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École affiliée à l'Université de Montréal

Store brand's performance: A cross-country and a cross-category analysis

par
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RÉSUMÉ

La croissance des ventes de la marque privée a dépassé celle de la marque nationale année après année, durant ce dernier siècle. Actuellement, plus d'un dollar sur cinq dépensés en biens de consommation est consacré aux marques de détaillant. Cette thèse comprend trois essais traitant deux problématiques cruciales liées à la performance de marque privée.

Le premier essai traite la variation de performance de la marque privée dans un contexte international. Nous étudions les facteurs qui ont permis à la marque privée de consolider sa position dans certains pays, alors qu'elle peine encore à s'imposer sur d'autres. Nous apportons un éclairage aux détaillants opérant à l'international lorsqu'ils sont amenés à choisir entre une stratégie d'intégration globale ou celle d'adaptation locale, lors de la mise en marché de leurs propres marques. Afin d'étudier empiriquement les facteurs derrière ces disparités géographiques, nous recourons à une large base de données inter-pays qui inclue des variables sociales, économiques et culturelles. Afin de traiter l'hétérogénéité inobservable potentiellement présente entre les pays, nous supposons que les pays appartiennent à un nombre fini de segments. Nous adoptons donc un modèle à classes latentes qui permet de grouper simultanément les pays en segments homogènes. Nous expliquons les déterminants sous-jacents à la performance de la marque privée dans chacun des segments.

Le deuxième essai aborde la question de la performance inter-catégories de la marque privée en présence d'une stratégie parapluie. La littérature existante soulève la présence d'un effet de synergie entre deux catégories complémentaires lorsqu' un détaillant et/ou un manufacturier décident d'utiliser le même nom pour ses produits. Nous proposons d'estimer l'effet de débordement qui résulte d'une stratégie parapluie en étudiant l'impact de la performance d'une marque dans une catégorie donnée sur sa performance dans une autre catégorie. Nous proposons une extension du modèle d'attraction de parts de marché pour tenir compte de

l'effet de débordement résultant de la mise en place d'une stratégie parapluie. L'effet de débordement est considéré au niveau de la marque. Contrairement à ce qui a été proposé par la littérature, il n'est pas spécifique aux instruments marketing mais généré par la performance globale de la marque.
La fonction d'attraction de la marque est modélisée sous la forme d'interaction multiplicative compétitive (MCI). À partir d'une base de données de deux catégories complémentaires d'hygiène buccale, nous estimons les effets de débordement à l'aide de la méthode des triples moindres carrés itérés (I3SLS). Nous comparons les résultats de trois scénarios : absence d'effet de débordement, effet de débordement constant à travers les marques, effet de débordement spécifique à chaque marque. Enfin, nous discutons de l'impact financier d'une stratégie parapluie dans une perspective inter-catégories.

Le dernier essai élargit le cadre de modélisation précédent de deux façons. Premièrement, nous analysons l'impact d'une stratégie parapluie entre multiples catégories. Ce sujet présente un intérêt particulier pour les détaillants vu que leurs maques privées sont présentes dans l'ensemble des catégories, ou presque. Ainsi, les détaillants cherchent à comprendre comment la performance de leur marque dans une catégorie donnée est affectée par ses répliques dans les autres catégories, et par la même occasion, comment l'effort marketing alloué à une catégorie influe-t-il les ventes des autres catégories. Deuxièmement, en plus de la dépendance causée par la stratégie parapluie, nous incluons une dépendance naturelle inter-catégories pouvant être générée par la consommation conjointe, les habitudes d'achat ou l'emplacement similaire des produits. Nous développons simultanément deux modèles : un modèle de parts de marché et un modèle de demande afin d'évaluer distinctement les deux niveaux de dépendance inter-catégories. L'estimation empirique des effets de débordement a été fournie pour cinq catégories, aussi bien complémentaires qu'indépendantes (mayonnaise, moutarde, saucisses, céréales et détergent pour lessive). Nous avons également effectué une simulation pour évaluer l'impact d'une activité marketing sur la performance globale du détaillant en termes de ventes et les profits.

Mots clés : Commerce de détail, marque de détaillant, marque privée, stratégie parapluie, performance de la marque, dépendance inter-catégories, gestion de catégories, effet de débordement, analyse des marchés internationaux, modèles à classes latentes, modèles de parts de marché, modèles d'équations simultanées.

ABSTRACT

The growth of store-brand sales has outpaced national-brand growth every year in the 21st century. Currently, more than one out of every five dollars spent on consumer packaged goods is spent on store-branded products. This thesis is composed of three essays dealing with two important issues about the store brand's performance.

The first essay addresses the variation of the store brand's performance within an international context. We investigate the reasons allowing store brands to consolidate their position in certain countries, while they are struggling in some other markets. We aim to assist retailers operating internationally to decide whether to opt for a global-integration or a local-adaptation strategy. We empirically investigate the factors behind the geographical disparities using a large, cross country, time-series dataset and following an encompassing approach including a number of relevant economic, social and cultural determinants. To consider unobservable heterogeneity, we assume that countries belong to a finite number of segments. We thus adopt a latent-class model to simultaneously group countries into homogeneous segments and explain the store brand's performance within each of them.

The second essay deals with the performance of store brands across categories in the presence of an umbrella-branding strategy. Existing literature states the presence of synergy effect between two complementary categories when a retailer and/or a manufacturer decide to use the same name for his products. We assess the umbrella-branding spillovers by investigating the impact of a brand's performance in one category on another category, and vice versa. An extended market-share model is proposed to account for the spillover effect at the brand level. The spillover was modeled to be generated by the brand's performance and not specific to marketing instruments, as done in the literature. We adopt a multiplicative competitive interaction (MCI) form for the attraction function. Based on aggregated data of

two complementary oral-hygiene categories, we estimate the spillover parameters using the iterate three-stage least squares (I3SLS) method. We contrast the results in three scenarios: no spillover, brand-constant spillover and brand-specific spillover. Finally, we discuss the financial impact of the umbrella-branding from a cross-category perspective.

The last essay extends our previous framework modeling in two ways. First, we consider spillover analysis in multiple categories context. Since store brands are available in almost all packaged goods, retailers are concerned about how their store brand's market share is affecting and being affected by their umbrella replicas, and how their marketing effort in one category affects the global sales across categories. Second, apart the umbrella-branding dependency, we include the natural cross-category dependency caused by joint utilization, purchasing patterns and similar placement. We simultaneously develop two models: a store-brand market-share model and a category-demand model, to distinctly assess the two levels of category dependency. The empirical estimation for category and brand spillovers was provided for five related, as well as unrelated, categories (mayonnaise, mustard, frankfurters, cereal and laundry detergent). We also conducted a simulation to assess precisely the impact of a marketing activity on the retailer's global performance across categories in terms of sales and profit.

Keywords: retailing, store brand, private label, umbrella branding, brand performance, cross-category dependency, cross-category management, spillover, international markets, latent-class model, market-share model, simultaneous-equations model.

TABLE OF CONTENTS

LIST OF TABLES

ACKNOWLEDGMENTS

AUTHOR CONTRIBUTIONS

The first essay entitled «Cross-Country Differences in Private-Label Success» is co-authored with Professor Georges Zaccour and submitted in «International Marketing Review». The second essay «Umbrella-Branding Spillovers» is also co-authored with Professor Georges Zaccour and submitted in «International Journal of Research in Marketing». Finally, the third essay «Cross-Category Effects and Umbrella-Store Brands» is co-authored with Professor Georges Zaccour and being prepared for submission. Authors have equal contributions.

General Introduction

The consolidation and expansion of retail chains has had a significant impact on consumers, manufacturers and retailers alike. While the retail landscape is vast, offering a wide range of packaged goods among grocery categories, there is a distinct divide between national and retail-owned products. Private labels (PLs) or store brands (SBs) have become a major force to reckon with in grocery products. SB unit share has been growing across the globe over the last few decades to rise to 23.6 percent in 2011, compared to about 15 percent in the 1980s. The Private Label Manufacturers Association (PLMA 2012) website reports that store-brand sales in grocery products in the United States increased 5.1 percent in 2011, pushing SB dollar share up half a point to 19.5 percent, a record high. By comparison, sales of national brands gained only 2 percent over the same period. SB shares are even higher in Europe, and are also growing in Asia and Australia (Kumar and Steenkamp 2007). The blatant success of the SBs can easily be explained by the innumerable benefits they provide to retailers as well as customers. In fact, retailers move into SBs to benefit from higher margins compared to manufacturers' national brands, and to exploit untapped segments or steal value-conscious consumers away from the national brands. Store brands were also found to help chain managers increase store traffic, build store loyalty and thus enhance their chain profitability. Some retailers have seen SBs as a strategic move to gain bargaining power against manufacturers by benefiting from better trade deals in negotiating supply terms for national brands. Motivated by those numerous advantages, retailers have seized every opportunity to extend their brand to new product categories. Retailers-owned brands are by now available in many, if not all, consumer-packaged-goods (CPG) category (IRI 2009). Despite this considerable growth, the store brand's performance is not uniform across categories, stores, retailers, and countries. From an international perspective, A.C Nielsen (2012) stated that SB market share for the United Kingdom was twice that for the U.S., and SB share in the U.S. was more than twice the share for most countries in Asia. More specifically, in Europe SB market shares were ranged from 3.8 per cent in Greece to 45 per cent in Switzerland. At the category level, the differences in store-brand share are also substantial. While they have clearly a huge impact in the grocery industry, their performance is characterized by large disparities between CPG categories. For instance within the U.S., average SB share for all packaged foods was three times as much as in household goods and five times the SB share in personal-care products (Euromonitor 2012).

This thesis is composed of three essays dealing with two important issues about the store brand's performance. The first essay focuses on the cross-country disparity of the SB success and aims to identify the main socio-economic and cultural factors behind this geographical variation. The next two essays deal with the performance of store brands across product categories, in the presence of an umbrella-branding strategy. We investigate the synergy that may exist across categories when the retailer and/or manufacturer decide to use the same name for his product in different categories.

The first essay addresses the issue of the store brand's performance within an international context. Unfortunately, existing research on the drivers of SB success is almost completely based on U.S. data. Consequently, internationally operating retailers have no guidance in deciding (1) whether they can apply existing U.S. insights to other countries as part of their internationalization strategy (global integration), or (2) whether they have to figure out again and again what is best for each market (local adaptation). By examining the geographical disparities of SB performance in the international market, we investigate the reasons that allowed the SBs to consolidate their position in certain countries, while they are still struggling in some other markets. Further, we suspect that countries having similar characteristics (e.g., cultural, economic, social, etc.) form small number of segments that differ in the relationship between the PL performance and the explanatory variables. To provide insight into how such differences in SB success originate, we use a large, time-series dataset for SB sales in fifty four countries. In deriving the model, we assume that countries belong to a finite number of groups and that, in addition to the available variables, exist unobservable moderating factors that account for heterogeneity. We thus adopt a latent-class model to simultaneously group countries into homogeneous segments and explain the performance of private labels within each of them. The results reveal that the international market for private labels is characterized by two differentiated patterns in terms of SB performance: (1) In PL-developing countries, store brands are a relatively new phenomenon, not yet part and parcel of consumers' shopping baskets or their consumption habits. In these geographical markets, the more concentrated is the retail market, the more the market power leads to credible and successful PL programs. The price differential in favour of PLs seems not to be a sufficient reason to divert consumers from national brands. In these countries, perceived risk emerges as a critical factor inhibiting consumers to buy PL products. Social and cultural stigmas remain a barrier to PL growth. Products are considered hedonic and viewed as symbols, so where there is a higher standard of living, national brands become more coveted, leading to a lesser demand for private labels. (2) In contrast, in PL-developed countries, customers have been since the 1970s exposed to private labels, and thus are accustomed to them and aware of their benefits. The PL brand has matured, making the PL a ”normal” product. In these economies, the maturity reached by the distribution sector diluted the significant impact that the retail power used to have on PL's performance. On the contrary, the larger the market size the greater the opportunity for PL to seize untapped market potential. Among this group, as a society gets urban and its consumers educated, store brands have a higher propensity to succeed. Consumers are more likely to be utilitarian and purchasing decisions made by lower-income are price driven.

The second essay addresses the issue of the store brand's performance across categories when retailer and/or manufacturer adopt an umbrella branding strategy in two categories. In fact, besides the cross-category dependency due to substitutability or complementarity effects, products can also be linked through their brand name when the manufacturer and/or the retailer use the same name for different products. Such umbrella-branding (UB) strategy allows firms to leverage the reputation attached to a brand name, and to generate savings in brand development and marketing costs. In this work, we assess the umbrella-branding spillovers by investigating the impact of a brand's performance in one category on another category, and vice versa. To do this, we introduce an extended market-share model including a UB spillover effect at the brand level between two complementary categories. Our model brings three contributions by: (i) extending the classical market-share to a cross-category context (ii) measuring the UB spillover effect at the brand level based on aggregated data that are more readily available for retailers and manufacturers and (iii) determining a spillover that is generated by the brand performance and not specific to marketing instruments, as done in the literature. We adopt the multiplicative competitive interaction (MCI) functional form for attraction, and contrast the results in three scenarios: no spillover, brand-constant spillover and brand-specific spillover. To handle the market-share endogeneity, we employ iterate three-stage least squares (I3SLS) to estimate the equations system using two complementary oral-hygiene categories data. The ensuing results indicate that the attraction of SBs, as well as of NBs, in the toothpaste category is boosted by its attraction in the toothbrush category, and vice versa. The brand-specific spillover is asymmetric and associated to the market strength of each competing brand. Moreover, we show that neglecting UB spillovers leads to misestimating the model parameters and has a considerable impact on price-elasticities computation. From a managerial perspective, our findings offer a relevant and straightforward method for decision makers to precisely assess the financial impact of each managerial decision within a cross-category perspective.

In the third essay, we present a generalization of our extended market-share model with brand-spillover effect. We consider more than two categories products. This issue has a substantial usefulness for retailers since SBs are available in almost all packaged-goods category. In fact when bearing the same name, products sold in even independent categories become related in the consumer's mind facilitating the introduction of retailers' new products in categories in which the private label is not yet present. The benefit of the UB comes, however, at the cost of complicating the task of category management and the measurement of the impact of a marketing move such as a price reduction of the PL in one category. Indeed, when promoting their store brand in a specific category, retailers' main purpose is not simply to induce brand switching within the category and to cannibalize regular sales of the competing national-brands. They also aim to increase sales of the product category, and if possible, generate more store traffic, resulting in higher sales in other product categories as well. Further, retailers are concerned about how their PL market-share is affecting and being affected by their umbrella replicas, and how their own marketing effort in one category affects performance across categories. Besides the generalization in terms of number of categories, our modeling framework includes another source of cross-category dependency caused by joint utilization, purchasing patterns and similar placement. This natural dependency characterizes the spillover at the category level. In a single framework, we simultaneously develop two models: a store-brand market-share model and a category-demand model, to distinctly assess two levels of category dependency, namely, the brand spillover and the category spillover.

Applying our model to store-level data for competing brands that describe sales in five categories (mayonnaise, mustard, frankfurters, cereal and laundry detergent), we find significant positive umbrella-branding effects for the store brand in some of the categories. Interestingly, the store-brand spillover effect is significantly present among even unrelated categories. At the category level, while the demand dependency between complementary categories is obvious, sales interdependence between unrelated categories points to the ability of marketing actions, e.g., promotions, in one category to influence sales in any other categories in the store. In line with the retailer's reality, we use the category and brand spillover measures to assess precisely the impact of a marketing activity on the retailer's global performance across categories in terms of sales and profit. We provide empirical evidence regarding the role of umbrella-branding in strengthening the position of the retailer's brand across categories. However, in term of total profit, this strategy proves to be profitable only when the SB margin is comparable or higher than the NB margin. Retailers would be well-served to develop store-brand tiers that are me-too/premium in addition to a generic PL line, instead of creating uniform umbrella brands. The combination of these two strategies would allow the retailer to improve his brand visibility and customers' store loyalty through the lure of the financial savings offered by generic store-brands while me-too/premium store-brands allow him to increase PL sales and market shares across categories.

Chapter 1

Cross-Country Differences in Private-Label Success

Abstract

Why do private labels (PLs) enjoy a large market in some countries while hardly penetrating others? What makes a market favourable to PL-product development? Can we identify drivers that explain differences between countries in terms of PL performance?

This study aims at addressing these relatively less-researched questions in international marketing literature. This paper overcomes this shortage and offers insights into international market mechanisms for private-label performance, providing an empirical guide for managers of determinants to consider when evaluating diverse international markets. We empirically investigate the factors behind these disparities, using a large, cross-country, time-series dataset and following a comprehensive approach including a number of relevant economic, social and cultural determinants. In deriving the model, we assume that countries belong to a finite number of groups and that, in addition to the available variables, exist unobservable moderating factors that account for heterogeneity. By adopting a latent structure formulation, we allow for the creation of latent-country segments in order to capture the potential heterogeneity among markets and outline their underlying determinants in terms of PL adoption. Our approach combines market structure, country segmentation and the sensitivity of potential factors in a unique framework.

Our results uncover that the international market for private label is characterized by two distinct, yet interesting patterns.

Key Words: Private Label, International markets, Censored model, Unobserved heterogeneity, Latent structure analysis.

