Price, Quality Retailer-Owned brands

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Chapter 1: Introduction

1.1 Motivation

The number of retailer-owned brands labelled with the retailers' name, that appear to be close competitors of the leading branded goods (also called national brands) has increased in recent years, especially in large supermarkets and pharmacies. In the supermarket industry they are found extensively in categories such as grocery, frozen foods and household and cleaning products, whereas in the pharmaceutical industry they are labelled as generic drugs or branded generics and are found in the main- and mass-market therapeutic categories such as analgesics, antacids and anti-inflammatory medication. In other markets such as large department and electronic device stores the firms have focused on own brands of inferior quality or low-technology devices under other brand names.

The common reasons behind supermarket and pharmacies' development of these brands discussed in the literature are: to take advantage of the dominant position and reputation of the firm; to negotiate better contracts with leading manufacturers; to optimise the use of the ofthe shelves; and to enhance customer loyalty and thus increase profits (Grewal, Levy and Lehmann, 2004). In particular, the fact that a large retailer decides on the quality of its label has important implications for interbrand competition, as the private label may be used as leverage to get better results from bargaining with manufacturers via such strategies as reduced wholesale prices, the imposition of a charge for shelf space and exclusivity contracts. The retailer may also put pressure on manufacturers to make own-brand products as a condition for selling the latters' branded products. Examples of manufacturers producing retailer-owned brands are found in England, France and Chile and include large firms such as Coca Cola, Findus, Kellogs and P&G. In the UK, some own brand products are also imported from countries such as China due to the enormous economies of scale available there in the production of agricultural goods and chemical products such as detergents

According to Zhang (2010), the decision to create an own brand involves many factors such as choosing the right product, developing the right price, choosing the right name and deciding on the number of varieties; Tesco, for instance, sells four different own brands. Zhang points out that

retailers have a big advantage over manufacturers because they deal directly with consumers and hence have more information about their needs and can respond rapidly to satisfy them.

The most significant development of retailer-owned brands world-wide is observed in the supermarket industry. According to the Symposium on Retail Competition (2008), the own-brand market share is 50% higher in several European countries than that in the US, with Germany at 35.1% market share and the UK, 39.6%. So far most categories of products have been covered and firms are now tending to adjust the market by increasing prices, introducing different own brands with a different price/quality ratio and expanding production to other types of products. The opposite is true in Latin America, where the own-brand trend started in 2005, which gives them a big market opportunity to grow over time. ACNielsen (2004) have achieved an 8% market share in Argentina and 5% in Chile and Colombia.

What is the future of these brands? According to the Institute of European and Comparative Law (2008), they have an average structural upper boundary of 45% market share because empirical evidence shows that a store offering up to 20% of own-brand goods is attractive to consumers whereas offering 40% or more discourages custom. The report also highlights that consumers are sensitive to the quality of unbranded goods and the presence of branded products. This last point is widely discussed by Gomez, McLaughlin and Wittink (2004) and Ward, Shimshack and Perloff (2002), who argue that higher-quality brands make only a marginal impact on customer satisfaction as people are sensitive to other factors, such as the technological advances involved in producing them.

In Latin America, and particularly in Chile, the development of these brands is strongly linked to the growing concentration of supermarket and pharmacy retail industries dominated by multinational firms such as Walmart. So far Chile has seen the most significant development in the production of the own brands in Latin countries.

The Chilean supermarket industry has seen an asymmetric growth depending on the size and location of the retailer since 2005. The large supermarkets have aggressively followed the own-brand strategy, covering most categories of grocery shopping items and differentiating strongly between low-quality

and medium-quality goods which are usually sold under the name of the store. They have also expanded to include premium products in categories such as groceries and frozen foods in line with UK supermarkets such as Morrisons. Their production has been entrusted to different-sized firms from small companies to leading multinational manufacturers that make high market-share products in the most competitive categories. The leading manufacturers have responded by differentiating their products via their packaging and formats and flooding the markets with new brands, pushing up the price of leading brands. They also negotiate more complex contracts to fix slotting allowances that reflect the importance of their goods on the shelves. There are various examples in which the conditions of these negotiations have changed over time, negatively impacting on the relationships between manufacturers and large supermarkets. In fact some cases have been reported to the competition authorities to control supermarkets fixing allowances or to imposing arbitrary payment schemes.[1]

The effect on consumers has been heterogeneous as they pay lower prices for more competitive grocery products but higher prices for leading brands. A clear benefit is the larger number of brands, as the varieties per product have increased strongly (Lira, 2005).

On the other hand, Chilean large pharmacies sell branded generic analgesics, anti-inflammatories and antiseptics under their own names in the mass market direct sales. As a consequence of lax laws regulating the pharmaceutical industry, the popular therapeutic categories are highly competitive and most are covered by pharmacy-owned brands. Nevertheless, the average price of drugs is considered high due to the low level of competition amongst retailers (Diario Oficial, 2011)[2]. There is also a big Prices also differ widely due to by promotions, discounts given to specific groups, differing transportation costs per geographic zone and advertising costs (Chumacero, 2010; Vasallo, 2010).

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[1] See Scl-econometrics. Final report (2008)
[2] Available in http://www.fne.gob.cl/wp-content/uploads/2012/01/Sentencia_119_2012.pdf.

A brief summary of the main literature

Bontems, Monier-Dilhan and Requillart's (1999) pioneer theoretical paper recognising the strategic effect of the entry of own brands suggests that the wholesale price of branded goods may increase if the own-brand product is a closer substitute of the leading brands. Berges, Bontems and Requillart (2003) affirm that the entry of private brands increases interbrand as well as retailer competition. The role played by stores switching customers defines the final outcome and profits for both the retailer and the leading manufacturer. On the empirical side, Cotterill, Putsis and Dhar (2000) show differences in the final prices of branded products across categories depending on the quantitative analysis methodology used. For cross-sectional data, the entry of private brands pushes up the price of leading brands in most cases. Bonfrer and Chintagunta (2004) find a mixed impact on prices using a panel of household- and store-level data from the US. Gabrielsen *et al* (2001) also show higher prices after introducing leading brands in Norway.

According to our knowledge three more theoretical papers contribute to understanding of the effect that own brands have on branded products, the degree of interbrand competition and competition between retailers, and the vertical relationship between manufacturers and large retailers (Berges-Sennou, 2006; Gabrielsen *et al*, 2007; Berges-Sennou *et al*, 2009).

Gabrielsen *et al* (2007) study supermarket-owned low-quality brands under the assumption of exogenous quality. They investigate why own brands are only distributed in some grocery categories, how the introduction of own brands affect the pricing of branded goods and the impact on social welfare. Like Berges *et al* (2003), they discuss the importance of consumer loyalty in the profitability of launching a low-quality own brand. Their main findings are that the mere threat of launching a private brand may be sufficient to bring down the wholesale and retail prices of branded goods. They also find higher prices for branded goods with a high proportion of loyal consumers following the launch of an own brand and consequently the possibility of an exclusive contract discussed with a manufacturer under the assumption that the the latter has bargaining power. The authors conclude that the own brand plays the same role a contract with two tariffs, because it is used to obtain a reduced

fixed slotting allowance. Shaffer's (1991) complementary argument proposes that a mixture of two tariffs and a higher wholesale price is a pricing scheme that will force the retailer to increase the prices.

Berges-Sennou (2006, 2009) expands the analysis considering elements of horizontal product differentiation such as transportation costs. One of his models takes into store and national brand account bargaining power and loyal consumers to look at the optimal number of products sold by retailers; how the retailer decides whom to entrust with the production of their brand; how its production affects the negotiation process and the decision to launch the retailer-own-brand; the optimal type of contract to regulate the relationship between retailers and manufacturers; and how the contract scheme between the manufacturer and the retailer is used to negotiate the entry of the own-brand product.

One of Berges-Sennou's most important findings is the role of store- and brand-switching consumers, as well as the proportion of each group in the demand as the retailer fixes its commercialisation policy[3] depending on how each group behaves. He also reports that if possible, the retailer entrusts own-brand production to a leading manufacturer with limited bargaining power, otherwise it uses a competitive firm. This point is also modelled in the last paper (2009) under the hypothesis that branded manufacturers would have incentives to produce a private brand in order to improve retailer contracts, maximise profits through economies of scale, and use excess production capacity to diminish costs. From the retailer's point of view it looks for manufacturers that assure good-quality products.

The entry of generics is a world-wide issue in this industry because it increases the degree of competition and helps the authorities to control for the high cost of the healthcare system. Most research in this context is carried out using US market data (Grabowski and Veron, 1992; Reiffen and Ward, 2003; Saha *et al*, 2006), and is mainly seeks to identify the determinants of entry. How does the entry of generic drugs affect the original drug's price and market share and the degree of competition?

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[3] It means selling strategies.

Empirical research has expanded towards other countries as a consequence of the expiration of patents of the original drugs (Hollis, 2005; Iizuka, 2009 and Kim, 2009).

1.2 Overview

We have written three independent papers about the interaction between store-named own brands that and leading branded goods. First, to investigate the strategic relationship between the branded good and the own brand, we developed a theoretical framework based on a vertical product differentiation model combined with elements of bargaining power in a vertical control scheme. We also followed different empirical papers about UK´s supermarkets Cotterill *et al* (2000), Gabrielsen *et al* (2001), Sayman *et al* (2002), Ward *et al* (2002) and Bonfrer *et al* (2004) and Chilean pharmacies (Bae, 1997, Frank and Salkever, 1997, Reiffen and Ward, 2003, Hollis, 2005, Saha *et al,* 2006, and Kim, 2009) to understand how own brands interact with branded products empirically.

Theoretical Approach

We constructed our model following Mussa and Rosen (1978) and Gabrielsen *et al*'s (2007) response and take some elements from Berges-Sennou (2006). The main aim of our research is to create a framework to help us to understand the effect of the own brand on the retailer, the branded good market and the manufacturers and discover whether it is profitable for a retailer to sell an own-brand product that closely resembles an existing branded product.

We considered a setup in which a monopolist retailer sells two differentiated goods – a high-quality branded product and an unbranded product of low quality, both manufactured by independent producers. The retailer considers backward vertical integration with the manufacturer of the unbranded product. As a result the new label becomes a retailer-owned brand and hence we checked the condition for the own brand to be launched. Next, we relaxed the exogeneity assumption about quality, as a result we suppose endogenous quality of the own brand to find the quality of this that maximises its total profits, and then we compared the outcomes for different frameworks (vertical separation and vertical integration).

Although the model can appear restrictive because of the monopolist retailer downstream, we believe that Steiner's (1993) argument, in which retailers compete in a geographical market, defined as the place where the distributors resell the products, can validate our assumptions. Community Competition Law defines the relevant market as a combination of the product and geographic markets (EEC, 1962) [4] and hence it is perfectly possible to find (mainly small) markets to which our model can be applied.

Empirical Research

Secondly, to test our theoretical results we used panel data techniques to analyse the interaction between branded products and own brands (supermarkets and pharmacies). On the one hand we measured the short-term sensitivity of how the branded product and the own brands interact in UK supermarkets with data obtained directly in the supermarkets; on the other, the empirical research deals with the branded drugs and pharmacy generics in Chile, which uses a real dataset obtained from a local wholesaler.

The UK Supermarket Industry

We constructed three different models to explain the interaction between retailer-owned brands and leading labels of a basket of 19 products sold by UK supermarkets. We estimated an equation for the logistic of relative prices, logit and probit models to estimate the product allocation on the shelves and a log specification for the number of brands sold by supermarkets.

Our dataset included a time trend, a dummy variable to identify any supermarket offer, price cut or discount, the number of manufacturing firms, and three dummy variables to control for supermarket-specific effects. The dataset was collected directly over 40 weeks from October 2008 to July 2009. The initial shopping basket contained 20 products from four of the largest UK supermarkets – Asda, Tesco, Morrison and Sainsbury – and included high-consumption goods in the following categories: groceries, toiletries, household products and cleaning products. We finally work with 19 products

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[4] Council Regulation No 17 (1962) Available in http://eur-lex.europa.eu/

because one of the supermarket-owned brand was highly differentiated with the branded product (tuna).

We believe that this paper contributes to current knowledge about supermarkets' strategic behaviour regarding pricing interactions between the brands considered and how the prices are established. Our specification is based partially on Cotterill *et al* (2000), Gabrielsen *et al* (2001) Ward *et al* (2002) and Bonfrer *et al* (2004).

We believe that our model on product allocation is innovative in this area, as there is no information (and it is very costly to obtain) about how supermarkets put the goods on the shelf, and hence we found no analytical research on this topic in the literature. We work under the assumptions of Sayman, Hoch and Raju's (2002), who argue that retailers target the leading brand on the shelf, as is validated in our dataset.

The Chilean Pharmaceutical Industry

The third independent paper is about pharmaceutical retailers in Chile. Our main motivation in carrying out this research was to analyse how the pharmacy-owned brands and the leading drugs (both generics and original brands) interact in Chile. To answer this question we estimated two econometric analysis models with panel data, a pricing model and an equation to analyse the determinants of the market share for own-brands and leading brands. We adjusted the existing methodology in order to construct our models, which are hence pioneering models in this type of research.

Why is this research justified? The Chilean market is attractive due to the state's low barriers to introducing new drugs in a framework of a highly concentrated retailer market. The country also has a weak healthcare reimbursement system and hence their medical costs are mainly paid by the patients themselves. In addition, a particular characteristic of the commercialisation is that sellers usually induce the purchase of a drug based on the unitary profit gained from a specific brand – mostly own-brands – which has allowed pharmacies to rapidly increase sales of their own drugs. This recently

justified a big legal reform in this sector aiming to encourage competition via the expansion of the type of retailers that can sell drugs in the country (supermarkets, convenience stores, among others).

There is a broad range of literature investigating the pharmaceutical industry, mainly in the US. Most focuses on the degree of competition caused by the entry of generic drugs, or changes to the institutional health system to control the increasing cost of drugs. We followed five papers to construct our models, including Bae, 1997, Frank and Salkever, 1997, Reiffen and Ward, 2003, Hollis, 2005, Saha *et al* (2006) and Kim, 2009.

To my knowledge this paper fills a gap in the literature on low-regulation markets such as Chile's. It also refreshes the existing research with updated data supplied by a friendly local wholesaler. However, whilst we were carrying out this research another factor appeared in the market: the competition authorities prosecuted large pharmacies (90% market share for three chains) and wholesalers for collusion to fix prices and finally punished them with the highest penalties available in Chile's competition laws, as recently confirmed by the Chilean Supreme Court. [5] Our dataset covers the last part of this period (2008).

Although there is no research on the impact of pharmacy-owned brands on the market, consumer rights organisations have pointed out that even though the pharmacies have recently been punished for collusive behaviour there is still a big differences between the prices of generics and of branded drugs, the latter being up to twenty times more expensive. They have also complained because since the introduction of the bioequivalence mechanism[6] only 23% of the medications that are permitted to be sold (over-the-counter, OTC) are available in these large pharmacies.[7]

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[5] http://www.fne.gob.cl/2012/09/07/corte-suprema-confirma-sentencia-del-tdlc-y-aplica-multa-maxima-a-farmacias-cruz-verde-s-a-y-salcobrand-s-a-por-caso-colusion/

[6] "The property wherein two drugs with identical active ingredients (as a brand-name drug and its generic equivalent) or two different dosage forms (as tablet and oral suspension) of the same drug possess similar bioavailability and produce the same effect at the site of physiological activity"(Cited in http://www.merriam-webster.com/dictionary/bioequivalence)

[7] http://cifchile.adminsite.cl/noticias/item/77-s%C3%B3lo-23-de-remedios-bioequivalentes-est%C3%A1-a-la-venta-en-farmacias

Chapter 2: Is it profitable for a large-retailer to sell an own-brand product similar to the branded product of a large manufacturer? A vertical product differentiation model

This research contributes a model that indicates that the possibility of increasing the quality of the retailer- owned brand, for a given production cost, allows the expansion of this label towards a greater number of grocery products on the shelves, which is supported by the fact that the restraint given by the vertical integration solution is relaxed for a higher quality-production cost ratio under the assumption of modelling with endogenous quality.

Another way of interpreting these results is that most competitive manufacturers can enjoy a dominant position by producing goods that the retailer could only produce inefficiently.

Under the endogenous assumption, the model also shows that the total production of the branded good is not altered, which can be explained by the argument that this brand is demanded by consumers with high willingness to pay for it. However, the wholesale price decreases and hence the manufacturer's profit always falls as the quality of the own brand rises, consistent with the argument that the retailer improves its negotiation capacity with the private manufacturer when it sells an own brand that is a close substitute for the manufacturer's label, which always forces the wholesale price of the branded product down.

2.1 Introduction

The number of retailer-owned brands or private brands sold under the same name of the store which appear to be close substitutes for national (leading) brands, has increased in recent years, especially in large supermarkets and the pharmacies.

In supermarkets, such products are mainly found in categories such as groceries, frozen foods and household and cleaning products: for instance in the UK the supermarket chain Tesco sells four quality-differentiated own brands – Value, Oak lines, Finest and Tesco – whereas Asda, another supermarket chain, manufactures and sells three different own brands, the largest of which is the Asda brand. In the pharmaceutical industry, these correspond to generic drugs in the main therapeutic categories such as analgesics, antacids, anti-inflammatories and anti-spasmodic medication. This strategy is uncommon so far in other retail markets such as electronics or clothing, where the retailers focus on low-quality own brands, usually with 'fantasy' names rather than the name of the store, so that consumers perceive them as an additional independent brand competing at the fringe of other competitive brands.

In general the development of own-brand products is closely related to the reputation of the large firms that seek to attach their name to them to enhance customer loyalty and thus increase their profits. Grewal, Levy and Lehmann (2004) offer theoretical arguments to support such a move. To achieve this aim, the retailers position their own-brand goods in the best locations in the store to maximise their profitability and mount advertising campaigns that benefit the firm as a whole and its entire range of products.

With the introduction of these products competition has become more aggressive, and hence it is likely that less competitive brands will disappear, creating an opportunity for the large retailer-owned brands to obtain a significant market share. In this context, we ask some basic questions: Is there an upper limit to their growth? Can the own brands be similar in terms of quality to high quality and leading goods? Is it possible to cover all the grocery categories with own brands for the large retailers?

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A report about the trends of private labels, brands and competition policy in the retailer industry (Institute of European and Comparative Law, 2008) states that the average structural upper boundary for the own-brand industry is a 45% share of the market. The report emphasises that empirical evidence shows that a store offering up to 20% of own brands is attractive to consumers, whereas there is a negative attitude when it offers 40% or more. Other findings coincide with this comment in the sense that the launching of these goods is not favourable for the groceries industry because they would have a restrictive ceiling in terms of production cost and qualiy to maximize profits.

The report highlights that consumers are sensitive to the quality of unbranded goods and the presence of branded products. Gomez, McLaughlin and Wittink (2004) found that higher-quality goods have only a marginal impact on customer satisfaction; however, if the quality falls, customer satisfaction declines significantly, causing a drop in both demand and store revenue. Ward, Shimshack and Perloff (2002) argue that people's perception of the quality of the own brands is highly sensitive to factors such as the technological advances made to produce them and public information about their manufacturers.

The fact that large retailers can decide on the quality of their own label has important implications for them, since it makes it possible to control costs and revenues during the whole of the manufacturing and merchandising process. These goods also get a positive externality from the supermarkets advertising as they have the same name as the store. In some cases they benefit by using packaging similar to that of successful brands, confusing consumers as they choose which brand to buy. Own-brand distribution can be used to soften the competition between brands and stores, because retailers can put pressure on branded manufacturers for a better (or exclusive) contract, given the higher bargaining power that their own brand gives them. In other words, the private label can be used as a lever to achieve better outcomes from bargaining with manufacturers, such as reducedwholesale prices, charging for shelf use – usually known as slotting allowances – obtaining resources for advertising and exclusivity contracts.

Big manufacturing companies such as Procter and Gamble, Kellogg in France and Coca Cola in the UK also produce own-brand products (mainly detergents, beverages and cereals) for large supermarkets in Europe (discussed by Berges-Sennou, 2006). Findus makes own-brand products for Tesco, and Weetabix, a producer of wholegrain breakfast cereals, makes this product for large supermarkets in UK. To my knowledge there is no public information about actions of abuse of dominance in the Europe. In some extreme cases the retailer may put pressure on such manufacturers to make an own-brand product as a condition for selling their branded products in the store, as in two cases in Chile: the largest supermarkets have forced a medium-sized domestic firm and a multinational firm to make their own-brands (FNE[8], 2006).

The main aim of this research is to determine large supermarkets' motivation for introducing own brands under the store's name. We examine whether there are market arguments such as the higher profitability of a certain product or of selling a bundle of high-quality goods that justify the vertical control of a product and the expectation of aggressive competition generated by the introduction of the own brand. We also interested in whether it is possible to equalise the quality of the high-quality brands or leading brands and the interaction between retailer-owned and high-quality leading products in terms of pricing, profits and the products' inherent qualities.

Quality improvement of own-brands has been observed during the last few years, at different speeds across supermarkets and countries. This non-price competition strategy is therefore another factor that affects not only interbrand and intrabrand competition but potentially also the vertical relationship between the retailer and the manufacturer, and may change the consumer's decision to buy a product.

Most theoretical and empirical research has focused on three big questions so far: (i) how does the entry of a low-quality own-brand affects the outcome of the branded product? (ii) What type of manufacturer produces own-brand products? (iii) How does retailer-manufacturer interaction affect social welfare?

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[8] Fiscalia Nacional Economica (The Chilean Competition Agency, www.fne.cl)

Our model has been built within a vertical differentiation model proposed by Tirole (1988), followed by Gabrielsen and Sorgard (2007) for supermarket products and by Davies and Lyons (2008) for the pharmaceutical industry. Gabrielsen *et al* (2007) focused on low-quality supermarket-owned brands to examine three issues: the condition of entry across categories; how the own brands affect the pricing of branded products; and the impact on social welfare. Davies *et al* (2008) simulated the effect of launching or suppressing medicines still under development to model the impact on an existing product and how this is affected by alternative ownership patterns.

We considered a set-up where a monopolist retailer sells two differentiated goods - a high-quality branded product and a lower-quality unbranded product produced by manufacturers with monopoly power. The monopolist retailer considers backward vertical integration with the manufacturer of the unbranded product as a mechanism to introduce its own brand rather than a direct increase in the number of brands. Thus the new label becomes an own brand of the large retailer and substitutes the unbranded product[9] sold within the vertical separation scheme. Next, it is analysed to see whether improving the quality of the retailer-owned brand will result in increased joint profit from selling a high-quality good along with its own brand with different qualities.

Our approach, based on a vertical product differentiation model combined with elements of bargaining power in a vertical control scheme, differs from that of Gabrielsen *et al* (2007) in many aspects. First, Gabrielsen *et al* suppose that the quality is exogenous whereas our main focus is the assumption of endogeneity, since we want to find the own-brand quality that maximises the retailer profit. Second, this paper emphasises the role of loyal consumers in investigating whether is profitable to introduce a low-quality good. The assumption about loyal consumers is not considered in our model because we suppose that all consumers decide on the ratio between quality and price. Third, Gabrielsen *et al* are interested in how consumers' surplus and welfare are affected by own brands. We did not explore this issue in our research. Fourth, the authors include the possibility that the producer offers an exclusivity contract to negotiate the launching of the retailer-owned brand. In contrast, we

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[9] According to Oxford Dictionaries, they are products that not bearing a brand name
(http://oxforddictionaries.com/definition/english/unbranded)

work with a linear price contract which supposes that the firms prefer not to be involved in a bargaining process.

Some common elements are that both investigations look for explanations about why retailers choose not to introduce an own brand in some categories; both studies are based on cases in which national brands and own brands are vertically differentiated. Finally, both models suppose a monopolist retailer downstream, which could be unrealistic from a national point of view but is realistic for small markets. We discussed the validation of this methodology in the literature review.

Beyond this approach, at the point when we started this research there were no specific studies on this topic looking at interbrand competition within a framework of vertical product differentiation, and to my knowledge Berges-Sennou and Bouamra-Mechemache (2009) offer the only attempt to model quality as an endogenous variable is that of.

As Berges-Sennou and Bouamra-Mechemache's research was developed in parallel with our own investigation, it is analysed in detail later. We were interested in their aim in that research and the assumptions considered used to construct the model and its findings, which we discuss in the literature review to contextualise our conclusions.

As a result, the main contribution of our paper is its framework based on a vertical product differentiation approach combined with elements of bargaining power in a vertical control scheme. Under this setup our findings are sensitive to the ratio between production cost and products' inherent quality, which allows us to understand the dynamic of why one own brand can be a close substitute or an excessively differentiated good in relation to the high-quality product. In addition, the endogenous quality solution shows that the retailers cannot create their ownbrands in every product category, confirming the view of the Institute of European and Comparative Law (2008) mentioned earlier and our empirical observation. Gabrielsen *et al* (2007) discuss this issue based on the literature

Finally, this topic is important from a public policy perspective because the own brands an be used as a tool to impose unilateral contracts, impose restraints on manufacturers, increase prices (as discussed by Gabrielsen *et al*, 2007) and diminish interbrand competition in a store. Most of the literature

focuses on this argument to explain how the relationship between manufacturers and retailers has changed over time as a consequence of the growing power of firms downstream, and how this has affected the social welfare.

Our key findings provide insights into how own-brand goods affect the outcomes of large retailers, manufacturers of branded goods and consumers under the assumption that the retailer can choose the quality of its own brand (endogenous solution). We also investigate whether the development of retailer-owned brands can be expanded to any product, and what conditions, if any, must be met.

This paper is organised as follows: in section 2 we review the existing literature; in section 3, we discuss some important issues for our model. We formulate the model in section 4 and present the benchmark between the outcomes of vertical separation and vertical integration, assuming that quality and production costs are fixed. In section 5 we relax the assumption of exogenous quality in order to estimate the new total profit and its main restraints to make profitable both the branded and own-brand products. In section 6 we sum up and discuss the main finding and their implications for both upstream and downstream competition. All calculations and complex proofs are shown in the Appendix.

2.2 Literature Review

The literature about own brands can be divided on two areas. The first focuses on the analysis of bargaining power in upstream and downstream relationships (Bernheim and Winston, 1985; Dobson and Waterson, 1996; Motta, 2004; and Reisenger and Schnitzer, 2007). An extension of this theme is the evaluation of the types of contract that regulate the relationship between manufacturers and retailers. The main aim of this first approach is to analyse the number of grocery products that a market is able to bear, and how those impact on social welfare. The second field of research is concerned with product differentiation models, which have been enriched by incorporating different assumptions about contracts. Its main focus is to understand the strategic effects of the competitive interaction between own brands and branded labels (national brands, NB).

This grouping, however, is restrictive, as some models are constructed using both approaches. Our model is a clear example of this as it is built from a vertical product differentiation model with elements of bargaining power in a vertical control scheme.

Analysis of bargaining power in the upstream and the downstream relationship

There is a wide range of research considering the vertical relationship between manufacturers and retailers and its extension to vertical restraints. The main focus of the existing research is analysing the bargaining power in the upstream-downstream relationship and how this affects the final outcome and social welfare (see for example Bernheim *et al,* 1985, Dobson *et al,* 1996, Motta, 2004 and Reisenger *et al*, 2007. The main strength of this field is that it is mostly devoted to studying the impact of different industrial structures (both upstream and downstream level) on social welfare. Another contribution of this research is that offers insights into the relationship between the degree of product differentiation and its impact on outcome and prices. Bernheim *et al* (1985) and Motta (2004) also analyse anticompetitive effects given by the incentive to soften the competition via collusive outcome. Their results are therefore easily applicable to inferring the number of varieties that the market is able to bear.

An extension of these models includes evaluation of the types of contract that regulate the relationship between manufacturers and retailers. It focuses on the tariff mechanism or slotting allowances (Sudhir and Rao, 2006) and how these determine the competition environment. At this respect, there is some research about competition policy in the retailing industry. Steiner (1993, 2003) and Jones (2004) discuss vertical restraints and how agencies must evaluate merger policy in the sector.

This type of research also addresses the analysis of the methodologies and assumptions used for their construction. Steiner (1993) and Dobson *et al* (1996) look at how economists construct models that effectively reflect the vertical link between manufacturers and retailers. They argue that economists have failed to represent this relationship correctly, especially in the case of bargaining power, and recommend that models should be constructed in at least two stages in order to clearly distinguish

three facts: intrabrand and interbrand competition, the linkages between them, and the distinction between restraints based upon agreements and those on dominance.

Steiner (1993) argues that economists usually build models for the retailing market under the assumption of perfect competition downstream, neglecting the fact that retailers try to differentiate themselves from each other. He points out that firms compete vertically on the manufacturing-distribution relationship, thus the models have to assume the existence of vertical relationships that drive out to an imperfect competition. Jones (2004) discusses a practical implication of the nature of retailing competition as brought out by Steiner, looking at antitrust law in the US. She argues that the Merger Horizontal Merger Guidelines (1992) are based on a single-stage approach, far from the real world in which we can appreciate anticompetitive behaviour. Moreover, according to Steiner (1993) when economists analyse the retailing industry it is necessary to include the geographical market, which is where distributors resell the products.

