1-s_m)}{s_j} \cdot SIS_{jm} \qquad \forall m \neq j$$

where SIS_{jm} is the element (j,m) of the SIS matrix and s_m is the market share of brand m (see Table 2, column 1).

In the market analyzed where six brands compete with each other, a value of 1 would show. The results reported in Table 9 show that for *LARGEBRAND 1*, its competitive brands are *LARGEBRAND 2, LARGEOTHERS* and *REGULARBRAND 1*, with values greater than 1. However, the competitiveness matrix also shows two clear different competition patterns between large and regular diapers. For large diapers, the main competitors are the brands with the same size of diapers followed by their regular brand diapers. For regular diapers, the main competitiveness is among their larger diapers and after that, between the regular diapers, especially between *Brand 1* and *Brand 2*. The basic result is that there is great substitution within the same brand but between different diaper sizes.

The existence of symmetric competition would imply that the SIS matrix would be equal to the transpose of the RC matrix, that is, the division of the RC element (j,m), by the SIS element (m,j), elements of the Asymmetry matrix, $a_{m,j} = \frac{RC_{j,m}}{SIS_{m,j}}$, must be one. As we mentioned above, *REGULARBRAND 1* has to reduce its price by 0,902 pesetas to maintain its brand share after *LARGEBRAND 1* has reduced 1 peseta, 2.77 times (row 4, column 1 of the Asymmetry matrix) the contribution of *REGULARBRAND 1* to the increase of *LARGEBRAND 1* market share, 32,6%. The last matrix reported in Table 9, the Asymmetry matrix, shows that *REGULARBRAND 1* is the main source of asymmetries in this market. Finally, Table 10 summarizes the relations between the different elements of the matrixes defined for the analysis of the demand.

CONCLUSIONS

For managerial and theoretical reasons it is important to verify the existence of asymmetries in competition and understand their causes and implications on brand management. Conceptually, its existence implies that these rival brands' demand most affected by the brand's marketing actions will not necessarily be those whose marketing actions will affect the managed brand's demand. Hence, it is important to break down the analysis of the competitive environment between the *competition in destination*, how the marketing actions of the managed brand affect the demand of competitors and the *competition in origin*, how affect the actions of the other brands on the demand of the managed brand. Traditionally it has been done respectively with the analysis of the Competitive Clout and Vulnerability Indexes respectively. We have proposed the Asymmetry matrix as a measure of the change that one brand has as competitor in destination and origin of another one. The asymmetric competition also implies that the information about market shares variations is incomplete to make the correct decisions on prices. To analyze the implications of asymmetric competition for the brand managers decisions, we have proposed the use of the Share Increase Sources matrix, a measure of the market shares captured from other firms, and the Reaction matrix, the increases in prices needed to counteract a price change in one brand.

Theoretically, we extend the current understanding of asymmetries in interbrand competition to wondering about their possible causes. We present an empirical test of the different causes of asymmetric competition suggested in the literature, the aggregation of consumers with different preferences or certain characteristics of the consumer choice, utility function. Methodologically, the study suggests a different approach for incorporating the unobserved heterogeneity into the multinomial logit model based on the idea of clustering consumers minimizing the reduction in the likelihood function.

The results indicate that asymmetric competition exists in the Spanish diaper market, suggesting that the heterogeneity in brand preference across consumers is a source of these asymmetries. However, the results suggest that this heterogeneity is not able to capture and explain completely asymmetries in the interbrand competition. So other explanations, such as the presence of wealth effect in the utility function of the consumers could explain these asymmetries. We test for the different implications of the wealth effect argument and we can not reject them. Therefore the combination of differences in utility function characteristics and consumer heterogeneity seems to explain the asymmetry in competition in the Spanish diaper market.

Obviously the research is not free of limitations. We provide empirical support for only one product category and market. The price information is restricted to the brand purchased so we estimate the prices faced. Despite these and other possible limitations we think that the paper offers important implications for managers and researchers.