1.1 Introduction

Private labels (PLs), which are brands controlled and sold exclusively by retailers, are no longer a marginal phenomenon in retailing. The PL industry is approaching US$1 trillion in annual sales (Bone and Collins 2008) and, as the recession of 2008-09 deepened, the industry experienced spikes in sales and product introductions. Worldwide, the largest markets for private labels are found primarily in Europe and North America. In 2007, private label spending in the United States reached just over US$94 billion and European Union spending was over US$365 billion (Bone and Collins 2008). In 2010, consumers spent 14.9% of the total value of sales on private labels (AC Nielsen 2010). Least recently, AC Nielsen (2005) conducted the only international investigation about performance factors, based on sales data for 80 categories of consumer packaged goods in 38 countries. It was found that growth rates for PLs outpaced those of manufacturers in nearly two-thirds of the countries studied (26 of 38). These averages hide some large disparities between regions around the globe. Indeed, whereas the PL market share is 23% in Europe, it is 16% in North America (i.e., 30% lower than in Europe), and it barely reaches 4% in some Asian markets. We also observe large differences within regions. To illustrate, the market share of PLs was 3.8% in Greece in 2005 and more than eleven times that in Switzerland (45% to be precise). New Zealand and Australia have a much higher performance level of PLs than Asian Pacific countries (e.g., South Korea, Thailand, Singapore). In terms of the growth rate of PL sales, while the performance was remarkable in the emerging markets of Croatia, the Czech Republic, Hungary, Slovakia and South Africa (11% increase in 2003 compared to 2002), it was comparatively modest in Latin America (5%).

The above numbers quite naturally trigger the following research questions:

1. Why did PL succeed in consolidating their position and reach maturity in some countries (e.g., Switzerland, Germany and the United States), while they are still struggling to enjoy a respectable position in other markets (e.g., Thailand, Turkey, Mexico)?

2. Why do PLs enjoy a much higher market share in Switzerland and the United Kingdom than in the United States? More generally, what makes a market more favorable than another for PL product performance?

3. Are there groups of countries that are differentiated in terms of PL performance drivers?

By answering these questions, our paper aims to redress the paucity of research into the cross-country private-label consumption, by providing a unique view of the factors leading to the growth of PL business in different markets. We aim at providing an empirical guide for managers of determinants they should consider when evaluating diverse international markets. For this purpose, we use a large, time-series dataset for PL sales in 54 countries. We adopt a latent-class model that allows us to simultaneously group countries into homogeneous segments and explain the performance of private labels within each of them. Our results reveal that the international market for private label is characterized by two distinct patterns.

In PL-developing countries, store brands are a relatively new phenomenon, not yet part and parcel of consumers' shopping baskets or their consumption habits. In these geographical markets, the more concentrated is the retail market, the more the market power leads to credible and successful PL programs. The price differential in favour of PLs seems not to be a sufficient reason to divert consumers from national brands. In these countries, perceived risk emerges as a critical factor inhibiting consumers to buy PL products. Social and cultural stigma remain a barrier to PL growth. Products are considered hedonic and viewed as symbols, so where there is a higher standard of living, national brands become more coveted, leading to a lesser demand for private labels.

In contrast, in developed countries, customers have been since the 1970s exposed to private labels, and thus are accustomed to them and aware of their benefits. The PL brand has matured, making the PL a "normal" product. In these economies, the maturity reached by the distribution sector diluted the significant impact that the retail power used to have on PL performance. On the contrary, the larger the market size the greater the opportunity for PL to seize untapped market potential. Among this group, as a society gets urban and its consumers educated, store brands have a higher propensity to succeed. Consumers are more likely to be utilitarian and purchasing decisions made by lower-income are price driven.

The rest of the paper is organized as follows: In Section 2, we review the literature, and in Section 3, we develop our model. In Section 4, we introduce the estimation methodology, and present the results in Section 5. Section 6 concludes with some managerial implications and future suggestions.

1.2 Literature Review

Few studies have been conducted on private labels outside the US and Europe, and even fewer have attempted to explain disparities in PL performance across different countries. In a recent literature survey, Hyman, Kopf and Lee (2010) reviewed 60 empirical studies and concluded that nearly 75% of them have used data totally or partially collected in the US. In the following paragraphs, we report the main findings of the sparse literature on PL performance in international markets.

Retail power. Comparing the US to some European markets, AC Nielsen (2005) associated the higher market penetration of PLs with the higher concentration of national chains in most West European countries. To illustrate, the top five chains command only 21% of national supermarket sales in the US versus 62% in the United Kingdom. More generally, of the ten most developed PL countries, nine had retailer concentrations of over 60% (AC Nielsen 2005). The concentration argument was put forward earlier by Hoch (1996) when comparing the US to European markets. Within Europe, Leeflang and Raaij (1995) also attributed large differences in PL's shares between different countries to retail concentration and to consumer appreciation of strong manufacturer brands. Several other studies (Tarzijan 2004; Erdem, Zhao and Valenzuela 2004; Gómez and Benito 2008) obtained similar result and argued that private-label performance is due to the degree of retailer power over suppliers. In the same vein, Burt (2000) explains the difference between retail brand development in the UK and US by the attitudinal and behavioral changes in the use of market power in the distribution channel, the centralization of management activities and the development of the retailer as a brand.

Although the positive relationship between retail power and PL performance holds in general, some exceptions exist, such as Australia. Indeed, Nenycz-thiel (2011) observed that whereas two retailers, Coles and Woolworths, hold a massive 74% of the Australian grocery market, the PL performance is only 24%, a level that lags behind other countries with much lower retailer concentration.

In terms of retail format, it was found that private-label products are much more prevalent in large grocery stores such as supermarkets than in small outlets. In markets where a large chain retailer dominates (versus a more fragmented competitive retail environment), PLs have a higher share compared to national brands.[1] Along the same lines, an increase in the number of chains of hard discounters (e.g., Aldi and Lidl in Europe) that mainly offer PL, also contributes significantly to the growth of PLs. A notable exception to this line of reasoning is South Korea, where the number of hypermarkets grew from 4 to 113 between 1994 and 1999, without any significant impact on PLs' market share (less than 1%).

Consumer behavior and culture. Hofstede's (2001) theory of cultural dimension describes the effects of a society's culture on the values of its members, and how these values relate to behavior. Based on this observation, many studies investigated empirically the impact of culture on product acceptance. Erdem, Zhao and Valenzuela (2004) conducted an empirical study on consumer choice behavior with respect to store brands in the US, UK and Spain. The authors found that consumer uncertainty about quality, consumer learning and perceived risk play an important role in consumers selecting PLs and contribute to differences in the brands' strength across the three countries. Lupton, Rawlinson and Braunstein (2010) compared the US and Asia (respectively, Thailand and China) on some attitudinal and behavioral factors associated to shoppers' PL acceptance or rejection. They obtained that Asian markets face a significant delay with respect to the US in terms of consumerism and modern marketing strategies, which has led to different consumer beliefs and perceptions about PLs. The authors concluded that poor market knowledge, a lack of understanding of private-label products and the tendency of Asian consumers to infer product quality through extrinsic cues such as high price were the principal factors in the retail-grocery shopping differences between the Western individualistic and the Eastern cultures. In a collectivist culture, consumers may be reluctant to offer PL products for fear of losing face. Actually, the role of culture as a determinant of the success or failure of PLs has been considered in few studies.

[1]See: United States PL food market, forecasts to 2013.

Herstein and al. (2012) investigated the association between three personality traits (individualism, materialism and the "need for cognition") and shoppers' predisposition to buy private-label brands, across four Mediterranean countries. They concluded that those personality traits, and more generally, culture affect consumers' preference for private versus national brands. The propensity to purchase private brands was negatively associated with materialism and positively associated with the need for cognition. There was no association with individualism. In their research, Lupton, Rawlinson and Braunstein (2010) noticed that, collectivist culture (China) and, individualist culture (US) had significant differences when addressing beliefs and perceptions concerning private-label brands. Chinese consumers believe that private-label food products may be of inferior quality compared to manufacturer brands. Additionally, Chinese either do not have an understanding of private-label products, or private-label names are not recognized as such. Finally, based on advertising expenditures in 37 countries, Deleersnyder et al. (2009) found that private-label growth is lower in countries deemed to be high in uncertainty avoidance.

Socio-demographics. In the absence of studies dealing with socio-demographic determinants in the performance of store brands in an international context, we dig in the literature dealing with socio-demographic factors in (mainly) the US market for some clues. Glynn and Chen (2009) found income, education and household size to be inhibitors of private-label products purchasing. Concerning the impact of revenue on PL performance, several authors stated that households with higher incomes are less likely to buy PLs (Hoch 1996; Ailawadi, Neslin, and Gedenk 2001). Lamey et al. (2007) investigated the link between PL success and the economic situation and confirmed the conventional wisdom that a PL's share increases when the economy is suffering (i.e., less disposable income to households, and hence more bargains searching) and shrinks when the economy is flourishing.

Research conclusions about the impact of education on PL performance are mixed. Glynn and Chen (2009) found a negative relationship between PL performance and education level. In fact, the latter is highly correlated with income, and therefore, highly educated people have a higher disposable income and can afford to buy manufacturers' brands. In contrast, other studies have shown that well-educated consumers are more confident in their evaluative ability with regard to products and have a higher tendency to purchase private brands (Hoch 1996). Herstein and al. (2012) argued that a high need for cognition is associated with a high inclination to purchase private brands. That suggests that well-educated individuals, who are inclined to analyze and process product-related information, are more likely to appreciate the cost-benefit advantage of private brands. In contrast, individuals with a low need for cognition are less confident in their evaluative ability with regard to products, and therefore, are more likely to base their evaluation on such brand characteristics as the manufacturer's identity.

As we can see from this overview of the literature, very little is known about what explains the variability of PL performance in international markets. In their literature review, Hyman, Kopf and Lee (2010) invited research effort in this direction when they wrote:"...Studies on inter-country differences in private label brands usage are needed." This study attempts to fill this important gap in the literature.

1.3 Model Specification

Based on our literature review, we postulate that the performance of a private label depends on (i) the retailing context, (ii) the culture reining in the country, and (iii) some socio-demographic variables. In compact form, our model reads as follows:

$$y_i = (R_i, S_i, C_i)\,,$$

where i is the country index; R_i a vector of retailing drivers; S_i is a vector of socio-demographic variables, and C_i a vector describing some culture facets. The PL performance y_i is measured by the market share of the private label in the product category. Obviously, many other measures of performance are (theoretically) available, e.g., sales, profitability. We retain market share because it has the huge advantage of being independent of measurement units, in particular of currencies, which avoid us some serious difficulties and errors when converting the data to a common currency. We shall interchangeably use performance and market share throughout the paper.

1.3.1 Explanatory Variables and Hypothesis

In the next paragraphs, we provide a conceptual justification to our model specification, and state the hypothesis to be verified empirically from the data made available from Datamonitor.

Retail Variables

Following the literature under this heading , we include retailer power and market size of the category.

Retailer Power. We hypothesize that retailer power has a positive impact on PL performance. Before stating how this variable is measured, it is relevant to recall the main three reasons explaining why retailers move into PLs. First, they typically yield higher margins than manufacturers' national brands (Hoch and Banerji 1993; Baltas 1997; Ailawadi and Harlam 2004). Second, PLs have the potential to increase store traffic, build store loyalty and thus enhance chain profitability (Baltas, Doyle, and Dyson 1997; Ailawadi, Pauwels, and Steenkamp 2008). Finally, PLs provide the opportunity of capturing untapped segments or stealing value-conscious consumers away from the national brands (Connor and Peterson 1992). Aside from these direct economic benefits to retailers, other studies have seen the private label as a strategic move for retailers to gain bargaining power against manufacturers (Ailawadi and Harlam 2004; Meza and Sudhir 2010).

To design a successful PL program and reap the above-mentioned benefits, the retailer must satisfy the two following intuitive conditions: (i) having access to a sufficiently large market, otherwise economics of scale will not be at work and the bargaining power with the providers will be low; and (ii) having financial means to develop and market its (store) brand. Retailers fulfilling these a priori conditions are obviously chain stores, that is, supermarkets, hypermarkets and warehouse clubs. Consequently, we adopt the following (relative) measure of retailer power:

$$\text{Retail power (RP)} = \frac{\text{Sales by chain stores (supermarkets, hypermarkets and warehouse clubs)}}{\text{Total sales of the product category}}.$$

As retail power adequately describes the retail landscape in terms of attractiveness for private label programs, our first hypothesis reads as follows:

Hypothesis 1. The private-label performance is positively related to retailer power, given by the share of sales made by chain stores.

Expenditure per capita for the category. We learned from the literature that looked at the success factors of PLs in (essentially) the US market that the size of the product category matters.[2] Indeed, Hoch et al. (1995) concluded that differences in market size have a significant impact on PL sales, implying that product categories with large sales are good terrain for launching and developing PLs. More specifically, the authors stated that categories with high household penetration and purchase opportunities are propitious to substantial private-label market shares. Hoch and Banerji (1993) obtained that PL shares are higher in categories with higher dollar sales. Based on this, we conjecture the following:

Hypothesis 2. The private-label performance is positively related to the expenditure per capita allocated by households to the category.

Socio-demographic Variables

According to the literature and based on available data, three variables are included as socio-demographic determinants of PL performance, namely, Gini index, educational level and urban population.

Gini Index. is a measure of inequality in income distribution (World Bank 2012), which takes its values in the interval $[0, 1]$, with a value of zero expressing perfect equality (everybody has the same income), and a value of one meaning maximal inequality among values (e.g., only one person has all the income). Countries (or cultures) characterized by social hierarchy tend to emphasize social class (Deleersnyder, Dekimpe, and Steenkamp 2009) making consumers motivated by the need to signal the class to which they belong or to which they aspire. As in hypersignified societies brands seems to have become major conduits to express class differences and social aspirations, we expect distinctions between social and economic classes to play an important role in the PL performance among countries.

[2] For an analysis of strategic interactions between PLs and national brands, see, e.g., Cotterill and al. (2000).

By assessing the distance between the "have" and "have-nots", the Gini index would indicate PL success among shoppers with the lowest disposable income (Glynn and Chen 2009). Our fourth hypothesis reads then as follows:

Hypothesis 3. The private label has a higher market in countries high in term of income distribution inequality.

Urban population. Due to its density of wealth, proximity, homogeneity and modernity, the urban market seems to be more profitable for large firms than the rural market (Ireland 2008). Similarly, urban agglomeration leads to greater market efficiency with larger and more varied supply of products and services to consumers (Talukdar, Sudhir, and Ainslie 2002). These intuitive arguments imply that countries characterized by higher urbanization rates are more attractive to PLs. Urban population is in relative term, that is, expressed as percentage of total population.

Hypothesis 4. The private-label performance is positively associated with a country's level of urbanization.

Literacy rate among adults. We measure education by the literacy rate among adults. While some authors (Richardson 1996; Hoch 1996; Herstein et al. 2012) suggest that well-educated individuals are very likely to appreciate the cost-benefit advantage of private brands, and prefer them to national brand, some other authors (Glynn and Chen 2009) consider education an index of wealth and state its negative impact on PL performance. In light of these conflicting results, we test the following hypotheses:

Hypothesis 5a. Educational qualifications have a positive impact in the performance of private label within international markets.

Hypothesis 5b. Educational qualifications have a negative impact in the performance of private label within international markets.

Cultural Variables

This variable is a direct transposition to an international context of the idea (and results) that consumers buy PLs when they perceive a low risk of making a mistake in brand choice (Batra and Sinha 2000).

Uncertainty avoidance, a variable that takes its values in the interval $[0, 100]$, refers to the degree to which the members of a society feel threatened by uncertain, risky, ambiguous or undefined situations, and the extent to which they try to avoid such situations by adopting strict codes of behavior (Hofstede 2001, p.161). In uncertainty-avoiding cultures (with scores approaching 100), consumers try to minimize the possibility of such situations through strict rules and through safety and security measures. According to Bao et al. (2011), the higher the preference for certainty, the greater the aversion to risk and the lower the tolerance for risk. One of the consumer benefits generally attributed to national manufacturer brands is that they reduce consumer risk, because national brands are perceived to have less variability in product quality than do PL brands (Burton et al. 1998). While many studies treat "perceived risk" as a single construct to predict consumer preferences for PLs, Dunn, Murphy and Skelly (1986) considered it instead a multidimensional phenomenon. According to the authors, the functional risk (the PL does not perform) and the financial risk (wasting money) appear to be important factors when buying supermarket products. On the other hand, the social risk (the PL may not be good enough for my friends) is much smaller and seems to be a relatively minor factor in PL buying behavior. More recently, Mieres, Martín, and Gutiérrez (2006) concluded that risk aversion negatively moderates the effect of store image, resulting in unsuccessful PL programs. This suggests that, since private labels involve purchase risks, risk-averse consumers are more likely to be more cautious in evaluating this type of brand and thus they may be less receptive to PL brands. Based on these arguments, we expect that a low threshold of uncertainty avoidance in a country will show a large social acceptance of new phenomenon, providing solid foundations for a successful PL environment.

Hypothesis 6. The private-label performance is negatively associated with a country's uncertainty-avoidance.