Bernheim *et al* (1985) and Motta (2004) develop theoretical models representing anticompetitive explanations derived from the vertical link. The first analyses the upstream-downstream relationship to represent the usual arrangement made by manufacturers to sell a product through a common agent. The main findings show that all decisions taken by manufacturers drive to a collusive equilibrium in prices pushed by a commission scheme to compensate the downstream firm[10]. Motta (2004) uses common agency theory to show the potential anti-competitive effect produced when two manufacturers use the same distribution channel for their goods. He assumes a two-part tariff contract delegating the price decision and the optimal output chosen by the retailer. Under this assumption the outcome is exactly the same as that given by manufacturers maximising profits together.

Reisenger *et al* (2007) develop an analytical model to obtain information about overall market output and the consequences on the regulation policies. The general framework assumes successive oligopolies at both the upstream and downstream levels with endogenous market entry. Some of the

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[10] Ivaldi, Rey, Tirole *et al* (2003) also discuss under what conditions the product's homogeneity affects the likelihood of collusion, noting ambiguous results depending on the initial assumptions. However, they highlight that the product differentiation strategy can have a positive effect when it contributes to the introduction of an asymmetry between firms (different qualities of a product is a good example).

results suggest that the upstream and downstream markets interact asymmetrically, which implies that a larger number of upstream firms leads to a larger number of downstream firms, whereas the inverse is not true. An easy interpretation of this finding can be applied to own brands, as their production is always possible when the number of upstream firms is greater than the number of supermarkets.

The final outcome shows that overall market prices are dominated by competitive conditions in the downstream market, while the overall two-tier market structure is uniquely determined by the degree of product differentiation, entry costs and the pricing strategies followed by firms. In term of social welfare, the final effect depends upon the assumptions of market endogeneity or exogeneity.

Models of product differentiation and the interaction between own brands and national brands

Most of the research about Models of product differentiation and the interaction between own brands and national brands has been undertaken by Bontems *et al* (1999), Berges-Sennou *et al* (2004, 2006) and Gabrielsen *et al* (2007) in the past twelve years. Most of their models try to explain the strategic interaction between own brands and national brands, taking into account bargaining power and consumers loyal to either the store or the national brand.

Bontems, Monier-Dilhan and Requillart (1999)'s pioneer paper recognising the strategic effect caused by the entry of own brands presents a model of a retailer-manufacturer interaction to study the impact of interbrand competition. The main result suggests that the wholesale price of branded goods may increase if the private label is a closer substitute of them. The intuition about this finding is that when the quality of the retailer-owned brand is close to that of the branded label the own brand is no longer competitive because of its higher production costs, and as a consequence the manufacturer behaves like a monopolist by increasing the wholesale price. In contrast, when the quality of the own brand is low, the manufacturer cannot act as a monopolist and must reduce the wholesale price to deter the entry of the private brand.

Berges-Sennou, Bontemps and Requillart (2004) expand the previous analysis to measure the impact of the entry of own brands on retailers, affirming that it increases competition not only between brands but also between retailers. They argue argued that the role played by customers switching stores define the final outcome and profits for both retailers and national brand manufacturer. They also find that retailers have exclusive rights to the products sold in their stores, in contrast to the traditional approach in which this role falls to the manufacturers.

A natural extension of the research on retailer-owned brands asks which firms have the incentive to manufacture them and under what conditions they do it. The results depend on the degree of competition upstream and the firms' production capacity. An advantage of entrusting production to a national brand manufacturer is that it can ensure quality as high as that of the branded product at a lower production cost, as the manufacturer can benefit from economies of scale by making both goods. This could be a good business for strong manufacturers with available capacity. On the other hand the retailer-manufacturer negotiation could become tougher because it involves a whole negotiation process, including the tariff of the own branded good.

Berges-Sennou (2006) constructs a generalised model taking into account bargaining power and loyal consumers. The main aims are to find the optimal number of products sold by retailers, how the retailer decides who to contract the production of his brand to, how this decision affects the negotiation process with the manufacturer and finally how the contract scheme between manufacturer and retailer is used to negotiate the entry of the own-brand product. He also explains consumer behaviour when they have to choose between stores (that implies transportation cost for the consumer) and between brands (implying different qualities). Berges-Sennou incorporates some elements of horizontal differentiation in a classical Hotelling framework in the analysis.

One of the most important findings using this model is the role of store- and brand-switching consumers and the proportion of each group in the demand, as the retailer fixes its sales policy depending on how each group behaves. An increase in national brand loyalty can influence a retailer's decision to introduce an own brand, which is highly likely when store-switching consumers are

numerous. In addition, the model indicates that the retailer contracts own-brand production to a leading manufacturer with low bargaining power or failing that, to a competitive firm. Berges-Sennou highlights that the manufacturer's best response is to flood the market with new brands when it has to face hard negotiation with retailers. Empirical evidence confirms this finding.[11] From the retailer's point of view failed negotiation is too costly as this firm has to support higher fixed fees to encourage the manufacturers to sell the goods.

As discussed in the introduction, this topic has been expanded by Berges-Sennou and Bouamra-Mechemache (2009), who investigate both retailers' and national manufacturers' decisions on retailer-owned brand production. They look into the details of why a national brand manufacturer would be motivated to produce a private brand. Three possibilities are considered: (a) to improve a contract with the retailer; (b) to secure revenue, otherwise another firm will capture it; (c) to use excess production capacity to bring down costs. From the retailer's side, the decision depends on the quality of the goods, i.e. the production of a medium quality good shold be given to a competitive firm while a high-quality own-brand should be produced by an incumbent manufacturer.

Another key contribution of Berges-Sennou and Bouamra-Mechemache's study is their discussion of the definition of quality and how it should be measured. They give a direct and simple definition – quality consists of a combination of product characteristics such as ingredients and recipes, as a consequence, in our research we proceed in that direction to interpret our findings.

Gabrielsen *et al* (2007) focus on low-quality supermarket-owned brands (exogenous quality) in their examination of why retailers choose not to introduce an own brand in some categories and how the new product affects the pricing of branded products. They are also concerned with the impact on social welfare. In order constructing their model they emphasise the role of loyal consumers in the decision of whether it will be profitable to launch a low-quality good. They also include the possibility of exclusivity in order to negotiate a contract with the manufacturer.

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[11] Another strategy often observed is product differentiation, mainly using new packaging and different sizes. Berges-Sennou *et al* (2004, 2006) offer theoretical and empirical proofs.

One of Gabrielsen *et al*'s main findings is that the mere threat of launching a private brand may be sufficient to create a drop in the wholesale and retail prices of national brands. In contrast, when the own brand is introduced the theory predicts higher prices for the national brand, which is reversed when the national brand has only a small market share or has small market coverage). As a consequence of the higher prices of the national brand, the theory predicts, society is worse off. However, this result can also go in the opposite direction if the own brand is not introduced. Thus, the impact on social welfare deserves more analysis, as the effect can be ambiguous.

The result associated with the composition of the demand shows that the more loyal consumers of the branded product there are, the higher its price increase will be when the own brand is introduced, as the manufacturer focuses on inelastic consumers. In contrast, when the market is highly fragmented with similar products, the new own-brand entry increases the competition and the prices go down. The same analysis can be applied to switching consumers, who abandon the branded product for the new own-brand, which also pushes up the price of high-quality goods.

The contracting assumption used is also discussed. It is assumed that contracts are constructed under uniform wholesale prices and that the manufacturer has all the bargaining power. The authors get the same result when including a contract for two-part tariffs. The explanation is that the private labels have the same objective as the the retailer-owned brand; i.e. they are used to threaten the manufacturer in order to obtain a lower wholesale price and as a tool of price discrimination between consumers. The first impact is therefore equivalent to obtaining a reduced fixed fee. Price discrimination also occurs when the retailer obtains lower wholesale prices and as a result, sets differentiated prices for both labels.

Miklos-Thal, Rey and Verge (2008) report opposite results from their a model addressing the competitive effects of vertical contracts in which rival retailers offer contracts to a manufacturer based on a 'three-parts tariff', including an upfront payment or slotting allowance. Under this assumption the welfare implications are ambiguous.

Davies *et al* (2008) also use a vertical product differentiation model to simulate the effect of launching a product or suppressing one still under development. They are interested in how this situation affects the prices of incumbent products, as commonly observed in the pharmaceutical industry. According to their findings the answer requires calibrating the range of consumer's preferences for quality and the proportion of inelastic consumers of dominant products, which is consistent with Gabrielsen *et al*'s (2007) findings in the supermarket industry. In the same way, the final equation of prices also requires estimation of production costs.

A topic that has been attracting research in recent years is the contract scheme based on slotting allowances. It is a good example of the application of dominance by a retailer (Foros and Kind, 2006), as previously modelled by Hamilton (2003) and Innes and Hamilton (2006). Studies by Berges-Sennou (2006) and Gabrielsen *et al* (2007) have considered the contract scheme to look at the strategic relationship between own brands and branded products. So far, the main findings point to the fact that the manufacturer is worse off, as it pre-commits him to more aggressive quantity-competition in the upstream market. The use of slotting allowances is consistent with the increase in buyer groups and retailer groups that operate retail chains, who expect lower competition within a given group.

Finally, the quantitative research also looks at slotting allowances as a tool to regulate the business between manufacturers and retailers. Sudhir and Rao (2006), analyse available US information to test this issue and report that efficiency theory has more quantitative support that the anticompetitive theories.

2.3 Some preliminaries

As mentioned, our model was built considering the vertical differentiation model proposed by Mussa *et al* (1978), discussed by Tirole (1988) and used by Gabrielsen *et al* (2007) for supermarket products and Davies *et al* (2008) for the pharmaceutical industry.

We consider a setup where a monopolist retailer sells two differentiated goods – a high-quality branded product and an unbranded product of lower quality – produced by manufacturers with monopoly power. The monopoly retailer considers backward vertical integration with the

manufacturer of the unbranded product. Thus the new label becomes a retailer owned-brand that substitutes the unbranded product sold within the vertical separation scheme. In other words, this strategy represents the introduction of an own-brand label instead of a direct increase in the number of brands.

The preliminary economic argument for selling an own brand is to take advantage of the vertical control of this product, which avoids double marginalisation within the vertical separation scheme. Thus the firm enjoys higher profits due to the elimination of price distortion caused by, two successive markups.

After calculating the final equations for this model, we compare the final equilibrium of the vertical separation and of the vertical integration schemes to see how final and wholesale prices and quantities vary after integration. We also determine the necessary conditions for these market structures to exist profitably. At this stage we assume that the product's quality and the production costs are exogenous. Later we assume the quality of the retailer-owned brand to be endogenous to estimate both, whether the previous constraints vary and how the retailer's total profit changes according to the inherent qualities of different products.

As the main objective of this paper is to check whether it is profitable for the large retailer to sell an own-brand close substitute for the branded product, we calculate the quality of the retailer-owned brand that maximises its total profit and the existence of new restraints, if any

As the large retailer has vertical control of its own-brand it may choose a different level of quality to that of the unbranded product in order to maximise the total profit obtained from selling both goods. For a given production cost, the retailer could operate within a range of higher-quality goods with a higher unitary profit in comparison to the profit from selling a product of inferior quality related to the former unbranded product.

The retailer increasing the quality of the own-brand to a level very close or similar to that of the high-quality product could impact negatively on the profit derived from selling the branded product. This causes a trade-off between the higher gains expected for selling its own brand and a drop in the gains

from selling the branded product. It makes sense for a retailer do this as long as selling a high-quality own-brand more than compensates for the potential drop in the profit variation from selling the branded product.

For simplicity, we assume that the retailer always sells both products, which means that the manufacturer cannot work as an independent seller even though particular pay-offs may be higher when it acts as an integrated duopolistic distributor rather than as a mere producer. Economically, the latter scheme makes sense because not all manufacturers can set up their own store, which involves financing fixed investment as well as other costs that can inhibit the profitablility of the product. As a consequence, the manufacturer cannot retaliate against the retailer removing its product from the store to eliminate interbrand competition.

We also explore upstream to determine how the manufacturer of the branded product is affected by both the vertical integration of the unbranded product and the raised quality of the retailer-owned brand. The methodology follows the same steps as before.

2.4 The model

In recent years, large retailers have secured a dominant position which has affected not only the final prices paid by consumers but also their negotiations with manufacturers. We consider an interbrand competition model that combines elements of vertical product differentiation and bargaining power in a vertical market structure. The model follows a methodology similar to that used by Gabrielsen *et al* (2007) and contributes to the the literature about strategic effects between two vertically-differentiated goods rather than a model of horizontal differentiation (Hotelling model) such as that of Berges-Sennou (2006).

We assume that a monopoly retailer distributes two differentiated goods, *i=1, 2,* which are produced by two independent manufacturers. Each product has different inherent qualities such that $s_1 > s_2$ and the production costs are fixed and equal to c_1 and c_2.

Following Bontemps *et al* (1999), we assume a linear price contract between retailer and manufacturers in the form $T_i(q_i)= P_{wi}q_i$, where P_{wi} denotes the wholesale price and q_i the final quantity of products *1* and *2*. According to Tirole (1989), much of the theory is concerned with the case of this scheme to fix prices, although vertical relationships involve more complex contracting arrangements.

One explanation to justify the choice of this type of contract supposes that firms prefer not to be involved in bargaining to set a fixed-fee transfer due to either high transaction costs or asymmetry in their capacity to negotiate.This scheme is also discussed in the literature, where it is used to measure interbrand competition (Sudhir *et al*, 2006, Miklos-Thal, Rey and Verge, 2008).

As stated earlier, there are two important differences here from the Gabrielsen *et al* (2007) model. Our model emphasises two elements: *the role of loyal consumers*, to define whether launching a low-quality good will be profitable, and *the possibility of exclusivity,* the objective of which is to negotiate a good contract with the manufacturer.

Initially we consider equilibrium with full vertical separation, as denoted by the superscript *vs*.[12] Then we allow the introduction of a retailer's own label through the backward vertical integration of product *2*. The superscript *vi* denotes this framework. Then we consider the retailer's choice of whether to integrate and produce an own brand. The timing of this game is as follows:

a. In the first stage, the retailer decides whether to backward integrate with manufacturer 2. If it does, its product becomes a retailer-owned brand, otherwise the retailer continues as a distributor of products 1 and 2

b. In the second stage, the independent manufacturers set the wholesale price.

c. In the third stage, the retailer sets prices P_1 and P_2.

For simplicity, retailer costs are assumed to be zero. In this section the quality of both products is exogenous.

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[12] Vertical separation is understood as the case where the retailer is a mere distributor, while in vertical integration the retailer sells the high-quality product along with its own brand.

Graphically the model can be expressed in the following figure:

Figure 1: Vertical separation and vertical integration framework
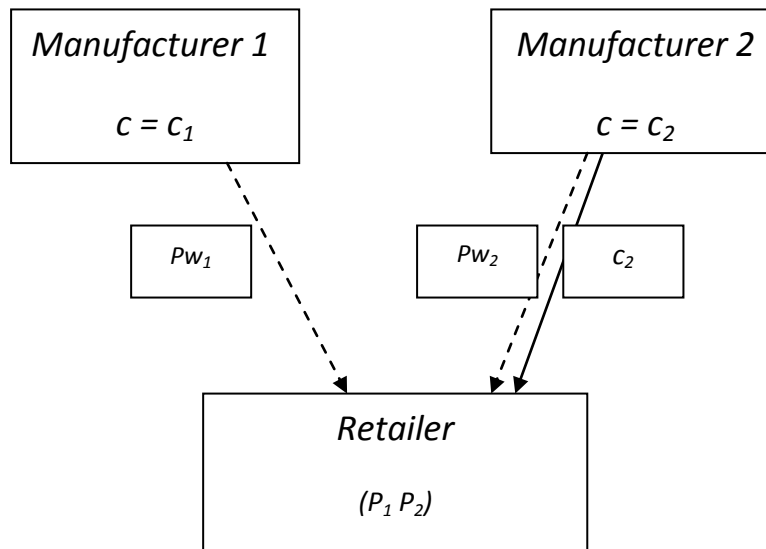
The arrows represent the vertical relationship between the manufacturers and the retailer. The dotted line shows the case of vertical separation and the continuous line reflects the vertical integration case.

Demand specification and notation

We define θ as a taste parameter for quality such that $\theta \ \varepsilon \ [\underline{\theta}, \bar{\theta}] \ \bar{\theta} > 0, \underline{\theta} = \bar{\theta} - 1$, and we assume a uniform distribution of consumer types. The utility for a consumer i is given by $U_i = \theta s_i - P_i$. Consumers do not try if $U_i < 0$. Thus, consumers do not buy if $\theta < p/s$. We suppose that a proportion of consumers is not served as they are willing only to pay lower prices for a given low quality product in comparison with the price which this is offered. One important difference with the Gabrielsen *et al (2007)* paper is that they incorporate as an assumption the existence of loyal consumers, which impact the demand function and allow the retailer offers an exclusivity contract when the demand is characterized mostly for this type of consumers.

To reflect our maintained assumption that the quantity of the high quality brand is exogenous, its quality is normalized to *1 ($s_1=1$)* and thus it is defined a lower quality product as that given by the expression $s_2 = s$, such that $s < 1$.

The marginal or switching consumer is indifferent to the difference between products 1 and 2. She is characterised by $\theta = \hat{\theta}$, where

$$\hat{\theta} - P_1 = \hat{\theta}s - P_2, \Rightarrow \hat{\theta} = (P_1 - P_2)/(1-s)$$

The demand for each product can be represented by the following linear expressions, which depend on prices and the inherent qualities of both products:

$$Q_1(P_1, P_2, s) = \bar{\theta} - \hat{\theta} = \bar{\theta} - (P_1 - P_2)/(1-s)$$

$$Q_2(P_1, P_2, s) = \hat{\theta} - P_2/s_2 = (P_1 - P_2)/(1-s) - P_2/s$$

The retail demand functions for each good are downward sloping and show that the products are substitutes in prices $(\partial Q_i/\partial P_j > 0)$, which I comment on later.

The first product has a positive demand $Q_1 > 0$ when $\bar{\theta}(1-s) > (P_1 - P_2)$. Note that we also require $Q_2 > 0$ if product 2 is to have a positive demand. Next, we check the own elasticity and cross elasticity for each product and proceed to interpret the valuesof those elasticities.

Elasticities for Q_1

We first derive the elasticities for good 1. The values and the analysis are discussed below.

$$\eta_{q1,p1} = (\partial Q_1/\partial P_1)(P_1/Q_1) = \{-P_1/[\bar{\theta}(1-s)-(P_1 - P_2)]\} < 0 \quad \text{Own elasticity}$$

The own elasticity depends on prices, the inherent quality of both products and the upper bound of the test parameter for quality$\bar{\theta}$. As $\varepsilon_{q1,p1}$ must be negative, given hat the numerator is always negative, the denominator in this expression must be positive to be consistent and so $[\bar{\theta}(1-s)-(P_1 - P_2)] > 0$, which is satisfied because of $Q_1 > 0$.

Now we move to cross elasticity.

$$\varepsilon_{q1, p2} = (\partial Q_1/\partial P_2)(P_2/Q_1) = P_2/[\bar{\theta}(1\text{-s}) - (P_1 - P_2)] \quad \textit{Cross elasticity with respect to } P_2$$

This elasticity is always positive because the products are substitutes and depends on the same

expression as $\eta_{q1,p1}$.

Elasticities for Q_2

We now proceed to analyse product 2.

$$\eta_{q2,p2} = (\partial Q_2/\partial P_2)(P_2/Q_2) = -P_2/(sP_1 - P_2) < 0 \qquad \textit{Own elasticity}$$

As this expression must be negative, $(P_1 s - P_2) > 0$, which requires that $P_1 s > P_2$. In the extreme case

of maximum differentiation, if $s \to 0$, $\varepsilon_{q2,p2} \to 1$, which is inconsistent with $\varepsilon_{q2,p2} < 0$. Generally

speaking, when $s \to 1$ (minimum differentiation), the prices converge to Bertrand solution. Next we

calculate the cross elasticity.

$$\varepsilon_{q2, p1} = (\partial Q_2/\partial P_1)(P_1/Q_2) = sP_1/[(sP_1 - P_2)] \qquad \textit{Cross elasticity with respect to } P_1$$

The condition to be consistent $\varepsilon_{q2, p1}$ *(it means higher than zero)* is the same as before $P_1 s > P_2$.

From the above we sum up these results in the following table.

Table 1: Own elasticity and cross elasticity results

Products	Own elasticity	Cross elasticity
Product 1	$-P_1/[\bar{\theta}(1\text{-s}) - (P_1 - P_2)]$	$P_2/[\bar{\theta}(1\text{-s}) - (P_1 - P_2)]$
Product 2	$-P_2/(P_1 s - P_2)$	$sP_1/[(P_1 s - P_2)]$

Both the own and cross elasticities for product 1 and product 2 depend on the same parameters. Their

values show that the denominators are the same, and as a consequence the comparison depends only

on the values of the numerator. In the case of product 1, own elasticity is always higher than cross

elasticity as $P_1 > P_2$. On the other hand, the own elasticity of demand and the cross elasticity of product 2 depend on the value of s, and thus if quality s is higher, both elasticities are closer.

What should we expect of these elasticities?

According to numerous studies those who move first achieve a long-term competitive advantage (see a summary discussed by Lieberman and Montgomery, 1998)[13] over their followers. We posit that this principle is also satisfied in the case of brands, and hence we believe that product 1 shoud be less elastic than product 2.

In the case of the cross elasticities, we believe that $\varepsilon_{q1, p2}$ should be higher than that for product 2 ($\varepsilon_{q2, p1}$) because the branded manufacturer has many advantages as was the first to enter the market: for example, first mover status (a long-term competitive advantage), sunk costs (advertising)[14] and technological leadership, among others, while the second label must bear switching costs to attract buyers from the incumbent, which in turn means that the cross elasticity of the branded good (product 1) is more elastic than that of the own brand.

2.4.1 Retailer as mere distributor

In this section we derive the equilibrium for the vertical separation framework. This solution will be the standard to compare how the equilibrium is modified after vertical integration of product 2.

Prior to developing the solution to interbrand competition, we suppose that the retailer simply distributes the high-quality brand to establish a baseline competition value.

Those outcomes are used to compare the impact of introducing a second good of lower quality on the outcome of the retailer and the manufacturers. The monopoly results and their demonstrations are developed in the appendix (case a).

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[13] http://mis.postech.ac.kr/class/MEIE780_AdvMIS/2012%20paper/Part1%20(Pack1-3)/05_Timing%20of%20Entry/12)%20First-mover%20(dis)advantages_Retrospective%20and%20link%20with%20the%20resource-based%20view.pdf
[14] It is discussed for Bontemps *et al* (1999)

Next, we move to the interbrand competition scheme by introducing a low-quality good with quality

$s_2 = s$.

Interbrand competition: vertical separation

Taking the wholesale price as given, the retailer sets its prices according to the following profit

function:

$$Max_{\{P_1^{vs}, P_2^{vs}\}} \pi^{vs} = [P_1^{vs} - P_{w1}^{vs}] Q_1^{vs} (P_1^{vs}, P_2^{vs}, s) + [P_2^{vs} - P_{w2}^{vs}] Q_2^{vs} (P_1^{vs}, P_2^{vs}, s) \qquad (1)$$

For each manufacturer the optimal decision requires the maximisation of the following expressions:

$$Max_{\{P_{w1}^{vs}\}} \pi_{M1}^{vs} = [P_{w1}^{vs} - c_1] Q_1^{vs} (P_1^{vs}, P_2^{vs}, s) \qquad\qquad \textit{Manufacturer 1}$$

$$Max_{\{P_{w2}^{vs}\}} \pi_{M2}^{vs} = [P_{w2}^{vs} - c_2] Q_2^{vs} (P_1^{vs}, P_2^{vs}, s) \qquad\qquad \textit{Manufacturer 2}$$

After substituting the demand functions, the first-order conditions for the retailer are given by the

price equations (P_1^{vs} and P_2^{vs}) shown below (see appendix, section b, solutions 4 and 5), which depend

on the inherent qualities as well as the wholesale prices.

$$P_1^{vs} = 1/2 \, [(1-s) + 2P_2^{vs} + P_{w1}^{vs} - P_{w2}^{vs}]$$

$$P_2^{vs} = 1/2 \, [2P_1^{vs} \, s - P_{w1}^{vs} \, s + P_{w2}^{vs}]$$

Solving both equations (see appendix, points 7 and 8), the equilibrium retail prices are:

$$P_1^{vs} = 1/2 \, [1 + P_{w1}^{vs}]$$

$$P_2^{vs} = 1/2 \, [s + P_{w2}^{vs}]$$

By substituting these retail prices into each manufacturer's profit function, the best reply wholesale

price functions (see solutions 9 and 10 in the appendix) are written as:

$$P_{w1}^{vs} = \tfrac{1}{2}[(1-s) + P_{w2}^{vs} + c_1]$$

$$P_{w2}^{vs} = \tfrac{1}{2}[c_2 + P_{w1}^{vs} s]$$

Solving these equations for markets 1 and 2, the calculation yields the equilibrium shown in Table 2, below:

Table 2: Prices and quantities under vertical separation

Variables	Retailer	Variables	Manufacturers
P_1^{vs}	$\tfrac{1}{2}[3(2-s) +2c_1 + c_2]/(4-s)$	P_{w1}^{vs}	$2[(1-s) + c_1 + c_2/2]/(4-s)$
Q_1^{vs}	$[1-\tfrac{1}{2}c_1(2-s)/(1-s)+\tfrac{1}{2}c_2/(1-s)]/(4-s)$		
P_2^{vs}	$\tfrac{1}{2}[s(5-2s)+ sc_1+ 2c_2]/(4-s)$	P_{w2}^{vs}	$[s(1-s) + sc_1+ 2c_2]/(4-s)$
Q_2^{vs}	$\tfrac{1}{2}[1+c_1/(1-s) -c_2(2-s)/s(1-s)]/(4-s)$		

Source: From Vertical Separation solutions, equations (8), (9), (10), (13), (14) and (15) in the appendix

**Proposition 1**: By generating interbrand competition via the sale of a close substitute for the monopolistic product, the retailer affects the outcome of the monopolist manufacturer of a high-quality brand. The manufacturer is always worse off when a competitor enters the market.

- *Proof*

Before proving this proposition, we return to the monopoly outcome (see appendix) to measure how the high-quality good is affected by the introduction of a low-quality good. Due to interbrand competition we would expect the price of the branded product to go down and hence the quantity demanded increases. In both cases there is a double marginalisation because retailer acts as a mere distributor; however in the separating solution the retailer strengthens its position with respect to the branded manufacturer because the introduction of an imperfect substitute allows him to negotiate a better contract with the monopolist. We initially suppose that $c_1=c_2=c$.

Table 3 summarises the monopolist equilibrium and the vertical separation results for product 1.

Table 3: Prices and quantity of product 1 under monopoly and inter-brand competition

Variables	Monopoly	Product 1 under inter-brand competition
P_1	*1/4 (3+c)*	*3/2 (2-s+c)/ (4- s)*
Q_1	*1/4 (1- c)*	*½(2-c)/(4-s)*
P_{w1}	*½ (1 + c)*	*2(1-s + 3/2 c)/(4-s)*

Source: Monopoly solution in Appendix, section a.

Drawing on the values shown in the table, we will demonstrate whether $P_1^m > P_1^{vs}$, $Q_1^m < Q_1^{vs}$ and

$P_{w1}^m > P_{w1}^{vs}$, as developed in the appendix.

Next we verify the last inequalities:

- $P_1^m > P_1^{vs}$. The calculation is shown in section c of the appendix. The main restraint of this

  condition is given by *3s/(2+s) >c*, which is the same as *s>2c/(3-c)*. As proved in the

  appendix, the latter is always satisfied and hence $P_1^m > P_1^{vs}$.

- $Q_1^m < Q_1^{vs}$. Replacing the values from the table above, the inequality left is

  (1-c) < (2-c)/(4-s). Rearranging it, *c(s-2) <s*. This inequality can be expressed as *-2c< s(1-c)*.

  The second term varies in the range *0<s(1-c)<1*, because *s≤1, c<1* and *(1-c)<1, ∀(c,s)*. As

  2c<0, the inequality is always satisfied and hence $Q_1^m < Q_1^{vs}$.

- $P_{w1}^m > P_{w1}^{vs}$. From the values of these wholesale prices shown above, we need to prove the

  conditions that allow to satisfy the following inequality, *½ +c/2>2(1-s+ 3/2 c)/(4-s).*

  Rearranging the latter algebraically, we find that *3s > c(2+s),* which in turn is equal to

  3s/(2+s) >c. This inequality is the same as the price expression seen above, which is always

  true, and hence $P_{w1}^m > P_{w1}^{vs}$.

From these expressions we have proved that the final outcome of the branded manufacturer always

drops with the entry of a competitor.

Next, we move to analyse the vertical separation outcome shown in Table 2. What do these equations say about relative prices and market share?