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APPENDIX A: SEGMENTATION PROCEDURE.

We can express the random utility function in a fixed effect model as

$$V_{jt} = (\alpha_{ij} + \alpha_j) + \beta_j Price_{jt} + \varepsilon_{jt}$$

where $(\alpha_{ij} + \alpha_j)$ is the fixed effect associated with the individual i and α_j the constant term when the model is estimated without fixed-effects ($V_{jt} = \alpha_j + \beta_j Price_{jt} + \varepsilon_{jt}$).[9]

The value of $(\alpha_{ij} + \alpha_j)$ that maximizes the log-likelihood function of the fixed-effects model (LL_{fixed}) establishes that

$$T_{ij} = exp(\alpha_{ij} + \alpha_j) \cdot \sum_{t=1}^{Tij} \frac{exp(-\beta \ P_{ijt})}{\sum_{j=1}^{J} exp(\alpha_{ij} + \alpha_j - \beta \ P_{ijt})} \qquad [A1]$$

where T_{ij} is the number of times that consumer i has brought brand j.

On the other hand, we can compute the sum of probabilities of choosing a brand j by individual i in a model without fixed effect, θ_{ij}. Therefore, we can compute with the data available the variables T_{ij} and θ_{ij}, for each consumer.

Under the next assumptions:

a) The price coefficients do not vary between the models with and without fixed effects.

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[9] For the simplicity of the exposition, we only consider one independent variable, the brand j price (P_{jt}). The arguments could be easily extended to equations with more dependent variables.

b) Given the expression, $exp(\tau_i) = \dfrac{\sum_{j=1}^{J} exp(\alpha_j - \beta\ P_{ijt})}{\sum_{j=1}^{J} exp(\alpha_{ij} + \alpha_j - \beta\ P_{ijt})}$

It could be deducted that

i. $\dfrac{T_{ik}}{\theta_{ik}} = exp(\tau_i)$ where brand k is the omitted brand

ii. $\dfrac{T_{ik}}{\theta_{ik}} = exp(\alpha_{ij} + \tau_i)$; so, $\ln\left(\dfrac{T_{ij}}{\theta_{ij}}\right) - \ln\left(\dfrac{T_{ik}}{\theta_{ik}}\right) = \alpha_{ij}$

iii. The log-likelihood function of the model with fixed effects (LL_{fixed}) can be expressed as

$$LL_{fixed} = \sum_{j=1}^{J}\sum_{t=1}^{Tij} \ln exp(\alpha_{ij} + \tau) + LL_{withoutfixed} = \sum_{j=1}^{J} T_{ij} * \ln\frac{T_{ij}}{\theta_{ij}} + LL_{withoutfixed}$$

where $LL_{withoutfixed}$ represents the log-likelihood function of a model without fixed effects.

On the basis of all of these results, we suggest a segmentation process that consists of three steps:

1.) Compute the variables T_{ij} and θ_{ij}. The computation of θ_{ij} is made with the estimations of a model without fixed effects (see Table 9, model A1).

2.) Aggregate consumers in a way that minimizes the reduction in the log-likelihood function with respect to the fixed-effects model given the number of segments. Algebraically,

$$\text{Min. } LL_{fixed} - LL_{withoutfixed} = \sum_{j=1}^{J} T_{ij} * \left(\ln\frac{T_{ij}}{\theta_{ij}} - \ln\frac{T_{Mj}}{\theta_{Mj}}\right) \qquad [A2]$$

where $T_{Mj} = \sum_{i=1}^{G_M} T_{ij}$ and $\theta_{Mj} = \sum_{i=1}^{G_M} \theta_{ij}$, G_M is the number of consumers that belong to segment M. In our case, $LL_{withoutfixed}$ will be the log-likelihood of the estimation model 1, that is, -16,100.57 (see Table 4).