1.3.2 Data

The data is obtained from Datamonitor and concerns yearly brand sales from the "household products category".[3] The data consists in both national brands and private-label sales over a 6-year period, from 2005 to 2010. Fifty four countries in 6 geographical regions are covered (see Table 1.1): 24 European countries, 3 North-American countries, 7 South-American countries, 14 Asian countries, 4 African countries and Australia and New Zealand from Oceania. For the considered product category, the private label had not been introduced in 17 of these 54 countries (see Table 1.2).

Table 1.1 Countries included in the analysis

	Countries
Africa	*Egypt**, *Morocco**, *Nigeria**, South Africa
Asia	*China**, Hong Kong, *India**, Indonesia, *Israel**, Japan, Malaysia, *Philippines**, Republic of Korea, Saudi Arabia, *Singapore**, *Thailand**, Turkey, *Vietnam**
Europe	Austria, Belgium, Bulgaria, *Croatia**, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Italy, *Lithuania**, Netherlands, Norway, Poland, Romania, Russia, Spain, Sweden, Switzerland, *Ukraine**, UK.
North America	Canada, Mexico, US
Oceania	Australia, New Zealand
South America	*Argentina**, *Brazil**, Chile, Colombia, Peru, *Uruguay**, *Venezuela**

*Countries** refer to those where the PL was not introduced during the analyzed period.

For each of the 54 countries, we aggregate sales for the household-products category across ten distribution channels[4], in order to account for the total retail-sales in a country. Sales generated by the private label in all the distribution channel were grouped to account for the private label sales.

$$\text{Private Label market share in a country} = \frac{\text{Private label sales for the category}}{\text{Total retail sales for the category}}.$$

[3]The category includes bleach, toilet care, dishwashing products, general purpose cleaners and paper products.

[4] (Supermarkets / hypermarkets, Independent retailers, Convenience stores, Cash & Carry, Warehouse clubs, Pharmacies / drugstores, Service stations, Department stores, Other)

Table 1.2 reflects the disparity of the private-label performance between countries. Table 1.3 provides some descriptive statistics.

Table 1.2 PL performance for the household products category

Highest PL performance	Market Share 2010 (%)	Lowest PL performance	Market Share 2010 (%)
Switzerland	44.92	Japan	0.07
Spain	42.21	Malaysia	0.08
Denmark	36.06	Estonia	0.22
Germany	35.59	Chile	0.25
France	35.37	Republic of Korea	0.30
Sweden	35.06	Hong Kong	0.40
United Kingdom	34.95	Colombia	0.50
Belgium	27.53	Russia	0.95
Canada	26.74	Peru	1.59
Austria	24.75	Indonesia	1.69

Independent variables in the present empirical analysis were made available from the same database as the dependant variable, that is, Datamonitor. All the variables, except Uncertainty avoidance index, are time varying on the 2005-10 period.

Table 1.3 Descriptive statistics

	N	Min	Max	Mean	St. deviation
Dependant Variable					
PL market share (%)- 37 countries	222	0.08	44.9	14.5	13.6
PL market share (%)- 54 countries	324	0.00	44.9	9.9	13.1
Independant Variables					
Retailer Power (%)	324	3	86.8	51.0	23.2
Expenditure per capita for the category ($)	324	0.5	97.9	33.6	27.2
Uncertainty avoidance index	300[5]	8	112	65.0	23
Gini Index	324	23	66	37.4	9.5
Literacy rate among adults (%)	324	52	100	94.0	9.5
Urban population (%)	324	25.6	100	71.15	17.1

[5]Observations are missing for four countries included in this study.

1.4 Methodological Framework

In this section, we introduce our modelling approach for the censored dependent variable and the latent-class model. It is important to note that, even if we are addressing the reasons beyond the PL introduction, we are not trying to model the product adoption cycle. We investigate the effect of several factors on the performance achieved by the store brand through countries, given that the product has already been introduced.

1.4.1 Censored Dependent Variable

As stated above, the dependent variable is the market share of the private labels for a product category, namely "household products" in each of the 54 countries in our database. A first decision to make is how to treat zero values.

In fact, a private label is launched only if its performance (in terms of market share, profit, sales, etc.) is expected to exceed a certain threshold. This threshold may be known or, more generally, may indicate some unobserved level of information at the retailer's disposal. When this threshold is not expected to be reached, then the PL is not launched, and a zero market-share value is recorded. In our data, the PL enjoys a 45% market share in the household products category in Switzerland but no PL is offered in this category in, e.g., Argentina, Vietnam or Croatia. One option is to exclude the 17 countries, where the PL was not introduced, and retain only those where PLs have a strictly positive market share. But, ignoring null dependent-variable observations leads to a selection bias and thus to biased estimates. Following an established literature in economics and statistics on limited dependent variables (Greene 1983; Maddala 1983), our approach includes the modelling of the portion of zeros characterizing the absence of a PL market share in some countries. The censored regression model in which the PL market share is censored (at zero, without loss of generality) can be expressed as

$$y_i^* = X_i\alpha + \mu_i, \qquad i = 1, \ldots, I, \tag{1.1}$$

where the random variable y_i^* is a partially latent variable whose observed value, y_i, is concentrated at zero when it is nonpositive. Hence,

$$y_i = \begin{cases} y_i^* & if\ y_i^* > 0, \\ 0 & if\ y_i^* \leq 0, \end{cases} \tag{1.2}$$

where y_i is the value of the observed censored dependent variable for country $i, i = 1, \ldots I$. In (1.1), X is the vector of D explanatory variables ($d = 1, \ldots, D$) for country i, and α is the vector of regression coefficients for these explanatory variables. The error terms μ_i are assumed to be iid drawn from a normal distribution, and σ its standard deviation. Note that y_i and X_i are known for each country i, but y_i^* is unobserved if it is nonpositive (i.e., $y_i = 0$) and is therefore partially latent. Once the performance of the PL in the category is continuous but observable only on an interval, then y_i is the value of the censored dependent variable for a given product category in country i. Under the normality assumption of the error term μ_i, we have

$$\begin{aligned} Pr\left[Y_i = y_i\right] &= Pr\left[\frac{\mu_i}{\sigma} = \frac{Y_i - X_i\beta}{\sigma}\right] = f\left(\frac{Y_i - X_i\beta}{\sigma}\right), \\ Pr\left[Y_i^* \leq 0\right] &= Pr\left[\frac{\mu_i}{\sigma} \leq \frac{-X_i\beta}{\sigma}\right] = 1 - \Phi\left(\frac{X_i\beta}{\sigma}\right). \end{aligned}$$

The expected value of

$$y_i = E(y_i) = Pr(y_i^* > 0).E(y_i|y_i^* > 0),$$

and the conditional expectation is given by

$$E(y_i|y_i^* > 0) = X_i\beta + E\left(\mu_i|\mu_i > -X_i\beta\right) = X_i\beta + \sigma\left(\frac{\phi\left(\frac{X_i\beta}{\sigma}\right)}{\Phi\left(\frac{X_i\beta}{\sigma}\right)}\right),$$

where $\phi(.)$ and $\Phi(.)$ are the density and distribution functions, respectively, of a standard normal variable. We recall that OLS regression is inappropriate when a dependent variable is censored, because it would lead to biased and inconsistent estimator, regardless of whether all the observations or only the positive observations are used. Using the normality assumption, the log-likelihood can be expressed as

$$\ln L = \sum_{i:y_i=0} \ln \left\{ 1 - \Phi\left(\frac{X_i\beta}{\sigma}\right) \right\} - \frac{1}{2} \sum_{i:y_i>0} \left\{ \ln 2\pi\sigma^2 + \frac{(y_i - X_i\beta)^2}{\sigma^2} \right\}. \tag{1.3}$$

1.4.2 Inter-Country Heterogeneity: A Modelling Approach

The literature review revealed some conflicting conclusions about the effect of some variables. For instance, the retail power was determinant in explaining the PL performance in some countries, while its impact was absent in some other markets. Even more, education was found to have a positive impact on PL performance in some studies, and a negative impact in some others. We conjecture that these conflicting conclusions are the result of some heterogeneity across countries, and not (only) due to differences in samples and research designs.

The quantitative marketing literature has handled the heterogeneity in two ways. The random effect approach would have allowed correcting for heterogeneity by assessing a specific coefficient to each country. In our case, this method would come at a huge cost in terms of number of parameters to estimate, while our number of observations is relatively reduced. More importantly, the random effect approach would allow comparisons between countries individually based on the random effects, making the interpretation irrelevant four our study purpose. Since it is more appropriate to compare groups of countries, and in accordance with McCutcheon and Hagenaars (2002), we favour the latent-class approach. The latter assumes that countries belong to a finite number of relatively more homogeneous classes or market segments (k) and that, in addition to the available variables, there exist discrete unobservable moderating factors that account for heterogeneity.

Specifically, the model considers the countries where the PL is launched (non-censored observations) and determines simultaneously the country segments [6] as well as the parameter estimates. In summary, countries classified in the same latent class tend to be similar to one another in terms of the associations between PL market share and outcome variables. Thus, the proposed model provides the effect of the variables by class, and assigns each country to

[6] Countries classification into groups is not induced by the PL performance (dependent variable) heterogeneity but, rather based on the heterogeneity of the impact of explanatory variables on the PL performance.

a given cluster, all simultaneously in a maximum likelihood framework. Such approach was used in, e.g., DeSarbo and Choi (1999), and Helsen, Jedidi, and DeSarbo (1993).

Unlike the conventional segmentation, the latent-class approach is preferable in our context. A prior segmentation followed by multi-group equation modelling would assume the homogeneity of a single population in the first step, while the second step would rest on the heterogeneity of multiple groups. Also, available clustering methods do not allow for performing a response-based segmentation on the basis of a hypothesized model structure (Jedidi, Harsharanjeet, and Wayne 1997).

In order to formulate a latent structure model for grouping countries into a small number of classes or market segments, and estimating different parameter vectors for each class, it is assumed that there are k $(1 \leq k \leq K)$ mutually exclusive and distinct international market segments. Each country i is assumed to belong to only one segment that is not known in advance. Given k different classes, the prior probabilities of country i belonging to each specific segment are expressed in a vector λ, as $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_k)$.

Assuming that the probability density function for the latent random variable, Y_i^*, is distributed as a finite mixture of conditional univariate normal densities, $f(.)$, that is,

$$Y_i^* \sim \sum_{k=1}^{K} \lambda_k f(Y_i^* \mid X_i, \sigma_k^2, \beta_k) = \sum_{k=1}^{K} \lambda_k \frac{1}{\sigma_k} \phi \left(\frac{Y_i^* - X_i \beta_k}{\sigma_k} \right),$$

where

- $k = 1, \ldots, K$ latent segments/classes,
- β_k : vector of regression coefficients β_{dk} for D explanatory variables $(d = 1, \ldots, D)$ for latent class k,
- σ_k^2 : variance parameter for latent class k,
- $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_k)$, vector of $K - 1$ independent mixing proportions indicating the probability for the country to belong to latent class k. Let us note that $\lambda_k > 0$ and $\sum_{k=1}^{K} \lambda_k = 1$,
- $\phi(.)$: the standard normal density.

1.4.3 Within Countries Correlation

As the performance of the private label in a given country is observed at repeated times, the response variable at any one time may be correlated with the response variable at another time. To handle this longitudinal aspect, we assume that for country i, the PL market share is possibly correlated between the observed $t = (t_1, t_2, \ldots, t_6)$ years. For $K = 1$, Maddala (1983, p.153; Helsen, Jedidi and DeSarbo, 1993) wrote the distribution of the censored dependent variable Y_i as follows:

$$h(Y_i \mid B, \Sigma, \lambda) = \sum_{k=1}^{K} \lambda_k \left[\left(1 - \Phi\left(\frac{X_i \beta_k}{\sigma_k} \right) \right) \right]^{1-\delta_i} \cdot \left[\frac{1}{\sigma_k} \phi \left(\frac{Y_i - X_i \beta_k}{\sigma_k} \right) \right]^{\delta_i}, \tag{1.4}$$

where

$$\delta_i = \begin{cases} 1 & \text{iff } Y_i > 0 \\ 0 & \text{iff } Y_i = 0, \end{cases}$$

$\Phi\,(.)$: the distribution function of the standard normal,

$B = (\beta_1, \ldots, \beta_K)$: the parameters for the K different international market segments, and,

$\sum_k$: the variance-covariance matrix for the kth market segment, so that we take into account the correlation driven by the repeated measures.

$$cov\,[Y] \;= \sum = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \ldots & \sigma_{1t} \\ \sigma_{12} & \sigma_2^2 & \ldots & \sigma_{2t} \\ \ldots\ldots & \ldots & \ldots & \ldots \\ \sigma_{1t} & \sigma_{2t} & \ldots & \sigma_n^2 \end{pmatrix}; \quad corr\,[Y] = \;\; \rho = \begin{pmatrix} 1 & \rho_{12} & \ldots & \rho_{1t} \\ \rho_{12} & 1 & \ldots & \rho_{2t} \\ \ldots\ldots & \ldots & \ldots & \ldots \\ \rho_{1t} & \rho_{2t} & \ldots & 1 \end{pmatrix}$$

Hence for a given category, assuming a sample $Y = (y_1, y_2, \ldots, y_I)$ drawn from a mixture of censored conditional normal densities $h(Y_i \mid B, \Sigma, \lambda)$, the likelihood function, is given by

$$L = \prod_{i=1}^{I} h(Y_i \mid B, \Sigma, \lambda). \tag{1.5}$$

Given the constraints imposed above on λ and all elements of the vector $\Sigma > 0$, the observed X and Y and the specified value of K, we maximize $\ln L$ in (1.4) to estimate B, Σ and λ. This is achieved through an E-M algorithm (Dempster, Laird, and Rubin 1977) by iteratively alternating between an E-step (expectation step) and M-step (maximization step). In the E-step, the estimated parameters $\hat{\beta}_k, \hat{\sigma_k}$ and $\hat{\lambda_k}$ make it possible to compute the posterior probabilities of membership, $\hat{P}_{ik}$,

$$\hat{P}_{ik} = \frac{\left[\hat{\lambda}_k \left(1 - \Phi\left(\frac{X_i\hat{\beta}_k}{\hat{\sigma}_k}\right)\right)\right]^{1-w_i} \cdot \left[\frac{\hat{\lambda}_k}{\hat{\sigma}_k}\phi\left(\frac{Y_i - X_i\hat{\beta}_k}{\hat{\sigma}_k}\right)\right]^{w_i}}{h(Y_i \mid \hat{B}, \hat{\Sigma}, \hat{\lambda})}, \tag{1.6}$$

of each country i into each of the K latent classes, by assigning each country i to the latent class whose $\hat{P}_{ik}$ is the highest. Note that $\sum_{k=1}^{K} \hat{P}_{ik} = 1$. Those posterior probabilities of membership are used to subsequently compute the mixing proportion λ_i. Then, the estimation moves to the M-step, where the log-likelihood function is maximized with respect to the latent structure parameters B and $\sum$. We continue to alternate between these two steps iteratively by applying an updating rule until convergence.

1.5 Results and Analyses

Consistent with the latent-class segmentation approach, we estimated the model assuming a fixed number of segments. On the basis of changes in model fit statistics (Bayesian information criterion (BIC)), we determined the appropriate model specification. This criterion is given by

$$BIC = \ln L - \frac{m}{2} \ln N,$$

where $\ln L$ is the log-likelihood function given in (1.3), m the number of parameters and N the number of observations (324 in this study). The model with the lowest BIC indicates the best number of segments to use. Based on the information in Table 1.4, and later confirmed by the results of segments description, we retain a two-segment configuration. (All solutions with more than three segments yield a larger BIC value.)

Table 1.5 summarizes the estimation results for the one-segment OLS model, the one-segment censored-data model and the two-segment latent-class model. A comparison of the two one-segment models shows that the OLS model underestimates the coefficients of the explanatory variables. A manager using this (here) naive model would significantly

Table 1.4 Fit of latent class models

	One segment	Two segments	Three segments
Log-likelihood	-912.1	**-720.7**	-509.2
Parameters	8	**17**	26
BIC	1,855.7	**1,508.2**	1,520.7

understate the sensitivity of PL performance to literacy rate, as well as to the Gini index in a given country. Further, we observe that with an R^2 of 0.863, the explanatory power of the two-segment latent-class model is much higher than the two others.

Table 1.5 Parameters estimates

	One segment				Two segments			
	OLS		Censored data		Segment 1		Segment 2	
	Parameter	s.e.	Parameter	s.e.	Parameter	s.e.	Parameter	s.e.
Intercept	12.47^*	6.81	-25.62^*	12.71	54.07^*	6.66	-68.54^*	24.86
Retail power	3.60	4.37	4.23	5.52	14.17^*	2.23	-10.03	5.62
Expenditure per cap. for the category	1.18^*	1.77	12.54^*	2.19	0.81	1.00	10.81^*	2.11
Gini Index	36.21^*	6.90	39.89^*	8.57	1.60	3.14	57.59^*	11.07
Urban population	-4.86	4.10	-4.60	5.41	-39.22^*	2.23	29.30^*	6.89
Literacy rate	6.63^*	7.46	43.99^*	13.46	-26.24^*	6.52	83.79^*	24.33
Uncertainty avoidance	-1.88	2.42	-0.92	3.12	-6.91^*	1.32	1.12	3.29
Error variances	83.46		118.88	11.33	7.74	1.03	53.84	6.93
Segment size (%)	100		100		45.1		54.9	
R^2(%)	52.5		54.5		86.3			

(*) $p< .005$

From these results, we clearly see two different structures in terms of significance and coefficient values of the independent variables. Indeed, we obtain the following for Segment 1: (i) H1, H5b and H6 are verified (retailer power, positive impact of literacy rate and uncertainty avoidance), (ii) H4 is rejected (urban population is significant and opposite direction), and (iii) the expenditures per capita and Gini index (H2 and H3) are not significant variables. For Segment 2, we obtain that H2, H3, H4 and H5a are verified and that retail power and uncertainty avoidance are not significant variables. To shed a light on these results, we provide the composition of the two segments where the PL was available in Table 1.6, and some descriptive statistics in Table 1.7.

