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M. Sebri
G. Zaccour

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GERAD HEC Montréal
3000, chemin de la Côte-Sainte-Catherine
Montréal (Québec) Canada H3T 2A7

Tél. : 514 340-6053
Téléc. : 514 340-5665
info@gerad.ca
www.gerad.ca

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Mouna Sebri [a]
Georges Zaccour [b]

[a] *GERAD & HEC Montréal, Montréal (Québec) Canada H3T 2A7*

[b] *GERAD & Chair in Game Theory and Management, HEC Montréal, Montréal (Québec) Canada H3T 2A7*

mouna.sebri@gerad.ca
georges.zaccour@gerad.ca

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Abstract: In this paper, we extend the classical market-share attraction model to a multi-category setting to include umbrella-branding spillover. Our starting conjecture is that the market share of a national or private brand in one category benefits from its performance in another category, and vice versa. There is an important literature dealing with cross-category interactions, but the thinking is in term of substitutability or complementarity between the products offered in the two or more categories under investigation. Here, our focal point (and contribution) is the link at the brand level. Indeed, we only require that at least one brand is offered in at least two of the categories of interest. Further, the spillover considered is not specific to marketing instruments, but is generated by the brand performance (attraction or market share), which is the result of both the firm's marketing-mix choice and competitors' marketing policies.

We illustrate our model with data concerning two hygiene categories, namely, toothpaste and toothbrushes. We obtain that umbrella-branding spillover is (i) significant and positive; (ii) asymmetric, i.e., the spillover is not equal in both directions; and (iii) variable across brands. Our results show that not accounting for umbrella-branding spillover leads to misestimating the parameters of a market-share model. Providing accurate assessment for category-spillover governing the competing brands, our results derive strategic implications for new-product introduction, product-portfolios building and brand-lines management in a cross-category perspective.

Key Words: Umbrella branding, spillover, store brands, market share attraction model.

Résumé : Dans cet article, nous proposons une extension du modèle d'attraction de parts de marché dans un cadre multi-catégories dans le but de considérer l'effet de débordement relié à la stratégie de marque 'parapluie'. Notre conjecture de départ est que la part de marché d'une marque (nationale ou privée) dans une catégorie a un impact sur sa performance dans une autre catégorie, et vice versa. Il existe une importante littérature traitant des interactions entre catégories, mais elle restreint l'analyse à des relations de substituabilité ou de complémentarité entre les produits offerts dans deux ou plusieurs catégories. Ici, notre point focal (et contribution) est le lien au niveau de la marque. En effet, le cadre d'analyse exige qu'au moins une marque soit offerte dans deux catégories de produits. En outre, les effets de débordements considérés ne sont pas spécifiques aux instruments marketing, mais sont générés en fonction de la performance de la marque (part de marché), elle-même résultat de la stratégie marketing de l'entreprise et des politiques marketing de ses compétiteurs.

Nous illustrons notre modèle avec une base de données relative à deux catégories d'hygiène dentaire, nommément dentifrice et brosses à dents. Nous obtenons que l'effet de débordement de la stratégie parapluie est (i) significatif et positif; (ii) asymétrique, à savoir, le débordement n'est pas égal dans les deux sens; et (iii) variable selon les marques. Nos résultats montrent que ne pas tenir compte du débordement de la stratégie parapluie conduit à une mauvaise estimation des paramètres de part de marché. En fournissant une mesure précise des effets de débordement entre catégories pour chacune des marques concurrentes, nos résultats permettent une implication stratégique au niveau de l'introduction des nouveaux produits, l'extension et la gestion de portefeuille de produits dans une perspective globale à travers les catégories de produits.

1 Introduction

How much is the performance of a (store or manufacturer) brand in one category affected by its performance in another category? This is essentially our research question. In a sense, this paper responds to the call made long ago by Chintagunta & Haldar (1998), who highlighted the need for analyzing cross-category effects at the brand level rather than at the category level.

There exists a vast literature assessing cross-category sales and marketing-mix dependencies (see, e.g., the review by Leeflang & Parreno-Selva, 2012). Using a multi-category choice and/or incidence model, several papers studied whether households exhibit similar marketing-mix sensitivities across categories (see, e.g., Seetharaman et al. 1999; Iyengar et al. 2003; Duvvuri et al., 2007; Niraj et al., 2008). Other studies considered multi-category choice models that allow a household's preferences to be correlated across categories (see, e.g., Erdem & Winer, 1999; Manchanda et al., 1999; Singh et al., 2005; and Hansen et al., 2006). Further, with store-level data, some contributions focused on cross-promotional sales effects between categories (see, e.g., Ailawadi et al., 2006;, Leeflang et al., 2008; Bezawada et al., 2009; Leeflang & Parreno-Selva, 2012). Typically, these consumer-purchasing decision models (brand choice, incidence and quantity outcomes) account for a household's preferences in related (complementary or substitutable) product categories, but restrict the analysis to the category level, that is, they ignore cross-category dependencies at the brand level.

Products belonging to different categories can also be linked through their brand name. Here, the association is initiated by the supplier; in other words, a manufacturer or a retailer decides to give the same label to different products, which may be complements, substitutes or totally independent. Examples of such umbrella branding (UB) abound in all kind of industries and circumstances. To illustrate, whereas Samsung uses UB for related products (i.e., flat-screen televisions, flat-screen monitors and laptop computers), Virgin adopts UB to sell music CDs, air travel, cola drinks and financial services. An umbrella-branding strategy allows firms to leverage the reputation attached to a brand name, and to generate savings in brand development and marketing costs over time (Sattler et al., 2010; Aaker, 2004; Kapferer, 1997). Also, assuming that the parent brand is strong, an umbrella strategy reduces the cost and risk of introducing new products by claiming (or signalling) that the new product is of a similar quality to existing products (Gierl & Huettl, 2011; Aaker 2004; Montgomery & Wernerfelt, 1992). Several studies have documented such brand interdependence in terms of consumer purchasing behavior across categories (see, e.g., Erdem, 1998; Erdem & Sun, 2002; Balachander & Ghose, 2003; Sayman & Raju, 2004; Wang et al., 2007; Erdem & Chang, 2012; Ma et al., 2012). In particular, in an early contribution in this area, Erdem (1998) estimated a correlation of 0.88 between consumers' prior quality perceptions of two umbrella-branded products (toothpaste and toothbrushes).