In order to approximate the function [A2], we apply the next two steps:

2.1.) To obtain the first values, we apply a K-means nonoverlapping clustering method where the observations are all choice occasions and the variables are the values $\frac{T_{ij}}{T_i} * \ln\left(\frac{T_{ij}}{\theta_{ij}}\right)$.

2.2.) We compute the differences $\left(\ln\frac{T_{ij}}{\theta_{ij}} - \ln\frac{T_{Mj}}{\theta_{Mj}}\right)$ between all consumers i and group M. We re-classify those consumers for whom this distance is inferior for a different group than the one currently classified. We repeat the process until nobody is misclassified.

3. We select the number of segments on the basis of Akaike Information Criterion (Judge et al., 1980; Kamakura and Russell, 1989),

$$AIC = -2*(LL - p)/N$$

where LL is the maximum value of the log-likelihood, p is the number of parameters (equal to $2M$+16 in this case) and N is the number of purchase occasions (N=10997). We choose the number of segments where the AIC value does not change appreciably.

Table 11 reports a summary of the segmentation process and its result. In Table 11, model A2 reflects that the price coefficient has varied when consumer segment parameters have been added. Actually, the price coefficient parameter has been quiet similar after two segments have been included. Therefore, we repeat the segmentation process fixing price coefficient to 0.05865 (the value of the price coefficient obtained when the segmentation process is run the first time- see

Model A2-) in Model A3. The final result of the segmentation process is reflected in model A4. Finally, Table 12 reports the number of segments chosen by Akaike Information Criterion.

Table 1: Sample (S) vs. Population (P)*.

Region	S %	P %	Habitat	S %	P %	Social Class	S %	P %	Gender	S %	P %
North-East	18.9	21.6	Lower 30 mil	36.2	26.0	High	32.5	30.8	male	51.1	51.6
East	20.5	16.0	30 a 200 mil	27.9	24.4	Medium	42.9	40.2	female	48.9	48.4
South	34.8	25.6	Higher200 mil	23.5	19.8	Low	24.6	29.0			
Center	10.7	23.0	Metropolis	12.3	29.8						
North	15.0	13.8									

* Source: Dympanel, Department of Statistics 1994). Population of Spanish babies aged from 0 to 2 ½ years old in 1993 was 380,654.

Table 2: Brand Summary

Brand	Brand Share	Average Unit Price		Baby Age		% Males
	%	ptas.	Std.	weeks	Std.	
LargeBrand 1	8.6	39.15	*(2.2)*	82.13	*(22.0)*	57.2
LargeBrand 2	7.8	39.30	*(3.0)*	78.79	*(23.4)*	48.2
LargeOthers	8.8	32.96	*(2.4)*	81.94	*(24.4)*	62.0
RegularBrand 1	19.9	33.36	*(2.7)*	46.60	*(25.9)*	52.1
RegularBrand 2	15.3	33.44	*(2.8)*	40.93	*(24.1)*	53.4
RegularOthers	39.6	27.30	*(2.9)*	51.66	*(28.0)*	47.5
Total	100.0	34.25	*(1.5)*	56.41	*(29.8)*	51.1

Table 3: Brand Summary by Store

	Hypermarket			Other stores		
	Brand Share	Average Unit Price		Brand Share	Average Unit Price	
	%	ptas.	Std.	%	ptas.	Std.
LargeBrand 1	2.1	36.78	*(6.2)*	6.6	39.74	*(4.1)*
LargeBrand 2	2.0	34.46	*(6.0)*	5.8	41.89	*(1.3)*
LargeOthers	3.2	31.99	*(6.8)*	6.6	31.99	*(4.8)*
RegularBrand 1	6.5	31.24	*(5.5)*	13.5	34.06	*(4.6)*
RegularBrand 2	3.4	29.96	*(4.9)*	11.9	34.23	*(4.7)*
RegularOthers	10.5	26.30	*(4.4)*	29.1	27.84	*(4.1)*
Total	26.6	32.45	*(1.5)*	73.4	34.91	*(1.9)*