From above, we verify whether $P_1^{vs} \geq P_2^{vs}$, $Q_1^{vs} \geq Q_2^{vs}$ and $P_{w1}^{vs} \geq P_{w2}^{vs}$ under the assumption that $c_1 = c_2 = c$, which will be developed in appendix, <u>Interbrand Competition: Vertical separation.</u>

Looking at the results, we have P_1^{vs} equal to or higher than P_2^{vs}; and the market share of product 1 is always higher than that of product 2 ($Q_1^{vs} \geq Q_2^{vs}$) and $P_{w1}^{vs} \geq P_{w2}^{vs}$. These results are consistent with our beliefs posited in the elasticities section, that by being the first to enter the market the branded product has advantages over the lower-quality good introduced later by the retailer.

2.4.2 The entry of the retailer-owned brand by vertical integration

Next, we develop the case of vertical integration. The retailer's price-setting problem is given by the equation written below in which product 2 is a retailer-owned brand (see appendix, section d)

$$\underset{\{P_1^{vi}, P_2^{vi}\}}{Max} \pi^{vi} = [P_1^{vi} - P_{w1}^{vi}] \, Q_1^{vi} (P_1^{vi}, P_2^{vi}, s) + [P_2^{vi} - c_2] \, Q_2^{vi} (P_1^{vi}, P_2^{vi}, s) \qquad (2)$$

On the other hand, manufacturer 1 chooses the wholesale price by optimising the following expression:

$$\underset{\{P_{w1}^{vi}\}}{Max} \pi_{M1}^{vi} = [P_{w1}^{vi} - c_1] \, Q_1^{vi} (P_1^{vi}, P_2^{vi}, s)$$

The first order conditions for the retailer (see appendix, equations 18 and 19) are written as:

$$P_1^{vi} = 1/2 \, [(1-s) + 2P_2^{vi} + P_{w1}^{vi} - c_2]$$

$$P_2^{vi} = 1/2 \, [2P_1^{vi} \, s - P_{w1}^{vi} \, s + c_2]$$

Solving this equations system, the retail prices are:

$$P_1^{vi} = 1/2 \, [1 + P_{w1}^{vi}]$$

$$P_2^{vi} = 1/2 \, [s + c_2]$$

Note that the prices of both products behave as we would expect; that is, in direct relationship to their production cost and the products' inherent quality. The calculating is done in the appendix in equations 20 and 21.

These prices are substituted in the final quantity of product 1 to get the independent manufacturer's profit function. By choosing P_{w1}^{vi}, the optimal wholesale price is calculated in equation 24, this is:

$$P_{w1}^{vi} = \tfrac{1}{2}[(1-s) + c_1 + c_2]$$

The wholesale price depends upon not only on the production cost and inherent qualities of the product, but also directly on the production cost of product 2. Indeed, the theoretical fact of avoiding the double marginalisation of the decentralised solution also impacts on the independent manufacturer, as they are strategic goods.

The table below summarises the partially integrated own-brand equilibrium:

Table 4: Prices and quantities under vertical integration

Variables	Retailer	Variable	Manufacturer
P_1^{vi}	$\tfrac{1}{4}[(3-s) + c_1 + c_2]$	P_{w1}^{vi}	$\tfrac{1}{2}[(1-s) + c_1 + c_2]$
Q_1^{vi}	$\tfrac{1}{4}[1 - (c_1 - c_2)/(1-s)]$		
P_2^{vi}	$1/2[s + c_2]$		
Q_2^{vi}	$\tfrac{1}{4}[(1-s) + c_1 - c_2(2-s)/s]/(1-s)$		

Source: From Appendix, see Vertical Integration solutions, equations (21), (24), (25), (26) and (27).

From the above, we posit that $P_1^{vi} \geq P_2^{vi}$ when $c_1 = c_2 = c$, because the first product has a higher (or equal) quality to that of product 2.

Proof:

- $P_1^{vi} \geq P_2^{vi}$. Rearranging the equation for each price, and omitting the denominator because of equal values, we get $P_1^{vi} = \tfrac{1}{4}(3-s) + 1/2c$ and, $P_2^{vi} = 1/2 s + 1/2c$. In this case, all that is needed is to compare the first term of both equations.

As $\frac{1}{4}(3\text{-}s) \geq 1/2s, \forall s \leq 1$, then $P_1^{vs} \geq P_2^{vs}$.

What about the market share for vertical integration when $c_1 = c_2 = c$?

Our expectation is that the branded product has a higher market share because it has the advantage of being the first mover in the market, even in the scenario where the retailer has a better position as a consequence of selling an own-brand that is a close substitute for the first brand. To prove this we first define $\alpha_i = Q_i / Q_t$ as the market share for product i, where $i = 1, 2$ and $Q_t^{vi} = Q_1^{vi} + Q_2^{vi}$

Prior to calculating how the market is shared after integration, we need to calculate total production. It is $Q_t^{vi} = 1/4 + 1/4(2\text{-}s)/s = (s\text{-}c)/2s$, from the expressions in Table 4. Hence the market share functions are $\alpha_1 = s / [2(s\text{-}c)]$ and $\alpha_2 = (s\text{-}2c)/[2(s\text{-}c)]$. As a result, we expect that $\alpha_1 > \alpha_2$.

Lemma 1: If $c_1 = c_2 = c$, the market share of the branded product is always higher than that of the retailer-owned brand because it depends on the difference between the inherent quality *s* of the two labels', whereas the market share of the own brand depends on the difference, given by (s-2c).

Proof: From the values of α_1 and α_2 above, it is observed that the denominators are the same *(2(s-c)*; we therefore need to compare the numerators of those expressions. They are *s* and *(s-2c)*. As $s \geq ($ *s-2c)* $\forall s$ and $c \leq \frac{1}{2}$, the market share satisfies $\alpha_1 > \alpha_2$.

2.4.3 Comparative analysis of separating and integration solutions

The table below sums up the retailer outcomes for separating and integration solutions assuming that $c_1 = c_2 = c$, even though the products have different qualities. Restrictions to the profitability of both goods are shown.

Table 5: Market equilibrium ($c_1=c_2=c$)

Variables	Vertical Separation	Vertical Integration (own brand)	Restraints
Market 1			
P_1	$3/2\ (2-s+c)/(4-s)$	$¼\ (3-s+2c)$	*No restraint*
Q_1	$½(2-c)/(4-s)$	$¼$	*No restraint*
P_{w1}	$2(1-s+3/2\ c)/(4-s)$	$½\ (1-s+2c)$	*No restraint*
Market 2			
P_2	$½\ [s(5-2s)+c\ (s+2)]/(4-s)$	$½\ (s+c)$	*No restraint*
Q_2	$½\ (s-2c)/\ s\ (4-s)$	$¼\ (s-2c)/\ s$	$Q_2^{vs},\ Q_2^{vi}>0$ when $c<s/2$
π_t	$1/2\{2+5s/2-(cs)/2-7c+3c^2/2\}/(4-s)^2$	$(1/16)\{1+3s-12c+4\ c^2/s\}$	-

Source: Equations (12.a), (13.a), (14.a), (15.a) (16.a), (17.a), (21.a), (24.a), (25.a), (26.a) and (27.a) in

the appendix.

Table 5 shows the restraints given by Q_2^{vs}, $Q_2^{vi}>0$ which are related to the values of the production

cost and the products' inherent quality. For both, this must satisfy the condition $c<s/2$. Thus, the

production cost has an upper bound of $1/2$ when $s=1$ and any value higher than or equal to $(c\geq 1/2)$

will make selling both products together unprofitable. According with those results we develop the

following lemmas for product 1 and product 2.

Lemma 2: If $c_1=c_2=c$, the necessary condition for the low-quality brand to exist with positive demand

under an interbrand competition framework is $c<1/2$. If $c>1/2$ the retailer earns positive profits selling

just one of the goods.

- ***Proof:*** The proof follows from the results summarised in Table 5. The lemma requires that

  $Q_2>0$ and $P_2>0$. As seen above, the quantities are positive for both the integrated and the

  separated solutions when $c<s/2$. On the other hand, if $Q_2>0$, P_2 is always satisfied ($P_2>0$).

Product 1

We now compare the solutions for vertical separation and vertical integration (See appendix, part e)

and as a result we get the following lemmas for prices and quantities of the product 1.

**Lemma 3**: If $c_1 = c_2 = c$, the impact on the price of product 1 is ambiguous as it depends on the values taken by the production cost c and the products' inherent quality, s; that is, when the production cost approaches zero, the price goes up for any inherent quality s in the range (¼, 1). If the quality is lower, the price declines. When the production cost moves towards ½, the consumer price decreases after integration. The wholesale price also moves according to the same rule (see appendix, part e).

**Lemma 4**: If $c_1 = c_2 = c$, the quantity of product 1 always decreases after integration.

- **_Proof:_** We define $\Delta Q_1 = Q_1^{vi} - Q_1^{vs}$. This can be demonstrated by contradiction. If we suppose that $\Delta Q_1 > 0$ after integration, then, taking the difference from Table 5, _$\Delta Q_1 = $¼-½(2-c)/ (4-s)→(2c-s)/(4-s)>0_, we obtain the condition to expand the quantity, which is c>s/2. However, to make the entry of the retailer-owned brand profitable we need c<s/2, then $\Delta Q_1 < 0$ (see appendix, part e).

Product 2

The comparison between vertical separation and vertical integration gives as result lemmas 5 and 6, which are demonstrated in appendix, part e.

**Lemma 5**: If $c_1 = c_2 = c$, the price of the retailer-owned brand varies depending on the values of the production cost and the products' inherent quality. That is, if c→0, the price falls if s takes any value in the range (0, ¼), while it goes up for any quality higher than ¼. In contrast when c→½ the price always goes down.

Proof: We define $\Delta P_2 = P_2^{vi} - P_2^{vs}$. The lemma requires that $\Delta P_2 > 0$. Thus, taking the difference we get a quadratic inequality equivalents to _s^2- s(1+2c)+2c>0_, whose solution is the same as that of lemma 2.

Lemma 6: If $c_1 = c_2 = c$, the quantity of product 2 increases after integration if $c < s/2$.

- **_Proof_**: We define $\Delta Q_2 = Q_2^{vi} - Q_2^{vs}$. The lemma requires that $\Delta Q_2 > 0$. Thus by taking the difference ΔQ_2 we get the following condition, calculated in appendix part c: *(s-2c) (2-s)>0*, which requires that $s_1/2 > c$ or $s_2 < 2$. As s_2 is not restrictive $\Delta Q_2 > 0$

Proposition 2: Backward integration is profitable if the production cost and the products' inherent quality *s* satisfies the conditions given in lemmas 3, 4, 5 and 6.

Proof: See lemmas 3, 4, 5 and 6.

What about the intuition behind this proposition?

In general, both goods behave as strategic complements. As shown earlier, the final prices of good 1 and good 2 and the wholesale price of good 1 move together, increasing or decreasing depending on the products' inherent quality and production costs. On the other hand, the quantity restraints show that they are substitutes (lemmas 4 and 6); that is, the quantity of product 1 decreases if $c < s/2$, while the quantity of product 2 rises.

We now characterise how production cost and quality affect the final outcome (quantities and prices).

If $c_1 = c_2 = c \rightarrow 0$, the market share for both is the same after integration $(Q_1 = Q_2 = 1/4)$. That is, if both products have a low cost, the main benefit of avoiding double marginalisation is that it increases the own brand's market share to approach or equal that of the higher-quality product. In sum, the introduction of a low cost retailer-owned brand allows to serve a greater number of consumers.

If $c_1 = c_2 = c \rightarrow \frac{1}{2}$, product 2's market share drops. In the extreme, this good does not exist if c=1/2.

Even though prices move in the same direction, final prices depend on the products' inherent quality *s*. If the inherent quality *s* is low *(s<1/4),* the prices go down. If *s>1/4* (lemmas 3 and 5).

Complementarily, the price of both products always falls after integration if the production cost approaches the upper bound $(c \rightarrow \frac{1}{2})$. In sum, the most robust implication in this case is related to the existence of the own brand, as proved earlier.

Lemma 7: If $c_1=c_2=c \rightarrow \frac{1}{2}$, the necessary condition for the own brand to exist with positive demand is given by $s>1/2$. If $s<1/2$, $P_2<c$. On the other hand, the price of product 1 varies between *(3/4, 7/8)* depending on the values taken by s in the range $(\frac{1}{2}, 1)$.

- ***Proof:*** As shown in Table 5, the prices approach the following values: $P_1 \rightarrow 1/4$ *(4-s)* and $P_2 \rightarrow 1/2$ *(s+1/2)*. We require that $P_2>c=1/2$. Then, $P_2 \rightarrow 1/2$ *(s+1/2)>1/2*. Hence rearranging this term, *s>1/2*.

  As a result, the price of product 1 moves in the range *(3/4, 7/8)* because s moves in the range *(½, 1)*.

Proposition 3: If the quality is exogenous and the production costs are $c_1=c_2=c \rightarrow \frac{1}{2}$, the high costs are a barrier to entry of the retailer-owned brand[15]. As a result it is only profitable for the retailer to sell own-brand products of close or similar quality to those of high quality. This implies that only low-quality independent brands will be profitable for the retailer.

- ***Proof:*** From lemma 7, if the goods are highly differentiated *(s<1/2)* the own brand does not exist as $P_2<c=1/2$, and hence the necessary condition for the own brand to exist is *s>1/2*, which in turn means a drop in the products. On the other hand, the products cannot be identical as the market would be served only by the independent brand. That is, if $s \rightarrow 1$, $P_1 \rightarrow 3/4$ and $P_2 \rightarrow 3/4$, but $Q_2 \rightarrow 0$.

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[15] It means that Q_2 is unprofitable when $c \rightarrow \frac{1}{2}$.

2.5 Endogenous quality solution

Next, we allow the retailer to choose the quality of its own brand. Consistent with lemma 2, we assume that $c \leq 1/2$.

The aim here is to investigate whether there is any combination of higher quality and production cost that justifies retailers' strategy of matching the quality of their own brands to those of the branded products.

We assume that improving the quality of the own brand affects only the retailer's fixed cost as it involves investment in R&D. In other words, the retailer can increase the inherent quality of its product without altering a given production cost in order to maximise the total profit.

First, let (s^*, c^*) denote any combination of quality-production costs of product 2 such that $s < s^* \leq 1$ and $0 \leq c^* \leq 1/2$. Hence π^* denotes the retailer's total profit after improving the quality of product 2.

Next we check whether $\pi^* > \pi^{vi}$ for at least one combination quality-production cost within the space defined in lemma 2, i.e. $c < 1/2$.

Before calculating π^*, we analyse the strategic effect on each variable when the inherent quality s changes marginally. On differentiating the equilibrium of the vertical integration solution we find the following direct and crossed effects. For convenience, we begin by explaining the effect on product 2.

Direct effect in the market 2:

   The own strategic effects caused by increasing s are as follows:

$$\partial P_2 / \partial s = \tfrac{1}{2} > 0$$

$$\partial Q_2 / \partial s = 1/2(c/s^2) > 0$$

Lemma 8: If $c_1 = c_2 = c$, any quality improvement of the retailer-owned brand is profitable as it triggers both higher prices and production.

- **_Proof_**: The retailer's profit is given by $(P_2 - c_2) Q_2$. By differentiating the profit margin we obtain $\partial (P_2 - c_2)/\partial s = \partial P_2 /\partial s - \partial c_2/\partial s = 1/2$, which is always positive because we assume that $\partial c_2/\partial s = 0$. Complementarily, the first derivative of the quantity under vertical integration is given by $\partial Q_2 /\partial s = \frac{1}{2} c/s^2 > 0$ because (c, s) > 0, and hence the effect is always positive.

The explanation behind this finding is as follows: if we assume that inherent quality s rises by 10%, the price effect is given by the product of $(\Delta s)(\partial P_2 /\partial s) = (10\%)(1/2) = 5\% > 0$. Complementarily, as $\partial Q_2 /\partial s > 0 \, \forall c, s$, the profit generated by the own-brand, rises by 5%..

Now we check whether or not there is any previous condition will satisfy lemma 8. From the equations shown in Table 5, $\pi_2 = (P_2 - c_2) Q_2 = 1/8 (s - c) (1 - 2c/s)$. The first-order condition is $\partial \pi_2 /\partial s = 1/8[1 - 2(c/s)^2] = 0$. The critical value is given by $s = \sqrt{2} \, c$, which implies that profit increases if $s > \sqrt{2} \, c$.

As the second derivative is always positive, $\partial^2 \pi_2 /\partial s^2 = 1/2 \, c^2 /s^3 > 0 \, \forall (c, s)$ the critical value given by $s = \sqrt{2} \, c$ corresponds to a minimum.

Proposition 4: With endogenous quality, the expansion of the own-brand industry depends on the efficiency of production of different type of goods.

- **_Proof_**: From the last paragraph of lemma 8 we know that $\partial \pi_2 /\partial s > 0$ if $s > \sqrt{2} \, c$, which in turn means that expansion of the retailer-owned brands has a restraint, given by the ratio $s/c > \sqrt{2}$. If this condition is not satisfied for a particular good, the best solution for the

retailer is to hold the quality at the same level as it was sold by the decentralised scheme or after integration.

Cross effect on the market 1:

The strategic effects on product 1 are obtained by differentiating equations showed in table 5. They are:

$$\partial P_1/\partial s = -1/4$$

$$\partial P_{w1}/\partial s = -1/2$$

$$\partial Q_1/\partial s = 0$$

Lemma 9: If $c_1 = c_2 = c$, the cross effect of a marginal increase in the own-brand's inherent quality is beneficial to the retailer, as the profit from selling the independent product rises.

- **Proof:** The retailer's profit is given by $(P_1 - P_{w1}) Q_1$, where the first term corresponds to the profit margin. By differentiating it with respect to s, we obtain $\partial (P_1 - P_{w1})/\partial s = \partial P_1/\partial s - \partial P_{w1}/\partial s = -1/4 - (-1/2) = 1/4 > 0$. Complementarily, as the quantity is fixed $\partial Q_1/\partial s = 0$, and hence the final effect is always positive.

Lemma 10: If $c_1 = c_2 = c$, the independent manufacturer is worse off after improving the inherent quality of the retailer-owned brand as its profit always drops.

- **Proof:** As shown in Table 5, the manufacturer's profit is given by $(P_{w1} - c_1) Q_1$. By differentiating $\partial (P_{w1} - c_1)/\partial s = \partial P_{w1}/\partial s - \partial c_1/\partial s = -1/2 - 0 = -1/2 < 0$. As the quantity is fixed, the manufacturer's profit goes down.

We now quantify the amount by which the manufacturer profit falls. Using the equations shown in Table 5, $\pi_{M1} = (P_{w1} - c_1) Q_1 = [\frac{1}{2}(1-s+2c)-c] (1/4)$. The first derivative is $\partial \pi / \partial s = (-\frac{1}{2}) (\frac{1}{4}) = -1/8 < 0$. This means that for each 10% of higher inherent quality of the own brand, the manufacturer's profit drops 12.5%.

How can we explain the last two lemmas?

If we assume that *s* rises by 10%, From lemma 9, the impact on the retailer's profit margin is equal to

$$(\Delta s) (\partial P_1 / \partial s - \partial P_{w1} / \partial s) = (10\%) (-1/4-(-1/2)) = 2.5\% > 0.$$

As the quantity is fixed, the retailer always increases the profit of this good by the latter percentage even though the consumer price falls due to the strategic effect of the introduction of a high-quality good.

This is explained by the fact that the wholesale price goes down by a greater magnitude that more than compensates for the lower final price. We now show the impact on the manufacturer:

$(\Delta s)(\partial P_{w1} - c_1)/\partial s = (10\%) (-1/2) = -5\% < 0.$

Proposition 5*:* Even though the monopolist retailer must price the high-quality good lower, it always increases the profit on selling this product when launching a high-quality own-brand, the introduction of which is used as a tool to secure lower wholesale prices in negotiations with the leading manufacturer.

- ***Proof***: Demonstrated in lemmas 9 and 10.

The intuition behind this proposition is as follows. The monopolist retailer always takes advantage of its strategic position as a distributor as well as a competitor with independent manufacturers, who

must reduce the wholesale price and transfer part of its surplus to compete *vis a vis* with a similar retailer-owned brand.

Impact on total profits

Next, we calculate the impact on total profit, written as:

$$\pi^\bullet = \pi^*_1 + \pi^*_2 = (P_1 - P_{w1})\, Q_1 + (P_2 - c_2)\, Q_2$$

By substituting the values shown in Table 5, the total profit becomes:

$$\pi^\bullet = [¼\,(3 - s + 2c) - ½\,(1 - s + 2c)]\, ¼ + [½\,(s + c) - c]\, ¼\,(s - 2c)/\,s$$

After rearranging this equation, the retailer sets the quality by optimising the total profit.

$$Max_{\{s\}}\, \pi^\bullet = (1/2)^4\,(1 + s - 4c) + (1/2)^3\,(s - c)(1 - 2c/s) \qquad (3)$$

Differentiating this expression with respect to s, we obtain the first order condition:

$$\partial \pi^* / \partial s = (1/2)^4\,[3 - 4\,(c/s)^2\,]^{16}$$

Thus total profit increases when $\partial \pi^* / \partial s > 0$ and the critical value is obtained when $[3 - 4\,(c/s)^2\,] = 0 \Rightarrow c = s\sqrt{3/4}$. We define the value of s as $s = \overline{s}$. Then, $c = \overline{s}\,\sqrt{3/4}$.

To demonstrate that this value is a maximum we obtain the second derivative of $\pi^\bullet$. Its value is given by $-3/2\,(c/s)^2\{3 - 4\,(c/s)^2\}^5$, which is always negative as the term $3 - 4\,(c/s)^2 > 0$ or $c < s\sqrt{3/4} = 0.8660s$, the same condition as before. In the same way, as s has an upper bound of 1, $c < s\sqrt{3/4} = 0.8660$, which is an upper bound for the production cost.

On the other hand, we know that $c < 1/2$ (lemma 2) for the vertical integration solution, and comparing this with the production cost for endogenous quality solution ($c < 0.866$), shows that the new restraint is less restrictive.

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[16] Second derivative equivalent to $\dfrac{-2}{1-s} < 0$

Lemma 11: If $c_1=c_2=c$, it is always profitable for the retailer to enhance the inherent quality of the

own-brand competing with other brands as long as the relationship between the production cost and

inherent quality is $c \leq \bar{s}\sqrt{3/4}$

- ***Proof***: From the first-order condition above, the restraint to the profitability of increasing of

    the own-brand's inherent quality is $[3\text{-}4\,c/\bar{s})^2]>0$, which implies that $c< \bar{s}\sqrt{3/4}$

Proposition 6: When the retailer can define the quality of its own brands it can sell own-brands in

other product categories or expand the scope of products within a category, as the after-integration

restraint given by lemma 2 (R_1: $c<\bar{s}/2$) is relaxed by the new restraint shown in lemma 11 (R_2:

$c<\bar{s}\sqrt{3/4}$. As a consequence the own-brand industry is profitable for a greater range of goods

whose production costs and inherent quality falls in the range $s/2<c<\bar{s}\sqrt{3/4}$ in comparison to the

basket of own brands produced under the condition $c<1/2$.

- ***Proof:*** We are now able to prove our key finding. The graph below depicts different

    combinations of inherent quality s in the independent product and the retailer-owned brand,

    and production costs under exogenous and endogenous quality. The dotted line represents the

    upper bound of the low-quality goods after integration (R_1), whereas the continuous line

    depicts the new upper bound assuming that the retailer decides the quality of its product (R_2).

    Thus as a direct consequence of discretionally improving the quality of the own brand as

    explained in lemma 11, the retailer can expand its own brands into a greater number of

    products with a less restrictive quality/production cost ratio ($R_1 < R_2$). All new possible

    combinations of quality-production costs in the new scenario are given by the area between

    the dotted line and the continuous line in the figure below ($s/2<c<\bar{s}\sqrt{3/4}$).

How can we interpret this expansion toward new combinations of quality and production costs? In the

vertical integration solution with exogenous quality, the retailer has an upper bound equivalent to

c<1/2 (s=1, the same quality as product 1) to get $Q_2 > 0$. Now this solution is relaxed to c< $\sqrt{3/4} \approx$ 0.866. In other words, if the retailer wishes to equalise the quality of the product 2 with that of the product 1, it could introduce this good at a higher cost because the profits in equation 1 (section 2.4.1) will be positive. Economically, this means that for a given quality level the retailer is able to launch goods that are more expensive than those introduced under vertical integration, and as a result the industry is open to the entry of more goods. We nevertheless need to calculate the new restraint's impact on total profit.

Figure 2: Restraints under exogenous and endogenous quality of the retailer-owned brand
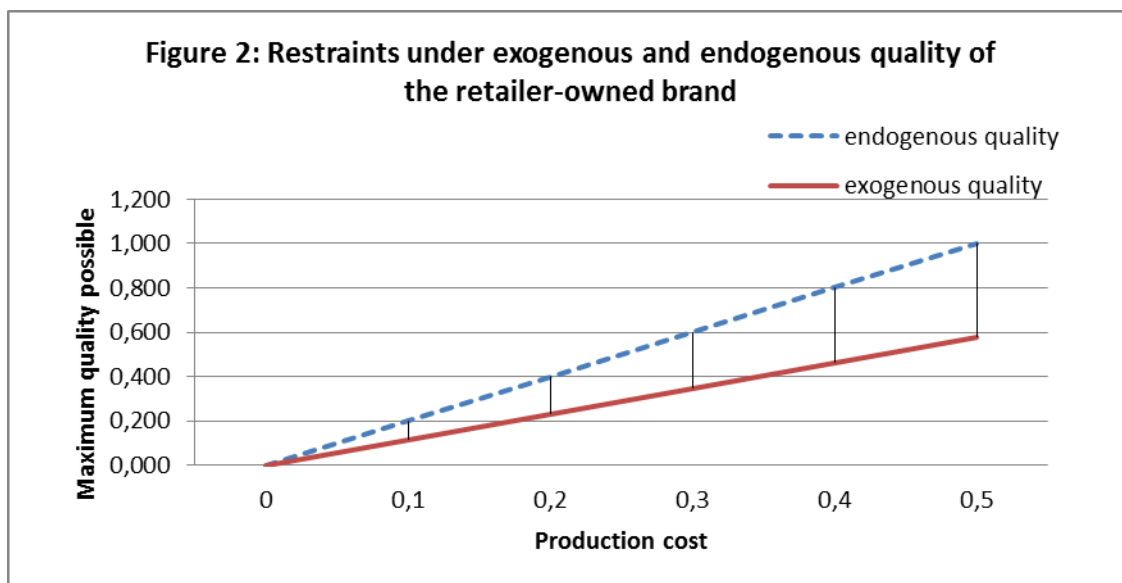
Next we compare total profit for exogenous and endogenous quality. We therefore use equations 2 and 3 (sections 2.2.2 and 2.3) under the vertical integration framework.

2.5.1 Exogenous and endogenous quality solutions

We now summarise how the retailer affects the branded product and the own brand when it can decide about the quality of the retailer-owned brand (endogenous quality). Table 6 presents the vertical integration solution for prices and quantities and shows how those variables are affected when the retailer increases the inherent quality *s* of the label that takes its same name. We also show the impact

on the retailer and branded manufacturer's total profits, assuming that total cost, c, is given, and hence the retailer looks to its products' inherent quality to maximise its profit.

Table 6: Endogenous quality and its impact on market variables

Variables	Vertical integration	Impact on variables
Market 1		
P_1	¼ (3- s+2 c)	-1/4
Q_1	¼	*No impact*
P_{w1}	½ (1-s +2c)	-1/2
Market 2		
P_2	½ (s + c)	1/2
Q_2	¼ (s-2c)/ s	$1/2 \; c/s^2$
Total profit		
π_t *(retailer)*	$(1/2)^4\{1+3s-12c +4 \, c^2 /s\}$	$(1/2)^4 \; [3-4 \, (c/s)^2 \,]$
π_t *(manufacturer)*	$(1/2)^3(1-s)$	-1/8

As discussed at the beginning of section 2.5, market 1 is affected negatively when the retailer increases the quality of its own brand because of lower prices for consumer and the branded wholesaler, which is consistent with what we would expect when competition intensifies due to less differentiation between products. Complementarily, as production Q_1 is constant in the vertical integration solution a higher-quality own brand does not affect the total production of the branded product, demonstrating that even though the retailer could take advantage of its monopolistic position and the facility to choose the quality of its own brand it continues selling the branded good, validating the argument that the retailer has an incentive to sell goods of different quality to satisfy consumers with different preferences.

On the other hand, the impact on market 2 shows that the price of the own brand increases by 50%, which is explained by the higher cost associated to its higher quality, whereas the effect on quantity is directly proportionate to the total cost c but inversely proportional to the square of the level of the inherent quality of this label $s,$ which is given by the expression $\{1/2 \; (c/s^2)\}$. In other words, if we assume a constant production cost c the own brand can achieve a higher market share when the retailer ensures its maximum differentiation (s→0) because of the term $1/2 \; (c/s^2)$ goes up.