Research on umbrella branding for private labels, which are of interest to us at the same level as national brands, is scarce. Sayman & Raju, 2004 observed that consumers make inferences about the brand *and* the retailer when they face a large number of PLs in different categories. They obtained that the number of PL items offered by the retailer in other categories increases the PL share in the "target category." Using a Bayesian multivariate Poisson-regression model, Wang et al. (2007) confirmed the role of umbrella branding in creating a high correlation between the perceived quality of PL products in different categories. Recently, Erdem & Chang (2012) studied umbrella branding in a cross-country setting. They confirmed the existence of cross-category learning effects between several pairs of categories for both store and national umbrella brands, albeit with a variable degree of cross-category learning. Finally, Amrouche et al. (2014) studied the profitability of umbrella branding for a retailer offering its brand in two independent categories, and obtained that there exists a region in the parameter space where such a strategy is not profitable.

We point out two shortcomings that are common to all the empirical studies cited above, and by the same token position our contribution.

1. The analysis of the spillover is done at a category- or, at best, subcategory-level (i.e., private label vs. national brands taken together). To the best of our knowledge, no study has dealt with spillovers between brands offered in two different categories. Our approach refines the traditional analysis of cross-category effects to dependencies at the brand level.
2. The umbrella-branding spillover is measured through the cross-category sales effects of marketing instruments (price spillover, display spillover, etc.). Unfortunately, this approach is often constrained by

the lack of data, and is limited to price variables. Further, several marketing factors are unobservable or hard to measure, e.g., long-term advertising impact, product-quality perception, brand equity, etc. By retaining market shares instead of sales, we provide a relative performance-measure that embeds such marketing factors in the categories under investigation.

Another difference between the above-cited studies and ours is the type of data. Whereas these studies typically used disaggregated household-panel data, we call upon aggregated marketing data for competing brands to analyze umbrella-branding spillover. As our required data are largely available and describe the whole state of the market and not only some of its facets, as is the case with household scanner data, we believe that our approach gives manufacturers and retailers a user-friendly tool to assess the impact of umbrella branding.

The rest of the paper is organized as follows. In the next section, we briefly review the attraction model in terms of structural characteristics and estimation requirements for endogeneity. Next, we develop our proposed multi-category model of market shares. Following this, we discuss the data and estimation results. Finally, we present some managerial implications of our estimation results, and conclude by proposing directions for future research.

2 Market-share models

Market-share models have been around for a long time; see Cooper and Nakanishi (1988) for comprehensive coverage of these models. However, no study has explicitly accounted for cross-category dependencies when brands are offered in more than one category. To fill in the gap, we extend the attraction-based market-share model to include umbrella-branding spillovers across categories.

Consider two product categories indexed by $c = 1, 2$ and carrying m_1 and m_2 competing brands, respectively. That is, we do not impose that the sets of brands in the two categories must be identical, but we do require that at least one brand be offered in both categories. Let t be the time period ($t = 1, \ldots, T$). Denote by $\mathcal{A}_{it}^c \geq 0$ the attraction of brand i in category c at time t, and by s_{it}^c its market share. Following the literature, we assume that a brand's market share is given by its attraction divided by the sum of all brands' attractions, that is,

$$s_{it}^c = \frac{\mathcal{A}_{it}^c}{\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c}. \tag{1}$$

Clearly, this market-share model satisfies the two desired logical consistency properties, namely, $0 \leq s_{it}^c \leq 1$, for all $i = 1, \ldots, m_c$, and $\sum_{i=1}^{m_c} s_{it}^c = 1$, for $c = 1, 2$. We suppose that the attraction $\mathcal{A}_{it}^c$ is influenced by marketing instruments (price, advertising, etc.) and possibly other economic and non-economic variables. Denote by $X_{it}^c = \left(X_{1it}^c, \ldots, X_{K_c it}^c\right)$ the vector of such variables, where X_{kit}^c is the value of the k^{th} explanatory variable for brand i in category c at time t, and K_c is the number of explanatory variables in this category.

Umbrella brands-whether national or store brands-carry information through their brand name. Consumers draw inferences from their experience with the quality of a product sold in different categories but under the same UB. For instance, if a consumer has a negative experience with a product, he may be less inclined to buy another product of the same brand. We thus assume that the attraction of a brand in one category depends on the performance (market share) of the same brand in category $3 - c$ and vice versa. This is the idea of having inter-category brand spillover. Consequently, we write the attraction as $\mathcal{A}_{it}^c \left(X_{it}^c, s_{it-1}^c, s_{it}^{3-c}\right)$, where $c = 1, 2$.

We adopt the multiplicative competitive interaction (MCI) functional form for attraction, and estimate and contrast the results in the following two scenarios:

No spillover. Notwithstanding that some brands are offered in the two categories under scrutiny, the assumption in this scenario is that a brand's performance in a given category is independent of its performance in the other category. This is our benchmark case, and corresponds to the setting typically retained in the empirical market-share-models literature. To have the most general model possible, we suppose that the impact of marketing (and other) instruments on market share varies across brands.

This differential effectiveness is intuitive and has been documented for instance in promotion studies (see, e.g., Aggarwal & Cha, 1998; Sethuraman et al., 1999; Ailawadi et al., 2008). Here, a price discount by a national or leader brand has a stronger negative effect on the sales of a competing store or other "weak" brand, than vice versa. The attraction of brand i in category c at time t is specified as follows:

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}, \quad i = 1,\ldots,m_c, \quad c = 1,2, \tag{2}$$

where α_i^c is the brand-specific constant, β_{ki}^c,$k = 1,2,\ldots,K_c$ and φ_i^c are parameters to be estimated, and ϵ_{it}^c is a random disturbance term.

Brand spillover. Traditionally, two product categories are considered related when the goods are substitutes or complements. Our focus here is on another link, namely, the brand name, and on its impact on a brand's performance (market share) rather than on its sales.

The existence of such cross effect may be due to several reasons. For instance, having a display for a brand in one category may help promote the brand in another category in which the brand is not promoted. A similar type of effect may occur with a price cut in one category. Further, advertising can be expected to increase not only awareness for a particular product but for all products carrying the same name. We recall that, contrary to what has been done in the literature, the spillover is not specific to marketing instruments. Instead, the whole marketing effort and unobserved phenomena (e.g., loyalty, long-term advertising effect, product quality, goodwill, etc.) are summarized in the expression of the brand performance. Two variants are considered for attraction in the presence of brand spillover.

Constant brand-spillover. In this first model, the assumption is that all brands present in both categories have the same directional spillover effect. The model is given by

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\gamma^c.s_{it}^{3-c}\right), \quad i = 1,\ldots,m_c, \quad c = 1,2, \tag{3}$$

where α_i^c is the brand-specific constant; β_{ki}^c,$k = 1,2,\ldots,K_c,\varphi_i^c$ and γ^c are parameters to be estimated, and ϵ_{it}^c is a random disturbance term. The additional parameter with respect to the previous model, γ^c, is the brand-spillover effect. A positive value for γ^c is expected; otherwise, the firm would not use umbrella branding. Note that spillover in one direction need not be equal to the spillover in the reverse direction, that is, $\gamma^c \neq \gamma^{3-c}$.