Table 4: Estimation Results for Conditional Logit Models

		Model 1	Model 2
Constant_LB1	(α_1)	-3.9731*	-5.6104*
Constant_LB2	(α_2)	-3.6143*	-5.1603*
Constant_LOthers	(α_3)	-4.6478*	-4.4940*
Constant_RB1	(α_4)	-0.4063*	-2.1240*
Constant_RB2	(α_5)	0.1175	-1.4387*
β_Price		-0.0322*	-0.0609*
Segm1_B1	(γ_{11})		2.9280*
Segm1_B2	(γ_{12})		4.5822*
Segm1_Others	(γ_{13})		0.8245*
Segm2_B1	(γ_{21})		2.4701*
Segm2_B2	(γ_{22})		2.8503*
Segm2_Others	(γ_{23})		0.3222**
Segm3_B1	(γ_{31})		4.4393*
Segm3_B2	(γ_{32})		2.5304*
Segm3_Others	(γ_{33})		0.2172
Segm4_B1	(γ_{41})		2.2951*
Segm4_B2	(γ_{42})		0.9906*
Segm4_Others	(γ_{43})		0.0031
Segm5_B1	(γ_{51})		0.9406*
Segm5_B2	(γ_{52})		1.5613*
Segm5_Others	(γ_{53})		0.3256*
Age_LB1	(δa_1)	0.0403*	0.0392*
Age_LB2	(δa_2)	0.0335*	0.0341*
Age_LOthers	(δa_3)	0.0417*	0.0399*
Age_RB1	(δa_4)	-0.0032*	-0.0052*
Age_RB2	(δa_5)	-0.0187*	-0.021*
Male_LB1	(δg_1)	0.3563*	0.4434*
Male_LB2	(δg_2)	0.2316*	0.2585*
Male_LOthers	(δg_3)	0.9124*	0.8662*
Male_RB1	(δg_4)	0.1083**	0.1411**
Male_RB2	(δg_5)	0.0814	0.1288
Log-Likelihood		-16100.57	-13246.76
d.f.		11	26
ρ^2		0.183	0.327

Number observations = 10997 (*p<.01, **p<.05).

Table 5: Description of the Segments

	Brand 1	Brand 2	Other brands	Size
	%	%	%	%
SEGMENT #1	1.7	8.3	1.3	11.4
SEGMENT #2	3.4	4.7	3.7	11.8
SEGMENT #3	12.0	1.7	1.8	15.5
SEGMENT #4	2.7	4.9	13.7	21.4
SEGMENT #5	7.2	1.8	8.6	17.7
SEGMENT #6	1.5	1.5	19.3	22.3
TOTAL	28.6	22.9	48.5	100.0

Table 6: Estimation Results for Conditional Logit Models.