Under this scheme, market size ($Q_t = Q_1 + Q_2$) also increases as total production of the branded good is not sensitive to the greater production of Q_2, consistent with the fact that the first label is demanded by consumers with a higher willingness to pay.

These theoretical results are similar to those of Berges-Sennou (2004, 2006), who affirms that the introduction of private labels increases interbrand competition as well as competition among retailers, which in turn means that the seller uses these brands to gain a greater market share or to satisfy consumers who prefer to buy goods in one place. The last argument is relevant when the retailer has a large proportion of loyal consumers however, this strategy is also important for switching consumers, as the retailer can satisfy the needs of different types of consumers (Berges-Sennou, 2006) and attract them to its stores. An additional argument found in the literature (Bourch and Lawrence, 2005) is that the retailer-owned brand ensures a continuous distribution of the products and hence the retailer can control manufacturers' opportunistic behaviour. As a result the retailer avoids harming its reputation by running out of stock.

Finally, the retailer's profit goes up as long as $c/s < \sqrt{3/4}$, an expression that represents the higher upper bound of the relationship between production cost and the inherent quality of the own brand, as shown in Figure 2. In contrast, the model shows that the manufacturer's profit always falls as the quality of the own brand rises, consistent with the argument that the retailer improves its negotiation capacity with the private manufacturer when it sells an own brand that is a close substitute for the manufacturer's label, which always forces the wholesale price of the branded product down.

This argument falls under the analysis of the bargaining power of large supermarkets mentioned in the introduction, as retailers are now not only distributors but also direct rivals of the manufacturers and can use their position to increase their negotiating power with leading manufacturers. This argument is widely discussed by Gabrielsen *et al* (2007), who point out that low-quality goods are used to impose unilateral contracts or restraints on manufacturers.

2.6 Discussion and concluding remarks

This research expands current knowledge about how own-brand goods affect the outcomes of large retailers, the manufacturers of branded goods and consumers. So far most theoretical and empirical research has focused on discussing the low-quality oaswn-brand industry. The dynamic entry of own brands that appear to be close substitutes for branded goods has motivated exploration of the effect that this type of good is having on large retailer's competition strategies.

Our model predicts important findings. After integration of the own brand by the retailer, the price of the branded good goes up when the own-brand production cost tends to zero and the inherent quality of the own brand is greater than 25% of that of the branded good. In contrast, if the percentage is lower than 25% its entry negatively affects the price of the branded good. According to Gabrielsen *et al* (2007), the national (branded) product price goes up when demand is dominated by loyal consumers, as that label concentrates on consumers with a greater willingness to pay for the good. The Gabrielsen result is not comparable with our finding because of different assumption, and hence we cannot affirm that the results are consistent.

Our result also shows that the wholesale price of the branded product moves according to the same rules as the consumer price of branded product (25% products´ inherent quality) discussed in the last paragraph. In contrast, Bontems *et al* (1999) affirm the strategic effect of the entry of own brands suggests that the wholesale price of branded goods may increase if the own-brand product is a closer substitute of the leading brands.

Perhaps one of the most important findings is that increasing the quality (endogenous solution) allows expansion towards a greater number of products on the shelf as post-integration restraint is relaxed by a higher quality-production cost ratio. This suggests that the expansion and diversification of own brands into other categories is feasible as its development does not reach to all grocery products, which would validate the opinion of the Institute of European and Comparative Law (2008) that own brands can grow in terms of their position in the markets until they reach an average structural upper boundary of a 45% market share.

We observe that the impact of higher inherent quality of the retailer-owned brand has a negative impact on the price of the branded good, as both labels become close substitutes for each other, in comparison to the initial situation where the quality of the own brand was exogenous. This means that the degree of competition increases with the quality of the own brand. The model also shows that the total production of the branded good is not altered, which can be explained by the argument that this brand is demanded by consumers with high willingness to pay for it.

The fact that the retailer defines the quality of its own brand could impact its price by 50%, which is explained by its higher quality for a constant production cost, whereas the effect on quantity is directly proportionate to the total cost, but inversely proportional to the square of the level of the inherent quality of this label in comparison to that of the branded good.

We find that the effect on the retailer's profit goes up as long as the ratio c/s is lower than $\sqrt{3/4}$, an expression that represents a upper bound of the relationship between the production cost and the inherent quality of the own brand.

Even though these findings are economic arguments that reject the complaints of some manufacturers, who argue that the strategy of developing of own brands that take the same name as the store is a tool that supermarkets use to abuse the former's dominant position in order to negotiate better conditions, the model shows that the increased competition caused by the entry of own brands does make the manufacturers worse off as their profits always drop However, the own brand production only makes sense for the types of goods that satisfy the quality-production cost restraint discussed previously, as the most competitive manufacturers can continue to enjoy their dominant position by producing goods that the retailer-owned brand industry cannot match.

Finally, our model has some limitations which in turn limit the scope of our results. First, it is restrictive in the sense that it sets a linear price contract, which can be unrealistic in the sense that slotting allowances are common in this industry. However, we believe that the incorporation of this assumption does not invalidate our results. Gabrielsen *et al* (2007) argue that the introduction of the own brand affects the retailer-manufacturer negotiation in the same way. In contrast, authors such as

Berges *et al* (2009) incorporate a fixed component that denotes the relative bargaining power between the manufacturer and the large-retailer. Secondly, the vertical product differentiation model restricts analysis of how retailers compete nowadays; nevertheless it provides good information about how goods of different quality interact. The weakness of this type of model is that firms compete on the basis of not only inter-brand competition but also other facilities or attributes that we have not included in our considerations. In fact, consumers choose between goods and stores, therefore the model based on a monopolist retailer can be seen as unrealistic.

APPENDIX

a. Monopoly Equilibrium

The demand function is represented as $Q_1 (P_1, P_2, s) = \bar{\theta} - P_1/s_1$. Thus, the retailer sets the monopoly price according to the following maximization function:

$$Max_{\{P_1^m\}} \pi^m = [P_1^m - P_{w1}^m] Q_1^m (P_1^m, s_1)$$

The first order condition is $P_1^m = 1/2 (s_1 + P_{w1}^m)$. By substituting it in the demand function, the market served is given by $Q_1^m = 1/2 (\bar{\theta} - P_{w1}^m /s_1)$.

On the upstream level, the manufacturer chooses the wholesale price by maximizing the function

$$Max_{\{P_{W1}^m\}} \pi_{M1}^m = (P_{w1}^m - c_1) Q_1^m (P_1^m, s_1)$$

Then, the wholesale price is $P_{w1}^m = \frac{1}{2} (s_1 + c_1)$

By substituting this value in the retailer outcome and imposing that the high quality good is normalized to 1 and $\bar{\theta} = 1$, the optimal monopoly equilibrium as well as the retailer and manufacturer profits are given by:

$$Q_1^m = 1/4 (1 - c_1); \quad P_1^m = 1/4 (3 + c_1); \quad \pi_R = 1/16 (1 - c_1)^2 \qquad Retailer$$

$$P_{w1}^m = \frac{1}{2}(1 + c_1), \quad \pi_{M1} = 1/8 (1 - c_1^2) \qquad\qquad Manufacturer$$

Thus if $c_1=c$ the necessary condition for the high quality good to exist under a decentralized structure is $c<1$.

- *Proof: From* Q_1^m above, we need to solve the following inequality $Q_1^m = 1/4 (1- c_1)>0$. Then, it requires that $c_1<1$.

Demonstration

$Max_{\{P_1^m\}} \pi^m = (P_1^m - P_{w1}^m)Q_1^m;$ *where* $Q_1^m = (1 - P_1^m)$ ***Retailer***

$\partial \pi^m/\partial P_1^m = 0;$ $\frac{\partial \pi_{m1}^m}{\partial P_{w1}^m} = 0$ *(first order condition)*

$\partial \pi^m/\partial P_1^m = (1 - P_1^m) - (P_1^m - P_{w1}^m) = 0 \rightarrow P_1^m = \frac{1}{2}(1+P_{w1}^m)$ *and hence,* $Q_1^m = \frac{1}{2}(1 - P_{w1}^m)$

The result of the second order condition is:

$\partial^2 \pi^m/\partial P_1^{m2} = -2 <0$

$Max_{\{Pw1\}}\pi_{m1}^m = (P_{w1}^m - c_1)Q_1^m = (P_{w1}^m - c_1)\frac{1}{2}(1 - P_{w1}^m)$ ***Manufacturer***

$\frac{\partial \pi_{m1}^m}{\partial P_{w1}^m} = \frac{1}{2}(1 - P_{w1}^m - P_{w1}^m + c_1) = 0$ *[with a Second derivative equivalent to* $-2 P_{w1}^m < 0$*]*

$\qquad\qquad\qquad \rightarrow P_{w1}^m = \frac{1}{2} (1+c_1)$ (1)

If $c_1 = c$

$\qquad\qquad\qquad P_{w1}^m = \frac{1}{2} (1+c)$ (1.a)

By substituting (1) in Q_1^m and P_1^m above,

$\qquad\qquad\qquad Q_1^m = \frac{1}{4}(1-c_1)$ (2)

If $c_1 = c$

$\qquad\qquad\qquad Q_1^m = \frac{1}{4}(1-c)$ (2.a)

$\qquad\qquad\qquad P_1^m = \frac{1}{2}(3+c_1)$ (3)

If $c_1 = c$

$\qquad\qquad\qquad P_1^m = \frac{1}{2}(3+c)$ (3.a)

b. *Interbrand Competition: Vertical separation*

- *Retailer*

$$Max_{\{P_1^{vs}, P_2^{vs}\}}\ \pi^{vs} = (P_1^{vs} - P_{w1}^{vs})\left[1 - \frac{(P_1^{vs} - P_2^{vs})}{1-s}\right] + (P_2^{vs} - P_{w2}^{vs})\left[\frac{P_1^{vs}}{1-s} - \frac{P_2^{vs}}{1-s} - \frac{P_2^{vs}}{s}\right]$$

$\partial\pi^{vs}/\partial P_1^{vs} = 0;\ \partial\pi^{vs}/\partial P_2^{vs} = 0$ \qquad *(first order conditions)*

- *Product 1*

$$\frac{\partial\pi^{vs}}{\partial P_1^{vs}} = \left[1 - \frac{(P_1^{vs} - P_2^{vs})}{1-s}\right] - \frac{(P_1^{vs} - P_{w1}^{vs})}{1-s} + \frac{(P_2^{vs} - P_{w2}^{vs})}{1-s} = 0$$

$1 - \frac{2P_1^{vs}}{1-s} + \frac{2P_2^{vs}}{1-s} + \frac{P_{w1}^{vs}}{1-s} + \frac{P_{w2}^{vs}}{1-s} = 0$ \quad *[with a second derivative equivalent to $\frac{-2}{1-s} < 0$]*

$P_1^{vs} = \frac{1}{2}(1 - s + 2P_2^{vs} + P_{w1}^{vs} - P_{w2}^{vs})$ \qquad (4)

- *Product 2*

$$\partial\pi^{vs}/\partial P_2^{vs} = \left[\frac{(P_1^{vs} - P_{w1}^{vs})}{1-s}\right] + \left[\frac{P_1^{vs}}{1-s} - \frac{P_2^{vs}}{s(1-s)}\right] - \frac{(P_2^{vs} - P_{w2}^{vs})}{s(1-s)}$$

$\frac{2P_1^{vs}}{1-s} - \frac{2P_2^{vs}}{s(1-s)} - \frac{P_{w1}^{vs}}{1-s} + \frac{P_{w2}^{vs}}{s(1-s)} = 0$ \quad *[with a second derivative equivalent to $\frac{-2}{s(1-s)} < 0$]*

$P_2^{vs} = \frac{1}{2}(2sP_1^{vs} - sP_{w1}^{vs} + P_{w2}^{vs})$ \qquad (5)

From (4) and (5) we obtain the following expressions:

$P_1^{vs} = \frac{1}{2}(1 - s + 2 * \frac{1}{2}(2sP_1^{vs} - sP_{w1}^{vs} + P_{w2}^{vs}) + P_{w1}^{vs} - P_{w2}^{vs})$

$P_1^{vs} = \frac{1}{2}(1 - s + 2sP_1^{vs} + (1-s)P_{w1}^{vs})$

$P_1^{vs}(1\text{-s}) = \frac{1}{2}(1 - s + (1-s)P_{w1}^{vs})$

$P_1^{vs} = \frac{1}{2}(1 + P_{w1}^{vs})$ \qquad (6)

$P_2^{vs} = \frac{1}{2}(2s * \frac{1}{2}(1 + P_{w1}^{vs}) - sP_{w1}^{vs} + P_{w2}^{vs})$

$P_2^{vs} = \frac{1}{2}(s + sP_{w1}^{vs} - sP_{w1}^{vs} + P_{w2}^{vs})$

$P_2^{vs} = \frac{1}{2}(s + P_{w2}^{vs})$ \qquad (7)

Thus, the total quantities for product 1 and product 2 are:

$$Q_1^{vs} = 1 - [½ (1 + P_{w1}^{vs}) - ½ (s + P_{w2}^{vs})]/(1 - s)$$

$$Q_1^{vs} = 1 - ½ [(1 - s) + P_{w1}^{vs} - P_{w2}^{vs}]/(1 - s)$$

$$Q_1^{vs} = ½[1 - (P_{w1}^{vs} - P_{w2}^{vs})/(1 - s)] \qquad (8)$$

$$Q_2^{vs} = [½ (1 + P_{w1}^{vs}) - ½ (s + P_{w2}^{vs})]/(1 - s) - ½ (s + P_{w2}^{vs})/s$$

$$Q_2^{vs} = ½(sP_{w1}^{vs} - P_{w2}^{vs})/s(1 - s) \qquad (9)$$

- *Manufacturer 1*

$$Max_{\{Pw1\}} \pi_{m1}^{vs} (P_{w1}^{vs} - c_1)Q_1^{vs}$$

$$Max \; \pi_{m1}^{vs} (P_{w1}^{vs} - c_1) \, ½[1 - (P_{w1}^{vs} - P_{w2}^{vs})/(1 - s)]$$

$$\partial \pi_{m1}^{vs}/\partial P_{w1}^{vs} = 0 \qquad \text{(first order condition)}$$

$$\frac{\partial \pi_{m1}^{vs}}{\partial P_{w1}^{vs}} = ½[1 - (P_{w1}^{vs} - P_{w2}^{vs})/(1 - s) - (P_{w1}^{vs} - c_1)/(1 - s)] = 0$$

$$1 - \frac{2P_{w1}^{vs}}{1-s} + \frac{P_{w2}^{vs}}{1-s} + \frac{c_1}{1-s} = 0 \quad \textit{[second derivative equivalent to } \frac{-2}{1-s} < 0]$$

$$P_{w1}^{vs} = ½(1 - s + P_{w2}^{vs} + c_1) \qquad (10)$$

- *Manufacturer 2*

$$Max \; \pi_{m2}^{vs} (P_{w2}^{vs} - c_2)Q_2^{vs}$$

$$Max \; \pi_{m2}^{vs} (P_{w2}^{vs} - c_2)[½(sP_{w1}^{vs} - P_{w2}^{vs})/s(1 - s)]$$

$$\partial \pi_{m2}^{vs}/\partial P_{w2}^{vs} = 0 \qquad \text{(first order condition)}$$

$$\frac{\partial \pi_{m2}^{vs}}{\partial P_{w2}^{vs}} = ½[(sP_{w1}^{vs} - P_{w2}^{vs})/s(1 - s) - (P_{w2}^{vs} - c_2)/s(1 - s)] = 0$$

$$\frac{P_{w1}^{vs}}{1-s} - \frac{2P_{w2}^{vs}}{s(1-s)} + \frac{c_2}{s(1-s)} = 0 \quad \textit{[second derivative equivalent to } \frac{-2}{s(1-s)} < 0]$$

$$P_{w2}^{vs} = ½(sP_{w1}^{vs} + c_2) \qquad (11)$$

From (10) and (11), the best reply functions of the manufacturers are:

- *Manufacturer 1*

$$P_{w1}^{vs} = \tfrac{1}{2}(1 - s + \tfrac{1}{2}(sP_{w1}^{vs} + c_2) + c_1) \rightarrow \tfrac{1}{4}P_{w1}^{vs}(4 - s) = \tfrac{1}{2}(1 - s + \tfrac{1}{2}c_2 + c_1)$$

$$P_{w1}^{vs} = \frac{2(1-s+c_1+\frac{1}{2}c_2)}{(4-s)} \qquad\qquad (12)$$

If $c_1 = c_2 = c$

$$P_{w1}^{vs} = \frac{2(1-s+3/2c)}{(4-s)} \qquad\qquad (12.a)$$

- *Manufacturer 2*

$$P_{w2}^{vs} = \tfrac{1}{2}[2s(1 - s + c_1 + \tfrac{1}{2}c_2)/(4 - s) + c_2] = [s(1 - s + c_1 + \tfrac{1}{2}c_2)/(4 - s) + \tfrac{1}{2}c_2]$$

$$P_{w2}^{vs} = \frac{s(1-s)}{(4-s)} + \frac{sc_1}{(4-s)} + \tfrac{1}{2}\frac{sc_2}{(4-s)} + \tfrac{1}{2}c_2 = \frac{s(1-s)}{(4-s)} + \frac{sc_1}{(4-s)} + \frac{2c_2}{(4-s)} =$$

$$P_{w2}^{vs} = \frac{s(1-s)+sc_1+2c_2}{(4-s)} \qquad\qquad (13)$$

If $c_1 = c_2 = c$

$$P_{w2}^{vs} = \frac{s(1-s)+c(s+2)}{(4-s)} \qquad\qquad (13.a)$$

- *Market Equilibrium:*

Substituting (12) and (13) in equations (6) and (7), we get the price of products 1 and 2:

$$P_1^{vs} = \tfrac{1}{2}(1 + P_{w1}^{vs})$$

$$P_1^{vs} = \tfrac{1}{2}[1 + 2(1 - s + c_1 + \tfrac{1}{2}c_2)/(4 - s)] = \tfrac{1}{2}\left[\frac{(4-s)}{(4-s)} + \frac{2}{(4-s)} - \frac{2s}{(4-s)} + \frac{2c_1}{(4-s)} + \frac{c_2}{(4-s)}\right]$$

$$P_1^{vs} = \tfrac{1}{2}\frac{3(2-s)+2c_1+c_2}{(4-s)} \qquad\qquad (14)$$

If $c_1 = c_2 = c$

$$P_1^{vs} = 3/2\frac{2-s+c}{(4-s)} \qquad\qquad (14.a)$$

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$$P_2^{vs} = \tfrac{1}{2}\,(s + P_{w2}^{vs})$$

$$P_2^{vs} = \tfrac{1}{2}\,(s + \frac{s(1-s)+sc_1+2c_2}{(4-s)}) = \tfrac{1}{2}\,[\frac{s(4-s)+s(1-s)+sc_1+2c_2}{(4-s)}]$$

$$P_2^{vs} = \tfrac{1}{2}\,\frac{s(s-2s)+sc_1+2c_2}{(4-s)} \qquad\qquad (15)$$

If $c_1 = c_2 = c$

$$P_2^{vs} = \tfrac{1}{2}\,\frac{s(5-2s)+c(s+2)}{(4-s)} \qquad\qquad (15.a)$$

Then, from equations (8) and (9), the total quantity of products 1 and 2:

$$Q_1^{vs} = 1 - (P_1 - P_2)/(1-s)$$

$$Q_1^{vs} = [1 - (\tfrac{1}{2}\,\frac{3(2-s)+2c_1+c_2}{(4-s)} - \tfrac{1}{2}\,\frac{s(5-2s)+sc_1+2c_2}{(4-s)})]/(1-s)]$$

$$Q_1^{vs} = [1 - \frac{\tfrac{1}{2}}{(4-s)(1-s)}(3(2-s)+2c_1+c_2 - s(5-2s) - sc_1 - 2c_2)]$$

$$Q_1^{vs} = [1 - \frac{\tfrac{1}{2}}{(4-s)(1-s)}(6-8s+2c_1 - sc_1 + 2s^2 - c_2)]$$

$$Q_1^{vs} = [4 - 5s + s^2 - 3 + 4s - \tfrac{1}{2}c_1(2-s) - s^2 + \tfrac{1}{2}c_2]$$

$$Q_1^{vs} = [1 - s - \tfrac{1}{2}c_1(2-s) + \tfrac{1}{2}c_2]/(4\text{-}s)(1\text{-}s)$$

$$Q_1^{vs} = [1 - \tfrac{1}{2}\,\frac{c_1(2-s)}{(1-s)} + \tfrac{1}{2}\,\frac{c_2}{(1-s)}]/(4\text{-}s) \qquad (16)$$

If $c_1 = c_2 = c$

$$Q_1^{vs} = [1 - \tfrac{1}{2}\,\frac{c(2-s)}{(1-s)} + \tfrac{1}{2}\,\frac{c}{(1-s)}]/(4\text{-}s) = [1 + \tfrac{1}{2}(\frac{c(s-2)}{(1-s)} + \frac{c}{(1-s)})]/(4\text{-}s) = [1 + \tfrac{1}{2}\,\frac{c(s-1)}{(1-s)}]/(4\text{-}s) =$$

$$Q_1^{vs} = \tfrac{1}{2}(2\text{-}c)/(4\text{-}s) \qquad\qquad (16.a)$$

$$Q_2^{vs} = \tfrac{1}{2}\,\frac{3(2-s)+2c_1+c_2}{(4-s)(1-s)} - \tfrac{1}{2}\,\frac{s(5-2s)+sc_1+2c_2}{s(1-s)(4-s)} = \tfrac{1}{2}\,\frac{[3(2-s)s+2c_1s+c_2s+s(5-2s)-c_1s-2c_2]}{s(4-s)(1-s)} = \tfrac{1}{2}\,\frac{s(1-s)+sc_1+c_2(s-2)}{s(4-s)(1-s)}$$

$$Q_2^{vs} = \tfrac{1}{2}[1 + \frac{c_1}{1-s} - \frac{c_2(2-s)}{s(1-s)}]/(4-s) \qquad (17)$$

If $c_1 = c_2 = c$

$$Q_2^{vs} = \tfrac{1}{2}[1 + \frac{c}{1-s} - \frac{c(2-s)}{s(1-s)}]/(4-s) = \tfrac{1}{2}[1 + \frac{c}{1-s}(1 - \frac{(2-s)}{s})]/(4\text{-}s)] = \tfrac{1}{2}(1 - \frac{2c}{s})/(4\text{-}s) =$$

$$Q_2^{vs} = \tfrac{1}{2}(\frac{s-2c}{s})/(4\text{-}s) \qquad\qquad (17.a)$$

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Proof of Restraint under vertical separation: $Q_2^{vs} > 0$

From17.a

$Q_2^{vs} = \frac{1}{2}(\frac{s-2c}{s})/(4-s)>0$; It implies that s > 2c.

Comparison of prices and quantites under vertical separation

$P_1^{vs} \geq P_2^{vs}$

First, we rearrange the equation for each one, and omitting the denominator because of equal values, we get P_1^{vs} = 3/2(2-s) +3/2 c and, P_2^{vs} =1/2 s(5-2s) +1/2 c(2+s). We now separate both terms in each equation and make a comparison between them. In the first, we know that $3/2(2-s) \geq 1/2s(5-2s)$ and for the second, $3/2c \geq 1/2 c(2+s) \forall s \leq 1$. Hence, P_1^{vs} is always equal to or higher than P_2^{vs}.

$Q_1^{vs} \geq Q_2^{vs}$

If $c_1=c_2=c$, Q_1^{vs} = ½(2-c)/(4-s) and Q_2^{vs} = ½ (s-2c)/s(4-s). To make a comparison, these expressions have been reduced to *(2-c)* and *(s-2c)/s* respectively. The term of product 2 can be written as *1-2c/s*, which is always lower than the total quantity of product 1 because *(2-c)>3/2* and *1-2c/s<1*. Hence, the market share for product 1 is always higher than that of the product 2.

$P_{w1}^{vs} \geq P_{w2}^{vs}$

Rearrange each expression, we get P_{w1}^{vs} = [2(1-s) +3c]/ (4-s), and P_{w2}^{vs} =[s(1-s) +c(s+2)]/(4-s). As the denominators are the same, it is only necessary to check the values in brackets. This is always greater for P_{w1}^{vs}, since *2(1-s)* $\geq$ *s(1-s)* and *3c* $\geq$ *c(s+2)*, $\forall(c,s)$.

c. Comparison between vertical separation and monopoly outcome

- *Price of product 1*

$\Delta P_{1=} P_1^m - P_1^{vs}$ =1/4 (3+c)-3/2 $\frac{2-s+c}{(4-s)}$>0. Rearrange this inequality, we obtain the following expression: $3+c-\frac{6c}{(4-s)}>6(\frac{(2-s)}{(4-s)} \rightarrow 3-\frac{c(2+s)}{(4-s)}>6\frac{(2-s)}{(4-s)}$

Multiplying by *(4-s),* the result is as follow *3s>c(2+s),* which is the same as $s>\frac{2c}{(3-c)}$ *(a)*

As we see in Lemma 1, $s_1>c_1$ is the necessary condition to exist Q_1^m. Then, by multiplying by s_1 and rearranging this inequality, we obtain s_1^2-cs_1>0 (b).

As $s_1 > s_1^2$ (due to $s_1 < 1$), then $s_1 - s_1^2 > 0$ (c). By adding (b) and (c), the result is as follow: $s_1^2 - cs_1 + s_1 - s_1^2 > 0$ and hence, $s_1 - cs_1 > 0$.