Specific brand-spillover. In the second case, we suppose that the spillover is brand specific, and we extend in a straightforward manner the above model as follows:

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\gamma_i^c.s_{it}^{3-c}\right), \quad i = 1,\ldots,m_c, \quad c = 1,2. \tag{4}$$

The only difference with the previous model is in the spillover parameter, that is, γ_i^c instead of γ^c. We draw attention that, as the model is nested, the exponential form allows the attraction expression 4 to revert its original shape (2) in two cases:

– The case where the brand i is present only in one category c, thus ($s_{it}^{3-c} = 0$).
– The case where the spillover is absent between the product categories for a given brand i, thus ($\gamma_i^c = 0$).

Remark 1 *To keep the notation simple and to be consistent with the empirical part of the paper, we wrote the above models for only two product categories. We note that it is straightforward to extend them to any number of categories. To show it, suppose that we have C categories, with $C > 2$. Denote by s_i^{-c} the vector of market shares of brand i in all categories but in c, that is,*

$$s_i^{-c} = \left(s_i^1,\ldots s_i^{c-1}, s_i^{c+1},\ldots s_i^C\right),$$

and similarly by

$$\gamma_i^{-c} = \left(s_i^1,\ldots s_i^{c-1}, s_i^{c+1},\ldots s_i^C\right),$$

Then, the specific brand-spillover attraction model will read as follows:

$$\mathcal{A}_{it}^{c} = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\sum_{\substack{j=1\\ j\neq i}}^{C} \gamma_i^j . s_{it}^j\right), \quad i=1,\ldots,m_c, \quad c=1,\ldots,C.$$

To obtain the constant brand-spillover attraction model, it suffices to set in the above equations $\gamma_i^j = \gamma^j$ *for all* i.

On top of the umbrella-branding relationships, we allow for unobservable inter-temporal and inter-category dependencies. The first dependency, which is typical in any model involving time series, can be accounted for by letting the residual-error terms in one category be correlated, as in, e.g., Chen et al. (1994), but we opt for including lagged market share as an explanatory variable because it is easier to interpret and allows the computation of long-term elasticities. Further, this choice allows the attraction function to account for phenomena such as brand loyalty, inertia in consumption habits, and the carry-over effects of advertising and other variables.

Else, the inter-category dependency can be attributed to some unobservable factors, e.g., market conditions affecting the market share of a brand in one category that may also systematically impact the same brand market share in the other category. To allow for this, we assume the following covariance structure:

$$cov\left(\epsilon_{it}^c, \epsilon_{jt'}^{3-c}\right) = \begin{cases} \sigma_i & \text{if } i=j \text{ and } t=t' \\ 0 & \text{otherwise} \end{cases}, \quad i,j=1,\ldots,m_c, \quad c=1,2.$$

To wrap up, our approach considers that spillovers are reminiscent to brand performance, which is the result of the owner's marketing policies, of market conditions and what the other brands are doing, and of not of a specific marketing instrument. Moreover, the models above make it possible: (i) measure umbrella-branding effects for both private labels and national brands; (ii) qualify the differences between these brands, that is, verify if private labels and manufacturers' brands are different in terms of spillover; and (iii) observe possible asymmetries in directional spillovers.

2.1 Estimation

Substituting for the attraction $\mathcal{A}_{it}^c$ of brand i by its value from (4) in the expression of market share (1), we get[1]

$$s_{it}^c = \frac{\exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\gamma_i^c . s_{it}^{3-c}\right)}{\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c}.$$

Taking the logarithm of both sides, we obtain

$$\ln\left(s_{it}^c\right) = \alpha_i^c + \epsilon_{it}^c + \sum_{k=1}^{K_c} \beta_{ki}^c \ln\left(X_{kit}^c\right) + \varphi_i^c \ln\left(s_{it-1}^c\right) + \gamma_i^c . s_{it}^{3-c} - \ln\left(\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c\right). \tag{5}$$

Now, consider any brand as the reference brand r in the category and repeat the same exercise as above to get

$$\ln\left(s_{rt}^c\right) = \alpha_r^c + \epsilon_{rt}^c + \sum_{k=1}^{K_c} \beta_{kr}^c \ln\left(X_{krt}^c\right) + \varphi_r^c \ln\left(s_{rt-1}^c\right) + \gamma_r^c . s_{rt}^{3-c} - \ln\left(\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c\right). \tag{6}$$

In the empirical illustration to follow, the private label, which is present in both categories, is taken as the reference brand. Substracting (6) from (5), we obtain the model to be estimated, namely:

[1] The same procedure is followed but not repeated for models (2)-(3).

$$\ln\left(\frac{s_{it}^c}{s_{rt}^c}\right) = \alpha_i^c - \alpha_r^c + \epsilon_{it}^c - \epsilon_{rt}^c + \sum_{k=1}^{K_c}\beta_{ki}^c \ln\left(X_{kit}^c\right) - \sum_{k=1}^{K_c}\beta_{kr}^c \ln\left(X_{krt}^c\right)$$
$$+\varphi_i^c \ln\left(s_{it-1}^c\right) - \varphi_r^c \ln\left(s_{rt-1}^c\right) + \gamma_i^c.s_{it}^{3-c} - \gamma_r^c.s_{rt}^{3-c}.$$

Clearly, the above model is linear in its parameters.

In its two versions with spillover, our model considers that the market shares in the two categories are jointly endogenous. Consequently, we employ iterate three-stage least squares (I3SLS) to estimate the $(m_1 + m_2)$ equations system, allowing for cross-equation error correlations in estimation.[2]

As differences in model specifications may have important implications for the normative use of market-share models in, e.g., setting marketing budgets, we compare alternative models on the basis of both their descriptive and predictive performance. The relative magnitude and the precision of the parameter estimates and the adjusted R^2 statistics are used for the descriptive comparison. We use Theil's coefficient (U) to rank the different models (each being a system of market-share equations) in terms of their predictive power (Brodie & de Kluyver, 1984) . We recall that Theil's U is given by

$$U = \frac{\sqrt{\sum_{j=1}^{n}\sum_{t=T}^{T=h}\frac{(m_{jt}-\hat{m_{jt}})^2}{h}}}{\sqrt{\sum_{j=1}^{n}\sum_{t=T}^{T=h}\frac{m_{jt}^2}{h}}}$$

where m_{jt} and $\hat{m_{jt}}$ denote respectively the actual and predicted market shares for brand j in period t, and where h is the number of periods in the holdout sample.