Coefficients		Model 3	Model 4	Model 5
Constant_LB1	(α_1)	-5.1881*	-5.6824*	-1.9702**
Constant_LB2	(α_2)	-5.2924*	-5.1424*	-2.3275*
Constant_LOthers	(α_3)	-4.3040*	-4.3297*	-2.5634*
Constant_RB1	(α_4)	1.5915*	-1.9260*	3.8389*
Constant_RB2	(α_5)	-1.6089*	-1.2070*	0.5355
β_Price		-0.0393**	-0.0953*	-0.0603*
ρ_1**_Price**		-0.0169		-0.1133*
ρ_2**_Price**		-0.0035		-0.0898*
ρ_3**_Price**		-0.0095		-0.0603**
ρ_4**_Price**		-0.1161*		-0.1782*
ρ_5**_Price**		0.0008		-0.0569**
Segm1_B1	(γ_{11})	2.9087*	-0.6988	-2.8334*
Segm1_B2	(γ_{12})	4.5665*	0.8868	-1.267
Segm1_Others	(γ_{13})	0.820*	-2.5057*	-4.5297*
Segm2_B1	(γ_{21})	2.4480*	2.7245*	0.5085
Segm2_B2	(γ_{22})	2.8458*	3.1151*	0.9049
Segm2_Others	(γ_{23})	0.3183*	0.5493	-1.5088**
Segm3_B1	(γ_{31})	4.4394*	0.1319	-2.1475*
Segm3_B2	(γ_{32})	2.5229*	-1.8283*	-4.1386*
Segm3_Others	(γ_{33})	0.2152	-3.6944*	-5.8535*
Segm4_B1	(γ_{41})	2.2528*	2.9974*	0.3677
Segm4_B2	(γ_{42})	0.9848*	1.7014*	-0.904
Segm4_Others	(γ_{43})	-0.0077	0.6346	-1.7854*
Segm5_B1	(γ_{51})	0.9199*	0.6859	-1.4570**
Segm5_B2	(γ_{52})	1.5554*	1.3145**	-0.8276
Segm5_Others	(γ_{53})	0.3205*	0.0940	-1.9071*
Price*Segm1	(λ_1)		0.1046*	0.1662*
Price*Segm2	(λ_2)		-0.0074	0.0560*
Price*Segm3	(λ_3)		0.1239*	0.1896*
Price*Segm4	(λ_4)		-0.0204	0.0545*
Price*Segm5	(λ_5)		-0.0073	0.0687*
Age_LB1	(δa_1)	0.0392*	0.0424*	0.0427*
Age_LB2	(δa_2)	0.0344*	0.0363*	0.0367*
Age_LOthers	(δa_3)	0.0401*	0.0399*	0.0402*
Age_RB1	(δa_4)	-0.0049*	-0.0036*	-0.0031*
Age_RB2	(δa_5)	-0.0207*	-0.0199*	-0.0192*
Male_LB1	(δg_1)	0.4455*	0.4815*	0.4902*
Male_LB2	(δg_2)	0.2580*	0.3284*	0.3336*
Male_LOthers	(δg_3)	0.8653*	0.8799*	0.8807*
Male_RB1	(δg_4)	0.1433**	0.1540**	0.1588*
Male_RB2	(δg_5)	0.1265	0.1126	0.1111
Log-Likelihood		-13222.57	-13170.90	-13138.65
d.f.		31	31	36
ρ^2		0.329	0.331	0.333

Number observations = 10997 (*p<.01, **p<.05).

Table 7: Own and Cross Price Response Matrix Analysis.

	Own and Cross Price Response Matrix [a]						
	Large Brand #1	*Large Brand #2*	*Large Others*	*Regular Brand #1*	*Regular Brand #2*	*Regular Others*	*Vulnerability*
LargeBrand 1	-0.389	0.04	0.052	0.351	0.025	0.079	0.13
LargeBrand 2	0.052	-0.248	0.044	0.145	0.05	0.068	0.03
LargeOthers	0.059	0.039	-0.347	0.133	0.023	0.145	0.04
RegularBrand 1	0.127	0.04	0.042	-1.886	0.108	0.208	0.07
RegularBrand 2	0.036	0.056	0.03	0.435	-0.386	0.184	0.23
RegularOthers	0.114	0.074	0.18	0.823	0.18	-0.685	0.76
Clout	0.04	0.01	0.04	1.03	0.05	0.11	

[a] Entries to be read change in share of row brand with unit change in price of column brand

Table 8: The Share Increase Sources and Reaction Capacity Matrix.