Rearranging the latter and adding $3s_1$ on both sides, we obtain, $3s_1 - cs_1 > 2s_1$. As $s > c$, $3s - cs > 2s > 2c$ ($s_1 = s$, $c_1 = c$). Then, $3s - cs > 2c$. The term can be rewritten as $s > \dfrac{2c}{(3-c)}$, which is the same as equation (a) above. Then, $P_1^m > P_1^{vs}$.

d. *Interbrand Competition: Vertical integration*

- *Retailer*

$$Max_{\{P_1^{vi}, P_2^{vi}\}} \pi^{vi} = \left(P_1^{vi} - P_{w1}^{vi}\right)\left[1 - \frac{(P_1^{vi} - P_2^{vi})}{1-s}\right] + \left(P_2^{vi} - c_2\right)\left[\frac{P_1^{vi}}{1-s} - \frac{P_2^{vi}}{1-s} - \frac{P_2^{vi}}{s}\right]$$

$\partial \pi^{vi}/\partial P_1^{vi} = 0$; $\partial \pi^{vi}/\partial P_2^{vi} = 0$ *(first order conditions)*

- *Product 1*

$$\partial \pi^{vi}/\partial P_1^{vi} = \left[1 - \frac{(P_1^{vi} - P_2^{vi})}{1-s}\right] - \frac{\left(P_1^{vi} - P_{w1}^{vi}\right)}{1-s} + \frac{\left(P_2^{vi} - c_2\right)}{1-s} = 0$$

$$\left[1 - \frac{2P_1^{vi}}{1-s} + \frac{2P_2^{vi}}{1-s} + \frac{P_{w1}^{vi}}{1-s} - \frac{c_2}{1-s}\right] = 0 \qquad \text{[second derivative equivalent to } \frac{-2}{1-s} < 0\text{]}$$

$$P_1^{vi} = \tfrac{1}{2}\left(1 - s + 2P_2^{vi} + P_{w1}^{vi} - c_2\right) \qquad\qquad (18)$$

- *Product 2*

$\partial \pi^{vi}/\partial P_2^{vi} = 0$

$$\partial \pi^{vi}/\partial P_2^{vi} = \frac{\left(P_1^{vi} - P_{w1}^{vi}\right)}{1-s} + \left[\frac{P_1^{vi}}{1-s} - \frac{P_2^{vi}}{1-s} - \frac{P_2^{vi}}{s}\right] - \left(\frac{1}{1-s} + \frac{1}{s}\right)\left(P_2^{vi} - c_2\right) = 0$$

$$\left[\frac{2P_1^{vi}}{1-s} - \frac{P_{w1}^{vi}}{1-s} - \frac{2P_2^{vi}}{1-s} - \frac{2P_2^{vi}}{s} + \frac{c_2}{s(1-s)}\right] = \frac{2P_1^{vi}}{1-s} - \frac{P_{w1}^{vi}}{1-s} + \frac{c_2}{s(1-s)} - 2P_2^{vi}\left(\frac{1}{1-s} + \frac{1}{s}\right) = 0$$

$$\frac{2P_1^{vi}}{1-s} - \frac{P_{w1}^{vi}}{1-s} + \frac{c_2}{s(1-s)} - \frac{2P_2^{vi}}{s(1-s)} = 0 \qquad \text{[second derivative equivalent to } \frac{-2}{s(1-s)} < 0\text{]}$$

$$P_2^{vi} = \tfrac{1}{2}\left(2sP_1^{vi} - sP_{w1}^{vi} + c_2\right) \qquad\qquad (19)$$

From (18) and (19), we obtain the following expression of prices:

$$P_1^{vi} = \tfrac{1}{2}\left(1 - s + 2[\tfrac{1}{2}\left(2sP_1^{vi} - sP_{w1}^{vi} + c_2\right)] + P_{w1}^{vi} - c_2\right)$$

$$P_1^{vi} = \tfrac{1}{2}\left(1 - s + 2sP_1^{vi} + P_{w1}^{vi}(1-s)\right)$$

$$P_1^{vi}(1-s) = \tfrac{1}{2}\left(1 - s + P_{w1}^{vi}(1-s)\right)$$

$$P_1^{vi} = \tfrac{1}{2}\left(1 + P_{w1}^{vi}\right) \qquad\qquad (20)$$

$P_2^{vi} = \frac{1}{2}\left(2sP_1^{vi} - sP_{w1}^{vi} + c_2\right)$

$P_2^{vi} = \frac{1}{2}\left(s\left(1 + P_{w1}^{vi}\right) - sP_{w1}^{vi} + c_2\right)$

$$P_2^{vi} = \frac{1}{2}\left(s + c_2\right) \tag{21}$$

If $c_1 = c_2 = c$

$$P_2^{vi} = \frac{1}{2}\left(s + c\right) \tag{21.a}$$

Then, the total quantities of products 1 and 2 are:

- ***Product 1***

$Q_1^{vi} = 1 - \frac{1}{2}\left[\dfrac{1 + P_{w1}^{vi}}{1 - s} - \dfrac{s + c_2}{1 - s}\right]$

$$Q_1^{vi} = \frac{1}{2}[(1 - s - P_{w1}^{vi} + c_2)/(1 - s)] \tag{22}$$

- ***Product 2***

$Q_2^{vi} = \frac{1}{2}\dfrac{1 + P_{w1}^{vi}}{1-s} - \frac{1}{2}\left(\dfrac{s+c_2}{1-s} + \dfrac{s+c_2}{s}\right) = \frac{1}{2}\dfrac{1 + P_{w1}^{vi}}{1-s} - \frac{1}{2}\left(\dfrac{s+c_2}{s(1-s)}\right)$

$$Q_2^{vi} = \frac{1}{2}\left(\dfrac{sP_{w1}^{vi} - c_2}{s(1-s)}\right) \tag{23}$$

- ***Manufacturer 1***

$Max\ \pi_{m1}^{vi}\ (P_{w1}^{vi} - c_1)Q_1^{vi}$

$Max\ \pi_{m1}^{vi}\ (P_{w1}^{vi} - c_1)\ \frac{1}{2}[\dfrac{1-s-P_{w1}^{vi}+c_2}{1-s})]$

$\partial\pi_{m1}^{vi}/\partial P_{w1}^{vi} = 0$ *(first order condition)*

$\partial\pi_{m1}^{vi}/\partial P_{w1}^{vi} = \frac{1}{2}[(1 - s - P_{w1}^{vi} + c_2) - (P_{w1}^{vi} - c_1)]/(1 - s) = 0$

$[1 - s - 2P_{w1}^{vi} + c_1 + c_2)]/(1 - s) = 0$ *[second derivative equivalent to $\dfrac{-2}{1-s} < 0$]*

$$P_{w1}^{vi} = \frac{1}{2}(1 - s + c_1 + c_2) \tag{24}$$

If $c_1 = c_2 = c$

$$P_{w1}^{vi} = \frac{1}{2}(1 - s + 2c) \tag{24.a}$$

- ***Market Equilibrium:***

Substituting (24) in (20), (22) and (23), we get the market conditions for products 1 and 2 are:

$$P_1^{vi} = \tfrac{1}{2} \left[1 + \tfrac{1}{2}(1 - s + c_1 + c_2)\right] = \tfrac{1}{2}\left(3\tfrac{1}{2} - \tfrac{1}{2}s + \tfrac{1}{2}(c_1 + c_2)\right)$$

$$P_1^{vi} = \tfrac{1}{4}(3 - s + c_1 + c_2) \qquad\qquad (25)$$

If $c_1 = c_2 = c$

$$P_1^{vi} = \tfrac{1}{4}(3 - s + 2c) \qquad\qquad (25.a)$$

$$Q_1^{vi} = \tfrac{1}{2}\left[(1 - s + c_2)/(1 - s)\right] - \tfrac{1}{2}\frac{P_{w1}^{vi}}{1-s}$$

$$Q_1^{vi} = \tfrac{1}{2}\left[(1 - s + c_2)/(1 - s)\right] - \tfrac{1}{2}\frac{\tfrac{1}{2}(1 - s + c_1 + c_2)}{1-s} =$$

$$Q_1^{vi} = \tfrac{1}{4}\left[(1 - (c_1 - c_2)/(1 - s)\right] \qquad\qquad (26)$$

If $c_1 = c_2 = c$

$$Q_1^{vi} = \tfrac{1}{4} \qquad\qquad (26.a)$$

$$Q_2^{vi} = \tfrac{1}{2}\left(\frac{sP_{w1}^{vi} - c_2}{s(1 - s)}\right)$$

$$Q_2^{vi} = \tfrac{1}{2}\left(\frac{\tfrac{1}{2}(1 - s + c_1 + c_2)s - c_2}{s(1-s)}\right) = \tfrac{1}{2}\left(\frac{\tfrac{1}{2}(1 - s + c_1 + c_2)s}{s(1-s)}\right) - \tfrac{1}{2}\frac{c_2}{s(1-s)}$$

$$Q_2^{vi} = \tfrac{1}{4} + \tfrac{1}{4}\frac{c_1}{(1-s)} + \tfrac{1}{4}\frac{c_2}{(1-s)} - \tfrac{1}{2}\frac{c_2}{s(1-s)} = \tfrac{1}{4} + \tfrac{1}{4}\frac{c_1}{(1-s)} - \tfrac{1}{4}\frac{c_2(2-s)}{s(1-s)}$$

$$Q_2^{vi} = \tfrac{1}{4}\left[1 - s + c_1 - c_2\frac{2-s}{s}\right]/(1\text{-}s) \qquad\qquad (27)$$

If $c_1 = c_2 = c$

$$Q_2^{vi} = \tfrac{1}{4}\left[1 - s + c(1 - \frac{2-s}{s})\right]/(1\text{-}s) = \tfrac{1}{4}\left[1 - s - \frac{2c}{s}(1 - s)\right]/(1\text{-}s) = \tfrac{1}{4}\left[1 - s - \frac{2c}{s}(1 - s)\right]/(1\text{-}s)$$

$$Q_2^{vi} = \tfrac{1}{4}\left(1 - \frac{2c}{s}\right) = \tfrac{1}{4}(s - 2c)/s \qquad\qquad (27.a)$$

e. *Comparison between Vertical integration and Vertical separation*

- *Quantities of Product 1 and 2*

- $\Delta Q_1 = Q_1^{vi} - Q_1^{vs} > 0$

From equations (16.a) and (26.a)

$$\Delta Q_1 = Q_1^{vi} - Q_1^{vs} = \tfrac{1}{4} - \tfrac{1}{2}\frac{(2 - c)}{(4 - s)} > 0$$

Rearrange this term, it is written as: $\frac{2c-s}{4(4-s)} > 0$, which implies that $2c - s > 0$ and hence $2c > s$.

- $\Delta Q_2 = Q_2^{vi} - Q_2^{vs} > 0$

From equations (17.a) and (27.a)

$$\Delta Q_2 = \tfrac{1}{4}\left(1 - s - 2\frac{c}{s}\right) - \frac{\tfrac{1}{2}(1-\frac{2c}{s})}{4-s} = \tfrac{1}{4}\frac{s-2c}{s} - \tfrac{1}{2}\frac{(s-2c)}{s(4-s)} > 0$$

$(s - 2c)(4 - s) - 2(s - 2c) = (s - 2c)(2 - s) > 0$ and hence, $s_1 > 2c$, Or $s_2 < 2$

- *Final Prices and wholesale prices*

- $\Delta P_1 = P_1^{vi} - P_1^{vs} \geq 0$

From equations (14.a) and (25.a); $\tfrac{1}{4}(3 - s + 2c) - \tfrac{1}{2}\frac{3(2-s)+3c}{(4-s)} \geq 0$

$(3 - s + 2c)(4\text{-}s)\text{-}6(2 - s) - 6c = 12\text{-}3s\text{-}4s + s^2 + 8c\text{-}2cs\text{-}12 + 6s\text{-}6c = s^2 - s - 2cs + 2c \geq 0$

$s^2 - s(1 + 2c) + 2c \geq 0$

$s \geq \frac{(1+2c) \pm \sqrt{4c^2 - 4c + 1}}{2}$. We need to verify the values taken by c in the latter term. It is:

$4c^2 - 4c + 1 > 0$,

$c = \frac{4 \pm \sqrt{16-16}}{8} = \tfrac{1}{2} \rightarrow s > \frac{(1+2c) \pm (c - \frac{1}{2})}{2}$. Then, the roots of s are: $s_1 > \left(\frac{1}{4} + \frac{3}{2}c\right)$; $s_2 > \left(\frac{3}{4} + \frac{c}{2}\right)$

Characterization of these roots:

$\lim_{c \to 0}\left(\frac{1}{4} + \frac{3}{2}c\right) \rightarrow 1/4$; $\lim_{c \to 0}\left(\frac{3}{4} + \frac{c}{2}\right) \rightarrow 3/4$

$\lim_{c \to \frac{1}{2}}\left(\frac{1}{4} + \frac{3}{2}c\right) \rightarrow 1$; $\lim_{c \to \frac{1}{2}}\left(\frac{3}{4} + \frac{c}{2}\right) \rightarrow 1$

Roots	s_1	s_2
$\lim_{c \to 0}$	1/4	3/4
$\lim_{c \to \frac{1}{2}}$	1	1

- $\Delta P_2 = P_2^{vi} - P_2^{vs} \geq 0$

From equations (15.a) and (21.a)

$$\Delta P_2 = \frac{1}{2}(s+c) - \frac{1}{2}\frac{s(5-2s)+c(s+2)}{(4-s)} = \frac{1}{2}\left[\frac{(s+c)(4-s)-5s+2s^2-cs-2c)}{(4-s)}\right] = \frac{1}{2}\frac{(s^2-s(2c+1)+2c)}{(4-s)} > 0,$$

This expression coincides with that of P_1, whose roots are $s_1 > \left(\frac{1}{4}+\frac{3}{2}c\right); s_2 > \left(\frac{3}{4}+\frac{c}{2}\right).$

- *Wholesale prices:* $\Delta P_{w1} = P_{w1}^{vi} - P_{w1}^{vs} \geq 0$

From equations (12.a) and (24.a)

$$\Delta P_{w1} = \frac{1}{2}(1-s+2c) - \frac{2\left(1-s+\frac{3}{2c}\right)}{(4-s)} = \frac{1}{2}\left[\frac{(1-s+2c)(4-s)-4\left(1-s+\frac{3}{2c}\right)}{(4-s)}\right]$$

This expression requires that s^2-s(1+2c)+2c $\geq$ 0, which was demonstrated before.

Chapter 3: Relation between supermarket-owned brand and leading labels in the UK

Abstract

We used panel data techniques to investigate how leading branded products and supermarket own brands in a basket of 19 major products interact in UK supermarkets in the short term. We estimated three specifications to look at the determinants of relative prices, shelf co-location and the number of brands that the supermarkets sell.

Using the logistic of relative prices between the supermarket-owned brand and the branded product (P_{ob}/P_{bg}) model, our findings show positive coefficients for the variables time trend, number of manufacturing firms, price cuts and for each supermarket dummy variable. The positive coefficient of the time effect may show that own brands are priced higher than branded products over time, which could be explained by their better-quality ingredients or by supermarkets' exploitation of loyal consumers, confirming most of relevant research of the last years. For the the number of manufacturing firms (nf), we believe that the positive coefficient indicates that competition affects both brands at different magnitudes. If this variable (nf) impacts negatively on both labels it should nevertheless impact less on the supermarket own brand as it is more cost-related, and it is not possible to cut its price beyond its floor. If the impact is positive (in percentage), $|\Delta^{+}Pob_{i,t}| > |\Delta^{+}Pbg_{i,t}|$, which in turn means that the supermarkets are taking advantage of their market power at the retailer level by increasing the price of their own brands. If this is so, the positive impact on $Pbg_{i,t}$ goes in the same direction as that reported in most literature so far (Gabrielsen *et al*, 2001; Bonfrer *et al*, 2004 and Bontemps *et al*, 2005, among others).

In terms of the dummies controlling for the supermarket-specific effect, our results show that Asda and Tesco set prices in a similar way whereas Sainsbury's and Morrisons follow other strategies. We believe that the latter make own brands of better quality following their strategies for creating loyal consumers and expertise in the production of food.

Second, when we estimated the equation about product allocation on the shelves, the model that fitted our dataset best was produced using the probit technique with three explanatory variables: time trend, number of manufacturing firms and price cuts (discount). The latter two show negative coefficients, demonstrating that the probability (odds ratio) of displaying the own brand next to, above or below the leading brand is smaller when the number of firms increases and the supermarket makes special offers, which is the traditional way determined by total shelf space allocation to product ranges and depending on unit size. The positive coefficient of the time trend shows a tendency to position both labels together over time. In the same way, the high mean of this discrete variable (0.5796) validates the view of Sayman *et al* (2002), who argue that large supermarkets target the leading brand to influence consumers' purchase decisions.

For the log-number of brands specification we obtained a low elasticity between the number of manufacturing firms and the number of brands, which indicates that few brands are displayed for these products.

3.1 Introduction

This chapter empirically analyses how the leading branded product and the supermarket brand interact in the short term. Large supermarkets have developed own-brand products that carry the supermarket's name to compete with branded goods in categories such as groceries, frozen foods and cleaning products. According to Oxera (2010), own brands have the highest level of penetration in categories without strong manufacturer brands, whereas the lowest penetration is observed where there are historically strong brands such as in toiletries, personal care and alcohol.

Retailer-owned brands similar to branded products were launched by large US supermarkets at the beginning of the 1990s, after appearing in most product categories in Europe in the late 1980s. Retailer-owned brands have become extremely sophisticated rather than just another generic product. Berges-Sennou, Bontemps and Requillart (2004); Gabrielsen and Sorgard (2006) and Daunfeldt, Orth and Rudholmz (2008) affirm that these brands are considered comparable in quality to national branded products. According to the UK Private Label Manufacturers Association they are produced and brought to market in much the same way as the familiar national brands that they sit next to on the store shelves (Oxera, 2010).

There are many British press reports on the Internet in which specialists affirm the similarity of the quality of both goods, even finding own brands better and healthier than the leading branded products in many cases, for instance in e tests carried out by the leading nutritionist Angel Dowden (2012) that were published in the *Mail Online*.[17] In the same way, according

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[17]www.dailymail.com, July 20 2012. http://www.dailymail.co.uk/news/article-2176700/Cheaper-certainly-brands-healthier-We-test-big-products-supermarket-rivals--surprising-results.html

to the Retail Analysts Datamonitor (2013), own brands have improved in recent years because of their higher-quality ingredients.[18]

The case of the UK is particularly relevant because own-brand products had a 44% penetration rate in 2009 (Oxera, 2010), the highest in Europe. According to the Key Note webpage[19], own-label products represented around 51% of total grocery sales in 2012 and 'supermarket own brands [are expected to] continue to dominate the grocery market over the next 5 years, with the share of the market represented by own brands likely to remain over 50% up until at least 2017'.[20]

The UK's largest supermarkets (Asda, Morrisons, Sainsbury's and Tesco) compete based on differences in the size, variety and number of the products that they sell. In the case of the basket of products, they offer a mix of own brands and branded products. Some are very own-brand focused, some are more mixed and others are very brand-focused.

According to the UK Office of Fair Trading (2002, cited in Oxera, 2010), own-brand products create vigorous competition with branded products: they can offer higher quality, greater innovation or lower prices and provide new products and more choice, which has gained retailer-owned brands a higher market share over time. An extra benefit for consumers is that own brands are on average less expensive than branded products.[21]

Tesco and Asda are the main providers of own brands. Tesco sells approximately 40,000 products, with own brands accounting for approximately 50% measured by total sales.

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[18]http://www.guardian.co.uk/lifeandstyle/wordofmouth/2013/feb/04/rise-of-the-own-brand
[19] http://www.keynote.co.uk/market-intelligence/view/product/10606/
[20]http://www.reuters.com/article/2013/07/19/research-and-markets-idUSnBw195749a+100+BSW20130719
[21]In the UK they are on average 22% cheaper than branded products.

According to its webpage, in a large store Asda sells the same number of products as Tesco. Asda's main focus is the development of own brands so it can compete worldwide (Oxera, 2010). In contrast, Sainsbury's sells 30,000 products at a large store[22] and Morrisons[23] sells more than 20,000 different products, of which about 55% of the volume of all products sold are own brand.

Tesco is the largest supermarket in the UK, with a 31% market share (TNS World Panel Data, 2010), and differentiates itself with a mixed strategy of independent and own-brands, offering a large number of own-brand products across categories (Oxera, 2010). Four different own brands with different prices/quality have developed: Value, Oak line, Finest and Tesco. According to the Retail Datamonitor (2013), this supermarket has widened its range to include more niche categories such as seasonal products for barbecues and picnics and occasions such as Christmas.

Asda has explicitly followed a strong strategy targeting the development of its own brands, low prices (under its 'price guarantee' in the UK or the promise of 'Low prices always' in the US), and a small variety of independent brands per product according to WalMart's worldwide rules.

Morrisons and Sainsbury's both sell few of their own brands because of the smaller number of products they sell, and their stores are of a similar size. According to its webpage, Morrisons is the only major retailer to own and operate fresh-food manufacturing and processing facilities. The Morrisons's operations are vertically integrated in the food category, which allows them to manufacture, distribute and retail the vast majority of its fresh

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[22]Source: www.j-sainsbury.co.uk/extras/faqs/media
[23]https://hwb.wales.gov.uk/cms/hwbcontent/Shared%20Documents/vtc/ngfl/bus_studies/13/company_info_unit _two/student_pack_morrisons.pdf

meat, fresh food own-label products and dairy requirements, and process and package fresh fruit and vegetables. Another report from the same source highlights Sainsbury's as a brand with a strong reputation built over 140 years of service, which has won it loyal consumers.

At the other extreme, the market share of the large retailer-owned brand accounts for just 8% in Latin America (ACNielsen, 2008). With WalMart's entry into the Chilean market in 2008, significant growth is expected on the continent as it has announced its impending arrival in Brazil and Peru.

Previous empirical and theoretical work related to this topic has focused on the effects of launching retailer-owned brands on the price of branded and leading goods, and how the manufacturers have responded. There is also empirical research on the attitude to demand own brands and the relationship between those goods and loyalty to the store.

Most research is based on the hypothesis that the introduction of an own label increases interbrand competition and hence the price of the leading goods go down. The empirical studies by Cotterill, Putsis and Dhar (2000), Gabrielsen, Steen and Sorgard (2001), Ward, Shimshack, Perloff and Harris (2002), Bonfrer and Chintagunta (2004) and Bontemps, Orozco and Requillart (2005) show that the impact of an own label depends on four factors: the product category, the inherent quality between goods, the market concentration and the degree of interbrand competition. The most common finding highlights prices increased for the leading labels in most categories. These studies also stress that manufacturers systematically use the proliferation of new brands, and strategies for product differentiation such as sizes, varieties and packaging, to counteract the entry of retailer-owned goods.

Studies on attitudes to supermarket own-brand products are numerous. One of the most commented-on papers in the marketing literature is a pioneering work by Chintagunta (1994) who, using a logit model highlights the higher positioning of these brands. An interesting paper by Binninger (2007) investigates the relationship between retailer brands and store loyalty and finds that the own-brand satisfaction and loyalty created in turn influences store loyalty, which is consistent with the importance that the consumers give to own brands.

Our paper investigates pricing and how the prices of the four largest UK supermarkets' branded goods and retailer-owned brands are established in the short term (40 weeks between October 2008 and July 2009). We developed two additional specifications to discover how the same supermarkets establish the location of both types of labels on the shelves. Our hypothesis is based on the ideas of Sayman, Hoch and Raju (2002), who affirm that supermarkets tend to target the leading brand. We also looked at how the supermarkets decide on the number of brands to sell, which we modelled with a log specification.

We used classical panel data techniques (OLS, fixed effect and random effect for pricing and number of brands regressions), and logit and probit models to explore our predictions about shelf co-location. We used four basic drivers as main supports for our hypothesis, which we discuss later to justify whether (and how) each is related to our specific dependent variables: number of manufacturing firms, to measure the degree of competition among manufacturing firms; a time-trend variable to control for price increase over time; a dummy variable to control for offers (or price cuts) implemented by supermarkets at particular points in time; and dummy variables to control for unmeasured supermarket-specific effects. We also looked at the interaction terms between the number of manufacturing firms and each supermarket to

measure the marginal effect of number of firms on our dependent variable for each supermarket, and we tested the inclusion of interaction terms between our predictors.

This methodology has been partially used by Cotterill *et al* (2000), Gabrielsen *et al* (2001), Ward *et al (2002)* and Bonfrer *et al* (2004)*, who mainly focus on the responses of manufacturers of leading goods after the launch of retailer-owned brands. Unlike these papers, our models do not include the market share as an independent variable because this information is unavailable publicly, which might be a problem as its omission may bias our estimates. However, we believe that the inclusion of dummies to measure supermarket-specific effects is a good proxy to correct that problem, and hence that our estimates are not biased.

In summary, this paper mainly contributes to the existing literature in two ways: first, the methodology used permits the examination of price movements in both brands based on weekly data. Second, to our knowledge this is the first empirical research to investigate the determinants of shelf allocation for own brands versus branded products and hence it sets a precedent for future research.

This paper has eight sections: The introduction in section 3.1, section 3.2 discusses the existing literature; sections 3.3, 3.4 and 3.5 introduce and make a discussion about the dataset, the model specifications for the three regressions and the estimation methodologies used. Sections 3.6, 3.7 and 3.8 present and discuss the results and conclusions of our research.

3.2 Literature Review

The launching of retailer-owned brands similar to branded goods has been discussed in the last ten years because they have increased both the variety of products per category to serve consumers, inter-manufacturing-firm inter-brand competition, and the rivalry between supermarkets, they have also achieved better terms and lower input prices from suppliers in response to large retailers' increased bargaining power.

To understand the interaction between a retailer-owned brand and a branded good, the literature review covers on a large number of fields. As mentioned, the first aim of most existing studies is to learn how the price of a branded good is affected by the entry of a new retailer-owned brand.

Empirical research has mainly been conducted in France and U.S in line with the strong development of retailer-owned brands in these countries, and Gabrielsen *et al* (2001p) contribute their empirical findings from the Norwegian food industry. The main motivations of these studies are: (a) to ascertain whether the price of the leading branded product changes with the introduction of a retailer-owned brand (Cotterill, Putsis and Dhar, 2000; Ward, Shimshack, Perloff and Harris, 2002; Bonfrer and Chintagunta, 2004; Bontemps and Orozco, 2005); and (b) how manufacturers react to the tougher competition (Manez, 1999; Cotterill *et al*, 2000; Ward *et al*, 2002; Bontemps and Orozco, 2005. There is another set of studies looking into the relationship between own brands and loyalty to both the store and the leading brand (Chintagunta, 1994, Binninger, 2007, Labeaga, Lado and Martos, 2007), and differences in the quality of leading and own brands (Sethuraman, 2003, Gabrielsen *et al*, 2006, Daunfeldt, Orth and Rudholmz, 2008).

To our knowledge, to date there is a limited number of quantitative studies investigating how large supermarkets decide on the allocation of goods on the shelves and how thisdecision affects prices (Sayman, Hoch and Raju, 2002; Fernandez and Gomez Suarez, 2005).

Most analysis has been based on the hypothesis that the entry of a new brand should push down the price of the leading product as the market becomes more competitive. However, the papers listed above show that in fact the price of leading goods has increased, although the authors emphasise that their results are highly sensitive to the econometric methodology used. The common elements across models are the inclusion of variables such as the degree of market concentration, the point at which the new brand is introduced, and some proxy variables to measure the degree of product differentiation and the development of new brands.

Methodologically, the statistical tools used fall into two types of models: panel data and dynamic equations, which have been considered both together and separately. Cotterill *et al* (2000); Gabrielsen *et al* (2001) and Bonfrer and Chintagunta (2004) use panel data, the latter incorporating an ordered probit model to measure the conditional likelihood of a consumer buying an own brand in a particular store; and Gabrielsen *et al* (2001), Ward *et al* (2002) and Bontemps and Orozco (2005) use dynamic regressions .

The pioneering empirical paper is by Cotterill *et al* (2000), who perform intracategory analysis using data for six individual categories as well as a pooled analysis of a sample of 125 categories and 59 geographic markets in the US. The model is developed in two ways; by including the determinants of demand and of firms' strategic pricing decisions, and by taking

into account strategic price interactions between goods when they are priced by the retailer and the manufacturer.

Cotterill *et al* (2000) estimate a regression for the market share of the leading goods against five variables: the retail prices of both the leading and the retailer-owned brand; total per capita expenditure on both goods; and a dummy variable to measure shifts in retail demand, caused by events such as retail promotions, and local market characteristics among others. The results of the pooling model show that leading brand is more sensitive to changes in the price of the retailer-owned brand in categories with high own-brand market share, whereas demand for own-brands is less sensitive to the price of leading good.

Gabrielsen *et al* (2001) look at the same effect in the food industry using two methodologies − 83 dynamic regressions and a dynamic panel data approach − based on yearly data for four periods. An autoregressive first order model is used to describe the development of the price of the leading good measured by log. The authors include two variables to control for price increases over time (a linear trend and the Consumer Price Index) and a dummy variable to control for the entry of the own brand. The panel data model was based on the former autoregressive model, which was conditioned on three variables: the own-brand's market share, the ranking of the leading goods, and the number of products sold per category. The justification for the inclusion of the latter was that it controls the degree of differentiation; for example, one chain produces three different coffee products.

The main finding from the use of both econometric tools is that the new own brand usually pushes up the price of the branded product, except in categories with strong homogeneity (flour, for example), where a new own-brand entry leads to a drastic price reduction.

Gabrielsen *et al* (2001) also show that the magnitude of the increase depends on the success of the new brand, the degree of product differentiation and the brand's proportion of loyal consumers, and find a positive relationship between the ranking of the branded product and the impact on the difference in prices of both labels.

Ward *et al* (2002) investigate how incumbent firms defend their brand when a supermarket brand is launched, under the hypothesis that this should affect differentiation strategies and promotional activities. Their dataset includes 32 food and beverage manufacturers whose products were sold by 5 large supermarkets in the US during 29 4-week periods between December 1996 and January 1999.

Ward *et al* (2002) begin by estimating a basic equation given by the log of the brand-name price regressed on the log of the private label share (total sales/total market share) and seasonal dummies to examine how the penetration of the own-brand affects both the price of the leading product and the average price of other leading goods. They expand the model with various combinations of measures of diversity and market power, such as the Gini index, for items (number of products per category) and firms, number of brands, number of firms, number of categories, fraction of births and deaths of firms and brands, different measures of concentration (share of the two largest, four largest, and eight largest brands), and a time-trend variable.

The authors find that private-label entry is correlated with higher prices for the leading product and reduced promotional activity, consistent with previous research. According to their findings, manufacturers react by improving the quality of their goods and flooding the

market with new labels to exploit switching consumers by selling the same product under several brand names.

Bonfrer and Chintagunta (2004) report a mixed impact on prices after using a household-level panel of 548 individuals and store-level data on 104 categories sold by five competing retailers in a particular US zone over 104 weeks. The authors use two models to study the indirect utility for a store-brand purchase and the effect of launching a new brand on the pricing of the remaining categories. For the first purpose, a probit model was used to measure the conditional likelihood that a consumer buys an own-brand item in a particular store. The explanatory variables include the good's relative price, how many times a consumer shopped in a store selling own-brand products, the money spent on a store brand in a particular category and a variable to validate consumers' brand loyalty. The second model is based on variables that control for the point in time at which a new product was introduced and when it launched in a specific store.

Bonfrer and Chintagunta's (2004) results confirm a positive impact on prices. They emphasise that this finding is mitigated by the market share distribution in each category and the number of competitors. On the demand side, they confirm the expectation that store-loyal consumers are more likely to purchase the retailer-owned brand. Another finding is that store-loyal consumers are not necessarily brand-loyal.

Bontemps *et al* (2005) consider 218 goods in the French food industry, separating the brands according to marketing definitions.[24] The authors estimate four models. The first is a reduced-form specification in which the log of the price of the leading good depends on the

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[24]They are: Low quality, me-too and high quality products.

log of the own-brand market share and quarterly dummies. Then the model is expanded by including a proxy variable to estimate the degree of differentiation (the ratio between leading-good sales within a specific subcategory over total leading-good sales by product category). The other models include the market share of each leading good.

The results confirm the previous study's findings for two-thirds of the products. In particular, Bontemps *et al* obtain a positive correlation between the relative prices of the leading and the own brands, and the market share of the leading goods. This is consistent with the view that consumers perceive both goods to be of similar quality when the leading good's market share is low and thus the competition is tougher. On the other hand, when the leading good has a large market share consumers think that this means it's quality is better and hence the competition is reduced.