3 Empirical illustration

To illustrate the type of insight provided by our model, we give an empirical example. The data set, which was made available by IRI (Bronnenberg et al., 2008), concerns two oral-hygiene product categories (toothpaste and toothbrushes) for a drug-store chain in the San Francisco market. For each brand in each category, we have 194 weekly observations on sales, prices, flyer advertisements and display activities for the period 2006-2010.[3] To ensure comparability, we express all toothpastes prices in dollars per ounce. Note that display activities, which include codes lobby and end-aisle, is a dichotomous variable taking a value of one if such activity took place during the week, and zero otherwise. Similarly, advertising is equal to one if an announcement was featured in the store's flyer, and 0 otherwise. Additional to these marketing instruments, we also include in the model a series of yearly dummy variables, $Y_l, l = 2007, \ldots, 2010$, to capture all the effects related to other, non-brand-specific, economic variables such as income variations from year to year, state of the economy, etc. (Note that 2006 is taken as the reference year and will be omitted in the estimation.) For clarity and to simplify the interpretation of the results, we rewrite the models in their explicit forms as follows:

Model 1, no spillover

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c) \cdot P_{it}^{\beta_{pi}^c} \cdot s_{it-1}^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c.A_{it}^c + \beta_{Di}^c.D_{it}^c + \sum_{l=2007}^{2010}\tau_l Y_l\right),$$

Model 2, constant brand-spillover

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c) \cdot (P_{it}^c)^{\beta_{pi}^c} \cdot \left(s_{it-1}^c\right)^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c.A_{it}^c + \beta_{Di}^c.D_{it}^c + \gamma^c.s_{it}^{3-c} + \sum_{l=2007}^{2010}\tau_l Y_l\right),$$

[2] This procedure is in three steps, namely: (i) first-stage regressions to get predicted values for the endogenous regressors; (ii) a two-stage least squares step to get residuals to estimate the cross-equation correlation matrix; and (iii) the final 3SLS estimation step is run iteratively to provide generalized least square (GLS) estimates, which are known to have better face validity and improved forecasting accuracy than OLS estimates.

[3] Note that a dummy variable "coupons" is also available. However, as only very few observations with coupons occur, we excluded this variable.

Model 3, specific brand-spillovers

$$\mathcal{A}_{it}^c = \exp(\alpha_i^c + \epsilon_{it}^c) \cdot (P_{it}^c)^{\beta_{pi}^c} \cdot \left(s_{it-1}^c\right)^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c.A_{it}^c + \beta_{Di}^c.D_{it}^c + \gamma_i^c.s_{it}^{3-c} + \sum_{l=2007}^{2010} \tau_l Y_l\right),$$

where P, A and D are price, advertising and display, respectively. All Greek letters are parameters to be estimated.

We retain the five most important brands in each category in terms of market share. These brands respectively accounted for 88.91% and 80.93% of the total toothbrush and toothpaste sales in 2010. In each category, we have four national brands and a (same) private label (PL). As stores within a given chain have similar marketing policies, e.g., pricing and promotion activities, the data were aggregated for the four available stores. Tables 1 and 2 give some descriptive statistics for the toothbrush and toothpaste categories, respectively. Note that Aquafresh, Colgate and the PL are present in both categories. Oral B and Reach are only available in the toothbrush category, whereas Crest and Arm & Hammer are present only in the toothpaste category. In the toothbrush category (T$\mathcal{B}$C), the dominant brand is the PL, with almost half of the total market, and Aquafresh is the marginal brand, with 3% market share. In the toothpaste category (T$\mathcal{P}$C), Colgate (43%) and Crest (33%) together have three-quarters of the market, with the rest being shared by the three remaining brands (Aquafresh, Arm & Hammer and the PL). The lowest average price in the T$\mathcal{B}$C is 1.59 for PL, and the highest is 4.49 for Oral B (almost triple of PL's price), which implies that the retailer toothbrush is a generic private label. In the T$\mathcal{P}$C, Aquafresh, Colgate and the PL are priced almost the same, whereas Arm & Hammer is priced at a noticeable higher level. The toothpaste category seems to carry a me-too private label.

Table 1: Descriptive statistics – Toothbrush category

Brand	*Statistic*	*Market share*	*Price ($)*	*Advertising*	*Display*
Aquafresh	Mean	0.03	2.99	0.11	0.03
	std	0.02	0.88	0.20	0.13
Colgate	Mean	0.12	3.66	0.07	0.07
	std	0.05	0.65	0.08	0.13
Oral B	Mean	0.27	4.49	0.04	0.05
	std	0.08	0.54	0.05	0.08
Private Label	Mean	0.48	1.59	0.19	0.04
	std	0.09	0.31	0.15	0.13
Reach	Mean	0.10	3.28	0.04	0.05
	std	0.04	0.68	0.08	0.12

Table 2: Descriptive statistics – Toothpaste category

Brand	*Statistic*	*Market share*	*Price ($/oz)*	*Advertising*	*Display*
Aquafresh	Mean	0.12	0.52	0.08	0.05
	std	0.07	0.10	0.10	0.15
Colgate	Mean	0.43	0.52	0.11	0.10
	std	0.09	0.08	0.06	0.16
Private label	Mean	0.05	0.50	0.02	0.02
	std	0.02	0.13	0.07	0.09
Crest	Mean	0.33	0.60	0.05	0.07
	std	0.07	0.07	0.04	0.15
Arm & Hammer	Mean	0.07	0.79	0.01	0.03
	std	0.03	0.15	0.05	0.16

3.1 Results

Of the 194 weekly observations, 174 were randomly selected to estimate the parameters of the different market-share models and 20 (approximatively 10% of observations) were held back to test the predictive performance of the different specifications. We start by looking at the general descriptive and predictive performance of the three models. From the results in Table 3, we first conclude that all models exhibit a very good descriptive and predictive performance, and second, that the two models with spillover do slightly better than the model with no spillover.

Table 3: Descriptive and predictive performance

	System Weighted R^2	Theil's U * 10^2	
		Toothbrush category	Toothpaste category
No spillover	80.16	12.09	13.32
Constant brand-spillover	80.83	11.17	13.09
Specific brand-spillover	81.19	10.96	13.21

Tables 4 and 5 give the parameter estimates for the three models, for the toothbrush and toothpaste categories, respectively.

3.1.1 Brand-spillover effects

We start by discussing the results pertaining to umbrella-branding spillover, which is a focal point in this study. We recall that the spillover considered here is not specific to a marketing instrument but is due to the brand performance (attraction or market share), which is the result of both the firm's marketing-mix choice and the competitors' marketing policies. The estimated spillover-parameters for the three brands present in both categories, namely, Colgate, Aquafresh and the private label, are all significant at 5% and positive (see Tables 4 and 5). These results call for two main comments.