Two details should be highlighted from Table.7. First, it's important to notice that, although the average of PL performance is lower for the first segment, both segments consist of performers and less performers in terms of PL market share. Second, note that while urban

Table 1.6 Composition of segments

Segment 1	Australia, Bulgaria, Chile, Columbia, Estonia, Greece, Hong Kong, Ireland, Japan, NZ, Peru, R. of Korea, Romania, Russia, Saudi Arabia, South Africa, Turkey.
Segment 2	Austria, Belgium, Canada, Czech R., Denmark, France, Germany, Hungary, Indonesia, Italy, Malaysia, Mexico, Netherlands, Norway, Poland, Spain, Sweden, Switzerland, UK, US.

Table 1.7 Segments description

	Segment 1				**Segment 2**			
	Min	Max	Mean	Std	Min	Max	Mean	Std
Private label share (%)	0.07	19.43	4.01	5.23	0.08	44.92	23.46	12.18
Retailer Power (%)	20.40	86.75	52.55	20.19	29.20	85.77	61.98	19.53
Expenditure per cap. for the category	7.15	79.74	31.74	23.44	1.40	97.93	51.30	26.57
Gini index	24	66	40.34	10.46	23	49	31.73	7.30
Urban population (%)	53.7	100	73.46	12.12	45.66	97.26	75.42	10.38
Literacy rate (%)	80	100	95.44	5.07	88	100	97.97	3.01
Uncertainty avoidance	29	112	72.82	22.74	23	94	61.65	21.56
Countries (N)	*102*				*120*			

population and literacy rate have comparable averages for both segments, their impact on PL performance is opposite. This is to confirm that the countries classification was not induced by the dependant variable heterogeneity, but by the heterogeneous impact of the explanatory variables on the PL performance.

The geographical breakdown provided by Table.6 shed light on some equivocal results in the literature. As Australia and South Korea are characterized by similar retailing characteristics that of modern-trade countries but witness low PL performance, some previous researches (Nenycz-thiel 2011; Mandhachitara 2007) have considered them as exceptions in modern-trade countries. Our results disprove this exception and explain that both countries obey to a different set of variables governing their PL performance. In the next section, we provide a profiling of the two segments in order to better assess factors conducive to private-labels performance in these two distinct markets.

1.5.1 Segments Description

Segment 1 profile.

The strong growth of large distribution chains and their high level of concentration in these countries give retailers an advantageous position in negotiations with manufacturers. The more concentrated the retail market, the greater the market power of these retailers leads to successful private label programs in these geographical markets (H1). In 2002, a report in international retailing (Global Retail Concentration report) stated that the battlegrounds of the future are likely to be fought in markets such as China, Russia, Japan and Africa. Recently, Howard (2009) confirmed that the emerging markets of Asia Pacific are particularly attractive to international retailers such as Wal-Mart, Tesco, Carrefour, I, Aldi and Seven. Indeed, in 2007 Carrefour opened 23 new stores, the largest number of hypermarkets it has ever opened in one country in a single year.

In this segment, perceived risk emerges as a critical factor influencing consumer intentions to buy PL products. As uncertainty avoidance gets higher, the tolerance to the risk associated with buying a PL decreases, making less likely its purchase by consumers (H6). Social and cultural characteristics in these markets seem to be the probable causes of the difficulty for PL to become a significant part of the consumer's shopping basket. In these countries, products are considered hedonic and viewed as symbols. Famous brand-name products signify class and status among consumers, so social stigma remains a barrier for PL growth. Moreover, these markets exhibit a negative association between PL performance and socio-economic development. If we consider that a higher literacy rate and larger urban population to be positively correlated with revenues, then our result indicates that in these countries, PL performance is decreasing in wealth (H5b and H4). The conjecture here is that where there is a higher standard of living, national brands become more coveted, leading to a lesser demand for private labels.

Countries belonging to the first segment present other interesting features on PL success in terms of PL performance. Against all odds, the potential offered by the market (H2) as well as the revenue inequality (H3) play no role in these markets. This last result can seem intriguing at first sight, but it comes to confirm our previous results. In fact, it would be expected that the inequality of wealth distribution would be conducive to PL success nearby lowest disposable income shoppers. But as these countries are characterized by a hedonic consumption, even low income consumers have the enduring desirability of acquiring and possessing things. The price differential in favour of PLs seems not to be a sufficient reason to divert segment 1 consumers from national brands. In these emerging (Turkey, Chile, South Africa...) and Eastern European developing countries (Bulgaria, Estonia, Romania...), consumers try to imitate the more extravagant consumption of their counterparts in more advanced economies with whom they come into contact.

Segment 2 profile.

The performance of PLs is not attributable to the power of retailers (H1). In the 1990s, retail industry in developed markets (USA, European Union) experienced accelerated levels of globalization until it reached saturation, and is now looking (probably in first segment countries) for growth opportunities. So in these economies, all characterized by a high retailer concentration, the maturity reached by the distribution sector diluted the significant impact that the retail power used to has on store brands performance.

On the contrary, what is decisive is found to be the size of the market. We state that the higher the expenses allocated by households to a product category, the larger the opportunity for PL to seize untapped market potential (H2). Interestingly, literacy rate and urbanity level have a strong positive impact on PL performance (H5a and H4). Among this group, as a society gets urban and its consumers educated, store brands have a higher propensity to succeed. This intriguing result may stem from the fact that highly qualified consumers are more confident about their ability to evaluate the products. Also, as higher education means (normally) higher revenues, well-educated consumers have many opportunities to signal their status other than by purchasing supermarket national brands. The explanation is more obvious when considering the cultural side of these countries. In fact, well-educated consumers are less dependent on the brand name as an extrinsic cue suggesting that they put relatively little importance on brand image. In these markets, product purchases are utilitarian and made in terms of functional considerations related to needs, fundamentals, necessity and problem solving. Further, urban areas are more attractive for large firms (retailers) than rural areas due to their density of wealth, proximity and modernity. As PLs are launched and developed by large retailers, the link between urbanity and PL performance is therefore easy to see. Unlike the first segment, the effect of Gini index is considerably significant suggesting that when the gap between low and high income consumers widens, the penetration of store-brand share gets more important in the country (H3). In these wealthy economies, product purchase is not guided by hedonism, thus the PL represents a convenient way to acquire a product that meets a need at an acceptable cost. This rationality shows that, in these markets, purchasing decisions by lower-income are price driven and that revenue inequality represents an opportunity for PLs diffusion.

1.5.2 Discussion

Our findings help to clarify some unexpected or controversial results in the literature concerning the impact of certain variables on the PL success. For instance, results with respect to education level have been equivocal. Some researchers (Glynn and Chen 2009; Dick, Jain, and Richardson 1996) have found consumers of private labels to be low-educated. Others (Talukdar, Sudhir, and Ainslie 2002; Herstein et al. 2012) have placed them in a higher education category, though no more recent study was found, to deny or confirm that counter-assertion. Dilemma regarding the impact of education on PL purchase motivation is answered by the present work results. It is found that the opposite effects of education are both true providing that we take into account the cultural context of the country where the observation was made. In fact for the first segment, higher literacy rate and larger urban population are positively correlated with revenues making PL performance decreasing in wealth. The conjecture here is that where there is a higher standard of living, national brands become more coveted, leading to a lesser demand for private labels. In these markets, products are considered hedonic and viewed as symbols. Famous brand-name products signify class and status among consumers, so social stigma remains a barrier for private-label growth. This recalls Sudhaman's (2004) finding that Chinese consumers give more importance to brand name, compared to US and European consumers.[7] In the second segment where revenues are higher, well-educated consumers are less dependent on the brand name as an extrinsic cue. In economic terms, our results show that whereas private labels are normal goods in segment 2, they somehow have the status of inferior goods in segment 1. In some sense, we confirm some cross-cultural studies (Leach 1993)[8] showing that materialism (which, in our context,

[7]Branding in China with Latin flair, *Media*, Dec (21).
[8]The Land of Desire

may more modestly be called value-seeking) is more common in the Western-world segment 2. In emerging and Eastern European countries (segment 1), consumers try to imitate the more extravagant consumption of their counterparts in more advanced economies with whom they come into contact.

In the same logic, the degree of maturity of the retailing sector in a country allows providing an explanation to the unexpected absence effect of the retailer power in certain countries. This duality of impact for a same phenomenon (retailer power and uncertainty avoidance) on the PL performance could be explained by the nature of the PL offer itself present in the country. In most Segment 1 countries, store brands are a relatively new phenomenon, not yet part and parcel neither of grocery shopping baskets of the customers neither of their consumption habits. Lupton, Rawlinson, and Braunstein (2010) explained that China is at the same point in the understanding of private label that the USA was approximately 30 years ago. In fact, in these geographical markets, the PL offered is generally of mediocre quality (generic brands) designating products without brand names, in very plain packages with simple labels and low prices (about 30% to 40% lower than NB prices), perceived as of inferior quality compared to national brands with which they compete (Fitzell 1982). In contrast, in developed-PL countries, customers have been lengthily (since the seventies) exposed to private labels, thus accustomed to them and aware of their benefits. The brand has grown up and gained maturity making the PL offer evolve towards an improved quality of PL products. So by the developments in the PL industry in these countries, the positioning of PL products has changed from just being low quality, low price alternatives to premium products (store brands) equal or superior quality compared to their branded counterparts, but usually lower price compared to the leading brand (Gocer and Ala 2006). Consumers perceptions on the quality and value of these PL brands are continuously increasing. In fact, quality has improved so much that almost seven out of ten US consumers surveyed felt that private label brands are as good, if not better than their national brand counterparts (PLMA 2007). That fully explains the lag in terms of retail consolidation between the two segments. It is as if the impulse of retail power needed to launch and develop PLs has already occurred in segment 2, whereas it is still in progress in the countries of segment 1 (Tarzijan 2004; AC Nielsen 2005; Gómez and Benito 2008).

Our findings are in line with some authors' (Talukdar, Sudhir, and Ainslie 2002; Ganesh 1998) statement concluding that cultural factors are found to be critical in the international diffusion process for new products. To sum up, our dual result is interesting for at least two reasons. First, in terms of marketing strategies, it is a reminder that what works in a given cultural setting may not be as successful in another. Second, in terms of methodology choice, this difference fully justifies our adoption of an approach that defines market segment endogenously, and provides information on how these segments differ.

1.6 Conclusion and Managerial Implications

The objective of this study was to explain the variability in performance of private labels in international markets. To the best of our knowledge, this is the first research to be conducted at this scale, i.e., 54 countries, with observations spanning a six-year period. Indeed, whereas almost all available studies focused on US and a few European markets, ours shed light on PLs' acceptance in a much more diversified setting. Our econometric model performs very well statistically and makes it possible to uncover the determinants of PLs' market shares in each market segment. In particular, we obtained that education, degree of retail modernity, uncertainty avoidance and urbanism significantly affect the performance of PLs, but not necessarily in the same way in the two endogenously determined market segments. Although store brands are an essential element in every large retailer's marketing strategy, neither they nor the manufacturers of these PLs know enough yet about their consumers' purchasing predispositions, beyond their socio-cultural profiles. As shown in this paper, cultural and other socio-economic characteristics are influential on PL success, making the rate of PL acceptance differing considerably between regions and across countries within the same region. In some geographical markets (segment 1's countries), PL products seem to be regarded as cheap and low-quality alternatives for branded products. In some other countries (segment 2) retail brands were attracting price-oriented customers, but with the improving emphasis on quality, these products have started to also attract value-conscious customers (Nandan and Dickinson 1994). The need for a complete and in-depth analysis of international variability in launching and positioning PLs was on the research agenda elaborated by Keller and Lehmann (2006). The findings reported here help to fill the gap and redress the paucity of research into the cross-cultural aspect of private-label consumption, by investigating cultural profiles and providing a unique view of the factors leading to the growth of PL business in different markets. While business managers have relatively little influence on such variables, our findings can still serve as an empirical guide for the variables that they should consider in evaluating diverse international markets and for performing sensitivity analysis with respect to their projected trends. Our results suggest that retailers should not take a generic approach to the marketing of their private brands (for instance, a single strategy for the whole Mediterranean region). Managers had better develop differentiated strategies for each country (or culturally similar group of countries) in which the brands are made available. This applies especially to such multinational retail chains as Walmart, Aldi, Carrefour, Tesco, etc. In order to maximize their marketing and sales efforts, retailers offering private brands in developed PL countries (segment 2) should target well-educated consumers by offering products in phase with the customers' utility-maximization decisions. Retailers have an incentive to maintain and enhance their products' quality. More preferably, retailers could expand their offerings to respond to more specific needs than simply offering quality products at lower prices. With PLs that offer healthy organic options as well as financial, insurance and telecommunication services, retailers with strong PL offerings would hardly be challenging the position of branded products in the minds of the consumers. In PL developing countries, customers are being increasingly exposed to private labels through retail expansion and are becoming more aware of their benefits. Still, retailers offering their brands should target consumers who expect to get much more than a good product for a fair price. The offer of PL products must be in line with consumer expectations to reflect their status or "rightful place" in society. Suitable packaging, promotions and advertising strategies can help achieve the appropriate product positioning. Early placement of PL products might better position them for success, as the popularity of brand image changes over time and grocery products will no longer deemed status items. In these developing countries, in order to develop the market and raise interest in store brands, retailers should consider educating their customers by explaining that the quality of the private brand is close or equivalent to that of alternative national brands, at a lower price.

Considering a limited set of variables, we were able to demonstrate that countries could be effectively grouped in terms of PL performance factors. As in any modeling effort, we omitted, by parsimony and for lack of data, some variables that could have possibly increased the explanatory power of the model. In this sense, this research should be seen as an initial step/attempt to explain differences in PL performance across many countries. In terms of other shortcomings that require further investigation, we wish to mention two. First, as usual in this macro-type of study, by describing a country with a single aggregate measure, we dilute the multitude of consumption patterns that could be observed within that same country. This suggests that a two-step segmentation approach, i.e., inter- and intra-country segmentation would be welcomed. Second, as retailers' decision to launch their own label varies across categories, depending on many factors characterizing each of the product categories (high margins, profitability enhancement, bargaining power, etc.), it would be interesting to integrate this first-stage decision into the model in order to explain what affects the PL-introduction decision across cultures and to present a clearer understanding of the whole process of a PL's performance.

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Chapter 2

Umbrella-Branding Spillovers

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.

Keywords: Umbrella branding - Spillover - Store brands - Market share attraction model.

2.1 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.

2.2 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,

$$s_{it}^{c} = \frac{\mathcal{A}_{it}^{c}}{\sum_{j=1}^{m_c} \mathcal{A}_{jt}^{c}}. \tag{2.1}$$

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:

$$\mathcal{A}_{it}^{c} = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}, \quad i = 1, \ldots, m_c, \quad c = 1, 2, \tag{2.2}$$

where α_i^c is the brand-specific constant, β_{ki}^c,$k = 1, 2, ..., K_c$ 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

$$\mathcal{A}_{it}^{c} = \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\gamma^c.s_{it}^{3-c}\right), \quad i = 1, \ldots, m_c, \quad c = 1, 2, \tag{2.3}$$

where α_i^c is the brand-specific constant; β_{ki}^c,$k = 1, 2, ..., K_c, \varphi_i^c$ 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:

$$\mathcal{A}_{it}^{c} = \exp(\alpha_i^c + \epsilon_{it}^c). \left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c} \right) . \left(s_{it-1}^c\right)^{\varphi_i^c} . \exp\left(\gamma_i^c . s_{it}^{3-c}\right), \quad i = 1, \ldots, m_c, \quad c = 1, 2. \tag{2.4}$$

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 2.4 to revert its original shape (2.2) 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 ($\gamma_i^c = 0$).

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:

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

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.

2.2.1 Estimation

Substituting for the attraction $\mathcal{A}_{it}^c$ of brand i by its value from (2.4) in the expression of market share (3.1), 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

$$\ln\left(s_{it}^c\right) = \alpha_i^c + \epsilon_{it}^c + \sum_{k=1}^{K_c} \beta_{ki}^c \ln\left(X_{kit}^c\right) + \varphi_i^c \ln\left(s_{it-1}^c\right) + \gamma_i^c.s_{it}^{3-c} - \ln\left(\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c\right). \tag{2.5}$$

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

$$\ln\left(s_{rt}^c\right) = \alpha_r^c + \epsilon_{rt}^c + \sum_{k=1}^{K_c} \beta_{kr}^c \ln\left(X_{krt}^c\right) + \varphi_r^c \ln\left(s_{rt-1}^c\right) + \gamma_r^c.s_{rt}^{3-c} - \ln\left(\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c\right). \tag{2.6}$$

In the empirical illustration to follow, the private label, which is present in both categories, is taken as the reference brand. Substracting (2.6) from (2.5), we obtain the model to be estimated, namely:

[1]The same procedure is followed but not repeated for models (2.2)-(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.