Mesa and Sudhir (2009) responded two questions for US market using a logit model: do private labels enhance a retailer´s bargaining power with manufacturers and as a result, does the retailer strategically set retail prices to favour and strengthen its product? Their result showed that the bargainig power increases through lower wholesale prices on imitated national brands. The result is significant for niche categories rather than in mass categories. In the case of the second question, their findings point out that the retailer uses strategically the own brands to gain market share in high volume mass market categories, but after a year, prices revert to the category profit maximizing price.

Manez (1999) studies the determinants of price differential dispersion and the intensity of price competition for 46 products sold by Tesco, Sainsbury's and Subway in Coventry in the UK. Their data include 27 price observations for vertically-differentiated goods, recorded

every two weeks throughout 1995-1997. Statistical tools were used to construct price dispersion indexes. The results show that price competition is more aggressive for goods with less potential for horizontal product differentiation[25]. Contrary to Manez's expectations, it was found friendly competition in the goods labelled with same name as the supermarkets.

Empirical research about product allocation on shelves focuses on four points: the determinants of the space allocated to both goods, the criteria used to define the label to target, how close to each other both labels are positioned and the degree of interbrand competition.

Sayman *et al*'s (2002) three-part empirical study first considers 75 categories sold by two leading US grocery chains and runs a logit model. The authors look at whether the own brand targets the top good or other brands of lower quality, and whether the targeting strategy influences consumers' purchasing decisions. The explanatory variable is the market share of each brand. They report that the own brand targets the leading good when this has a higher market share than the underdog brand.[26] In contrast, the retailer positions low-quality own brands close to the leading low-quality good. No evidence was obtained to explain the consumers' purchase choices.

Next they test the aggressiveness of the interbrand competition. They construct demand functions that depend on retail prices and sales promotionsfor the own brand and for two stronger leading goods'. They use secondary data on 19 product categories and 122 retailers obtained from an ACNielsen database. Their finding indicates that price competition is tougher in the

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[25] Manez supposes that consumers get utility not only from the quality of the good but also from the supermarket (and its facilities) that sells that product.

[26] It means a brand that is less likely lo be successful

majority of categories when the own brand competes with the leading branded product. Competition between the own brand and the second leading good is weaker.

The third piece of research is based on a survey testing consumers' perceptions of brand quality. The dataset includes 102 consumers and 8 different categories of goods sold by 2 supermarkets. The first result shows that consumers believe that the quality is similar when the price differential is low. Second, people react weakly to similar physical cues between the goods. In this case, consumers rated the own brand as similar to lower-quality leading goods. Finally, to attract price-sensitive consumers it is better to position the own brand on its own shelf far from the leading branded products.

Fernandez and Gomez Suarez (2005), using information collected directly from Spanish stores, find that more space is allocated to retailer-owned brands than to other brands. This finding changes when the market is dominated by a strong leader or greater differentiation between the leading goods. Another interesting result is that the price of the own brand significantly affects that of the leading good when the former is of high-quality. The authors highlight how the results provide weak information about individual categories.

There is a lot of research on attitudes to consuming own brands. A paper by Chintagunta *et al* (1994) is widely used as a basis for similar, later studies (1994). Good examples are provided by Binninger (2007) and Labeaga *et al* (2007), who investigate the interaction between independent and own brands and loyalty to own-brand goods and stores.

Finally, discussion of the similarity between own brands has widely been part of most of this research and is summarised by Daunfeldt *et al* (2008), who conclude that the literature distinguishes between low-priced (lower quality) brands and medium-priced brands of

similar quality to leading branded products. The first are used strategically to provide the consumer with a greater price range, while medium-priced store brands are of comparable quality to national brand leaders and hence compete more strongly with them. A complementary discussion can be found in Gabrielsen *et al* (2001), who give products such as milk and plain flour as examples of homogenous goods.

Sethuraman's (2003) paper is interesting: he investigates the price differential between the studied brands, assuming no objective quality differential. The idea is to measure the overall brand equity of national brands on customers' reservation price differential and the quality differential of these goods. His work is based on 20 grocery product categories and the hypothesis that consumers may pay a premium for a reputed brand even if they perceive the quality of an own brand to be the same, and found that brand equity is higher in heavily-advertised, hedonistic and highly-priced product categories.

To summarise, our review of the empirical modelling literature reveals that most studies analyse how the prices of leading goods are affected by the launch of retailer-owned brands. Most results show a positive impact, contrary to the general belief that the resulting increased competition bring prices down. The research points to the importance of strategies to counteract supermarket buying power such as the proliferation of brands and strategies of product differentiation.

3.3 Data

Because of the lack of public micro-data with the level of detail required to carry out this research, we constructed our own database based on the following criteria and steps.

First, we selected 20 major basic consumption goods from the main categories (groceries, frozen food, drinks, toiletries and cleaning products) with the highest development of retailer-owned brands.

Second, because information about brands' market share is unavailable publicly, we identify leading products ranked as top brands in different public surveys and sold by the four largest grocery supermarkets: Asda, Morrisons, Sainsbury's and Tesco (see TNS World Panel Data, 2008-2009). According to the local manager of Asda, a good way of identifying a leading independent branded product is by the amount of space assigned to it on the shelf. This opinion is consistent with the findings of Fernandez *et al* (2005), who conclude that the space assigned to the branded product is larger than that assigned to the remaining brands when the national brand dominates the market or is a strong leader.Our brands satisfy this principle. The list in Table 1 gives the full information about the brands selected. Three sources were used to select each product: the Centre for Brand Analysis (CBA), the Core Brand Company and ACNielsen, all institutions that periodically carry out UK surveys to measure the positioning of brands. They ask consumers what brands they remember without a prompt list. CBA ranks the 500 brands most named by people; the final position of our national brands are in the 'ranking position' column in Table 1. For homogenous goods such as salt and plain flour we had no information about ranking and hence picked the brand with the most shelf space.

Third, we matched these products with supermarket brands named with the store's name. No premium or value brands were considered.

We collected our dataset over 40 weeks from October 2 2008 to Thursday July 2 2009 in supermarkets located in Norwich (UK), preferably always on the same day of the week. We paid special attention to promotions and offers to identify and differentiate them from normal prices tendency, following the criteria proposed by Cotteril *et al* (2000). We then compared these prices with those published on the supermarkets' web-pages. We found marginal deviations in Tesco for a couple of weeks, as confirmed by the manager of the Earlham Road Tesco Express. In parallel, we directly observed how each supermarket positioned the goods on the shelf. We also collected information about the number of rival brands and their manufacturers (see the Annex for the product categories included in the basket analized).

We wondered whether this methodology of taking prices from particular supermarket branches is whether the prices are representative for all of the UK. This was answered on reading some UK Competition Commission notes (2007).[27] According to that institution a national pricing policy exists in the supermarket industry which means that there is no differential in prices per supermarket across the UK, even between large and small branches or according to where the branch is located. This was originally motivated by antitrust concerns about local price flexing.

In sum, our dataset includes information on prices of the retailer-owned brand and the leading good, including promotions in the four supermarkets. Table 1 summarises the main information for our basket. In Annex 1 we list our products, the brands per product and their rivals.

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[27] http://www.competition-commission.org.uk/assets/competitioncommission/docs/pdf/non-inquiry/press_rel/2007/oct/pdf/61-07

Table 1: List of Products and their specifications

PRODUCTS	FORMAT	LEADING BRAND	MANUFACTURER	SOURCE	RANKING POSITION	CATEGORY
1 Baked beans	Can	Heinz	Heinz	CBA	80	Food - General
2 Beverage (Cola)	6 cans	Coca Cola	Coca Cola	CBA	7	Drinks - Carbonated
3 Cat food in gravy selection	6 cans	Felix	Purina	ACNielsen	N.A.	Food - Pets
4 Instant Coffee	200 g	Nescafe	Nestle	CBA	57	Drinks - Coffee and Tea
5 Cereal (Cornflakes)	500 g	Kellogg's	Kellogg´s	CBA	10	Food - General
6 Orange juice	1 litre	Tropicana	Tropicana	CBA	367	Drinks - General
7 Mayonnaise	400 g	Hellmann's	Unilever	ACNielsen	N.A.	Food - General
8 Milk	4 pints	Cravendale	Arla	ACNielsen	N.A.	Food - General
9 Pasta	500 g	Classic Napolitana	Unilever	*	N.A.	Food - General
10 Petit pois	640 g	Petit Pois	Birds Eye	CBA	443	Food - General
11 Plain flour	500 g	McDougall's	McDougalls	*	N.A.	Food - General
12 Table salt	550 g	Saxa	Saxa	*	N.A.	Food - General
13 Teabags	40 bags	Pg Tips	P&G	CBA	87	Drinks - Coffee and Tea
14 Toilet tissue	4 rolls	Andrex	Kimberley Clark	CBA	25	Household - General consumables
15 Tomato sauce (Bolognese)	500 g	Dolmio Sauce	Dolmio	AC Nielsen	N.A.	Food - General
16 Toothpaste	100 g	Colgate	Palmolive	SyncForce	N.A.	Toiletries & Cosmetics
17 Tuna	4 cans (185g)	John West	John West	CBA	376	Food - General
18 Vegetable oil	1 litre	Flora	Unilever	CBA	247	Food - General
19 Washing powder	2.2 kg	Ariel	P&G	CBA	132	Household - Cleaning products
20 Washing up liquid	500 ml	Fairy	P&G	CBA	32	Household - Cleaning products

Note: N.A. not available, (*) no information

We wanted to know if it is possible to compare supermarkets' (Asda, Morrisons, Sainsbury's and Tesco) own brands with the leading branded goods we use in this research. Are they of the same quality as the leading branded products?

To answer these questions we analyse previous research literature and press reports to check the nutritional information on our grocery products under the assumption that this is a good proxy for measuring differences in quality. Berges-Sennou and Bouamra-Mechemache (2009) propose an alternative measure, affirming that quality is revealed by a combination of product characteristics such as ingredients. As we are not able to use this mechanism because there is no information about that we follow the steps proposed earlier.

As we commented at the end of the literature review, there are numerous papers that discuss hypothesise and further validate the fact that the leading brand and the won brand interact and are comparable in terms of quality. A summary can be found in Daunfeldt *et al* (2008) who, after analysing many updated studies undertaken in Europe and the US, found that supermarket and brands are of comparable quality because of their low differentiation. They also highlight previous discussion by Bontemps *et al* (2005) and Gabrielsen *et al* (2006) among others. In the UK, these results are confirmed by the Private Label Manufacturers' Association, who find that its production meets the same standards as the familiar national brands (see Oxera, 2010).

Various press reports in recent years confirm that leading branded products and supermarket brands are comparable because of their similar quality.We sum up four reports published on the Internet that confirm this similarity, along with the consumers' evaluations of these brands in the UK. First, the nutritionist Angela Dowden (2012) compares leading branded products and supermarket brands of salt, fat, sugar and calories for pasta sauce, mayonnaise, and baked beans for both brands. Surprisingly, her main finding is that prices of the retailer-

owned brands are not only lower but also healthier (www.dailymail.com[28]; www.angeladowden.co.uk). Second, Datamonitor informed (2011) [29] that two thirds of British people believe that own-brand foods are as good as the leading famous brands, if not better, and half believe that they are identical in quality. This same source reported in February 2013 that the quality of own brands has improved because supermarkets are using better ingredients. Finally, some webpages[30] carry a comparative analysis of the brands we analyse here, with the same conclusions about the quality of the own brands.

Another important point that confirms this analysis is evidence that large manufacturers produce own brands for the main UK supermarkets. Recently the international firm Findus[31], manufacturer of ready meals, peas and crispy pancakes, confirmed that they produce frozen food for Tesco such us spaghetti Bolognese and beef lasagne.[32] In addition it is easy to find information in many British blogs by workers for important manufacturers who comment on the same topic. According to these sources, Heinz and Kellogg also produce their products for Asda and Tesco.[33] Big companies such as Del Monte, Heinz and Kraft also make own brands for the food chain Aldi and Weetabix, the producer of wholegrain breakfast cereals, makes this product for large supermarkets. Chicken products sold by Kentucky Fried Chicken, Burger King, Marks & Spencer and Asda are made by the same company as well.

Some products sold by Tesco and Asda are imported from China[34]. The list includes detergents and frozen foods, among others.

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[28] Report dated 20/07/2012
[29] http://conversation.which.co.uk/consumer-rights/own-label-vs-big-brand-food-whats-in-your-trolley/
[30] For example, www.supermarketownbrandguide.co.uk
[31] www.findus.co.uk
[32] http://www.theguardian.com/world/2013/feb/08/how-horsemeat-scandal-unfolded-timeline
[33] It is often difficult to identify the true producer because the manufacturers identify themselves by other names in order to consumers do not know that the retailer-owned brand is the same with a lower price.
[34] www.made-in-china.com

Oxera (2010) confirms that branded products and own brands are similar in terms of quality (or the same). Their report also highlights that the fierce rivalry between leading brands and own brands in categories such as food, drink and household-care products creates vigorous competition resulting in higher quality, increased innovation, lower prices, new products and more choice in the UK.

This tougher competition has also impacted on the market share of some supermarket products such as milk (43%) and vegetables (36%), and leading manufacturers are creating more brands with different prices/quality. For instance Proctor and Gamble is developing strategies to compete with own brands across a range of price/quality combinations rather than concentrating solely on premium products.

Nutritional Information

To confirm this information for our products, we collected nutritional information about the foods in our basket (see Annex 2). Public information is published for each product by its manufacturer according to British law (see, for example, www.mysupermarket.co.uk).

After making a comparison across brands, we conclude that for all the goods chosen, supermarket-owned brands have similar values to the leading branded products in terms of calories, fat, saturated fat, sugar, salt, protein, carbohydrates, sodium and fibre, except for tinned tuna, where there are considerable differences in most indicators, highlighting a big difference in total calories (over 60% more than in each supermarket's own brand), fat, saturated fat and salt: as a consequence we decided to exclude this good from our dataset.

In sum, as most of our products have similar or exactly the same nutritional properties as the leading branded good, they can be considered as homogenous products. Our basket now contained 19 products.

3.4 Model specification

We next investigated the interaction between leading branded products and retailer-owned brands in terms of pricing, location on the shelf and the determinants of the number of brands each supermarket sells. We begin below with an examination of our main specification about the relative prices of the own brand and leading branded products (P_{ob}/P_{bg}) using a logistic regression. Next we analyse the position of both goods on the shelf to find the determinants of their relative locations (next to, above or below) using regression logit and probit models for binary dependent variables and then construct a log-linear model for the number of brands sold by UK supermarkets.[35]

a. <u>Model specification for prices</u>

To examine the relative prices (P_{ob}/P_{bg}), we estimate a logistic regression $\{ln\,[(\pi_{i,t}/\,(1-\pi_{i,t})]\}$ with, as independent variables, a time-trend variable to measure changes in relative prices over time, the degree of inter-manufacturing-firm competition, a dummy to control for supermarket price cuts (discounts) and dummy variables to control the supermarket-specific effect. We also include two interaction terms to expand understanding of the relationships among relative prices with the number of manufacturing firms and the price cuts (discounts).

The specification is mainly based on Ward *et al*'s (2002) US supermarkets time series analysis and Cotterill *et al* (2000). Because of the lack of public information about market share in most literature, we believe that including the "'supermarket specific effectsupermarket-specific effect (differences among supermarkets) dummy variables is a

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[35]With this last specification we recognise that the number of brands is an endogenous variable when it is regressed against the number of firms. In the same way, we also want to highlight that in some points of this research had doubt (not clear) whether or not the latter is an independent variable, especially when is used as a price predictor. In fact some research is used as an endogenous variable such as Ward *et al*, 2002.

good proxy to capture that effect. However, we are conscious of a potential problem generated by the omission of this variable in our model: its causal effect could be captured by the other variables to compensate for its exclusion, and as a result it could generate positive or negative biases in the effects of the included variables (Greene, 2008).

On the right-hand side of the estimation equation we use the logistic function of prices to prevent negative or extreme values in the predicted dependent variable from the linear model or log-linear specification. This transformation allows the right-hand side to be a linear function of our independent variables that does not affect the sign of the coefficients. Our justifications and expectations of our variables follow below.

Time-trend variable (time effect)

We include this variable to control changes in price over time. We think that the value of this variable should be close to zero because the prices of both labels should increase with inflation at a very similar rate over time. If this is not so we must look for explanations of the movement of price over time. One explanation occurs in the literature: Binninger (2007) finds that satisfaction with and loyalty to supermarket brands influence store loyalty which is consistent with the importance that supermarkets afford their own brands. We believe that it is perfectly possible that supermarkets with a high percentage of loyal customers easily take advantage of their position to increase the prices of their own brands over time.

We found a press report in *The Guardian* (2013)[36] to the effect that according to David Bird, of the retail analyst Datamonitor, the quality of own-label goods has improved, which implies that if the cost of the ingredients rises the price of own brands should be increasing as well.

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[36] http://www.guardian.co.uk/lifeandstyle/wordofmouth/2013/feb/04/rise-of-the-own-brand

We believe that according to the latter arguments the relative price P_{ob}/P_{bg} should go up

(*ceteris paribus* P_{bg}) over time, and thus the coefficients of t should be positive.

Number of manufacturing firms (nf)

The inclusion of this variable follows Ward *et al*'s (2002) paper. Under this justification, we

know that if the number of manufacturers increases, so does the number of products sold by

the supermarkets and hence consumers have more choice to choose the good that meet their

needs. This should generate more aggressive competition, which can negatively affect the

price of a leading branded product and possibly also the own-brand price; the final effect is

ambiguous as it depends on the magnitude of both variations. What is our belief?

Even though we know that the findings obtained in previous empirical works show a positive

relationship between number of brands and leading-brand price (Coterill *et al*, 2000; Gabrielsen

et al, 2001; Ward *et al*, 2002; Bonfrer *et al*, 2004; Bontemps *et al*, 2005), we opt to follow the

hypothesis tested in the literature, and thus we expect the net effect of more firms to be a

positive impact on relative price P_{ob}/P_{bg} as the competition pushes the price of the branded

good (P_{bg}) down more than that of the own-brand (P_{ob}). This is because the latter may be

more cost-related and hence this cost provides a floor below which the price cannot drop in

the long run.

An alternative way of measuring the impact on relative prices is based on the fact that a

larger number of firms can be understood as a situation where there is a space for any

manufacturer that provides a product with different qualities to cover the needs of different

types of consumers, and hence each manufacturer has the market power to price its brand

over marginal cost. Thus each consumer buys the good that satisfies her particular preference. As a result, if an independent brand introduced by a new manufacturing firm is perceived as a differentiated brand, the impact on P_{ob}/P_{bg} will be negative (*ceteris paribus the others*) as the incumbent manufacturer of the branded good may increase its price to protect itself and serve more inelastic consumers.

Two additional points are related to the endogeneity of the number of firms and the inclusion of this variable instead of the number of brands.

We believe that *nf* could be endogenous if we include supermarkets that purchase at very low wholesale prices, which is highly likely in supermarkets that sell few brands such as Aldi in the UK, which focuses on cheaper brands. As the largest supermarkets buy a wide variety of brands we posit that wholesale prices depend on the volume they buy and hence the number of firms should be exogenous. Second, we believe that the competition depends on the number of firms rather than the number of brands sold, because the latter is a tool to either defend the more competitive brands or exploit ignorant consumers. Bergers-Sennou (2006) and Gabrielsen *et al* (2007) offer two additional arguments: the number of brands produced by a manufacturer is a tool with which to negotiate better contracts; and leading manufacturers are interested in inelastic consumers, implying that the other brands compete with the remaining independent brands.

Discount dummy variable

We include a dummy variable **Ddiscount** to control for the effect produced by particular price cuts on the 'normal price' of a good. In other words, we want to control for any

abnormal price deviations observed in our data. This dummy is equal to 1 when there is a price cut and 0 otherwise, and is used by Cotterill *et al* (2000) to isolate its effect on the price trend.

The supermarket-specific effect (dummy variables)

From a statistical perspective, the inclusion of this variable is key for us as it not only provides information about intra-supermarket competition but also, it would have to capture the causal effect of exclusion of the products' market share commented on in the literature review, where we observed that most models include the brand's market share as an independent variable to evaluate impact on relative prices,. The implication for our model is discussed in section 3.5, Estimation Methodology

To control for each supermarket we include three dummies: DAs (Asda), DMo (Morrisons) and DSa (Sainsbury's), i.e. we compare these with Tesco. Our justification and expectations are as follows.

As we said in the introduction, the supermarkets compete in different ways in terms of the number of products, varieties and the development of their own brands, which would justify differences in the prices of their products.

Asda and Tesco sell a similar number of own brands and products (40,000) and hence should price their goods similarly. The fact that manufacturers such as Heinz and Kellogg produce own brands for Asda and Tesco confirms that the prices of those goods should be similar. As we believe that Asda and Tesco use the same pricing scheme, we expect similar coefficients

for both. As Tesco was excluded from the equation, Asda's coefficient should be close to zero.

In contrast, Morrisons and Sainsbury's cover a smaller number of products and have developed fewer own brands. Additionally, they follow different strategies for developing and selling their own brands and in competing with their rivals. Morrisons is strongly focused on fresh food own-label products and Sainsbury's on high-quality products due to its strong reputation and loyal customers.

We believe that there are differences in the values of the dummy variables for Morrisons (DMo) and Sainsbury's (DSa) for two reasons. First, we posit that the quality of their own brands is higher than that of Asda and Tesco's. The latter has four own brands aimed at different consumers and hence we posit that the own brand named after the supermarket ('Tesco') is the biggest brand, which implies that this should compete in the fringe of the more competitive brands. In the same way, we think that Asda tries to reduce its costs to assure its low prices and may do so by using lower-quality ingredients in some of their own brands (for example its tinned tuna). Second, we expect a positive coefficient for Sainsbury's as it focuses on satisfying loyal customers. Although we have doubts about Morrisons because it focuses on fresh foods, which are not included in our basket, we think that to protect its reputation,[37] the quality of its own brands in our bundle should also be higher than those of Asda and Tesco and hence should be priced higher, thus we posit a positive coefficient of these dummy variables as well.

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[37]Morrisons's advertising for its own brands is based on quality and value, as we commented in the introduction.

Interaction term between number of manufacturing firms and supermarket-specific effects (FS)

We also include an interaction variable to control for the degree of inter-firm competition within each supermarket. With this variable the logistic model relates the relative price $\frac{P_{ob}}{P_{bg}}$ to the degree of inter-firm competition (nF) for each supermarket. For example, if we hold P_{ob} constant, the marginal effect of more (less) competition on the relative price P_{ob}/P_{bg} is increased (decreased) when the supermarket's strategy is to compete based on a higher (lower) number of manufacturers selling their products in a specific supermarket, given that the effect on the denominator of P_{ob}/P_{bg} by a lower P_{bg} should be higher and as a result, the relative price P_{ob}/P_{bg} should go up more.

Looking at our supermarkets, we would expect a negative impact on Asda due to the smaller number of manufacturing firms involved in comparison to its rivals, whereas it would be similar for Morrisons and Sainsbury's as they sell the brands of fewer manufacturing firms than Tesco but more than Asda (Oxera, 2010). We posit that the sign of the coefficients FDMo and FDSa should be negative due to the lower degree of competition observed in these supermarkets in comparison to Tesco.

Interaction term between price cut (discount) strategies and the supermarket-specific effect (DiscS)

Finally, we include this interaction variable to control for abnormal changes in the prices (price cuts or discounts) of each supermarket. The more aggressively a supermarket uses this

strategy to compete, the more the marginal effect of cutting relative prices increases. In short, this term controls the degree of aggressiveness of each supermarket when they compete by cutting prices.

The relative prices model is given by the following expression:

$$\ln\left[(\pi_{i,t}/(1-\pi_{i,t})\right] = \alpha + \beta_1 t + \beta_2 nf_i + \beta_3\, Ddiscount_{i,t} + \Sigma_{j=4}^{6}\beta_j\, DS_{i,j} + \Sigma_{j=7}^{9}\beta_j FS_{j,it} + \Sigma_{k=10}^{12}\beta_k\, DiscS_{k,it} + \varepsilon_{i,t} \quad (1)$$

where i is product, i= 1,…,19; and t=1,…,40 weeks. The variables are as follows:

- the dependent variable corresponds to the logistic function such that $\pi_{i,j}=Pob/Pbg_{i,t}$, ratio of prices of the retailer-owned brand ($Pob_{i,t}$) and the leading branded good ($Pbg_{i,t}$) defined weekly in British pounds;

- t is the time-trend variable (Thursday October 2 2008 to Thursday July 2 2009);

- nf_i is the number of manufacturing firms per product;

- $Ddiscount_{i,t}$ is a dummy that captures price cuts (offers or sale) in a specific period t;

- $DS_{i,j}$ is a dummy variable to control for each supermarket, where j=4 (Asda), j=5 (Morrisons) and j=6 (Sainsbury's). Effects are measured relative to Tesco;

- $FS_{i,j}$ is an interaction term between the number of manufacturing firms per product i sold by supermarket j where j=7 (Asda), j=8 (Morrisons) and j=9 (Sainsbury's);

- $DiscS_{k,i,t}$ is an interaction term between any discount per product i in the period t by a supermarket k (k=10 (Asda), k=11 (Morrisons) and k=12 (Sainsbury's));

- $\varepsilon_{it} \sim (0,\sigma^2)$.

Our specification has a time-invariant variable number of firms *(nf),* although it varies across supermarkets and product categories. We discuss an alternative variable as a predictor: the number of brands sold by supermarkets, which is also time-invariant (for example, Asda presents the smallest and Tesco, the largest number of brands per category). However, this was not included in the end because we believe that its number is a strategic decision by the supermarket and hence is endogenous in the pricing model.

In summary, the short-term sensitivity of the relative price $Pob/Pbg_{i,t}$ between of the retailer-owned brand and the leading good is expected to be related to a time-trend variable, inter-firm market competition, a dummy variable to measure discounts undertaken by supermarkets, supermarket-specific effects and two interaction variables between our main independent variables and each supermarket.

b. <u>Model specification for shelf allocation</u>

In our second regression, investigate how the supermarkets decide on the location of their own brand and the leading branded product on the shelves. As we commented in the review of the empirical literature, this topic has been analysed by Sayman *et al* (2002), who use a logit model to find whether the own brand targets the top good or other brands of lower quality. Our model follows the same concern. We then attempt to determine whether the retailer targets her brand to the leading branded product, and the determinants of that decision.

Our dependent variable is a binary response (also known as a qualitative response model) because the shelf allocation is a discrete choice. As a result, the maximum likelihood is the method of estimation.

The right-hand side of this model contains the same variables as the prices logistic model because we believe that the basic elements that determine the location of both goods depend on the degree of competition per product measured by the number of firms (structural variable) and the supermarket's price cuts or discounts (conduct variable). It also includes the time-trend variable to control for the evolution of this strategy over time, and supermarket-specific effects to capture differences across each supermarket.

As we are interested in the particularities of each supermarket, we also included two interaction variables to measure the number of manufacturing firms for each supermarket and the discounts each supermarket offers. The details of our main predictions are presented below.

Number of manufacturing firms (nf)

In general, the position of goods in the supermarket is relevant to the analysis because it reflects the reasons behind why the supermarket assigns such a location and amount of shelf-space. In fact product location may either be traditional (determined by total shelf space allocated to product ranges and depending on unit size) or chosen strategically by the retailer to achieve a specific goal.

In terms of the first argument, we can suppose that the larger the number of manufacturing firms that provide a product to the supermarket (structural variable), the lower the chance of the supermarket's own brand being positioned above, below or next to the branded product. Thus when supermarkets compete based on the high (low) number of manufacturers' brands on their shelves there is a low (high) probability that they will display the branded products and their own brand next to, above or below each other and thus the coefficient is negative.

The second hypothesis is called the strategic effect (Sayman *et al*, 2002) and supposes that the supermarket might locate both products together if it wants to signal that its brand competes with the branded product rather than with other brands, but at a lower price; in this case the coefficient would be positive. This effect would also work in the opposite way if the leading brand has inelastic consumers; as a result, it is not good business to be positioned close to the leading brand as the chance of capturing its consumers is marginal; hence this coefficient will be negative.

Ddiscount

If retailers want to emphasise the value of their own brands by inflating the price differential to induce purchase of the cheaper one (their own brands) without affecting either the sales of the leading branded product' or total profits, the best way to create higher demand is to place the two goods far from each other. We observed that in many cases supermarkets place their special offers either at the head of the shelf or on another shelf in the middle of the corridor in such a way that customers find them isolated and far from rival brands.

We can also assume that a product traditionally located next to other similar products may affect pricing; however, this prediction supposes that shelf location is the independent variable. Some literature emphasises that shelf-space allocation is used as a strategic tool to negotiate a better contract and obtain lower wholesale prices from manufacturers, under the assumption that the production of a retailer-owned brand increases supermarkets' bargaining power.