First, when the spillover is constrained to be the same across brands, we obtain that the impact of the toothbrush category on the toothpaste category is 53% greater (1.171 vs. 0.764) than the spillover in the other direction. This clearly shows that the spillovers are highly asymmetric. Second, based on the Wald test[4] of parameter equality (Table 6), we conclude that the hypothesis of constant spillover across brands is rejected for Colgate and the private label, but not for Aquafresh. Based on this, we will henceforth focus from on the results of Model 3.

The highest spillover parameters qualify the Aquafresh toothpaste and the private label toothbrush. In fact, with a coefficient of 2.83, Aquafresh-paste attraction is boosted by its performance in the toothbrush category. Otherwise, the PL performance in the paste category strongly (γ_i^c=2.78) impacts the PL attraction in the toothbrush category.

Thus, results considering specific brand-spillovers show that the spillover asymmetry occurs in the opposite direction for national brands and for the private label; we refrain from attempting to make any generalization on the ordering of cross-category spillovers. More specifically, the same ordering still holds true for Colgate (1.816 vs. 0.533) and Aquafresh (2.833 vs. 1.961), but not for the private label (0.905 vs. 2.780). In fact, while the spillover induced by the toothpaste is higher for national brands, the highest spillover benefiting the private label is induced by the toothbrush category. This is likely due to the fact that the spillover is higher when it is generated by a me-too private label than the one generated by a generic brand.

The term $\exp\left(\gamma_i^c . s_{it}^{3-c}\right)$ can be interpreted as the *umbrella-branding multiplier* (UBM), that is, the boost that brand i in category c gets from its presence in category $3-c$. Computing this term for the three brands offered in both categories, at their 2010-average-market share, yields the results in Table 7. Clearly, a value "close" to one indicates either the absence of any umbrella-branding effect (very small γ_i^c), or a very low market share in the other category, which would mean that the basis for leverage is small. The lowest obtained UBM is 1.079 for Aquafresh toothpaste; recall that the average market share of Aquafresh in the

[4] Null hypothesis tested H0: The brand spillover is the same for the three brands (Colgate, Aquafresh and private label).

Table 4: Results for the toothbrush category

Brands	Variables	No spillover Parameter	No spillover Standard error	Constant brand-spillover Parameter	Constant brand-spillover Standard error	Specific brand-spillovers Parameter	Specific brand-spillovers Standard error
Colgate	Intercept	-0.640*	0.235	-0.974*	0.263	-0.719*	0.286
	Y_{2007}	0.149*	0.062	0.154*	0.061	0.141*	0.061
	Y_{2008}	0.046	0.066	0.080	0.066	0.054	0.067
	Y_{2009}	-0.094	0.092	-0.089	0.091	-0.120	0.092
	Y_{2010}	0.030	0.089	0.040	0.088	0.031	0.088
	Price	-1.235*	0.105	-1.152*	0.113	-1.167*	0.112
	Display	0.405	0.262	0.504**	0.260	0.495**	0.254
	Ad	0.421*	0.133	0.335*	0.133	0.323*	0.130
	Lagged share	-0.024	0.056	0.027	0.056	0.025	0.054
	Spillover	-	-	**0.764***	**0.207**	**0.533***	**0.225**
Aquafresh	Intercept	-1.735*	0.374	-1.805*	0.372	-1.937*	0.397
	Y_{2007}	-0.358*	0.128	-0.367*	0.126	-0.385*	0.123
	Y_{2008}	-0.987*	0.144	-0.987*	0.142	-1.040*	0.141
	Y_{2009}	-2.020*	0.209	-2.042*	0.207	-2.104*	0.205
	Y_{2010}	-3.909*	0.357	-3.923*	0.356	-3.989*	0.351
	Price	-0.587*	0.217	-0.596*	0.217	-0.518*	0.218
	Display	0.723**	0.384	0.824*	0.383	0.966*	0.379
	Ads	0.861*	0.334	0.810*	0.334	0.691*	0.335
	Lagged share	0.132*	0.059	0.134*	0.059	0.121*	0.059
	Spillover	-	-	**0.764***	**0.207**	**1.961***	**0.592**
Oral B	Intercept	0.730*	0.251	0.614*	0.251	0.688*	0.256
	Y_{2007}	-0.086	0.058	-0.088	0.058	-0.091	0.058
	Y_{2008}	-0.461*	0.062	-0.448*	0.062	-0.462*	0.063
	Y_{2009}	-0.788*	0.077	-0.780*	0.077	-0.805*	0.078
	Y_{2010}	-0.671*	0.081	-0.671*	0.080	-0.682*	0.081
	Price	-1.134*	0.149	-1.061*	0.149	-1.024*	0.149
	Display	1.934*	0.388	1.696*	0.387	1.677*	0.384
	Ads	0.611*	0.235	0.591*	0.234	0.627*	0.233
	Lagged share	0.015	0.082	0.004	0.082	0.002	0.081
Reach	Intercept	-0.197	0.197	-0.221	0.199	-0.090	0.215
	Y_{2007}	-0.266*	0.077	-0.267*	0.077	-0.271*	0.078
	Y_{2008}	-0.582*	0.078	-0.571*	0.078	-0.584*	0.079
	Y_{2009}	-0.528*	0.092	-0.521*	0.092	-0.543*	0.093
	Y_{2010}	-0.299*	0.094	-0.282*	0.094	-0.286*	0.095
	Price	-1.125*	0.126	-1.115*	0.126	-1.109*	0.126
	Display	0.967*	0.305	1.025*	0.306	0.997*	0.307
	Ads	0.913*	0.166	0.928*	0.166	0.941*	0.166
	Lagged share	0.235*	0.057	0.233*	0.057	0.235*	0.057
Private Label	Price	-0.768*	0.101	-0.728*	0.099	-0.697*	0.101
	Display	0.270*	0.110	0.302*	0.107	0.271*	0.102
	Ads	0.096	0.108	0.116	0.274	0.121	0.107
	Lagged share	0.461*	0.102	0.523*	0.101	0.500*	0.104
	Spillover	-	-	**0.764***	**0.207**	**2.780***	**1.023**

(*) significant parameters at 5%
(**) significant parameters at 10%

source category (toothbrush) is less than 3%. The largest multiplier value benefits the PL toothpaste, whose attraction is multiplied by 1.549, as a result of its dominant market share in the T$\mathcal{B}$C (48.4%).