[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.

2.3 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:

$$\begin{aligned}
& \quad \text{Model 1, no spillover} \\
\mathcal{A}_{it}^c &= \exp(\alpha_i^c + \epsilon_{it}^c) \cdot P_{it}^{\beta_{pi}^c} \cdot s_{it-1}^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c . A_{it}^c + \beta_{Di}^c . D_{it}^c + \sum_{l=2007}^{2010} \tau_l Y_l\right), \\
& \quad \text{Model 2, constant brand-spillover} \\
\mathcal{A}_{it}^c &= \exp(\alpha_i^c + \epsilon_{it}^c) \cdot (P_{it}^c)^{\beta_{pi}^c} \cdot \left(s_{it-1}^c\right)^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c . A_{it}^c + \beta_{Di}^c . D_{it}^c + \gamma^c . s_{it}^{3-c} + \sum_{l=2007}^{2010} \tau_l Y_l\right), \\
& \quad \text{Model 3, specific brand-spillovers} \\
\mathcal{A}_{it}^c &= \exp(\alpha_i^c + \epsilon_{it}^c) \cdot (P_{it}^c)^{\beta_{pi}^c} \cdot \left(s_{it-1}^c\right)^{\varphi_i^c} \cdot \exp\left(\beta_{Ai}^c . A_{it}^c + \beta_{Di}^c . D_{it}^c + \gamma_i^c . s_{it}^{3-c} + \sum_{l=2007}^{2010} \tau_l Y_l\right),
\end{aligned}$$

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

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

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 2.1 and 2.2 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 2.1 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

2.3.1 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

Table 2.2 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

at the general descriptive and predictive performance of the three models. From the results in Table 2.3, 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.

Tables 2.4 and 2.5 give the parameter estimates for the three models, for the toothbrush and toothpaste categories, respectively.

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, Col-

Table 2.3 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

Table 2.4 Results for the toothbrush category

Brands	Variables	No spillover		Constant brand-spillover		Specific brand-spillovers	
		Parameter	Standard error	Parameter	Standard error	Parameter	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
	Ads	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%

Table 2.5 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%

gate, Aquafresh and the private label, are all significant at 5% and positive (see Tables 2.4 and 2.5). 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 2.6), 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 2.7. 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).

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%).

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 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:

$$\text{No spillover}: \varepsilon^{s_i^c}_{p_i^c} = \beta^c_{pi}\left(1 - s_i^c\right); \qquad \varepsilon^{s_i^{3-c}}_{p_i^c} = 0.$$

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

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

Table 2.6 Wald test of spillover-parameter equality between categories

	Constant brand-spillover			Specific brand-spillover		
	DF	F Value	Pr > F	DF	F Value	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 2.7 Brand-attraction multiplier

Brand	Category	Attraction-multiplier expression	s^{3-c} Market share 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)	$\exp(1.962 \times s_{it}^{3-c})$	0.122	**1.269**
	Toothpaste (c)	$\exp(2.833 \times s_{it}^{3-c})$	0.027	**1.079**
Private Label	Toothbrush (c)	$\exp(2.780 \times s_{it}^{3-c})$	0.047	**1.140**
	Toothpaste (c)	$\exp(0.905 \times s_{it}^{3-c})$	0.484	**1.549**

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

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

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 $(m_1 \times m_2) \times (m_2 \times m_1)$:

$$\begin{bmatrix} I_{m1} & A^1 \\ A^2 & I_{m2} \end{bmatrix} \times \begin{bmatrix} \frac{\partial s_{jt}^c}{\partial P_{it}^c} \\ \frac{\partial s_{kt}^{3-c}}{\partial P_{it}^c} \end{bmatrix}_{\text{with spillover}} = B = \begin{bmatrix} \frac{\partial s_{jt}^c}{\partial P_{it}^c} \\ \frac{\partial s_{kt}^{3-c}}{\partial P_{it}^c} \end{bmatrix}_{\text{No spillover}},$$

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

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

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

The solution to the above system is given by:

$$\begin{bmatrix} \frac{\partial s^c_t}{\partial P^c_{it}} \\ \frac{\partial s^{3-c}_t}{\partial P^c_{it}} \end{bmatrix}_{\text{with spillover}} = A^{-1}B = A^{-1}. \begin{bmatrix} \frac{\partial s^c_t}{\partial P^c_{it}} \\ \frac{\partial s^{3-c}_t}{\partial P^c_{it}} \end{bmatrix}_{\text{No spillover}}.$$

When brands spillovers across categories are not considered, elasticities terms clearly indicate a misspecification. In fact, when acounting for interactions at the brand level, the elasticity is but the expression of elasticities with no spillover multiplied by the matrix A^{-1}.As an illustration, we provide in Table 2.8 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.

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

Table 2.8 Market-share price elasticities

Brand	Category	Market share(%)	**No spillover** Toothbrush	Toothpaste	**Specific brand-spillover** Toothbrush	Toothpaste
Colgate	Toothbrush	12.3	-1.083	-	-1.063	-0.139
	Toothpaste	43.5	-	-0.827	-0.204	-0.788
Aquafresh	Toothbrush	2.7	-0.572	-	-0.513	-0.036
	Toothpaste	12.2	-	-1.685	-0.420	-1.671
Oral B	Toothbrush	26.9	-0.829	-	-0.754	-
Reach	Toothbrush	9.7	-1.016	-	-1.004	-
Crest	Toothpaste	32.9	-	-1.009	-	-1.005
Arm & Hammer	Toothpaste	6.7	-	-1.332	-	-1.324
Private Label	Toothbrush	48.4	-0.397	-	-0.374	-0.194
	Toothpaste	4.7	-	-0.931	-0.064	-0.914

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 2.9, 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%.

2.4 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

Table 2.9 Temporal effects

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

(*) Significant at 5%
(**) Significant at 10%

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 2.10.

Table 2.10 Simulated impact of a price reduction for Colgate[5]

	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 %)	

It is observed in Table 2.10 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 rela-

[5] 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%.

tionships 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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Chapter 3

Cross-Category Effects and Umbrella Store-Brands

Abstract

Umbrella effects, or the ability of a brand, such as a store brand, in one category to generate sales for that brand in other categories, may affect the brand positioning, the effectiveness of retailers' pricing strategies and the coordination of all marketing efforts across categories. Previous research identifies a number of reasons why retailers offer store brands: both horizontal reasons (attracting consumers) and vertical (improving leverage over manufacturers). None, however, consider the umbrella effects of offering a private label in one category in order to increase market share in another.

We use an extended market-share model to estimate the potential umbrella effects among private-label products in all the categories in which the store brand is present. The model is applied to a set of five related as well as unrelated product categories. In a single framework, we simultaneously develop two models: a store-brand market-share model, and a category demand model, to distinctly assess two levels of category dependency, namely, the umbrella-branding spillover and the cross-category spillover.

We find significant positive umbrella-branding effects among private labels in some of the categories. The umbrella store-brand effects strengthen the position of the retailer's brand even between unrelated categories. Our results suggest that an UB strategy proves to be profitable only in the case where the margin made on the store brand is comparable to or even higher than that made on national brands. Retailers would be well-served to develop store-brand tiers that are me-too/premium, in addition to a generic PL line, instead of creating uniform umbrella brands, as is often the practice.

The combination of these two strategies would allow the retailer to improve his brand visibility and customers' store loyalty through the lure of the financial savings offered by generic store brands while me-too/premium store brands allow him to increase PL sales and market shares across categories. We provide empirical evidence regarding the impact of umbrella spillover on the retailer's global performance.

Keywords: Umbrella branding spillover - Store brands - Market share attraction model - Demand interdependency - Cross-category model - Cross-elasticities - Cross category management - Retail strategy - Supermarket retailing.

3.1 Introduction

Retailer-owned brands are now available in many, if not all, consumer packaged-goods category (de Jong 2011; IRI 2009), ensuring that the store brand illustrates an extensive umbrella-branding (UB) strategy. By bearing the same name, products sold in even independent categories become related in the consumer's mind. In fact, this is what a retailer is after when using an umbrella-branding strategy to introduce new products in categories in which its private label (PL) is not yet present. The benefit of UB comes, however, at the cost of complicating the task of category management and the measurement of the impact of a marketing move such as a price reduction of the PL in one category. Indeed, when promoting their store brand in a specific category, retailers' main purpose is not simply to induce brand switching within the category and to cannibalize regular sales of the competing national brands (NBs). They also aim to increase sales of the product category, and if possible, generate more store traffic, resulting in higher sales in other product categories as well (Hruschka et al. 1999). Further, retailers are concerned about how their PL is affecting and being affected by their umbrella replicas, and how their own marketing effort in one category affects performance across categories. Therefore, it is critical to have access to reliable measures of marketing-effort response at both the store-brand and at the whole product-category levels.

From an empirical perspective, providing such measures requires that a distinction be made between two levels of inter-category dependency: First, there is an *umbrella-branding spillover* that is reminiscent to the presence of the same store brand in different categories.

In other words, two PL items belonging to different categories may be purchased because consumers transfer their positive perceptions from a previous purchasing experience in one category to another, new one. Second, there is a *cross-category spillover* that is related to "natural" dependencies between categories. These dependencies can be caused by joint utilization (complementarity, substitutability), or by purchasing patterns or similar placement (Natter et al. 2007). The umbrella-brand argument maintains that there are significant complementarity effects among private-label offerings across categories. Identifying cross-category effects among private labels has received little academic interest, but is widely discussed in the retailing press (Thompson, 1999; Steiner, 2004). Yet, there is little research on whether such cross-category, or umbrella, effects are an empirical reality.

The objective of this research is to test for the existence of umbrella-branding effects among private-label products offered in different related, as well as unrelated, categories. We aim to identify umbrella effects as independent influences on private-label performance, distinct from natural dependencies, in several different product categories. In a single framework, we develop two models of multiple store-brand market share and multiple-category demand to distinctly account for the two levels of dependency, namely, the cross-category spillover and the umbrella-branding spillover.

Our work contributes to the literature and on management of private labels in a number of ways.

1. We propose an extended market-share model to account for the umbrella-branding effect in all the categories in which the store brand is present. This allows us to investigate how much each store brand's performance affects its counterpart umbrella brands' performance, not only across related but also across unrelated categories.

2. We introduce a modeling framework that incorporates the cross-category dependency at two levels, namely, the brand level and the category level. The model structure allows the retailer to implement a store-wide cross-category marketing strategy.

3. We provide a parsimonious way to account for the direct and cross-elasticities inherent to the spillover presence across multiple categories. We offer empirical evidence regarding the impact of umbrella spillover on the retailer's global performance.

Applying our model to store-level data for competing brands that describe sales in five categories (mayonnaise, mustard, frankfurters, cereal and laundry detergent) in a large US retailing chain, we find significant positive private-label umbrella-branding effects in some of the categories. Interestingly, this spillover is present among even unrelated categories, and it is asymmetric, that is, the influence of the PL's market share in one category on its market share in another category is not the same both ways. Umbrella-branding spillover certainly helps strengthen the position of the retailer's brand across categories. However in terms of profit, this strategy proves to be profitable only in the case where the margin made on the store brand is comparable to or even higher than that made on national brands. Retailers would be well-served to develop store-brand tiers that are me-too/premium in addition to a generic PL line, instead of creating uniform umbrella brands, as is often the practice. The combination of these two strategies would allow the retailer to improve his brand visibility and customers' store loyalty through the lure of the financial savings offered by generic store brands while me-too/premium store brands allow him to increase PL sales and market shares across categories. We provide empirical evidence regarding the impact of umbrella spillover on the retailer's global performance.

The rest of the paper is organized as follows: Section 2 briefly discusses the relevant literature on private labels as umbrella brands. In Section 3, we introduce our model and the estimation procedure. Section 3 describes the data used, and Section 4 presents the estimation results. In Section 5, we illustrate how the model can be used to assess the impact of a marketing move on the market shares of all items in all retained categories, as well as the impact on the retailer's profits. Section 6 briefly concludes.

3.2 Literature Review

Why the Umbrella Strategy for Store Brands?

According to the literature, retailers move into PLs to benefit from higher margins compared to manufacturers' national brands (Ailawadi and Harlam 2004; Pauwels and Srinivasan 2004). Some authors have seen the store brand as a strategic move for retailers to gain bargaining power against manufacturers (Pauwels and Srinivasan 2004; Meza and Sudhir 2010), while other studies (Ailawadi, Pauwels and Steenkamp 2008; Sudhir and Talukdar 2004) have found PLs to help increase store traffic and loyalty to the store and thus enhance chain profitability.

Motivated by higher margins, retailers have seized every opportunity to extend their brand to new product categories. This results in a complex umbrella-branding problem. Indeed, as the brand bears the chain name or refers to it (store name or logo in the brand or on the package), positive and negative externalities or spillovers have a much higher escalation effect than in the case of a manufacturer focusing on a few product categories in which its brands are present. This high-stake situation invites for the design of a sophisticated umbrella-branding strategy that takes into account interdependencies across categories.

While an abundant literature has analyzed line extensions under the same name (Alexander and Colgate 2005; Laforet 2008; Nijssen and Agustin 2005), store brands have not been investigated in depth as "umbrella brands," and even less so, their impact on the retailer's performance. Hansen,Singh and Chintagunta (2006) developed a multi-category brand-choice model and found strong empirical evidence of correlations in household preferences for store brands across categories. Sayman and Raju (2004) stated that the number of PL items carried by the retailer in other categories was found to increase the PL share in the "target category." Wang, Kalwani and Tolga (2007) used a multivariate count model to highlight the benefits of the UB in creating a positive association between the purchases of an umbrella store brand across even dissimilar categories, albeit less strong than across categories with similar attributes. In a theoretical paper, Amrouche et al. (2014) demonstrated that the profitability of a store-brand UB strategy is not always guaranteed for the retailer. Surprisingly, they obtained that a profitable UB strategy is conditioned by the market potential of the competing brands in the various categories together with the degree of competition between the NB and PL.

The driving force governing the umbrella-branding strategy is the spillovers generated by a brand across the different categories. In fact, products belonging to different categories are linked through their brand name, as consumers may make inferences about the retailer when they face a large number of store brands across categories (Sayman and Raju 2004). The argument is that consumers use positive experiences with the store brand in one category to update their overall beliefs about the umbrella brand. In turn, those positive perceptions may be transferred from one category to another and thereby reduce consumers' perceived risk and uncertainty in purchasing the same brand in another category (Erdem and Sun 2002; Erdem 1998).

The existing literature has provided empirical evidence of spillover effects between manufacturers' brands (Chen and Liu 2004; Moorthy 2010; Erdem 1998). Two studies dealt with umbrella branding in the context of retailers' private labels. Wang, Kalwani and Tolga (2007) showed the existence of high positive correlations across related, and even unrelated, categories, due to the high-quality positioning of the focal store brand and to the spillover effects induced by the UB strategy adopted by the retailer. Recently, Erdem and Chang (2012) confirmed the existence of cross-category learning effects between several pairs of categories for both store and national umbrella brands, although with a variable degree of cross-category learning between categories. These two studies (Wang, Kalwani and Tolga 2007; Erdem and Chang 2012) have considered the store brands as umbrella brands from a consumer perspective, without broaching the impact of this strategy on the retailer's performance or the interactions this generates among other categories. These cross-category effects need to be measured at the store-brand level rather than at a consumer level since retailers can only implement category management by varying marketing actions at the SKU level or, at very least, at the brand level.

While the interdependence of both brand and category sales induced by the UB spillover is crucial to the retailer's decision and performance, the literature has instead dwelt on the natural dependencies caused by complementarity, substitutability, purchasing patterns or similar placement (Natter et al. 2007).

Cross-category Dependencies

Two different explanations for cross-category linkages have been suggested in the literature: global utility and store choice. Global utility models argue that cross-category dependence is present within teach consumer's selection process. In these models, cross-category choice correlations exist because the consumer's preference for an item in one category is contingent (in a substitutability or complementarity sense) on the consumption of items in other product categories. These purchasing-behavior dependencies have been extensively studied by marketing researchers (Leeflang et al. 2008; Song and Chintagunta 2007; Bell and Lattin 1998). For instance, the model of Leeflang et al. (2008) permits both positive (complementary) and negative (substitution) cross-category effects. They estimated the effects between complementary categories to be approximately 20% of the own-brand effect on revenues, and those between substitutable categories to be roughly 9%.

Store-choice models argue that sales in different categories are related because the profile of consumers visiting a store changes over time due to marketing activity. Because product preferences are correlated across categories (Russell and Kamakura 1997), this variation over time creates cross-category correlations in store-level sales data. Bell and Lattin (1998) develop a model that relates store choice to its pricing strategy across multiple product categories. The decision to make a major shopping trip alters store choice and also increases the number of items in the market basket. Some other studies (e.g., Russell and Kamakura 1997; Seetharaman, Ainslie and Chintagunta 1999) revealed demand interdependencies between categories that are not a priori perceived as complements or substitutes. In the same line, Leeflang and Parreño-Selva (2012) and Niraj et al. (2008) considered cross-promotion effects of related and less-related/unrelated product categories and concluded that promotional spillover vary systematically across product-categories revenues.