Thus we posit that if the retailer cuts the price of an own brand it will locate the good separately from other similar brands, and the coefficient should be negative.

The supermarket-specific effect (dummy variables)

We believe that these dummy variables capture the different strategies that supermarkets follow in competing with each other. Following the traditional argument about location, as Asda competes based on few manufacturers per product the probability that it will display its own brand next to, above or below the others is higher than that for Tesco (the excluded supermarket), which has more varieties, and hence the probability is lower for the latter. In other words, behind this argument is the hypothesis that Asda does not use the shelf as a strategic tool, which is in line with their slogan – Saving your money every day– on which they mainly focus, rather than other strategies. As a consequence, the dummy DAs should be positive.

On the other hand, we believe that the strategic effect dominates decisions at Morrisons and Sainsbury's. As we posit that they sell own brands of higher quality than those of Tesco, which in turn means that they are closer to the quality of the branded product, we expect that

these supermarkets display their own brands next to, above or below the branded product more often to show customers the more convenient price/quality of the own brand. Therefore the sign of the coefficients DMo and DSa should be positive.

The other variables

We include the time-trend variable *t* to measure the time effects and two interaction terms. FDS is the interaction variable between the number of firms and the supermarket-specific effect. The second is DiscS (between Ddiscount and each supermarket) to control for supermarket discounts, as we commented earlier. In sum, our specification is:

$$Pr(Shelf = 1) = a + \beta_1 t + \beta_2 nf_j + \beta_3 Ddiscount_{i,t} + \Sigma_{j=4}^{6} \beta_j DS_{i,j} + \Sigma_{j=7}^{9} \beta_j FDS_{i,j,t} + \Sigma_{k=10}^{12} \beta_k DiscS_{k,i,t} + \varepsilon_{i,j} \ (2)$$

where i is product, i= 1,…,19; and t=1,…,40 weeks. The left-hand term is the latent variable, which is assumed to be 1 when the supermarket displays its own-brand product and the leading branded good together (i.e. next to, above or below) in the shelf. The coefficients indicate how a one-unit change in an independent variable affects Pr (Shelf=1).

c. **Model Specification for the number of brands**

Taking advantage of our dataset, we add a third study on the relationship of the number of brands and large supermarkets, as we think that the number of brands affects not only interbrand competition but also the development and the variety of retailer-owned brands. Consequently we believe that a supermarket with a wide range of own-brand products will protect them from the competition by controlling the number of brands it sells. At the same

time, we aim to understand the relationship between the number of brands (interbrand competition), the number of manufacturers per product and intrabrand competition per supermarket for our products. Understanding these relationships can tell us whether displaying a large number of brands is a strategy followed by the manufacturing firms and how large supermarkets' strategies affect them.

In this specification the dependent variable 'number of brands'sold by supermarkets and the independent variable 'number of manufacturing firms' are time-invariant, although they vary across supermarkets and product categories.

We believe that the number of brands is an endogenous variable because it reflects the particular strategies followed by `supermarkets (for example, offering more or fewer varieties of brands to satisfy specific customers, or protecting their own brands), which is captured by the dummy variable for each supermarket. We also control for the number of manufacturers to learn their strategies for these types of goods.

On the left of the equation we use the number of brands measured by log. In sum, the third specification is given as:

$$lognb_{i,t} = \alpha + \beta_1 lognf_i + \Sigma_{j=2}^{4}\beta_j DS_{i,j} + \Sigma_{j=5}^{7}\beta_j FDS_{i,j} + \varepsilon_{i,j} \qquad (3)$$

where i is the product, i= 1,…,19; and t=1,…,40 weeks. As we can see above, the number of brands measured by log (lognbn) is estimated against the log of the number of firms (lognf), three dummy variables to identify each supermarket (excluding Tesco) and three interaction variables between the number of firms and the supermarket-specific effect.

We pay special attention to the coefficient of the number of firms (β_1), which gives us information about national manufacturers' competition strategies; i.e. whether the manufacturers of our products display a large number of brands as a strategy. This coefficient corresponds to the elasticity (or responsiveness) of the number of product brands to a change in the number of manufacturing firms (*ceteris paribus*), as both variables are expressed in log. Thus we posit a positive coefficient. To be consistent with the theory, its value should be higher than 1 if an independent manufacturer produces a large number of brands as a strategy to compete in the market, or equal to 1 if the manufacturer is a mono-producer.

The supermarket-specific effect is also important: this coefficient can help us to validate the similarities and differences between each supermarket's competition strategy (a wide variety or a low variety of brands).

We also incorporate interaction variables between the number of firms and the supermarketspecific effect. We expect the impact on brands to be smaller for Asda (DAs) than for the others because it follows a strategy based on a small number of brands (and hence few firms) due to its major emphasis in its own brands (Oxera, 2010).

3.5 Estimation methodology

The literature makes little attempt to justify the estimation techniques used and provides few diagnostic tests to check the validity of results. We discuss here the most popular panel data models used by researchers, the assumptions that support each model and the tests chosen to check the significance of the estimates and the validity of our models.

There is a variety of estimation techniques for panel data models. In this paper we use the following tools: first, the ordinary least squares estimator (OLS) model, which assumes no heterogeneity between products (pooled model); second, the OLS considering the existence of individual effects correlated with the explanatory variables (the fixed effect model (FEM)). Third, we implement the generalised least squares (GLS) used by the random effect model (REM). We discuss the properties, strengths and weaknesses of each model in the next section. To choose the best approach, we paid particular attention to the theoretical justification of our regression, violations of standard econometric assumptions, the tests used to validate the models, and the remedies applied to improve the estimations.

Consider the linear regression model for the main specification, expressed in the following terms:

$$y_{it} = \alpha + x_{it}^{'}\beta + \varepsilon_{it} \quad [\text{i} = 1,\dots,19 \text{ product, and t} = 1,\dots.40 \text{ time}] \tag{1}$$

where y_{it} isthe logistic function of $\pi_{i,t}$=$Pob/Pbg_{i,t}$;x_{it} is a vector of explanatory variables of size 7x1 not including a constant; β is a 12x1 vector of parameters (including two interaction terms on three supermarkets), and α is a scalar (the intercept). The variable ε_{it} denotes the stochastic error term. Thus we have 19x40 observations for each of the four supermarkets, with the total number of observations 3040.

The first and simplest model used is the pooled model, which assumes that the Gauss Markov Theorem is satisfied: that is, the errors $\varepsilon_{it} \sim (0,\sigma^2)$, which means that they are independent and identically distributed (IID). Thus we can estimate the parameters α, β using OLS technique. The model supposes that any heterogeneity or individual effect among the groups (products) is insignificant and hence the OLS provides consistent (minimum variance) and efficient (lower variance) estimates.

One weakness of this model is that it is only consistent under weak assumptions such as strict orthogonality between the explanatory variables matrix and the standard errors, the autocorrelation or cross-observation correlation observed in a longitudinal data (Greene, 2008). Another weakness is the generation of specification biases caused by omitted variables, which is particularly important in our model as the market share variable is not included due to the lack of weekly detailed information that we need.

The application of this technique in our regression assumes no difference across products in different categories. However, it is likely to observe differences for three reasons: the different strategies followed by supermarkets in the development of their own-brand products are relatively heterogeneous (Oxera, 2010); the products are in five different categories (food, petfood, beverages (coffee and tea), general household consumables, and toiletries and cosmetics); and there is differing interbrand competition across categories.

Cotterill *et al* (2000) validate this technique for intracategory analysis without taking into account what happens with each individual product. However we believe that excluding market share as an explanatory variable can be a problem, as it may lead to a specification error in the model and bias the OLS estimates.

Next, we move to the FEM, also known as the 'within estimator', which assumes that differences between our 19 products can be captured by examining the intercepts, represented by the following equation:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \qquad (2)$$

where α_i captures all the observable effects and specifies an estimable conditional mean. To estimate the FEM the empirical model assumes the existence of unobserved heterogeneity,

which is correlated with the regressors x'_{it}. This model is also called the least square dummy variable (LSDV) because it uses dummy variables to designate a particular group. According to Sayrs (1989) the model can be estimated by OLS when the errors are independent and homoscedastic. If not satisfied, this can be solved by either estimated or feasible generalised least square (EGLS or FGLS).

According to Wilson and Butler (2007), one advantage of this specification is that it allows for comparison with the pooled model using an easy diagnostic procedure to measure whether the unit (product) effect influences the parameters. In terms of a statistical tool, it only needs the F test to be compared. Its main weakness is the exclusion of time-invariant variables, which yields higher standard errors due to the high correlation with the fixed effect. In economic terms it is difficult to explain the exclusion of these types of variables when theory suggests they are vital as explanatory variables. We deal with two invariant variables in our research – the number of firms and the number of brands – although they differ across supermarkets.

The F ratio to test the significance of differences across products is as follows:

$$F(n-1, nT-n-K) = \frac{(R^2_{LSDV} - R^2_{Pooled})/(n-1)}{(1-R^2_{LSDV})/(nT-n-K)}$$

where LSDV indicates the dummy variable model and 'pooled' indicates the pooled with only a single overall constant. In the null hypothesis we assume that the constant terms are all equal.

Gabrielsen *et al* (2001) justify this model by the need to take into account the differences between each category analysed, because each includes a different number of products.

Third, we consider the REM. This technique has a random constant term. The model assumes that the unobserved individual heterogeneity is uncorrelated with the explanatory variables x'_{it}. Thus its specification is given by:

$$y_{it} = \alpha + x'_{it}\beta + u_i + \varepsilon_{it} \qquad (3)$$

We define the random constant term as $\alpha_i = \alpha + u_i$, where α is the mean and u_{it} a random error that represents a product-specific random element. As we can infer from (3), the error is now compounded by two terms, $u_i + \varepsilon_{it}$, which implies that the variance-covariance matrix of this term is not scalar as assumed for OLS, and hence this is not the best estimator. Now, the variance is $Var\{\sigma_\varepsilon^2 + \sigma_u^2\} = \sigma^2$ and the covariance $Corr\{\varepsilon_{it}+u_i, \varepsilon_{is}+u_i\} = \sigma_u^2 / (\sigma_\varepsilon^2 + \sigma_u^2)$. The model is estimated using GLS under the assumption that the variance-covariance matrix is known. Let us define this as $\sigma^2\Omega$, where Ω is called the unconditional variance matrix. One strong indication for applying GLS is that the researchers know Ω, or at least it is easy to approximate (Greene, 2008). As this model is a generalised regression model with a known structure, the GLS is more efficient than the OLS model. In other words, when we allow the explanatory variables to be random, the GLS model requires a stronger assumption than the OLS model to be consistent. One additional advantage of this approach is that it allows for the inclusion of time-invariant variables among the explanatory variables.

<u>FEM or REM?</u>

Hausman (1978) has developed a formal test to evaluate the significance between FEM and REM models. The test is based on the statistical properties of each model, which are used to determine which is most efficient and consistent. Because the FEM model captures the individual effect by the intercepts, which can be highly correlated with x_{it}'. The individual effect u_i is supposed to not be correlated with x_{it}', in the REM. If this assumption is not satisfied, the random effect estimator will be biased. The test is:

H_0: individual effect uncorrelated with x_{it}'.

H_1: individual effect correlated with x_{it}'

The Hausman test statistic is as follows:

$$H = (\beta_{FE} - \beta_{RE})' \{Var(\beta_{FE}) - Var(\beta_{RE})\}^{-1}(\beta_{FE} - \beta_{RE})$$

Where β_{FE} and β_{RE} are the FEM and REM estimators, $Var(\beta_{FE})$ and $Var(\beta_{RE})$ are their respective variances and H is asymptotically distributed as $\chi^2(K)$ under H_0 (K is the number of parameters). If H $> \chi^2_{K,0.05}$ we reject the REM in favour of the FEM.

Tests for Autocorrelation and Heteroscedasticity

There are several tests for checking the violation of homoscedasticity and no correlation assumptions. Here, we pay particular attention to two of these: the Breusch and Pagan test for heteroscedasticity and the Wooldridge test for autocorrelation in panel data. We discuss our justifications for choosing these in the following paragraphs.

Heteroscedasticity

'Panel heteroscedasticity' means that the variance of the error term within a product is constant but varies across products; that is, $E(\varepsilon_{is}^2) = E(\varepsilon_{it}^2) = \sigma_i^2$, but $E(\varepsilon_{it}^2) \neq E(\varepsilon_{jt}^2)$, where i, j are products and s, t are two points in time. The main consequence of this problem is that OLS estimates do not provide the smallest variance, even though they are unbiased. OLS estimates are based on the assumption that the observations have equal weight, and hence are not optimal when the error term does not have constant variance. As a consequence, the standard errors are biased, which in turn leads to bias in the statistical tests and the confidence intervals.

The presence of heteroscedasticity could be a problem in our model because we have selected products from heterogeneous categories. A second problem is the exclusion of the market share of the product as an explanatory variable, due to lack of information.

There are several tests to detect the presence of heteroscedasticity. The most commonly used are White's general test and The Breusch and Pagan test. The first is considered a particular case of the latter because that assumes a linear form of heteroscedasticity. In the case of random effects, the test used is the Lagrange multiplier (LM), which is based on the OLS residuals. The hypotheses are $H_0: \sigma_\varepsilon^2 = 0$ and $H_1: \sigma_\varepsilon^2 \neq 0$.

The test statistic is:

$$LM = \frac{nT}{2(T-1)} \left[\left(\sum_{i=1}^{n} (T\,\bar{\varepsilon})^2 \Big/ \sum_{i=1}^{n} \sum_{t=1}^{T} \varepsilon_{it}^2 \right) - 1 \right]^2$$

Under the null hypothesis, LM is χ^2 (1).

Autocorrelation

According to Greene (2008), it is common to find that the errors are serially correlated in a group on any type of panel data model. This is mainly caused by a misspecification of the model. This yields less efficient results in panel data due to standard error bias and thus the inference based on OLS estimates is affected.

Most panel data literature assumes the first order auto-regressive process AR (1); that is

$$\varepsilon_{it} = \rho \varepsilon_{i,t-1} + v_{it} \qquad\qquad (4)$$

where v_{it} is a stationary, non-autocorrelated process and ρ is a parameter. In our model $i = 1, \dots, 19$ products, $t = 1, \dots .40$. The technique consists of calculating the value of ρ. Under the null hypothesis of no serial correlation, $\rho = 0$.

Prais and Winsten (1954, cited in Greene, 2008) provide one of the pioneer tests for auto-correlation. They propose a procedure to transform the variables y_{it} and x'_{it} in regression (3) above to restore the panel data, and thus this is no longer a common effect. Details of this methodology are documented in Greene (ibid). Other tests widely used to deal with this problem in FEM and REM models are provided by Arellano and Bond (1991), Baltagi and Li (1991), Baltagi and Wu (1999) and Wooldridge (2002), all of which are cited in Greene

(ibid). We focus on the latter three to define the best test for our regression, as the Arellano and Bond test is based on a dynamic model.

Baltagi *et al* (1991) propose the FGLS technique to deal with balanced REM. FGLS estimates the model through OLS and then uses this regression to estimate the covariance matrix of the errors, which is used to transform the data to satisfy the Gauss Markov assumptions (Beck, 2001). This procedure is complicated for the FEM model because there is no simple transformation comparable to differences from group means that will remove the common effect in the transformed model discussed above. Baltagi and Wu (1999) reformulated the former test. The new test is based on fixed assumptions about the nature of individual effects (standard errors) or tests for individual-level effects jointly. Wooldridge (2002) builds his test using the residuals from regression in first differences to remove the individual-level effect, the time-invariant covariates and the constant. This bases the test on fewer assumptions and hence it should be more robust, albeit less powerful that the more highly parameterised tests (Drukker, 2003).

Let us recall the test from the starting point. We apply the REM equation from (3):

$$y_{it} = \alpha + x'_{it}\beta + u_i + \varepsilon_{it}$$

The first differences regression is as follows:

$$y_{it} - y_{it-1} = (x'_{it} - x'_{it-1})\beta + \varepsilon_{it} - \varepsilon_{it-1}$$

$$\Delta y_{it} = \Delta x'_{it}\beta + \Delta\varepsilon_{it} \text{ where } \Delta \text{ is the first difference operator} \qquad (5)$$

The procedure requires estimating regression (5) to get the residuals $\hat{\epsilon} = \Delta\varepsilon_{it}$ under the hypothesis that if $\hat{\epsilon}$ are not serially correlated, Corr $\{\Delta\varepsilon_{it}, \Delta\varepsilon_{it-1}\} = -0.5$. The second step is

to regress $\hat{\epsilon}$ on their lags and test that the coefficient on the lagged residuals is equal to -0.5. Drukker (2003) suggests that the test is also robust to conditional heteroscedasticity.

Omitted variables and endogeneity problems

As we commented in the literature review, most models for evaluating impact on relative prices include, as an independent variable, the brand's market share, which is not publicly available. However, we believe that the inclusion of three dummy variables to control for the supermarket-specific effect is a good proxy for the excluded variables, because those dummies capture the relative importance of each brand within each of the supermarkets, which usually assign the biggest and best locations to the leading brands.

On the other hand, as we commented in the pricing specification section, we also have doubts about the potential endogeneity of the independent variable *nf*, which could create misspecification problems. However, we believe that in the case of leading supermarkets this variable is exogenous, as they sell a large variety of products compared to small supermarket chains which sell few brands, the number of which is decided by the firms.

__Implications for our models__

Most research about panel data with autocorrelation and heteroscedasticy suggests the need to employ either FGLS or OLS with panel-corrected standard errors (PCSE) as mechanisms to solve them.

The PCSE estimator produces accurate standard error estimates, whereas the FGLS yields coefficient standard errors that can be severely underestimated (Beck and Katz, 1995). The latter is explained by the fact that the process of repeatedly estimating the unconditional variance matrix Ω can compound inaccuracy in the standard error of the estimates. Beck and

Katz have also shown, however, that test statistics based on FGLS are more powerful when there are substantially more time points than cross-sectional units, which our model satisfies. Reed and Webb (2010) recently applied Beck and Katz's research using the Monte Carlo setup with poor results for the PCSE estimator in comparison with FGLS. We therefore also use the FGLS estimator.

Finally, we also tested for endogeneity using the Sargan-Hansen statistic (test for over-identifying restrictions) to check for problems of misspecification caused by endogenous variables.

3.6 Results

Descriptive statistics

Table 2 summarises the main variables of panel nature on 3,040 observations. We have included the original variables of branded good prices (P_{bg}), own-brand price (P_{ob}), relative price P_{ob} /P_{bg}, number of brands, number of manufacturing firms, and the information of the dummy variables (Ddiscount and DShelf) to know the frequency in which they are present.

Table 2:Summary Statistics

Variables	Mean	Std.Dev	Min	Max
Branded good price (Pbg)	2.0986	1.6081	0.38	6.79
Own brand price (P_{ob})	1.2654	1.0197	0.24	5.00
Pob/Pbg	0.6336	0.1907	0.191	1.224
Ddiscount	0.0845	0.2782	0	1
Number of firms (nf)	3.4605	2.5728	1	10
number of brands (nb)	4.1316	3.0671	1	13
DShelf	0.5796	0.4937	0	1

The table shows the high heterogeneity of our products due to the high standard deviation of most variables.

Looking at number of firms and number of brands, we observe the high degree of competition and the degree of proliferation of brands in the 19 products of our basket. Our dataset has both products competing with a large number of rival firms and brands and products operating on a monopoly scheme.

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The number of brands is greater than the number of manufacturing firms, suggesting that in some industries firms use a proliferation of brands as a strategy to compete or protect their leading branded products from competitors. The importance of location on the shelf is demonstrated by the mean of this variable, which indicates that the leading branded product and the retailer-owned brand are located next to, above or below each other in 58% of the weeks covered by this research. This percentage is influenced by some products for which only two brands (i.e. the leading and the own brand) are sold, for example milk and salt.

The price information shows that the branded good prices are superior in level to those of the retailer-owned brands. The mean of relative price for both brands P_{ob}/P_{bg} is 63.4%, consistent with the findings of Apelbaum, Gerstner and Naik (2003), and in line with the theoretical explanations because the prices of branded goods are set under double marginalisation, which is not the case for supermarket brands. This difference might be seen as excessive, raising the question of whether the matched products are close substitutes. To validate this ratio we also look at information from the Datamonitor report (Oxera, 2010), which maintains that own-brand products are 22% cheaper than branded products.

We present the matrix of correlations between and among the dependent and independent variables in Table 3, below, expressed in the terms of the original information. We have included the relative price P_{ob}/P_{bg} as we are interested in that variable for the logistic equation. The first column stresses a positive and significant correlation for all variables except relative prices P_{ob}/P_{bg} and DShelf. This dummy is also negatively associated with all variables except relative price P_{ob}/P_{bg}. However, the dummy is negatively related to the

individual prices of either the own-brand or the branded product. This effect is less sensitive in the case of the retailer-owned brand.

Table 3: Matrix of Correlations

Variables	Pbg	Pob	Pob/Pbg	Ddiscount	nfirms	nbrands	Dshelf
Branded good price (Pbg)	1.0000						
Own-brand price (Pob)	0.9068*	1.0000					
Pob/Pbg	-0.2099*	-0.1489	1.0000				
Ddiscount	0.1284*	0.0528*	-0.1771*	1.0000			
Number of manufacturing firms (nf)	0.0747*	-0.0082*	-0.0762*	0.0371*	1.0000		
Number of brands (nb)	0.2709*	0.1531*	-0.1799*	0.0787*	0.9364*	1.0000	
DShelf	-0.0608*	-0.0014*	0.0814*	-0.2107*	-0.0835*	-0.1636*	1.0000

* Significance at p=0.05

It is important to notice the positive and significant correlation between the number of firms (*nf*) and branded good prices P_{bg}, validating the empirical result in the literature that competition pushes prices up, which is contra to our intuition. The opposite correlation is seen in the case of own-brand price P_{ob}.

The other value that deserves attention is the positive correlation between number of brands (*nb*) and price of the own brand (P_{ob}), which is counter-intuitive for us. We wonder if the supermarket takes advantage of the increasing number of brands while pricing their own brands higher. Is this a strategy to confuse consumers?

For the branded good, the positive sign of the number of brands and price validates the explanation associated with the diversification of brands in the market which benefits leading manufacturers because the price goes up.

The positive correlation between prices P_{bg} and P_{ob} (value of 0.9068) shows that they move together in our basket of products over time, implying that the branded good and the

supermarket own brand are strategic complements, as we expected. In the figure below the positive slope is easily observed.

Figure 1: Correlation matrix of the continuous variables
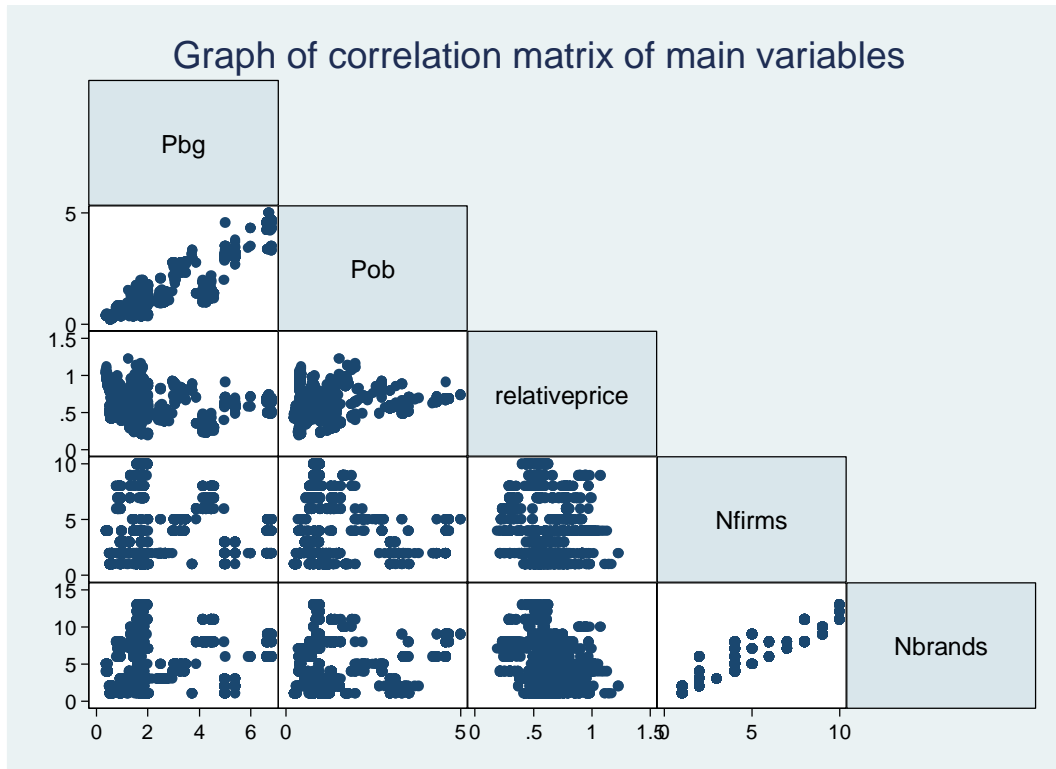
The summary statistics for each product, as shown in Table 4, confirm the high heterogeneity of our dataset. At one extreme we have three products served by an independent monopolistic producer (cornflakes, frozen petits pois and salt). On the other hand we have seven products that are highly competitive with at least four brands of each on the shelves (coffee, fruit juice, plain flour, teabags, tomato sauce, toothpaste and washing powder). Some of the manufacturers of five of these products produce them under more than one brand name.

Looking at the price information on the leading and the own brand, we observe that the prices of the leading branded products are always higher than those of the retailer-owned brands; however the latter are more stable than the first. Nine own-brand products show a standard deviation of less than 0.10; the lowest is obtained by six products – baked beans,

milk, plain flour, salt, teabags and washing up liquid – which is explained by the high homogeneity of these products. As a result the difference in prices presented in the last column shows a low standard deviation for four of the products.

We can also group the price differences. The first group is formed by coffee and toothpaste, whose price difference increased greatly in this period. Second, this group includes milk and plain flour, with similar prices between labels and hence with a small difference in prices. This result is consistent with Fernandez *et al*'s (2005) argument that the price of the own brand significantly affects that of the leading good when the first is a high quality good or they are very close in quality. Gabrielsen *et al* (2001) found similar results for these goods in the Norwegian food industry.

Third, the prices of the remaining products went up by 0.10-0.80.

Table 4: Summary Statistics for product

Product	P_{bg} (£) Mean (Std.Dev)	P_{ob} (£) Mean (Std.Dev)	Number of brands Min	Max	$\ln n\,brands$ Mean (Std.Dev)	Number of firms Min	Max	$\ln n\,firms$ Mean (Std.Dev)	shelf Mean (Std.Dev)	$\ln dif$ Mean (Std.Dev)
Baked beans	0.609 (0.054)	0.407 (0.020)	2	2	0.693 (0.000)	2	2	0.693 (0.000)	0.750 (0.434)	0.399 (0.095)
Cat food	3.251 (0.239)	2.533 (0.304)	4	5	1.554 (0.097)	4	5	1.554 (0.097)	0.950 (0.219)	0.242 (0.131)
Cornflakes	1.759 (0.191)	0.938 (0.231)	1	1	0.000 (0.000)	1	1	0.000 (0.000)	0.944 (0.231)	0.625 (0.149)
Coca Cola	2.499 (0.229)	1.162 (0.141)	3	3	1.099 (0.000)	2	2	0.693 (0.000)	0.000 (0.000)	0.767 (0.145)
Coffee	3.932 (0.629)	1.443 (0.376)	8	11	2.079 (2.398)	6	8	1.792 (2.079)	0569 (0.497)	1.012 (0.286)
Juice	1.724 (0.155)	0.932 (0.069)	5	13	2.264 (0.384)	4	10	2.074 (0.398)	0.500 (0.502)	0.613 (0.134)
Mayonnaise	1.665 (0.215)	0.950 (0.146)	1	4	0.795 (0.522)	1	4	0.795 (0.522)	0.225 (0.419)	0.562 (0.215)
Milk	1.645 (0.052)	1.524 (0.045)	2	2	0.693 (0.000)	2	2	0.693 (0.000)	0.494 (0.501)	0.077 (0.048)
Pasta	1.012 (0.181)	0.663 (0.106)	2	3	0.997 (0.176)	2	3	0.997 (0.176)	0.207 (0.406)	0.415 (0.239)
Petits pois	1.783 (0.277)	1.280 (0.294)	1	1	0.000 (0.000)	1	1	0.000 (0.000)	0.925 (0.265)	0.342 (0.259)
Plain flour	0.422 (0.020)	0.414 (0.017)	4	5	1.498 (0.112)	4	4	1.386 (0.000)	0.490 (0.502)	0.013 (0.049)
Salt	0.567 (0.052)	0.289 (0.054)	1	1	0.000 (0.000)	1	1	0.000 (0.000)	0.750 (0.434)	0.684 (0.128)
Tea bags	0.888 (0.075)	0.705 (0.069)	6	8	1.974 (0.119)	6	8	1.974 (0.119)	0.428 (0.496)	0.231 (0.138)
Toilet tissue	2.103 (0.209)	1.860 (0.122)	2	4	1.141 (0.285)	2	3	0.997 (0.176)	0.472 (0.501)	0.119 (0.131)

Tomato sauce	1.711 (0.157)	1.042 (0.286)	7	10	2.131 (0.133)	7	9	2.105 (0.104)	0.706 (0.457)	0.521 (0.224)
Toothpaste	1.319 (0.316)	0.428 (0.042)	4	7	1.767 (0.230)	2	5	1.269 (0.346)	0.513 (0.501)	1.103 (0.250)
Vegetable oil	1.607 (0.121)	1.201 (0.085)	2	3	0.795 (0.176)	1	2	0.173 (0.301)	0.500 (0.502)	0.291 (0.088)
Washing powder	6.308 (0.820)	4.119 (0.813)	6	9	1.965 (0.179)	2	5	1.096 (0.411)	0.188 (0.392)	0.443 (0.310)
Washing-up liquid	0.961 (0.035)	0.704 (0.047)	1	2	0.520 (0.301)	1	2	0.520 (0.301)	0.994 (0.079)	0.313 (0.076)

Before running our equations we plot the relative price P_{ob}/P_{bg} for each product to look for

outliers in our data (Figure 2).