	Marketing Decision Analysis						
SIS Matrix	*Large Brand #1*	*Large Brand #2*	*Large Others*	*Regular Brand #1*	*Regular Brand #2*	*Regular Others*	*Vulnerability*
LargeBrand 1	-1	0.161	0.150	0.186	0.065	0.115	0.10
LargeBrand 2	0.134	-1-	0.127	0.077	0.130	0.099	0.07
LargeOthers	0.152	0.157	-1	0.071	0.060	0.212	0.10
RegularBrand 1	0.326	0.161	0.121	-1	0.280	0.304	0.32
RegularBrand 2	0.093	0.226	0.086	0.231	-1	0.269	0.19
RegularOthers	0.293	0.298	0.519	0.436	0.466	-1	0.85
Clout	0.24	0.22	0.33	0.29	0.32	0.23	
RC Matrix	*Large Brand #1*	*Large Brand #2*	*Large Others*	*Regular Brand #1*	*Regular Brand #2*	*Regular Others*	*Vulnerability*
LargeBrand 1	-1	0.103	0.134	0.902	0.064	0.203	1.41
LargeBrand 2	0.210	-1	0.177	0.585	0.202	0.274	1.45
LargeOthers	0.170	0.112	-1	0.383	0.066	0.418	1.15
RegularBrand 1	0.067	0.021	0.022	-1	0.057	0.110	0.28
RegularBrand 2	0.093	0.145	0.078	1.127	-1	0.477	1.92
RegularOthers	0.166	0.108	0.263	1.201	0.263	-1	2.00
Clout	0.71	0.49	0.67	4.20	0.65	1.48	

Table 9: The Competitiveness and Asymmetry Matrix.

	Theoretical Explanations					
Competitiveness Matrix	*Large Brand #1*	*Large Brand #2*	*Large Others*	*Regular Brand #1*	*Regular Brand #2*	*Regular Others*
LargeBrand 1	1	1.726	1.591	1.732	0.640	0.808
LargeBrand 2	1.570	1	1.485	0.791	1.412	0.767
LargeOthers	1.579	1.645	1	0.646	0.577	1.455
RegularBrand 1	1.497	0.746	0.554	1	1.192	0.923
RegularBrand 2	0.555	1.362	0.513	1.209	1	1.062
RegularOthers	0.676	0.694	1.195	0.882	0.997	1

Asymmetric Matrix	*Large Brand #1*	*Large Brand #2*	*Large Others*	*Regular Brand #1*	*Regular Brand #2*	*Regular Others*
LargeBrand 1	1	1.304	1.133	0.360	1.431	1.443
LargeBrand 2	0.768	1	0.881	0.272	1.115	1.091
LargeOthers	0.881	1.127	1	0.309	1.300	1.240
RegularBrand 1	2.766	3.633	3.165	1	4.025	3.950
RegularBrand 2	0.688	0.893	0.767	0.246	1	0.977
RegularOthers	0.692	0.919	0.805	0.252	1.023	1

Table 10: Relationships between the different matrixes defined.

SUMMARY OF THE MATRIX AND VECTOR ELEMENTS DEFINED THROUGHOUT THE TEXT.	
ζ_{jm} is the element (row *j*, column m) of the **Price Response** matrix. $-\zeta_{jj}$ is the **Attraction Power** of the brand *j*. RC_{jm} is the element (row *j*, column *m*) of the **Reaction Capacity** matrix. a_{jm} is the element (row *j*, column *m*) of the **Asymmetry** matrix. SIS_{mj} is the element (row *m*, column *j*) of the **Share Increase Sources** matrix. c_{mj} is the element (row *m*, column *j*) of the **Competitiveness** matrix. *J* is the number of brands competing in the market. s_j is the brand *j* share.	
SUMMARY OF THE RELATIONSHIPS ESTABLISHED.	
$\zeta_{jm} = -\zeta_{jj} \cdot RC_{jm}$ $\downarrow$ $RC_{jm} = a_{mj} \cdot SIS_{mj}$ $\downarrow$ $SIS_{mj} = c_{mj} \cdot \frac{s_j}{1-s_m}$	$\rightarrow$ $\zeta_{jm} = -\zeta_{jj} \cdot a_{mj} \cdot c_{mj} \cdot \frac{s_j}{1-s_m}$
IMPLICATIONS OF THE DIFFERENT ASSUMPTIONS DESCRIBED.	
The **symmetric competition** imposes that $a_{jm} = 1$ and consequently, $RC_{jm} = SIS_{mj}$. The **equal competitiveness** among brands imposes that $c_{mj} = 1$ and consequently, $SIS_{mj} = \frac{s_j}{1-s_m}$.	