3.3 Model Development and Estimation

A main takeaway from our brief literature review is that our understanding of umbrella-branding spillover in the context of private labels is still elementary. More specifically, what we know is insufficient to provide retailers with specific measurements of *store-brand spillover* effects across categories and their impact on the retailer's brand performance (market shares). Similarly, *category-spillover* effects have to be considered on marketing decisions. In this paper, we simultaneously develop two models: one of multiple store-brand market share, and one of multiple-category demand. We specify a market-share model to investigate the presence of umbrella effects among private labels. The specification of the demand model, meanwhile, accounts for the relationship between category sales. Next, we use both models' results to estimate the impact of varying the value of a marketing-mix variable such as e.g price, on the performance (market share) of the store brand in all categories in which it is present, as well as on the retailer's profit.

3.3.1 Market-Share Model

Consider C product categories, with $C > 2$, each carrying m_c competing brands, including a store-owned brand. We mention from the outset that: (i) we do not impose that the sets of brands in the C categories be identical; and (ii) only the private label is sold in more than one category. This last item allows us to focus on umbrella branding for only the retailer's brand.

Denote by s_{it}^c the market share of brand i at time t in category C, and by S_{it}^{-c} the vector of market shares of brand i in all categories but c, that is,

$$S_{it}^{-c} = \left(s_{it}^1, \ldots s_{it}^{c-1}, s_{it}^{c+1}, \ldots s_{it}^C\right).$$

Denote by $\mathcal{A}_{it}^c \geq 0$ the attraction of brand i in category c at time $(t = 1, \ldots, T)$. Following the literature, we assume that the market share of a brand is given by its attraction divided by the sum of all brands' attractions, that is,

$$s_{it}^c = \frac{\mathcal{A}_{it}^c}{\sum_{j=1}^{m_c} \mathcal{A}_{jt}^c}. \tag{3.1}$$

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 $c = 1, \ldots, C$. We suppose that the attraction $\mathcal{A}_{it}^c$ is influenced by marketing instruments (price, advertising, etc.) and possibly by other economic and non-economic variables. Denote by $X_{it}^c = \left(X_{1it}^c, \ldots, X_{K_cit}^c\right)$ 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.

As stores' umbrella brands carry information through their brand name, consumers use use their experience with one store brand, be it positive or negative, to update their beliefs about products sold in different categories under the same UB. We can thus assume that the attraction of a brand?and more specifically a store brand?in a category c depends on its performance (market share) in the other categories and vice versa. Denote by γ^{jc} the spillover impact of the private label's performance in category j on its performance in category c. By introducing this store-brand spillover, we extend the attraction model in a straightforward manner to let a brand performance benefit from spillovers emanating from one or more categories. Consequently, we write the attraction, $\mathcal{A}_{it}^{c}\left(X_{it}^{c}, s_{it-1}^{c}, s_{it}^{-c}\right)$, as follows:

$$\mathcal{A}_{it}^{c} = \begin{cases} \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c}.\exp\left(\sum_{\substack{j=1\\ j\neq c}}^{C} \gamma^{jc}.s_{it}^{j}\right) & \text{if } i \text{ is the private label} \\ \exp(\alpha_i^c + \epsilon_{it}^c).\left(\prod_{k=1}^{K_c} (X_{kit}^c)^{\beta_{ki}^c}\right).\left(s_{it-1}^c\right)^{\varphi_i^c} & \text{otherwise} \end{cases} \quad (3.2)$$

for $i = 1, \ldots, m_c,\ c = 1, \ldots, C.$

where α_i^c is the brand-specific constant, $\beta_{ki}^c, k = 1, 2, ..., K_c$ and φ_i^c are parameters to be estimated, and ϵ_{it}^c is a random disturbance term. We expect the price coefficients to be negative and all other variables (display, advertising and lagged market share) to positively impact the brand's market shares. Given its presence in each of the product categories, we consider the private label as a reference brand (r). Substituting for the attraction A_{it}^c of brand i by its value from (3.2) in the expression of market share (3.1) and taking the logarithm of both sides, we obtain the model to be estimated for each competing brand, namely:

$$\begin{aligned} \ln\left(\frac{s_{it}^c}{s_{rt}^c}\right) &= \alpha_i^c - \alpha_r^c + \epsilon_{it}^c - \epsilon_{rt}^c + \sum_{k=1}^{K_c} \beta_{ki}^c \ln\left(X_{kit}^c\right) - \sum_{k=1}^{K_c} \beta_{kr}^c \ln\left(X_{krt}^c\right) \\ &\quad + \varphi_i^c \ln\left(s_{it-1}^c\right) - \varphi_r^c \ln\left(s_{rt-1}^c\right) - \left(\sum_{\substack{j=1\\ j\neq c}}^{C} \gamma^{jc}.s_{rt}^{j}\right). \end{aligned} \quad (3.3)$$

3.3.2 Cross-Category Demand Model

We develop a cross-category model for store-level weekly sales data. Our approach is to specify a log-linear demand model in which the log of unit sales for each category is regressed on the log of the price of the brands offered in that category (Natter et al. 2007; Divakar, Ratchford and Shankar 2005). As the location and proximity of displays of one category with respect to another category can have a significant effect on the sales of both categories, we include display placement together with flyer-advertisement activities in each category equation. The lagged sales-volume effect is the same across brands in the same category to accommodate serial correlation introduced by forward-buying or inventorying behavior (Van Heerde, Leeflang, and Wittink 2004).

As there are often large increases in demand at holiday periods, it is important to account for holiday/event effects (Divakar, Ratchford and Shankar 2005). A dummy variable was created to account for the following holidays: New Year's Day, Super Bowl Sunday, Valentine's Day, Easter, Memorial Day, Independence Day, Labor Day, Halloween, Thanksgivin, and Christmas. Because many of these holidays fall on a Monday and IRI weeks end on Sunday, we used a dummy variable for the week prior to the holiday. To capture troughs in sales after holidays, we also tested a dummy variable for the week following the holiday one. Finally, as seasonality plays an important effect (Natter et al. 2007; Divakar, Ratchford and Shankar 2005), we include seasonal effects for winter, spring, summer and fall, and weekly trends as predictors.

In addition to the above elements, we intend to consider between-category spillovers at the level of store sales. Existing research has identified different moderators that influence demand sensitivity. Factors such as promotion frequency and promotion depth (Grewal and Levy 2007) and location of a promoted category (Leeflang and Parreño-Selva 2012) were found to be tools managers might use to influence sales in other categories. The challenge in assessing sales response to changes in the marketing instruments for individual brands in multiple categories is the large number of parameters that needs to be estimated (I brands $\times C$ categories $\times K$ marketing instruments); and as assessing marketing instruments' impact individually is not our goal, our approach would be to account for the demand of categories other than the one in question within the regression model. Given that the level of demand reflects the whole marketing effort and unobserved phenomena (e.g., loyalty, long-term advertising effect, product quality, goodwill, etc.), our structure reduces the number of parameters to a single demand-sensitivity parameter to estimate.

Thus based on all these specifications, we specify a log-linear demand equation for each of the C categories. Denote by q_t^c the unit sales (standardized by size) for category c during week t, and by p_{it}^c the price of brand i in category c during the week t. Recalling that m_c

stands for the number of brands in category c, the sales equation is then given by

$$\ln\left(q_t^c\right) = \alpha_0^c + \alpha_1^c \cdot \ln\left(t\right) + \sum_{i=1}^{m_c} \beta_i^c \ln\left(P_{it}^c\right) + \sum_{i=1}^{m_c} \lambda_i^c A_{it}^c + \sum_{i=1}^{m_c} \rho_i^c D_{it}^c \tag{3.4}$$

$$+ \sum_{k\in\{-1,0,1\}} \eta_{1+k}^c H_{t-k}^c + \sum_{l=1}^{3} \delta_l^c Z_{lt}^c + \theta^c \ln\left(q_{t-1}^c\right) + \sum_{\substack{j=1\\ j\neq c}}^{C} \psi^{cj} \ln\left(q_t^j\right) + \mu_t^c, \tag{3.5}$$

$$\text{for } c = 1, \ldots, C,$$

where

$$A_{it}^c = \begin{cases} 1, & \text{if product } i \text{ is advertised in week } t, \\ 0, & \text{otherwise,} \end{cases}$$

$$D_{it}^c = \begin{cases} 1, & \text{if product } i \text{ is displayed in week } t, \\ 0, & \text{otherwise,} \end{cases},$$

$$H_{t-k}^c = \begin{cases} 1, & \text{if a holiday took place during week } t, \\ 0, & \text{otherwise,} \end{cases}, k \in \{-1, 0, 1\},$$

with Z_{lt}^c being a dichotomous variable capturing the seasonality effect. The lagged value of the dependent variable is denoted by q_{t-1}^c, and the weekly trend by t. In addition, $\beta, \lambda, \rho, \eta, \delta$ and θ represent vectors of coefficients for the corresponding variables. We suppose that the price coefficient β_i^c is negative and the advertising (λ_i^c) and display coefficients (ρ_i^c) are negative. The parameter Ψ^{cj} is the synergetic effects of having category c and j together in the basket. We expect this cross-category dependency parameter to be positive for a pair of complements and to be negative for a pair of substitutes. We make no assumptions on the sign of the remaining coefficients. Finally, μ is a vector of residual errors.

3.3.3 Price Elasticities

Varying the price of a private label r in one particular category c has two general effects. First, it affects the total demand (in units) in the same category, and as the different categories may be related, it may also affect the total number of units sold in each of these categories. Second, this variation affects its market share and the market shares of the competing brands in the same category; also, due to umbrella-branding spillovers, this variation may affect the market share of the private label in other categories, and consequently, the market shares of the other brands.

Market-share Elasticities

Let us first consider the impact of varying the price of the private label r in category c on the market shares of all brands in all retained categories. These impacts can be categorized as follows:

Direct impact: the variation of the market share of r in the same category, that is, $\frac{\partial s^c_{rt}}{\partial P^c_{rt}}$;

Intra-category impact: the variations in all competing national brands in c given by $\frac{\partial s^c_{it}}{\partial P^c_{rt}}$, for $i = 1, \ldots, m_c, i \neq r$.

Umbrella-branding impact: the variations in the market shares of the private label r in other categories, that is, $\frac{\partial s^l_{rt}}{\partial P^c_{rt}}$,for $l = 1, \ldots, C, l \neq c$;

Inter-category impact: the variations in the market shares of national brands in other categories, that is, $\frac{\partial s^l_{it}}{\partial P^c_{rt}}$, for $l = 1, \ldots, C, l \neq c$, and $i = 1, \ldots, m_c, i \neq r$.

Long but straightforward computations lead to the following values for the above derivatives:

$$
\begin{aligned}
\frac{\partial s^c_{rt}}{\partial P^c_{rt}} &= s^c_{rt}\left(1 - s^c_{rt}\right)\left(\frac{\beta^c_r}{P^c_{rt}} + \sum_{\substack{j=1 \\ j\neq c}}^{C} \gamma^{jc} \frac{\partial s^j_{rt}}{\partial P^c_{rt}}\right), \\
\frac{\partial s^c_{it}}{\partial P^c_{rt}} &= -s^c_{rt} s^c_{it}\left(\frac{\beta^c_r}{P^c_{rt}} + \sum_{\substack{j=1 \\ j\neq c}}^{C} \gamma^{jc} \frac{\partial s^j_{rt}}{\partial P^c_{rt}}\right), \quad i = 1, \ldots, m_c, i \neq r, \\
\frac{\partial s^l_{rt}}{\partial P^c_{rt}} &= s^l_{rt}\left(1 - s^l_{rt}\right)\sum_{\substack{j=1 \\ j\neq l}}^{C} \gamma^{jc} \frac{\partial s^j_{rt}}{\partial P^c_{rt}}, \quad l = 1, \ldots, C, l \neq c, \\
\frac{\partial s^l_{it}}{\partial P^c_{rt}} &= -s^l_{rt} s^l_{it}\sum_{\substack{j=1 \\ j\neq l}}^{C} \gamma^{jc} \frac{\partial s^j_{rt}}{\partial P^c_{rt}},\; l = 1, \ldots, C, l \neq c, \text{ and } i = 1, \ldots, m_c, i \neq r.
\end{aligned}
$$

For clarity, it is useful to rewrite the above system of equations with the unknown to be estimated (the price derivatives) on the left-hand side of each equation and a constant term on the right-hand side, that is

$$\text{Category } c \quad : \quad \begin{cases} \frac{\partial s^c_{rt}}{\partial P^c_{rt}} - s^c_{rt}\left(1 - s^c_{rt}\right)\sum_{\substack{j=1\\ j\neq c}}^{C}\gamma^{jc}\frac{\partial s^j_{rt}}{\partial P^c_{rt}} = s^c_{rt}\left(1 - s^c_{rt}\right)\frac{\beta^c_r}{P^c_{rt}}, & \text{brand } r \text{ (private label)},\\ \frac{\partial s^c_{it}}{\partial P^c_{rt}} + s^c_{rt}s^c_{it}\sum_{\substack{j=1\\ j\neq c}}^{C}\gamma^{jc}\frac{\partial s^j_{rt}}{\partial P^c_{rt}} = -s^c_{rt}s^c_{it}\frac{\beta^c_r}{P^c_{rt}}, & i = 1,\ldots,m_c, i\neq r, \end{cases}$$

$$\text{Category } l \quad : \quad \begin{cases} \frac{\partial s^l_{rt}}{\partial P^c_{rt}} - s^l_{rt}\left(1 - s^l_{rt}\right)\sum_{\substack{j=1\\ j\neq l}}^{C}\gamma^{jc}\frac{\partial s^j_{rt}}{\partial P^c_{rt}} = 0, & l = 1,\ldots,C, l\neq c,\\ \frac{\partial s^l_{it}}{\partial P^c_{rt}} + s^l_{rt}s^l_{it}\sum_{\substack{j=1\\ j\neq l}}^{C}\gamma^{jc}\frac{\partial s^j_{rt}}{\partial P^c_{rt}} = 0, & l = 1,\ldots,C, l\neq c, \text{ and } i = 1,\ldots,m_c, i\neq r. \end{cases}$$

To wrap up, for a variation of the price of the private label in ONE category, we need to estimate the above $\sum_{c=1}^{C} m_c$ effects.

Category-Demand Model Elasticity

Recall that the total demand model in category c ($c = 1,\ldots,C$) is given by

$$\begin{aligned} \ln\left(q^c_t\right) &= \alpha^c_0 + \alpha^c_1 \cdot \ln(t) + \sum_{i=1}^{m_c}\beta^c_i \ln\left(P^c_{it}\right) + \sum_{i=1}^{m_c}\lambda^c_i A^c_{it} + \sum_{i=1}^{m_c}\rho^c_i D^c_{it} \\ &\quad + \sum_{k\in\{-1,0,1\}}\eta^c_{1+k}H^c_{t-k} + \sum_{l=1}^{3}\delta^c_l Z^c_{lt} + \theta^c \ln\left(q^c_{t-1}\right) + \sum_{\substack{j=1\\ j\neq c}}^{C}\psi^{cj}\ln\left(q^j_t\right) + \mu^c_t. \end{aligned} \tag{3.6}$$

Clearly, varying the price of the private label in category c has two intra-category effects, namely, one direct impact given by β^c_r and one indirect effect measured by $\sum_{j\neq c}\psi^{cj}\frac{\partial\ln\left(q^j_t\right)}{\partial\ln\left(P^c_{it}\right)}$. We denote the total variations by

$$\zeta_{q^c_t/P^c_{rt}} = \frac{\partial\ln\left(q^c_t\right)}{\partial\ln\left(P^c_{rt}\right)} = \beta^c_i + \sum_{j\neq c}\psi^{cj}\frac{\partial\ln\left(q^j_t\right)}{\partial\ln\left(P^c_{rt}\right)}.$$

Now, the inter-category effect, which is due to what the literature has referred to as natural dependencies (complementarity or substitutability), is given by

$$\zeta_{q_t^l/P_{rt}^c} = \sum_{j\neq l} \psi^{lj} \frac{\partial \ln\left(q_t^j\right)}{\partial \ln\left(P_{rt}^c\right)}, \quad j = 1, \ldots, C, \; j \neq c.$$

3.3.4 Estimation

Our market-share model involves $\sum_{c=1}^{C} m_c$ interrelated equations, and consequently, their parameters must be estimated simultaneously to account for the endogeneity of the market share of each brand across the C categories. To do so, we assume the following covariance structure Ω^1:

$$\Omega^1 : cov\left(\epsilon_{it}^c, \epsilon_{jt'}^{c'}\right) = \begin{cases} \sigma_i^c & \text{if } c = c' \text{ and } i = j \text{ and } t = t' \\ \sigma_{ij}^{cc'} & \text{if } t = t' \\ 0 & \text{otherwise} \end{cases} , \quad \begin{array}{c} i = 1, \ldots, m_c; \quad j = 1, \ldots, m_{c'}; \\ c, c' = 1, .., j, ., C; \; t, t' = 1, .., T \end{array}$$

Further, because we estimate sales(3.4) simultaneously for all categories $c = 1, .., C$, the residual term μ_t^c in the demand model is contemporaneously correlated with $\mu_t^{c'}, \;\; c \neq c'$. In order to account for heteroscedasticity and contemporaneous correlation in the errors across the C equations, we adopt the seemingly unrelated regressions (SUR) estimation procedure (Zellner 1962). The variance-covariance matrix of the disturbances is denoted by Ω^2 referring to 'sales coincidences' that are not explained by any of the effects that are controlled for in the model. The following covariance structure is retained:

$$\Omega^2 : cov\left(\mu_t^c, \mu_{t'}^{c'}\right) = \begin{cases} \sigma^c & \text{if } c = c' \text{ and } t = t' \\ \sigma^{cc'} & \text{if } t = t' \\ 0 & \text{otherwise} \end{cases} , \quad c, c' = 1, ..., C; \quad t, t' = 1, ...T$$

We keep in mind that price variables may be affected by sales and therefore may be determined endogenously. We address the possible endogeneity of demand and price variables by using instruments. Consequently, and in order to handle the endogeneity of the two equations systems, we employ three-stage least squares (3SLS), allowing for cross-equation error correlations in estimation.