3.1.2 Price effects

All price coefficients are significant and, as expected, negative. A clear-cut result is that attraction-price elasticities, given by the β_{pi}, for national brands (NBs), are much higher than those for the private label (PL) in both categories. This national-brand/private-label asymmetry has also been observed in price-promotion studies, where it has been obtained that a cut in an NB's price significantly affects the sales of a PL, whereas a price reduction of the PL has a barely noticeable effect on the sales of national brands. This asymmetry has been explained by the PL's customer base being more price sensitive (Aggarwal & Cha, 1998), less brand

Table 5: Results for the toothpaste category

Brands	Variables	No spillover Parameter	No spillover Standard error	Constant brand-spillover Parameter	Constant brand-spillover Standard error	Specific brand-spillovers Parameter	Specific brand-spillovers Standard error
Colgate	Intercept	1.459*	0.180	1.933*	0.199	1.773*	0.214
	Y_{2007}	-0.033	0.063	-0.028	0.062	-0.053	0.063
	Y_{2008}	-0.115**	0.068	-0.038	0.068	-0.083	0.074
	Y_{2009}	-0.139**	0.072	-0.080	0.072	-0.151**	0.085
	Y_{2010}	-0.085	0.072	-0.012	0.072	-0.098	0.088
	Price	-1.463*	0.077	-1.388*	0.077	-1.344*	0.081
	Display	1.041*	0.210	1.033*	0.202	1.053*	0.202
	Ads	0.011	0.080	0.018	0.077	0.022	0.077
	Lagged share	-0.007	0.048	-0.024	0.046	-0.029	0.046
	Spillover	-	-	**1.171***	**0.217**	**1.816***	**0.403**
Aquafresh	Intercept	-0.156	0.190	0.320	0.209	0.124	0.224
	Y_{2007}	-0.058	0.067	-0.024	0.066	-0.027	0.065
	Y_{2008}	-0.159	0.068	-0.008	0.073	0.012	0.079
	Y_{2009}	-0.251	0.074	-0.070	0.081	-0.034	0.093
	Y_{2010}	-0.378*	0.073	-0.153**	0.083	-0.111	0.101
	Price	-1.918*	0.074	-1.930*	0.074	-1.916*	0.078
	Display	0.808*	0.171	0.850*	0.171	0.887*	0.173
	Ads	0.458*	0.119	0.426*	0.119	0.371*	0.124
	Lagged share	-0.004	0.030	0.001	0.029	0.002	0.030
	Spillover	-	-	**1.171***	**0.217**	**2.833***	**1.401**
Crest	Intercept	1.303*	0.175	1.864*	0.202	1.738*	0.210
	Y_{2007}	0.076	0.057	0.106**	0.059	0.096	0.058
	Y_{2008}	0.018	0.060	0.138*	0.066	0.118**	0.067
	Y_{2009}	0.013	0.063	0.153*	0.071	0.132**	0.072
	Y_{2010}	0.043	0.064	0.208*	0.074	0.177*	0.076
	Price	-1.503*	0.076	-1.472*	0.076	-1.487*	0.076
	Display	0.717*	0.246	0.632*	0.245	0.573*	0.244
	Ads	0.057	0.072	0.013	0.072	0.007	0.071
	Lagged share	-0.041	0.038	-0.039	0.038	-0.030	0.038
Arm & Hammer	Intercept	0.242	0.212	0.796*	0.234	0.679*	0.240
	Y_{2007}	-0.035	0.068	-0.002	0.070	-0.010	0.070
	Y_{2008}	-0.112	0.070	0.011	0.075	-0.007	0.077
	Y_{2009}	-0.210*	0.073	-0.062	0.080	-0.083	0.081
	Y_{2010}	-0.120	0.075	0.053	0.083	0.022	0.086
	Price	-1.428*	0.093	-1.426*	0.094	-1.418*	0.095
	Display	1.310*	0.339	1.298*	0.342	1.280*	0.343
	Ads	0.071	0.104	0.078	0.105	0.082	0.105
	Lagged share	-0.006	0.041	0.001	0.042	0.006	0.042
Private Label	Price	-0.976*	0.083	-0.938*	0.082	-0.924*	0.081
	Display	-0.002	0.298	-0.137	0.296	-0.149	0.288
	Ads	0.156	0.186	0.133	0.185	0.153	0.181
	Lagged share	0.159*	0.040	0.132*	0.040	0.135*	0.040
	Spillover	-	-	**1.171***	**0.217**	**0.905***	**0.270**

(*) significant parameters at 5%
(**) significant parameters at 10%

Table 6: Wald test of spillover-parameter equality between categories

	Constant brand-spillover DF	Constant brand-spillover F Value	Constant brand-spillover Pr > F	Specific brand-spillover DF	Specific brand-spillover F Value	Specific brand-spillover Pr > F
Colgate	1302	1.85	0.1738	1298	7.81	0.0053
Aquafresh	1302	1.85	0.1738	1298	0.32	0.5693
Private Label	1302	1.85	0.1738	1298	3.11	0.0782

Table 7: Brand-attraction multiplier

Brand	Category	Attraction-multiplier expression	Market share s^{3-c} average	Attraction multiplier
Colgate	Toothbrush (c)	$\exp(0.533 \times s^{3-c})$	0.435	**1.261**
	Toothpaste (c)	$\exp(1.817 \times s^{3-c})$	0.123	**1.250**
Aquafresh	Toothbrush (c)	$\exp(1.962 \times s_{jt}^{3-c})$	0.122	**1.269**
	Toothpaste (c)	$\exp(2.833 \times s_{it}^{3-c})$	0.027	**1.079**
Private Label	Toothbrush (c)	$\exp(2.780 \times s_{jt}^{3-c})$	0.047	**1.140**
	Toothpaste (c)	$\exp(0.905 \times s_{it}^{3-c})$	0.484	**1.549**

conscious (Ailawadi et al., 2008), and less loyal (Sethuraman et al., 1999) than the customer base of national brands.

The price market-share elasticities, which are of more practical use than their attraction counterparts, are given by the following expressions for the model without spillover:

$$\text{No spillover}: \varepsilon_{p_i^c}^{s_i^c} = \beta_{pi}^c \left(1 - s_i^c\right); \quad \varepsilon_{p_i^c}^{s_i^{3-c}} = 0.$$