Table 11: Estimation of the Logit Models for the Segment Process

		Model A1	Model A2	Model A3	Model A4
Constant_LB1	(α_1)	-3.9731*	-5.6933*	-3.6533*	-5.6104*
Constant_LB2	(α_2)	-3.6143*	-5.2062*	-3.2723*	-5.1603*
Constant_LOthers	(α_3)	-4.6478*	-4.4756*	-4.4846*	-4.4940*
Constant_RB1	(α_4)	-0.4063*	-2.1935*	-0.2511*	-2.1240*
Constant_RB2	(α_5)	0.1175	-1.4684*	0.2944	-1.4387*
β_Price		-0.0322*	-0.05865*	-0.05865ª	-0.0609*
Segm1_B1	(γ_{11})		2.9755*		2.9280*
Segm1_B2	(γ_{12})		4.5882*		4.5822*
Segm1_Others	(γ_{13})		0.7956*		0.8245*
Segm2_B1	(γ_{21})		2.4984*		2.4701*
Segm2_B2	(γ_{22})		2.8322*		2.8503*
Segm2_Others	(γ_{23})		0.2698		0.3222**
Segm3_B1	(γ_{31})		4.4874*		4.4393*
Segm3_B2	(γ_{32})		2.5389*		2.5304*
Segm3_Others	(γ_{33})		0.1891		0.2172
Segm4_B1	(γ_{41})		0.9701*		2.2951*
Segm4_B2	(γ_{42})		1.5239*		0.9906*
Segm4_Others	(γ_{43})		0.2427**		0.0031
Segm5_B1	(γ_{51})		2.3424*		0.9406*
Segm5_B2	(γ_{52})		0.9988*		1.5613*
Segm5_Others	(γ_{53})		-0.0255		0.3256*
Age_LB1	(δa_1)	0.0403*	0.0394*	0.0402*	0.0392*
Age_LB2	(δa_2)	0.0335*	0.0344*	0.0330*	0.0341*
Age_LOthers	(δa_3)	0.0417*	0.0400*	0.0415*	0.0399*
Age_RB1	(δa_4)	-0.0032*	-0.005*	-0.0031*	-0.0052*
Age_RB2	(δa_5)	-0.0187*	-0.0206*	-0.0189*	-0.021*
Male_LB1	(δg_1)	0.3563*	0.4337*	0.3592*	0.4434*
Male_LB2	(δg_2)	0.2316*	0.2444*	0.2354*	0.2585*
Male_LOthers	(δg_3)	0.9124*	0.8654*	0.9161*	0.8662*
Male_RB1	(δg_4)	0.1083**	0.1317**	0.1078**	0.1411**
Male_RB2	(δg_5)	0.0814	0.1092	0.0821	0.1288
Log-Likelihood		-16100.57	-13253.13	-16105.03	-13246.76
d.f.		11	26	11	26
ρ^2		0.183	0.327	0.183	0.327

Number observations = 10997 (ª fixed, *p<.01, **p<.05).

Table 12: Comparative Results.

M	Approximation Log-Likelihood Step 2.1	Approximation Log-Likelihood Step 2.2	Estimated Log-Likelihood	AIC
1			-16100.6	2.931
2	-14889.0	-14290.9	-14523.3	2.645
3	-13821.6	-13525.3	-13737.4	2.502
4	-13613.2	-13258.4	-13460.1	2.452
5	-13454.0	-13125.6	-13324.4	2.428
6	**-13355.2**	**-13040.7**	**-13246.7**	**2.415**
7	-13333.7	-12985.6	-13193.5	2.406
305	-12723.6	-12723.6	-	-

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