3.4 Data Description

To illustrate the estimation of our model, we use an item-level scanner dataset provided by IRI (Bronnenberg et al., 2008) for a supermarket chain in the United States. Weekly transaction data are available for five categories, namely, Refrigerated Frankfurters, Mustard, Mayonnaise, Ready-To-Eat Cereal and Liquid Laundry Detergent, for a period of roughly 208 weeks from January 2008 to December 2011. They include information on sales, shelf price, advertising and display activities. Note that that these products were chosen to have categories that are prima facie complementary (Frankfurters-Mustard; Frankfurters-Mayonnaise), whereas the two products Mustard and Mayonnaise can be complements, substitutes or independent, depending on the taste of each consumer. All other pairs of products can be considered a priori independent.

To simplify the estimation procedure, we refer to previous studies (Song and Chintagunta 2006; Sayman and Raju 2004) that provided evidence that the store brand competes more with the category leader than it does with other national brands. Thereby, we limit the number of brands in each category to the store brand and three competing national brands, which consist of a leading brand in each category (LEADER) in terms of market-share volume, a secondary national brand (FOLLOWER), and a composite of all other brands (OTHER).

Table 3.1 provides descriptive statistics. The store-brand items have the lowest price in all the product categories and a market share of 9% to 24%. Note that the store brand's market share is higher than that of the follower national brand in three of the five product categories.

3.5 Results

We estimated the parameters of the two models, that is, the market-share model in (3.3) and the total category demand model in (3.4). As the focus is on analyzing the spillover effects for the private label and on the determination of the profitability of a marketing action (e.g., price reduction) for the whole offer (all retained categories), we only exhibit and discuss the results that are needed in this respect.

Table 3.1 Market descriptive statistics

	Brand	Category market size (units)	Market share	Unit price	Display	Ads
	PL		9.5%	0.10$	0.128	0.048
Mayonnaise	Leader NB	160,500	43.7%	0.16 $	0.092	0.072
	Follower NB		45.5%	0.16 $	0.063	0.051
	Other NB		1.2%	0.18 $	0.075	0.001
	PL		24.3%	0.10$	0.191	0.026
Mustard	Leader NB	46,500	25.5%	0.14 $	0.014	0.018
	Follower NB		8.9%	0.12 $	0.033	0.032
	Other NB		41.3%	0.24 $	0.124	0.019
	PL		17.3%	0.17$	0.108	0.141
Refrigerated	Leader NB	241,000	33.6%	0.25 $	0.046	0.143
Frankfurters	Follower NB		14.4%	0.12 $	0.158	0.110
	Other NB		34.7%	0.27 $	0.106	0.092
	PL		7.9%	0.14$	0.120	0.057
Ready-To-Eat	Leader NB	492,500	32.7%	0.23 $	0.138	0.095
Cereal	Follower NB		33.1%	0.21 $	0.218	0.188
	Other NB		26.3%	0.21 $	0.126	0.135
	PL		19.7%	0.03$	0.250	0.087
Liquid Laundry	Leader NB	418,000	29.2%	0.14 $	0.150	0.115
Detergent	Follower NB		12.3%	0.07 $	0.141	0.117
	Other NB		38.6%	0.09 $	0.110	0.090

Table 3.2 presents the estimation of the market-share model. For the store brand, all price parameters are significant and, as expected, negative. A clear-cut result is that the price impact on store-brand attraction is lower than for national brands in the Mustard and Liquid Laundry Detergent categories. For Mayonnaise and Refrigerated frankfurters, these store-brand price parameters are lower than those for Leader national brands. The PL performance is found to be more responsive to a price change in food categories compared to the hygiene category. Price parameters specific to the store brand were used to calculate their price market-share elasticities (see Appendix 1).

Private-label consumers are more responsive to advertising effort than to displaying activities. The lagged market-share effects are positive, and consumers are loyal to store brands in all product categories without exception.

Table 3.2 Market share parameters estimates

Categories	Variables	Leader NB Parameter	Leader NB S.E.	Follower NB Parameter	Follower NB S.E.	Other NB Parameter	Other NB S.E.	Store Brand Parameter	Store Brand S.E.
Mayonnaise	Intercept	3.044*	0.596	4.547*	0.573	3.488*	0.673	-	-
	Price	-2.058*	0.136	-1.468*	0.141	-0.533*	0.135	-1.716*	0.176
	Display	0.093	0.147	0.149	0.232	0.397	0.146*	0.048	0.097
	Ads	0.165	0.186	1.102*	0.283	2.785*	1.083	0.602*	0.127
	Lagged share	0.015	0.043	0.030	0.040	0.267*	0.044	0.055*	0.026
	Time	0.002	0.035	-0.090*	0.032	-0.010	0.040	-	-
Mustard	Intercept	-0.629**	0.375	-2.102*	0.416	1.582	0.342	-	-
	Price	-1.397*	0.096	-1.566*	0.105	-0.922*	0.137	-0.934*	0.106
	Display	0.413*	0.139	0.274*	0.116	0.404*	0.090	0.013	0.091
	Ads	0.628*	0.142	0.452*	0.116	0.152	0.161	0.284*	0.140
	Lagged share	0.155*	0.057	0.104*	0.0466	0.379*	0.103	0.274*	0.059
	Time	0.012	0.020	-0.025	0.023	-0.027	0.019	-	-
Refrigerated Frankfurters	Intercept	-0.570	0.412	-0.284	0.488	1.786*	0.428	-	-
	Price	-2.310*	0.084	-1.505*	0.133	-1.348*	0.119	-1.568*	0.177
	Display	0.117	0.198	0.342*	0.083	0.427*	0.137	0.129	0.161
	Ads	0.442*	0.081	0.306*	0.061	1.289*	0.179	0.768*	0.086
	Lagged share	-0.150*	0.042	0.144*	0.039	0.206*	0.049	0.177*	0.036
	Time	0.074*	0.030	-0.075*	0.035	-0.040	0.033	-	-
Ready-To-Eat Cereal	Intercept	4.618*	0.526	4.403*	0.530	4.683*	0.510	-	-
	Price	-2.074*	0.118	-2.108*	0.116	-1.924*	0.078	-3.157*	0.236
	Display	0.689*	0.116	0.690*	0.085	0.590*	0.078	0.023	0.092
	Ads	0.226*	0.058	0.147*	0.034	0.170*	0.060	-0.018	0.067
	Lagged share	-0.054**	0.029	-0.072*	0.025	-0.042**	0.025	0.146*	0.038
	Time	-0.124*	0.016	-0.153*	0.015	-0.176*	0.014	-	-
Liquid Laundry Detergent	Intercept	-2.045*	0.633	-6.200*	0.650	-1.967*	0.534	-	-
	Price	-1.831*	0.172	-2.599*	0.144	-1.748*	0.083	-0.516*	0.134
	Display	0.417*	0.147	0.406*	0.144	0.562*	0.139	0.167*	0.047
	Ads	0.700*	0.140	0.430*	0.127	0.696*	0.161	0.249*	0.052
	Lagged share	-0.120*	0.032	0.004	0.027	0.096*	0.033	0.234*	0.046
	Time	0.119*	0.024	0.120*	0.025	0.095*	0.019	-	-

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

3.5.1 Umbrella Store-Brand Spillover Effects

Encompassing both the retailer's marketing-mix choice and the competing national brands' policies, the PL performance (attraction or market share) in one category potentially impacts the performance of the same brand in the other categories. We refer to this interaction as the umbrella store-brand spillover. Table 3.3 reports the values of the spillover parameters for the five retained categories. Our main findings here are as follows:

1. Out of twenty estimated parameters, nine are statistically significant (four for Mayonnaise, two for Mustard and Liquid Laundry Detergent and one in Ready-To-Eat Cereal).

2. When significant, the spillover between two categories can be highly asymmetric. For instance, whereas the influence of Mayonnaise on Mustard is 1.459, the influence in the reverse direction is more than double, with a coefficient value of 3.131. Another interesting example is provided by the pair RFG Frankfurters-Mayonnaise, where the coefficients are respectively 0.387 (and significant) and 0.403 (and not significant).

3. The fact that complementary categories mutually influence one another is not that surprising. What is really interesting here is the umbrella-branding spillover effect between completely independent categories. To illustrate, the market-share of the private label in the Mustard and Cereal (two food products) categories has a significant influence on the market share of the same private label in the Detergent category.

The spillover parameters will be used to simulate the impact of varying the price of the private label in one category on the retailer's performance.

Table 3.3 Brand spillover results

Spillover Source	**Mayonnaise**		**Mustard**		**RFG Frankfurters**		**Cereal**		**Detergent**	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
Mayonnaise	-	-	**1.459***	**0.266**	0.403	0.466	-0.275	0.201	-0.182	0.273
Mustard	**3.131***	**0.436**	-	-	-0.594	0.568	-0.394	0.254	**1.587***	**0.330**
RFG Frankfurters	**0.387***	**0.191**	-0.033	0.147	-	-	**0.282****	**0.105**	-0.004	0.147
Cereal	**3.247***	**1.215**	-0.119	0.927	1.757	1.521	-	-	**2.718***	**0.923**
Detergent	**1.051***	**0.333**	**0.457****	**0.247**	-0.254	0.438	0.093	0.213	-	-

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

3.5.2 Category-Demand Spillover Effects

Table 3.4 gives the results of the estimation of the sales model for all categories. The main takeaways are the following:

1. When significant, all price coefficients have the expected negative sign, that is, a price reduction leads to higher total sales.

2. All display parameters are positive as postulated, with nine out of twenty coefficients being statistically significant.

3. A similar result is obtained for the advertising variable, however with one exception, namely, that the impact of advertising the private label in the Cereal category has a negative effect on total sales.

4. The results concerning the other variables are straightforward to interpret and are not of focal value.

Table 3.4 Demand-function model results

	Mayonnaise		**Mustard**		**RFG Frankfurters**		**Cereal**		**Detergent**	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
Intercept	8.801*	1.890	5.283*	1.360	1.456	1.744	6.255*	1.202	7.296*	1.340
Price LEADER	-1.040*	0.253	-0.468*	0.166	-0.371*	0.121	-0.024	0.191	-0.384**	0.222
Price FOLLOWER	0.020	0.254	0.008	0.090	-0.153	0.162	-0.500*	0.230	-0.268*	0.117
Price PL	0.161	0.233	-0.005	0.155	0.131	0.165	-0.551*	0.273	-0.750*	0.122
Price OTHER	0.135**	0.080	-0.216	0.236	-0.395*	0.098	-0.366*	0.106	-0.063	0.077
Display LEADER	0.044	0.148	0.461*	0.152	0.339*	0.160	0.684*	0.160	0.203*	0.103
Display FOLLOWER	0.381**	0.227	0.102	0.081	0.056	0.091	0.127	0.127	0.022	0.069
Display PL	0.134	0.087	0.093	0.075	0.073	0.099	0.205*	0.098	-0.006	0.038
Display OTHER	0.067	0.076	0.282*	0.121	0.579*	0.171	-0.071	0.102	0.074	0.110
Ads LEADER	0.119	0.267	0.007	0.152	0.417*	0.089	0.098**	0.057	0.124	0.113
Ads FOLLOWER	1.274*	0.389	0.086	0.067	0.145*	0.055	0.006	0.034	-0.019	0.063
Ads PL	0.139	0.121	0.243*	0.110	0.120*	0.051	-0.106**	0.061	-0.005	0.039
Ads OTHER	-0.360	0.644	0.247	0.183	0.427*	0.145	0.284*	0.079	0.167	0.139
Lagged Market Volume	-0.048	0.033	0.058	0.051	0.118*	0.031	0.061	0.054	-0.137*	0.056
Spring	0.026	0.035	-0.056*	0.024	-0.008	0.031	-0.017	0.023	0.025	0.024
Summer	0.019	0.041	0.108*	0.031	0.154*	0.037	-0.018	0.026	-0.054**	0.028
Fall	0.058	0.041	0.007	0.031	0.070	0.047	0.010	0.025	-0.056*	0.026
Time	0.051**	0.030	0.022**	0.012	0.017	0.017	0.008	0.011	0.046*	0.021
Holiday	0.062**	0.033	0.022	0.025	-0.152*	0.029	-0.082*	0.019	0.036	0.022
Pre-Holiday week	0.176*	0.038	0.128*	0.024	-0.059**	0.032	-0.070*	0.023	0.048**	0.024
Post-Holiday week	-0.038	0.029	-0.021	0.021	-0.005	0.027	0.015	0.019	0.030	0.020

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

Now, focusing on the main issue, namely, the cross-category effect, we can make the following observations based on the results in Table 3.5:

1. Each of the five categories take advantage of at least one category spillover that impacts positively and significantly on its sales. This confirms that the classical inter-category dependencies exist.

2. The category-spillover effect varies across categories. This confirms previous results obtained in., e.g., Leeflang and Parreño-Selva 2012; Niraj et al. 2008. The highest observed spillover is the one provided by the Mustard category to its complementary category of RFG Frankfurters (the coefficient is 0.44). Moreover, we obtain cross-category dependencies between categories that are a priori unrelated, a result that has also been shown by Russell and Kamakura (1997) and Seetharaman, Ainslie and Chintagunta (1999). As an example, sales of a hygiene category (Liquid Laundry Detergent) have a positive impact of 0.265 on sales of a food category (RFG Frankfurters). In the opposite direction, this impact is estimated at 0.135. While the demand dependency between related categories can be easily explained by the complementarity of products, sales interdependence between unrelated categories points to the ability of marketing actions, e.g., promotions, in one category to influence sales in any other categories in the store. In fact, promotions are found not only to increase sales of the promoted items but also to attract more consumers into the store because once these "new "consumers are on the premises, they are likely to also buy products other than those being promoted. This result is consistent with the one in Ailawadi et al. (2006), which states that on average, promotions have a significant positive 'halo effect' namely, that for every unit of gross promotional increase, 0.16 units of some other product are purchased elsewhere in the store.

Finally, we note the cascade or multiplicative feature of category spillovers. If we want to determine the impact of a marketing action in one category, we have to bear in mind that this action will affect not only the sales in this category, but also the sales in all other categories. For instance, the Liquid Laundry Detergent sales enjoy a spillover effect from the RTE Cereal of 0.18, which in turn positively affects the RFG Frankfurters category demand (0.265). The latter positively affects the Mustard and the Liquid Laundry Detergent and so forth.

Table 3.5 Demand-function spillovers

Spillover Source	Mayonnaise		Mustard		RFG Frankfurters		Cereal		Detergent	
	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.	Parameter	S.E.
Mayonnaise	-	-	**0.094***	**0.029**	-0.013	0.0407	-0.017	0.027	-0.016	0.030
Mustard	**0.286***	**0.112**	-	-	**0.440***	**0.107**	**0.217***	**0.073**	-0.139	0.091
RFG Frankfurters	-0.001	0.0510	**0.081***	**0.034**	-	-	-0.054	0.034	**0.135***	**0.035**
Cereal	0.006	0.100	0.012	0.084	-0.040	0.096	-	-	**0.180***	**0.072**
Detergent	-0.147	0.107	0.029	0.081	**0.265***	**0.093**	**0.122****	**0.068**	-	-

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

3.6 Simulation Results

In this section, we demonstrate how a retail chain can gain similar insights regarding the umbrella store-brand effect of its price promotions across all categories. In order to provide retail managers with tools to help coordinate marketing efforts across categories, we answer what-if questions about the optimality of various promotional offerings.

To do so, we use the "marketing profit" concept (Chen et al. 1999), which is about the intra- and cross-category profit implications of promotional retail activity. We present a quantification of the profit implications of both estimated cross-category and umbrella-strategy effects for the retailer managing a store brand across several categories.

We consider a situation where the retailer has to decide the brand category that will benefit promotional spending. In our context, we ask the following: which among the Mayonnaise, Mustard, RFG Frankfurters, Ready-To-Eat Cereal, Liquid Laundry Detergent is worth benefiting from a 10% price cut? Such an understanding of cross-category competition enables retailers to enhance the positioning of their store brand and the effectiveness of their pricing strategies. We answer this question based on the estimated market-share and demand-model parameters[1]. We proceed to simulate demand and profits–the five store brand products at their average prices–for the base case. We present two promotional scenarios (i.e., (1) RTE Cereal PL at a 10% price promotion, and (2) Liquid Laundry Detergent PL at a 10% price promotion) in Table 3.6 and Table 3.7, respectively. These two categories were selected for the empirical simulations, as their price parameters in the category-demand model were significant. As the information about the retailer's margin on the store brand is not available, we follow the literature and set the gross retail margins at 35% on store-branded products versus

[1]Non-significant spillover parameters are set to zero for the empirical estimation.