As expected, the cross-category market-share price elasticity is zero for this model. The direct price elasticity depends on price market share of a brand in category is given by

$$\text{market share elasticity} \times \text{competitors' market share.}$$

The expressions for the model with specific brand spillover, are much more complicated. Indeed, the derivative of the market share with respect to the price is given by

$$\frac{\partial s_{it}^c}{\partial P_{it}^c} = \frac{\beta_{pi}^c}{P_{it}^c} s_{it}^c (1 - s_{it}^c) + \gamma_i^c s_{it}^c (1 - s_{it}^c) \frac{\partial s_{it}^{3-c}}{\partial P_{it}^c} - \sum_{j \neq i}^{m_c} \gamma_j^c s_{it}^c s_{jt}^c \frac{\partial s_{jt}^{3-c}}{\partial P_{it}^c},$$

which shows that it is dependent of the impact on market shares of all the brands the other category, that is, for both the same brand (i.e., $\frac{\partial s_{it}^{3-c}}{\partial P_{it}^c}$) and the other brands ($\frac{\partial s_{jt}^{3-c}}{\partial P_{it}^c}$). Computing the partial derivatives appearing in the right-hand side of the above expression, we get

$$\frac{\partial s_{jt}^{3-c}}{\partial P_{it}^c} - \gamma_j^{3-c} s_{jt}^{3-c} (1 - s_{jt}^{3-c}) \frac{\partial s_{jt}^c}{\partial P_{it}^c} + \sum_{k \neq j}^{m_c} \gamma_k^{3-c} s_{kt}^{3-c} s_{jt}^{3-c} \frac{\partial s_{kt}^c}{\partial P_{it}^c} = 0,$$

$$\frac{\partial s_{jt}^c}{\partial P_{it}^c} - \gamma_j^c s_{jt}^c (1 - s_{jt}^c) \frac{\partial s_{jt}^{3-c}}{\partial P_{it}^c} + \sum_{k \neq j}^{m_c} \gamma_k^c s_{jt}^c s_{kt}^c \frac{\partial s_{kt}^{3-c}}{\partial P_{it}^c} = -\frac{\beta_{pi}^c}{P_{it}^c} s_{it}^c s_{jt}^c.$$

Consequently, to obtain the actual numerical values for these elasticities, we need to solve the following linear system of dimension $(m_1 \times m_2) \times (m_2 \times m_1)$:

$$\begin{bmatrix} I_{m1} & A^1 \\ A^2 & I_{m2} \end{bmatrix} \times \begin{bmatrix} \frac{\partial s_{jt}^c}{\partial P_{it}^c} \\ \frac{\partial s_{kt}^{3-c}}{\partial P_{it}^c} \end{bmatrix} = B,$$

where: m_c is the number of brands in category $c = 1, 2$; B is a vector $(1 \times m_1 + m_2)$; I_{m_c} is the identity matrix with rank $m_c, c = 1, 2$; A^1 and A^2 are matrices of dimensions $(m_1 \times m_2)$ and $(m_2 \times m_1)$, respectively, where

$$A^1_{jk} = \begin{cases} -\gamma^c_j s^c_{jt}(1 - s^c_{jt}) & \text{if } k = j \\ \gamma^c_k s^c_{jt} s^c_{kt} & \text{otherwise} \end{cases}, \qquad j = 1, \ldots, m_c, k = 1, \ldots, m_{3-c},$$

$$A^2_{kj} = \begin{cases} -\gamma^{3-c}_k s^{3-c}_{kt}(1 - s^{3-c}_{kt}) & \text{if } j = k \\ \gamma^{3-c}_j s^{3-c}_{kt} s^{3-c}_{jt} & \text{otherwise} \end{cases}, \qquad j = 1, \ldots, m_c, k = 1, \ldots, m_{3-c},$$

The solution to the above system is given by:

$$\begin{bmatrix} \frac{\partial s^c_t}{\partial P^c_{it}} \\ \frac{\partial s^{3-c}_t}{\partial P^c_{it}} \end{bmatrix} = A^{-1}B.$$

As an illustration, we provide in Table 8 the numerical values for these elasticities computed at the 2010 average market share of each brand for models 1 and 3, i.e., without spillover and with differential umbrella-branding spillover.

For all brands, but more visibly for those present in both categories, not accounting for interaction between categories leads to an overestimation of the price sensitivity. The spillover corrects these coefficient estimates downward. This seems to imply that umbrella branding renders consumers less sensitive to a price increase. We will discuss later on how these elasticities can be used to make, e.g., promotion decisions.

Table 8: Market-share price elasticities

			No spillover		**Specific brand-spillover**	
Brand	Category	Market share(%)	Toothbrush	Toothpaste	Toothbrush	Toothpaste
Colgate	Toothbrush	12.3	-1.083		-0.1063	-0.0139
	Toothpaste	43.5		-0.827	-0.0204	-0.0788
Aquafresh	Toothbrush	2.7	-0.572		-0.0513	-0.0036
	Toothpaste	12.2		-1.685	-0.0420	-0.1716
Oral B	Toothbrush	26.9	-0.829		-0.0754	
Reach	Toothbrush	9.7	-1.016		-0.1004	
Crest						
	Toothpaste	32.9		-1.009		-0.1005
Arm & Hammer						
	Toothpaste	6.7		-1.332		-0.1324
Private Label	Toothbrush	48.4	-0.397		-0.0374	-0.0194
	Toothpaste	4.7		-0.931	-0.0064	-0.0914

3.1.3 Other variables

Advertising and display effects. Whereas advertising is significant only for Aquafresh in the toothpaste category, its impact is significant and positive for all brands in the toothbrush category. One explanation is that these brands are well established as suppliers of toothpaste in consumers' minds, and consequently, advertising has no additional lifting effect on attraction and market share. With an exception for the private label toothpaste, all display coefficients are significant and, as expected, positive. Note that display coefficients are larger than advertising coefficients for all brands in both categories.

Lagged market-share effects. For national brands, lagged market share is significant only for Aquafresh (coefficient of 0.121) and Reach (coefficient of 0.235). We conclude that past-performance-attraction elasticity is either non significant, or takes low values. Note that Aquafresh and Reach are the two national brands with the lowest market shares, that is, 2.7% and 9.8%, respectively. If one interprets a positive coefficient as an indication of a loyal customer base, then we obtain that niche-brand customers are more loyal than other customers of national brands. However, what is worth reporting along these lines is the impact of the PL's lagged market share on its current performance in both categories. Indeed, in the toothpaste category, the PL is the only brand showing a significant lagged-market-share parameter. In the toothbrush category, the PL coefficient takes the highest value for PL (0.50 versus 0.121 for Aquafresh, and 0.235 for Reach).

Temporal effects. Recall that the data run for 5 years (from 2006 till 2010) and that we have four binary variables to account for a possible temporal effect. The intercept is for the omitted year, i.e., the reference year 2006. For each brand, the impact of a particular year is given by the sum of the intercept and the coefficient of that year.

A positive result reflects an advantage for that (national) brand over the PL in terms of performance, due to variables not accounted for in the model, such as economic conditions, structural change in the retailing sector, etc.