25% for nationally advertised brands (The Food Retailing Industry Speaks 2009; Ailawadi and Harlam 2004).

3.6.1 Umbrella Store-Brand Spillovers and Cross-Category Effects

Store-Brand Profit Results

It's observed in Table 3.6 that a promoted store brand strengthens the position, market share and thus sales, of the retailer brand in all categories in which it was made available, thanks to the umbrella strategy. However, in terms of profits, this statement is more ambivalent. A 10% price decrease made in the Cereal store brand leads to a profit loss for the Cereal PL (-2.7%), but still slightly increases the global PL profit of the five categories by 1%. In fact, the consequent decline in the PL cereal profit (-$50) is offset by the gain generated by the spillover existing between the umbrella store brands ($114). In the case of an equivalent price drop made by the Laundry detergent store brand, the umbrella branding spillover effects remain insufficient to counterbalance the profit decrease ($172) generated by the promotion. When noting that the retailer's margin on the cereal Leader NB is 22% higher than its margin for the store brand; while in the Laundry Detergent this percentage is set to 228%. A comparison between both ratios suggests that when promoting a generic store brand, the retailer should expect a negative impact on the profit of umbrella store-branded products.

Table 3.6 Cereal price-promotion simulation results

	Mayonnaise	Mustard	RFG Frankfurters	Ready-To-Eat Cereal	Liquid Laundry Detergent	Total
Incremental Total Sales	**10** *0.62E^{-4}%*	**11** *0.24E^{-3}%*	**684** *0.3%*	**27,162** *5.5%*	**4,311** *1.0%*	
Incremental sales due to price drop				27,137		
Incremental sales due to category spillover	10	11	684	25	4,311	
Incremental PL Sales	**1 332** *8.7%*	**148** *1.3%*	**118** *0.3%*	**14,145** *36.2%*	**5,379** *6.5%*	
Incremental PL sales due to price drop				14,142		
Incremental PL sales due to category spillover	1	3	118	3	851	
Incremental PL sales due to brand spillover	1,331	145	0	0	4,528	
Total Profit Variation	**($9.36)** *(0.1)%*	**($1.16)** *(0.1)%*	**$40.44** *0.3%*	**$656.26** *2.5%*	**$29.02** *0.3%*	**$715.20** *1.2%*
Profit Δ due to price drop				$654.96		$654.96
Profit Δ due to category spillover	$0.45	$0.48	$40.44	$1.30	$99.94	$142.60
Profit Δ due to brand spillover	($9.81)	($1.64)	-$	-$	($70.92)	($82.37)
PL Profit Variation	**$45.07** *8.7%*	**$5.40** *1.3%*	**$7.12** *0.3%*	**($50.35)** *(2.7)%*	**$57.09** *6.5%*	**$64.33** *1.0%*
PL Profit Δ due to price drop				($50.45)		($50.45)
PL Profit Δ due to category spillover	$0.03	$0.11	$7.12	$0.10	$9.03	$16.39
PL Profit Δ due to brand spillover	$45.04	$5.29	-$	-$	$48.06	$98.39

Retailer Profit Result

Taken together, both price promotion scenarios allow an increment in total profit of 1.2%. This gain–$715 and $736, respectively, caused by Cereal and Detergent PL promotion–would have been higher if spillover effects were not considered between umbrella-store brands. Thus, although the umbrella-branding spillover boosts PL performance across categories, the retailer's total profit declines due to the growing market share of PLs at the expense of NBs. This reasoning stands since the retailer's margin on his brand is lower than for the branded products, which prevents the incremental PL profit from offsetting the decrease in the NB profit. This leads to the conclusion that, when promoting a store brand, the retailer increases his profit across categories thanks to the price drop in the promoted category and thanks to the spillover effects at the category level that boost demand in related and unrelated categories. Umbrella store spillover does not contribute to this profit increase. So the retailer's only incentive when promoting his brand appears to be in prospecting new customers and taking advantage of the inter-category spillover to increase demand.

To sum up, umbrella-branding spillover certainly strengthens the position of the retailer's brand by reinforcing its market share across categories. However, in terms of profit, the story is quite different. The UB strategy proves to be profitable for the retailer in the case where the margin made on the store brand is comparable to or even higher than that made on national brands. As a generic store brand turns out not to be profitable, the retailer has no incentive to use the same label for his owned products, on condition that the PL is not targeting the same segment of customers and that the resulting costs make the PL differentiation strategy possible. In fact, adopting an umbrella strategy for me-too/premium store brands assures the retailer of a synergy in his PL performance across categories as well as an increase in his profitability.

Despite the harmful effect of the SB umbrella strategy on the retailer's profit, promoting the store brand could be beneficial in the long term. If the retailer can stand the immediate negative pecuniary effect of the promotion in favor of improving his brand visibility and customer' loyalty to the store, the UB strategy will prove to pay off since the brand spillover is efficient in increasing PL sales and market shares across categories.

Table 3.7 Detergent price-promotion simulation results

	Mayonnaise	Mustard	RFG Frankfurters	Ready-To-Eat Cereal	Liquid Laundry Detergent	Total
Incremental Total Sales	81 0.1%	82 0.2%	5,169 2.1%	191 $0.39E^{-3}$%	32,590 7.8%	
Incremental sales due to price drop					31,350	
Incremental sales due to category spillover	81	82	5,169	191	1,240	
Incremental PL Sales	173 1.1%	66 0.6%	892 2.1%	15 $0.39E^{-3}$%	10,229 12.4%	
Incremental PL sales due to price drop					9,863	
Incremental PL sales due to category spillover	8	20	892	15	254	
Incremental PL sales due to brand spillover	165	46	0	0	112	
Total Profit Variation	\$2.06 $0.32E^{-3}$%	\$3.18 0.2%	\$305.63 2.1%	\$10.26 $0.39E^{-3}$%	\$414.95 4.3%	\$736.08 1.2%
Profit Δ due to price drop					\$389.26	\$389.26
Profit Δ due to category spillover	\$3.32	\$3.70	\$305.63	\$10.26	\$27.78	\$350.69
Profit Δ due to brand spillover	(\$1.25)	(\$0.52)	-\$	-\$	(\$2.10)	(\$3.87)
PL Profit Variation	\$5.85 1.1%	\$2.41 0.6%	\$53.79 2.1%	\$0.71 $0.38E^{-3}$%	(\$172.67) −19.7%	(\$109.91) −1.8%
PL Profit Δ due to price drop					(\$175.45)	(\$175.45)
PL Profit Δ due to category spillover	\$0.27	\$0.73	\$53.79	\$0.71	\$1.93	\$57.43
PL Profit Δ due to brand spillover	\$5.58	\$1.68	-\$	-\$	\$0.85	\$8.11

3.7 Conclusion

The main purpose of this study is to present a relatively simple, feasible and easy-to-implement approach for chain-wide, store-level cross-category analysis. This analysis is intended to help retail managers make both category-wide and specific store-brand decisions. Our model produces precise estimates of the umbrella-brand effect when the store brand is offered in multiple categories, while accounting for the correlation between demand by category. We apply a market-share model to data describing a chain retailing weekly sales of national brands and of the retailer's own brand, competing in five categories that include related and unrelated categories. From a substantive point of view, we confirm some of the results found in previous studies. Unlike these previous results obtained for product categories, we show that the spillover between categories is present at two levels, namely, the store-brand level and the category-demand level. In doing so, our proposed model provides more precise and robust "global" category-level estimates while also producing "local" store-brand estimates.

Finally, we mention four possible extensions to our work. First, in the empirical simulation we make a plausible link between the UB profitability for the retailer and the different tiers of SBs (premium, me-too, generic). However, our modeling framework doesn't consider this dimension, as our IRI data does not differentiate between premium or lower-tier store brands. A richer dataset in terms of pre-established categorization for the store-brand tiers would allow us to address more specific issues of umbrella branding for private labels. Second, this paper assesses the UB spillovers under a short-term financial perspective. However, UB strategy could have been seen as a source of long-term effect on customer loyalty and retailer's reputation (Steiner, 2004). An extended model could take into account this long-term effect of UB spillovers. Third, results show that UB spillover effects vary across categories. It would be interesting to investigate this disparity by including category attributes (quality perception, perceived risk, etc.). Further, some authors (Pinjari and Bhat 2010; Kamakura, Kang 2007) stated that the implementation of marketing strategy should take into account the fact that each store caters to a different market with different needs and responses to marketing programs. Thus, UB spillover could also be seen as variable across retailers and chain stores. Lastly, many questions underlying consumers' motives for buying store brands cannot be answered with aggregated data. Experimental methods, however, can provide more specific guidance on what features of store brands consumers prefer, and why one type of SB may have significant cross-category effects, while another may not. We leave this for future research.

3.8 Appendix

Table 3.8 Price elasticities

		Mayonnaise	Mustard	RFG Frankfurters	Ready-To-Eat Cereal	Liquid Laundry Detergent
Mayonnaise	PL	-0.169	-0.059	0	-0.087	-0.011
	Leader NB	0.018	0.006	0	0.009	0.001
	Follower NB	0.018	0.006	0	0.009	0.001
	Other NB	0.018	0.006	0	0.009	0.001
Mustard	PL	-0.018	-0.079	-0.001	-0.013	-0.004
	Leader NB	0.006	0.025	0	0.004	0.001
	Follower NB	0.006	0.025	0	0.004	0.001
	Other NB	0.006	0.025	0	0.004	0.001
Refrigerated Frankfurters	PL	0	0	-0.130	0	0
	Leader NB	0	0	0.027	0	0
	Follower NB	0	0	0.027	0	0
	Other NB	0	0	0.027	0	0
Ready-To-Eat Cereal	PL	0	0	0	-0.291	0
	Leader NB	0	0	0	0.025	0
	Follower NB	0	0	0	0.025	0
	Other NB	0	0	0	0.025	0
Liquid Laundry Detergent	PL	-0.006	-0.024	-0.001	-0.054	-0.043
	Leader NB	0.001	0.006	0	0.013	0.010
	Follower NB	0.001	0.006	0	0.013	0.010
	Other NB	0.001	0.006	0	0.013	0.010

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General Conclusion

Although store brands are becoming increasingly important across the world, their success varies dramatically across consumer packaged goods categories, stores, retailers, and countries. This research dealt with two important issues about the store brand's performance. In a first article, we focused on the cross-country disparity of the SB success and identified the main socio-economic and cultural factors behind the geographical variation. The rest of the thesis dealt with the performance of store brands across product categories, in the presence of an umbrella-branding strategy. We investigated the cross-category synergy when the retailer and/or manufacturer decide to use the same name for his brand in different categories.

Specifically, in the first essay we investigate the reasons having allowed the SBs to consolidate their position in certain countries, while they are struggling in some other markets. The results reveal that the international market for private labels is characterized by two differentiated patterns in terms of SB's performance. (1) In SB-developing countries, store brands are a relatively new phenomenon. SB products seem to be regarded as cheap and low-quality alternatives for branded products. Perceived risk emerges as a critical factor inhibiting consumers to buy SB products. The price differential favouring the SB seems not to be a sufficient reason to divert consumers from national brands. In these geographical markets, social and cultural stigmas remain a barrier to SB growth. This leads to consider the products as hedonic, so where there is a higher standard of living, national brands become more coveted, leading to a lesser demand for private labels. These social and cultural factors make the retail market leads to credible and successful SB programs as he gets more concentrated. (2) In contrast, in developed countries in terms of SB, customers have been long exposed and accustomed to them and thus aware of their benefits. The maturity reached by the distribution sector diluted the significant impact that the retail power used to have on

SB's performance. On the contrary, the market size has a strong positive impact on the SB'S performance. In these countries, consumers are more likely to be utilitarian and purchasing decisions made by lower-income are price driven. Among this group, as a society gets urban and its consumers educated, store brands have a higher propensity to succeed. This research should be seen as an initial step attempt to explain differences in PL's performance across many countries and can be extended in several directions. A strength of this study is that it encompasses many countries. However, its broad scope makes it impossible to collect data at the level of individual retail chains and geographical regions within countries. Thus, our analysis is conducted at the country level. Within a country, individual NBs may differ in their ability to fight SBs from specific retailers. Future research should broaden the lens by examining brand and retailer-specific effects in an international context, and it should include within-country regional factors. Macro data used dilutes the multitude of consumption patterns that could be observed within a country. This suggests that a two-step segmentation approach, i.e., inter- and intra-country segmentation would be welcomed. Future research could examine whether some of the retailers' strategies and countries specificities to capture a larger SB share are equally effective for premium SBs than for standard SBs. Finally, it would be interesting to integrate a first-stage decision into the model in order to explain what affects the PL-introduction decision (high margins, profitability enhancement, bargaining power, etc.). This would offer a clearer understanding of the whole process of SBs performance. In sum, we call for a deeper understanding of commonalities and differences in the SB phenomenon across countries in the world.

The rest of the thesis dealt with the performance of store brands across product categories, in the presence of an umbrella-branding strategy. In a first place, we investigated this issue when a retailer and/or a manufacturer adopt this strategy in two complementary categories. The ensuing results indicate that the attraction of SBs, as well as of NBs, in the toothpaste category is boosted by its attraction in the toothbrush category, and vice versa. The brand-specific spillover is asymmetric and associated to the market strength of each competing brand. Moreover, we show that neglecting UB spillover leads to misestimating the model parameters and has a considerable impact on price-elasticities computation. From a managerial perspective, our findings offer a relevant and straightforward method for decision makers to precisely assess the financial impact of each managerial decision within a cross-category perspective. In a second place, we extend this modeling framework modeling in two ways. First, we consider the spillover analysis in multiple-categories context. Second, apart the umbrella branding dependency, we include the natural cross-category dependency caused by joint utilization, purchasing patterns and similar placement. We find significant positive umbrella-branding effects for the store brand in some of the categories. Interestingly, the store-brand spillover-effect is significantly present among even unrelated categories. At the category level, sales interdependence between unrelated categories points to the ability of marketing actions in one category to influence sales in any other categories in the store. In sum the umbrella-branding strategy was found efficient in strengthening the position of the retailer's brand across categories. However, in term of total profit, the strategy proves to be profitable only when the SB margin is comparable or higher than the NB margin. Based on category and brand-spillover measures, we assess precisely the impact of a marketing activity on the retailer's global performance across categories.

The third essay presents an attempt to remedy to some of the second-essay shortcomings by providing empirical evidence regarding the role of umbrella-branding on the retailer's global performance across categories in terms of sales and profit. Although the insightful role of this generalisation, we believe that there are some interesting directions for future research. Future research should broaden the analysis with a richer dataset in terms of pre-established categorization for the SB tiers to address more specific issues of the umbrella branding for different tiers of the store brand (premium, me-too, generic). One extension worth conducting would be to examine the UB spillovers on the long term to consider its effects on customer loyalty and retailer's reputation. As the implementation of marketing strategy should take into account the fact that each store caters to a different market with different needs and responses to marketing programs, future research could examine whether the UB spillover could also be seen as variable across retailers and chain stores. Finally, it would be interesting to look to the underlying consumers' motives for buying store brands that cannot be answered with aggregated data. Experimental methods, however, could provide more specific guidance on what features of store brands consumers prefer, and why one type of SB may have significant cross-category effects, while another may not. This thesis certainly contributes to the understanding of the store brand's performance under an international perspective; and also under a cross-category perspective in the presence of an umbrella-branding strategy. In this line, it would be insightful to extend this research to consider premium PLs which have emerged recently and have been referred as the hottest trend in PL retailing. Premium PLs are positioned at the top end of the market, and their unique features in terms of taste, origin, and ingredients enable retailers to compete with the highest-quality national brands. However, research on premium PLs is still scarce. Western Europe is the most mature premium PL market in the world. It would be interesting to see whether the same principles hold in other markets where PLs are still in the growth stage of their life cycle (as in many emerging markets), and/or in markets where standard PLs have a lower quality perception (as in the U.S.). It may be worthwhile to investigate the extent to which this quality differential increases the hurdle for premium PL introductions, or whether it offers instead more differentiation opportunities. Future research could investigate whether they were guided by the same principles in their introductions. Relatedly, it would be interesting to explore whether our findings also generalize to other formats as, for example, (hard) discounters. Germany's leading discounter Aldi, for example, recently introduced a premium PL line (PlanetRetail2008). The recent economic downturn has driven many consumers toward PLs. However, consumers increasingly feel a frugal fatigue, and long to indulge themselves with something more expensive (Store Brand Decisions 2012). Responding to this desire, Spar Austria's CEO Gerhard Drexel, when launching the SPAR PREMIUM tier, emphasized their objective to "democratize luxury" (Press release of October 7, 2010) by offering premium quality at affordable prices. This evolution could help explain why the premium tier has been the fastest-growing PL segment. This leaves us applicant to investigate the umbrella-branding impact for premium, as well as standard, tiers store-brands. We leave these topics for future research.