Considering the last column of Table 9, we conclude that, with the exception of Crest in 2007 and 2008, the PL has had the upper hand during these years in the toothbrush category (that is, that the sum of the intercept and a year coefficient is negative). These results may be explained by the fact that customers turn to more affordable products during recession periods, like the one occurring during the period under investigation. Interestingly, however, this reasoning does not extend to the toothpaste category, where we obtain positive intercepts for all national brands and few significant coefficients of the yearly dummy-variables. One interpretation is as follows: as toothpaste is a hygiene product, consumers seem unwilling to trade, for a small saving, a reputed brand for a private label that may be perceived as a low-quality or risky brand. Incidentally, recall that the PL has a market share of less than 5%.

Table 9: Temporal effects

Toothpaste Category		Constant brand-spillovers	**Toothbrush Category**		Specific brand-spillovers
Colgate	Intercept	1.773*	Colgate	Intercept	-0.719*
	Y_{2007}	-0.053		Y_{2007}	0.141*
	Y_{2008}	-0.083		Y_{2008}	0.054
	Y_{2009}	-0.151**		Y_{2009}	-0.120
	Y_{2010}	-0.098		Y_{2010}	0.031
Aquafresh	Intercept	0.124	Aquafresh	Intercept	-1.937*
	Y_{2007}	-0.027		Y_{2007}	-0.385*
	Y_{2008}	0.012		Y_{2008}	-1.040*
	Y_{2009}	-0.034		Y_{2009}	-2.104*
	Y_{2010}	-0.111		Y_{2010}	-3.989*
Crest	Intercept	1.738*	Oral B	Intercept	0.688*
	Y_{2007}	0.096		Y_{2007}	-0.091
	Y_{2008}	0.118**		Y_{2008}	-0.462*
	Y_{2009}	0.132**		Y_{2009}	-0.805*
	Y_{2010}	0.177*		Y_{2010}	-0.682*
Arm & Hammer	Intercept	0.679*	Reach	Intercept	-0.090
	Y_{2007}	-0.010		Y_{2007}	-0.271*
	Y_{2008}	-0.007		Y_{2008}	-0.584*
	Y_{2009}	-0.083		Y_{2009}	-0.543*
	Y_{2010}	0.022		Y_{2010}	-0.286*

4 Managerial implications and concluding remarks

Based on the paper's findings, we derive some managerial recommendations for manufacturers and retailers. Whether they are national or store brands, umbrella brands need to provide consistent experiences across categories, as the existence of cross-learning effects creates the potential for brand-dilution effects when consumers are not satisfied with their brand experience.

Due to the breadth of their extensions across categories, store brands constitute a perfect case for this examination, making our methodology helpful for retailers in new-products introduction and positioning decisions. The implication is that, when a new product is considered a candidate for extension, the retailer needs to determine how the use of extension will affect the profitability of the brand's entire portfolio of products. Managers can decide whether to benefit from the brand building efforts of pioneering brands or opt for new brand-name for the late-entry product. Also, for retailers, brand extension is highly challenging since the brand name is not carried only by the products but also by the retail chain as a whole. Once an umbrella strategy is used across categories and bears the chain's name or refers to it, the retailer must be aware that its reputation is largely influenced by the success or failure of its PL extension. For manufacturers, our results suggest that their promotional—and more globally, marketing—strategies be implemented more efficiently and with a cross-category perspective. As we examine the spillover at a brand level, it is valuable for the manufacturer to test whether it is better to promote toothpaste or toothbrushes. An exact measure of own and cross-category revenue derived from a price-reduction activity would help managers decide on the promotional spending across categories. To do so, we consider the estimated parameters of the proposed model. The simulated volume and revenues—as well as their elasticity counterparts—for the base case (i.e., both products at their average prices and market share), as well as the two promotional scenarios (i.e., (1) toothbrush at 10% price promotion, and (2) toothpaste at 10% price promotion), are presented for Colgate in Table 10.

Table 10: Simulated impact of a price reduction for Colgate*

	Impact of 10% price-reduction in TBC		Impact of 10% price-reduction in TPC	
	Toothbrush	Toothpaste	Toothbrush	Toothpaste
Market share	12.3%	43.5%	12.3%	43.5%
Sales	123	3913	123	3913
Incremental sales	131	-	-	3084
Incremental sales due to spillover	-	544	25	-
Revenues ($)	449.69	2050.48	449.69	2050.48
Incremental revenues ($)	385.25	-	-	1249.15
Incremental revenues due to spillover ($)	-	285.02	91.74	-
Brand total profits ($)	2500.17		2500.17	
Brand incremental total profits $	670.2 (26.8 %)		1340.9 (53.6 %)	

* For these computations, we assume a weekly market size of 1,000 toothbrushes and 9,000 oz for toothpaste. We consider retail pass-through to be 100%.

It is observed in Table 10 that, when not considering the spillover derived from Colgate, the total brand revenue is misspecified for both promotional scenarios. In fact, the Colgate's toothbrush revenue generated directly by the 10% price-cut is $385 and indirectly boosted by a $285 representing the incremental revenue due to spillover. In sum, the total Colgate's revenue increases by almost 27% for a 10% price cut on toothbrushes, whereas the revenue increases by 53% ($1341) if the toothpaste price is cut by 10%. This type of result helps managers implement efficient promotional strategies by taking into account brand specificities (brand-category elasticity, brand price, brand performance) to decide which category is better off being promoted.

Although there is a large literature dealing with branding issues (e.g., branding extensions, umbrella branding) and cross-category relationships in terms of, e.g., complementarity and substitutability effects, this study is, to the best of our knowledge, the first to develop and estimate a market-share model with the aim of measuring brand-category spillover effects. Based on a competitive structure and using data pertaining to the toothbrush and toothpaste categories, with several brands offered in both categories, we obtained that such spillover effects are significant. The framework used and our results call for some straightforward comments.

First, the results clearly show that our modelling approach has an empirical support for positive spillovers between categories at the brand level. The brand performance is boosted by its performance in a related category, through the so-called "brand-attraction multiplier." The implication here is that not accounting for umbrella-branding spillover could lead to the misestimation of some parameter values.

Second, each brand delivers and benefits from asymmetrical spillover associated to its reputation and strength in the market. Further, our model offers a relevant and straightforward method for decision-makers to precisely assess the financial impact of each managerial decision with a cross-category perspective.

In light of the above discussion, we believe that there are some interesting directions for future research. One extension worth conducting would be to run the model for a large number of pairs of categories, with the aim of characterizing and separating the usual relationships that exist between categories (complementarity, substitutability or independence) from umbrella-branding effects. Studying the strength of spillover interactions and their variation along the relationship governing them would be valuable to manufacturers of national brands, and even more so to retailers developing their store brands. Second, because store brands and some national brands exist in many categories, and thus because consumers make inferences when they face a large number of brands in different categories, spillover effects cannot be labelled as simply complementary or substitution-related. Future research may provide insight about the spillover phenomenon in a more general framework that would consider the spillover occurring between more than two product categories.

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