Figure 2: Relative price (P_{ob}/P_{bg})

Graphs by products
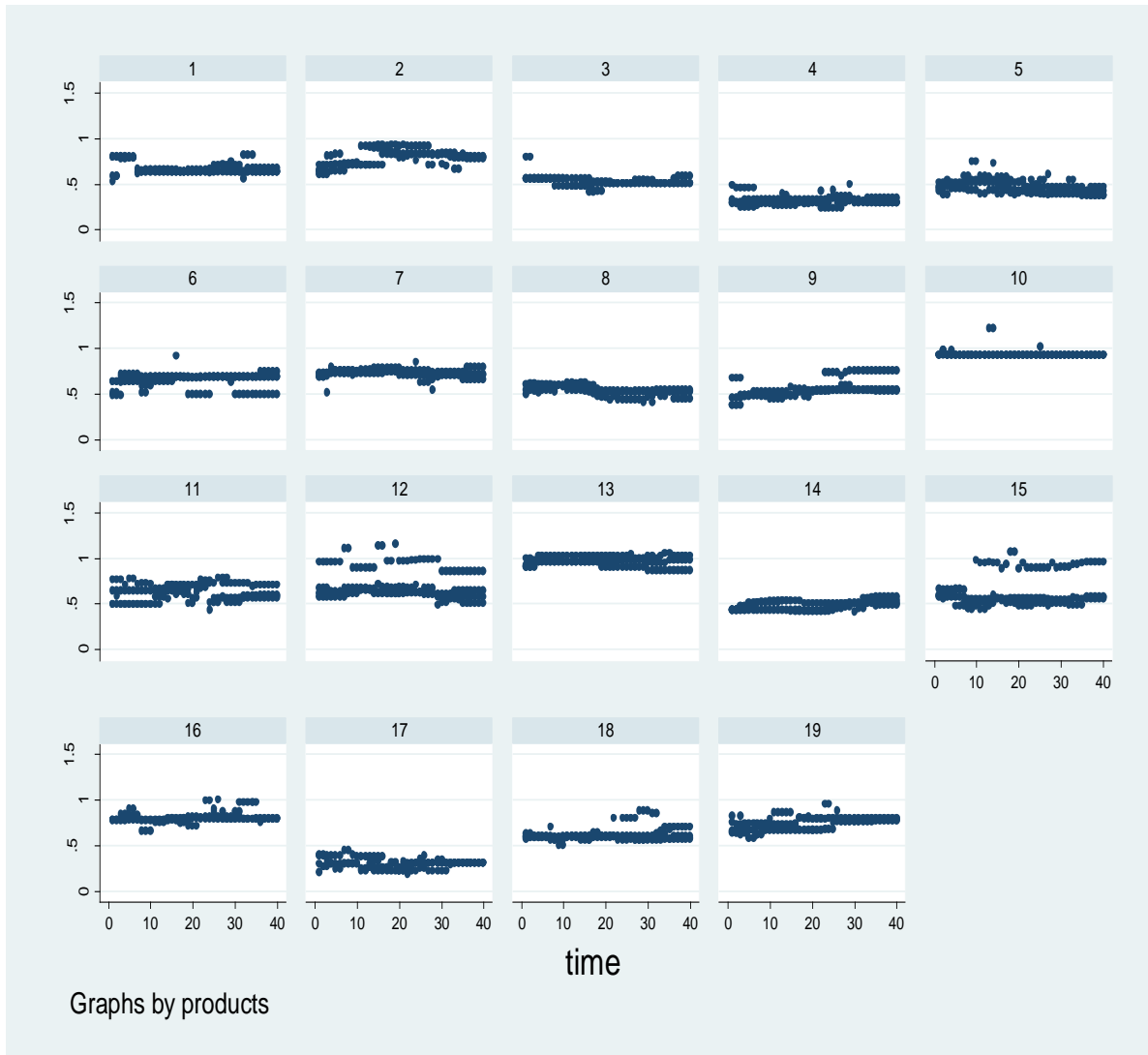
As Figure 2 shows, all of the observations are concentrated around the average price of each

product. Next, we looked at results in which relative price P_{ob} / P_{bg}>1 under the hypothesis

that all values should be lower than 1 for two reasons: the own brands may be cost-related

(discussed in section 3.4), and the double marginalisation of the branded good. The dataset

validates the data, even though it is counterintuitive for us. Products 12 (salt) and 13

(teabags) showed such differences which can be justified by the fact that they are highly homogenous. Some outliers were observed in petits poi (10), which is in essence a homogenous good and hence very difficult to differentiate.

3.7 Results of the regressions

Next we show and discuss the results of our three specifications. The estimates, the interpretation of the coefficients and the development of the tests to validate them are shown in this section.

Logistic of price regressions

We start by modelling our logistic equation of relative price (P_{ob} /P_{bg}) with a basic specification that only includes the independent variables of equation (1) in section 3.4. We then expand this specification to find whether the statistical significance of the model and the coefficients is increased by including the interaction variables between both number of firms and the *Ddiscount* dummy variable with each supermarket, under the assumption that they use different strategies to compete (number of varieties per product, with Asda and Tesco at opposite ends of the spectrum; prices; location) and to develop their own brands. All analysis is relative to Tesco, the excluded variable.

Table 5: Logistic of P_{ob} / P_{bg} basic model for alternative methods

Variables	Pooled Reg. Model (OLS)	MLE Reg. Model	Fixed Effect Model	Random Effect Model
t (time)	0.00064**	0.00163**	0.00163**	0.00163**
	(0.00157)	(0.00074)	(0.00074)	(0.00074)
Nf	-0.01938***	0.01110	0.01159	0.01075
	(0.00706)	(0.01046)	(0.01055)	(0.01045)
Ddiscount	-0.58727***	0.00436	0.00550	0.00354
	(0.06500)	(0.03210)	(0.03213)	(0.03220)
Das	-0.09961*	-0.03770	-0.03637	-0.03705
	(0.04655)	(0.02300)	(0.02304)	(0.02307)
DMo	-0.02925	0.01904	0.01912	0.01899
	(0.04643)	(0.02207)	(0.02209)	(0.02214)
DSa	-0.29391***	-0.00712	-0.00669	-0.00743
	(0.06260)	(0.03279)	(0.03283)	(0.03289)
Constant	0.81343***	0.62406***	0.57640***	0.62539***
	(0.05020)	(0.21922)	(0.04305)	(0.16977)

Number of Observations	2,971	2,971	2,971	2,971
Wald χ^2 (6)		13.35		13,23
Prob> χ^2 (6)		0.00378		0.0395
F(6, 2964)	19,65		2.24	
R^2overall	0,0383		0,0006	0,0004
Log-likelihood		-2,001.9		

*** Significance at p=0.01; ** significance at p=0.05; * sign. at p=0.10

Table 5 shows the estimates of logistic equation of prices using the pooled OLS model, FEM, Maximum likelihood estimator (MLE) regression model and REM. The OLS model results show important differences from the estimates of the other three regressions. The coefficients of number of firms (*nf*) and discount dummy (*Ddiscount*) are negative and more sensitive that the coefficients obtained using the other techniques. In the first case, this finding may be consistent with the expectation of higher competition and hence the price of the retailer-owned brand drops (all others remaining constant).

Even though the coefficients of our basic variables for the other models are statistically insignificant, their signs, magnitude and standard deviations are very similar, except for the coefficient of Morrisons (DMo). To improve the model, we expanded it with interaction variables.

The key interaction variable is the number of firms per supermarket. This allows us to control for the degree of inter-manufacturing-firm competition. We also include an interaction variable between the discount dummy variable and each supermarket which shows an insignificant statistical effect on the coefficients. Both expanded specifications for FEM (1a, 2a) and REM (1b, 2b) are shown below in Table 6.

With the first adjusted specification, the coefficients of our regression were all significant except for the value of the dummy variable that controls for price cuts, Ddiscount. On the other hand, the completely expanded model showed statistically insignificant coefficients for the interactive variable discount-supermarket (in the end of the columns). We now comment the expanded regression with the interaction term relating the relative price to number of firms and each supermarket (models (1a) and (1b)). We also validate the models statistically using the tests for significance mentioned earlier. The analysis of each variable effect is presented below.

Table 6: Logistic of P_{ob} / P_{bg} with interaction terms for Fixed Effect and Random Effect Models

Variables	Fixed Effect Model (1a)	Fixed Effect Model (2a)	Random Effect Model (1b)	Random Effect Model (2b)
t (time)	0.00161**	0.00160*	0.00161**	0.00160**
	(0.00072)	(0.00072)	(0.00072)	(0.00072)
Nf	0.05046***	0.05016***	0.04976***	0.04959***
	(0.01114)	(0.01118)	(0.01105)	(0.01111)
Ddiscount	0.00017	-0.02501***	-0.00171	-0.02679
	(0.03135)	(0.04532)	(0.03143)	(0.04539)
Das	0.13235***	0.12919***	0.13164***	0.12859***
	(0.03470)	(0.03524)	(0.03478)	(0.03528)
DMo	0.42616***	0.422845***	0.42592***	0.42261***
	(0.03876)	(0.03908)	(0.03886)	(0.03914)
DSa	0.19101***	0.018299***	0.19060***	0.18257***
	(0.05408)	(0.05455)	(0.05421)	(0.05462)
FDAs	-0.05009***	-0.05011***	-0.05005***	-0.05008***
	(0.00852)	(0.00854)	(0.00854)	(0.00855)
FDMo	-0.11444***	-0.11427***	-0.11441***	-0.01142***
	(0.00905)	(0.00906)	(0.00907)	(0.00907)
FDSa	-0.05261***	-0.05304***	-0.05270***	-0.05311***
	(0.01079)	(0.01081)	(0.01082)	(0.01082)
DiscSAs	-	0.02987	-	0.03009
	-	(0.07068)	-	(0.07079)
DiscSMo	-	0.02954	-	0.02992
	-	(0.09468)	-	(0.09482)
DiscSSa	-	0.12188	-	0.12329
	-	(0.10578)	-	(0.10594)
Constant	0.44151***	0.44151***	0.44531***	0.49342***
	(0.04450)	(0.04452)	(0.04476)	(0.18559)

Number of Observations	2,971	2,971	2,971	2,971
Wald $\chi 2$			177.6	179.31
Prob> $\chi 2$			0	0
F(9, 2943) and F(12, 2940)	19.6	17.34		
Prob> F	0			
R^2overall	0.0072	0.0118	0.0076	0.0084

*** Significance at p=0.01; ** significance at p=0.05; * significance at p=0.10

Time variable (t)

The time trend coefficient t shows a positive sign and is statistically significant for all models. One interpretation of this value is that the price of the own brand P_{ob} went up by a higher percentage than that of the branded good P_{bg} over time.[38] However, the table above shows that the coefficient is very low (0.0016) confirming our belief, as expressed in the hypothesis section (3.4 part a).

One way of explaining this positive value is through the argument that the supermarkets raise the price of their own brands to take advantage of the loyalty of their customers'. Alternatively, they do it to signal that their own brands are as good as the leading brands and hence once they are positioned in the customers' minds, higher prices are seen as synonymous with higher quality.

Number of manufacturing firms (nf)

The coefficient of number of firms (*nf*) is positive and significant at 1% for both panel data techniques and hence the greater the number of manufacturing firms, the higher the relative price P_{ob} /P_{bg} . However, this positive relationship can be interpreted from different perspectives depending on how the competition affects both brands and the magnitude of these effects.

The first interpretation is that the more inter-firm competition, the higher the price of the own brand (P_{ob}) or the lower the price of the independent brand (P_{bg}), which suggests that the competition affects the price of the leading brand negatively or the supermarket brand positively, which we do not find credible due to the different signs for their prices obtained from the matrix of correlations.

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[38] During the period for which we collected prices the inflation rate went up by 0.6% (see www.ons.gov.uk).

An alternative explanation for this positive coefficient is that the competition affects both brands in the same direction but to a different extent. We again sought explanations in the matrix and graph of correlations (section 3.6), which do not show a clear pattern of behavior, and the values between the variables are weak. We could not infer anything from this.

Beyond these steps (and in accord with our hypothesis earlier) if this variable (*nf*) negatively affects the price of both brands it should nevertheless have a smaller impact on the supermarket brand, which is more cost-related and cannot be cut beyond its floor. If the number of firms (*nf*) goes up this should increase the degree of competition and hence the price of both brands should fall (in percentage) such that $\mid \Delta^- Pob_{i,t} \mid < \mid \Delta^- Pbg_{i,t} \mid$, and as a result the relative price (P_{ob} / P_{bg}) increases. On the other hand, if we assume that the number of manufacturing firms positively affects the prices of both brands $\mid \Delta^+ Pob_{i,t} \mid > \mid \Delta^+ Pbg_{i,t} \mid$, which could be explained by the fact that the price of the supermarket brand $Pob_{i,t}$ increases (in percentage) by more than $Pbg_{i,t}$ because the floor of the own brand is closer to the marginal cost (more elastic) and hence the supermarkets take advantage of their market power at the retailer level

This latter result goes in the same direction as most literature to date (Gabrielsen *et al,* 2001; Bonfrer *et al,* 2004, Bontemps *et al,* 2005, among others).

Ddiscount dummy variable

The third coefficient to control for 'abnormal'[39] cut prices observed empirically (Ddiscount dummy variable) is opposite for the FEM and REM, although with low sensitivity, and is statistically insignificant for three of the models. It is only significant (at 1%) in the case of

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[39] It was definedin section 3.4 a (about the model specification)..

the extensive model estimated using FEM. It is important to highlight the contrary sign of the first model, even though the value of the coefficient is the same.

The supermarket-specific effect

Looking at the supermarkets' dummy variables we observe that all coefficients are positive and significant at 1%. Asda's coefficient (DAs) is the lowest among the supermarkets (i.e. similar to Tesco), followed by Sainsbury's and finally Morrisons (the most differentiated), consistent with our hypothesis. We predict that Asda and Tesco price their goods in a similar way due to the similar development of their own brands (*ceteris paribus* the price of the branded goods), whereas the higher values of DMo and DSa confirm that Morrisons and Sainsbury's compete using other strategies. Following what the supermarkets report on their websites we validate that they offer high-quality own brands to attract customers who are willing to pay and loyal customers, respectively.

The highest coefficient of the dummy DMo surprised us, as we expected a coefficient closer than that of Sainsbury's (DSa). We can justify this difference under the assumption that Morrisons follows the same strategy of high quality for all of its own brands due to its historical expertise and capacity to produce goods. We believe that Sainsbury's positive and higher coefficient (DSa) than that of Asda also reflects its production of higher quality goods than those of Asda and Tesco, aimed at increasing customer loyalty.

Interaction variables

The coefficients of the interaction term between number of firms (*nf*) and supermarket-specific effects (FDAs, FDMo and FDSa) are all negative and significant at 1%, each coefficient being similar for each estimation technique.

The coefficient is more sensitive for Morrisons (FDMo), doubling the coefficients of FDAs and FDSa, which confirms our doubts about its strategy being similar to that of Sainsbury's. The coefficients of FDAs and FDSa are almost the same, implying that the marginal effect of more manufacturing firms competing in the supermarkets on the relative price P_{ob} /P_{bg} is diminished as much as for Asda and Sainsbury's.

On the othe hand, the coefficients of the interaction terms between the price cuts and the supermarket-specific effect (DiscSAs, DiscSMo and DiscSSa) are all positive but statistically insignificant, and hence there is no marginal effect related to the degree of each supermarket's aggressiveness when they compete by cutting prices.

What is the best model?

We start to answer this question by examining and discussing the results of each test commented on the Econometric Methodologies section to check the significance and validation of the techniques used. Then, we test for auto-correlation and heteroscedasticity in the fixed and random effect models by running the Hausman test. The Wooldridge test is used to check the presence of autocorrelation.

First, the F statistic for testing the significance of the fixed effects is 574.48 with 18 and 2,943 degrees of freedom (Prob> F = 0). The critical value, as shown in the table, is 1.88 at 1% and 1.57 at 5%. On this basis we reject the hypothesis that the constant terms are all equal given by the OLS model. The fit of our model increases greatly when the individual effects are added.

Next, we test the FEM versus the REM by running the Hausman test. However, the model fitted on these data fails to meet the asymptotic assumptions of this test, moreover giving a negative statistic (-1.37). The interpretation of this value is not clear to us and so we try to solve the problem by running the generalised Sargan-Hansen statistic test. The value is 24.877, chi-sq (9), P-value = 0.0031.In this case, the null hypothesis is the same as the standard Hausman fixed vs. random effects models and the null hypothesis is rejected, which in turn means that the random effect estimator is not consistent. Thus we validate the FEM.

Next, we test the presence of autocorrelation using the Wooldridge test) and heteroscedasticty with the Breusch and Pagan test to validate the REM.

The Wooldridge test for autocorrelation in panel data produces an F statistic of 5.788 with 1 and 18 degrees of freedom (Prob> F = 0). The critical value in the F distribution table is 8.18 at 1% and 4.38 at 5%, so the null hypothesis of no first-order autocorrelation is rejected.

The Breusch and Pagan multiplier test for heteroscedasticity in the REM produces a chi-squared value with a Prob> F = 0, whereas the critical value in the chi-squared table is 3.84, so the null hypothesis of no heteroscedasticity is rejected.

We also test the joint hypothesis of the supermarket coefficients, H_0: $\beta_4 = \beta_5 = \beta_6 = 0$; $H_1: Coefficients \neq 0$ and the coefficients of the interactive variables H_o: $\beta_7 = \beta_8 = \beta_9 = 0$ against the alternative hypothesis H_1: coefficients $\neq 0$. The results are F (3, 2943) = 42.33 (Prob> F = 0.00) andF (3, 2943) = 58.24 (Prob> F = 0.00) respectively, and hence both groups are significant.

As a result, our best specification is given by the FEM, considering our basic variables. Taking our model into account, Table 7 shows the coefficient for each product. It shows a high heterogeneity across groups, with two of the groups being statistically insignificant.

Table 7: FEM estimates per group

Products	FEM estimates	St. Deviation
Cat Food	0.71417***	(0.05809)
Cornflakes	-0.64076***	(0.05171)
Coca Cola	-1.48093***	(0.07134)
Coffee	-0.87091***	(0.05066)
Juice	-0.02662	(0.05278)
Mayonnaise	0.29043***	(0.05075)
Milk	-0.64602***	(0.08412)
Pasta	-0.52354***	(0.05200)
Petit Pois	1.81222***	(0.05182)
Plain Flour	-0.21316***	(0.05229)
Salt	0.31648***	(0.05314)
Tea Bags	2.18016***	(0.06190)
Toilet Tissue	-0.75594***	(0.05272)
Tomato sauce	-0.11981	(0.08406)
Toothpaste	0.70442***	(0.07613)
Vegetable Oil	-1.61946***	(0.05551)
Washing Powder	-0.21726***	(0.05188)
Washing Up Liquid	0.43746***	(0.05225)

Does Asda set its prices below those of the other supermarkets?

Another question we test is whether Asda sets its prices lower as promised by its public 'price guarantee', as if so we could be interpreting the results in a wrong way. We address this question by estimating two additional specifications in which the prices of both the branded good and the own brand are normalised with Tesco's prices. In the first case, the left side of the logistic specification is normalised with Tesco's leading product price (i.e. $Pob_{i,j}/Pbg(tesco)_{i,j}$) whereas the left side of the second specification is constructed using the ratio between the Tesco brand price and the leading brand price ($Pobtesco_{i,j}/Pbg_{i,j}$), with Tesco's own-brand price the numeraire.

Table 8: Logistic of $Pobtesco_{i,j}/Pbg_{i,j}$ (Branded good and own brand)

Variables	Fixed Effect Model Branded good Base=Tesco	Fixed Effect Model Own brand Base=Tesco
t (time)	0.00280***	0.00380***
	(0.00066)	(0.00085)
nf	0.052127***	-0.00594
	(0.28640)	(0.01311)
Ddiscount	-0.00280	-0.03314
	(0.02864)	(0.03702)
DAs	0.03599	0.09568**
	(0.03169)	(0.04082)
DMo	0.29273***	-0,01228
	(0.03587)	(0.04540)
DSa	0.17368***	-0.01172
	(0.04942)	(0.06367)
FDAs	-0.04273***	-0.00600
	(0.00778)	(0.01006)
FDMo	-0.08505***	0.00329
	(0.00832)	(0.01063)
FDSa	-0.04602***	-0.00028
	(0.00986)	(0.01270)
Constant	0.39490***	0.60245***
	(0.04071)	(0.05223)

Number of Obs.	2,936	2,982
F(9, 2908)/F(9, 2954)	20.15	3.98
Prob> F	0	0
R-squared	0.0033	0.0019

*** Significance at p=0.01; ** at p=0.05; * at p=0.10

Table 8 shows the results for both types of brands. With the new logistic specification we lose some observations because the relative values are lower than zero. The DAs coefficient in both columns is positive. However, the statistical significance is different, as the coefficient is insignificant for the first specification and significant at 1% in the second. As a result we can

affirm from the coefficient of this second equation that, Asda sells the leading brands in our basket at lower prices in comparison to Tesco.

Shelf specification regression

Our second model investigates how supermarket brands interact with leading brands on the shelves. We use our original dataset, which also details when these products were positioned next to, above or below each other. As the response about the position of the goods is binary, we use the probit and logit models, estimated by means of maximum likelihood (ML). ML estimators give the greatest likelihood of observing the joint location of both goods on a shelf.

We also include the OLS specification, even though this model is not appropriate for binary responses. The problems that are mentioned most often in the literature related to linear probability models are the following: (a) unbounded predicted values, which means that the left side of the equation can take values greater than 1 and less than 0; (b) the variance of the residual is related to the value of x, i.e., conditional heteroscedasticity; and (c) the errors can never be normally distributed, causing problems in hypothesis testing. Thus we cannot use tests like the likelihood ratio test (LR) or the Wald test to determine the best fit related to the logit and probit models. As the literature explains, none of these problems actually cause a problem with the estimates, and hence this technique (OLS) does not cause bias; nevertheless, the logit and probit models are better techniques compared to the OLS specification for dealing with binary dependent variables.

In sum, the main goal of this specification is to determine the effects on the response probability Pr (Shelf=$1/\overline{X}$, where $\overline{X}$ is the vector independent variables) resulting from a change in the degree of interfirm competition, promotion strategies (price cuts or discounts)

and the supermarket-specific effect. We also include the time-trend variable to control for changes over time, and interaction variables to measure the degree of inter-firm competition per supermarket.

We note that all explanatory variables are discrete, which poses an additional problem because it is difficult to check relationships between variables from graphics.

Table 9 shows the distribution of responses between groups and within each group according to the dataset.

Table 9: Distribution of the binary responses for the position on the shelf

Shelf	Overall		Between		Within
	Frequency	Percent	Frequency	Percent	Percent
0	1,278	42.04%	19	100.0%	42.04
1	1,762	57.96%	18	94.74%	61.18
Total	3,040	100.0%	37	194.74	51.35

Which model should we use?

As the setup for the logit and probit models is essentially the same, we cannot say which model fits our dataset best. On the other hand, although most literature (Sayman *et al*, 2002, Mesa *et al*, 2009) generally uses the former, both models predict the same probability.

Before stating the consistency and statistic results of our models, we estimate our equation by the FEM; however, all outputs were negative so we moved to the REM. Table 10 shows the estimates for the three techniques.

Table 10: Logit Model, Probit Model and OLS Model

(Shelf location without interaction variables)

Variables	Logit Model	Probit Model	OLS Model
t (time)	0.01198**	0.00770***	0.00125*
	(0.00469)	(0.00269)	(0.00072)
Nf	-1.00582***	-0.58241***	-0.02229***
	(0.10115)	(0.05780)	(0.00328)
Ddiscount	-2.61159***	-1.44228***	-0.33259***
	(0.22167)	(0.11507)	(0.03017)
Das	-1.87207***	-1.06847***	-0.17228***
	(0.15757)	(0.09012)	(0.02141)
DMo	1.05515***	0.65679***	0.13395***
	(0.14151)	(0.08353)	(0.02141)
DSa	6.84987***	3.81421***	0.29132***
	(0.63267)	(0.30607)	(0.02907)
Constant	3.29995***	2.01335***	0.63799***
	(0.96533)	(0.57659)	(0.02315)

Number of Obs.	3,040	3,040	3,040
Wald Chi^2 (9)	399.69	449.28	
Prob> Chi ^{2} (9)	0.0000	0.0000	
F(9, 3030)			77.35
Prob> F			0.0000
R-squared			0.1327
Log-likelihood	-1,120.6631	-1,120.7769	

*** Sign at p=0.01; ** sign. at p=0.05; * sign. at p=0.1

Looking across the models we observe that all the coefficients have the same signs and are statistically significant at 1% (except *t*). The OLS model, however, shows the lower sensitive values. The models are significant as well. The Asda coefficient (DAs) is interesting in that it shows a negative value in comparison to Sainsbury's and Morrisons' positive values. This may validate the fact that Asda competes in a friendly way with the leading brands, by placing its own brands in a different place on the shelf. On the other side, the positive coefficient of Morrisons and Sainsbury's (DMo, DSa) shows that their own brands compete *vis a vis* with the leading brands, as we pointed out in the hypothesis section 3.4 part b.

Now we expand the model with the interaction variables, relating the degree of inter-firm competition for supermarket. Table 11 sums up the estimates for the relevant techniques to analyse a discrete variable on the left-hand side.

Table 11: Logit Model, Probit Model and OLS Model for location of the retailer-owned brand and the branded good on the shelf

Variables	Logit Model	Probit Model
t (time)	0.01302*	0.00811*
	(0.00476)	(0.00273)
nf	-0.91363***	-0.53433***
	(0.09218)	(0.05204)
Ddiscount	-2.71659***	-1.51752***
	(0.22511)	(0.1166)
DAs	-2.84853***	-1.60815***
	(0.25581)	(0.13946)
DMo	1.89206***	1.10572***
	(0.28563)	(0.16686)
DSa	6.41224	3.59794
	(1.49991)	(0.7926)
FDAs	0.33360***	0.19004
	(0.06067)	(0.03388)
FDMo	-0.18597	-0.10131
	(0.05512)	(0.03297)
FDSa	0.07006**	0.03705***
	(0.20977)	(0.10675)
Constant	3.29995***	1.87782***
	(0.96533)	(0.54985)
Linear Prediction	0.72223	0.38588
	(0.90283)	**(0.51520)**

Number of Obs.	3,040	3,040
Wald Chi^2 (9)	432.62	503.96
Prob> Chi^2 (9)	0.0000	0.0000
F(9, 3030)		
Prob> F		
R-squared		
Log-likelihood	-1,092.278	-10,941.631

*** Significance at p=0.01; ** significance at p=0.05; * sign. at 0.10

Before interpreting the coefficients we show the predicted value of DShelf. Because most of the values are outside the range [0, 1], we proceed to eliminate explanatory variables to look for the best model for our dataset. See Annex 3 for the interpretation of the extensive model.

The best model

We select the probit model because it presents the lower quantities of predicted values out of range. As a result we exclude the dummies controlling for the supermarket-specific effect. When we estimate the model excluding the time variable it shows numerous values out of range [0,1]. When we control those outliers with a dummy variable, the result shows a greater number of predicted values out of range. The best model includes time, number of firms and Ddiscount as explanatory variables.

The estimates of our best model are shown in the following table:

Table 12: Probit model of the location regression

Variables	Probit Model
t (time)	0.00590***
	(0.00237)
nf	-0.07594***
	(0.02822)
Ddiscount	-1.25637**
	(0.10247)
Constant	0.53133*
	(0.29231)
Number of Observations	3,040
Wald Chi^2 (3)	161.84
Prob> Chi^2 (3)	0.0000
Log-likelihood	-1,432.8136

How can we interpret the marginal effect in our model?

The marginal effect expressed by percentage change in the odds associated with a one-unit change in any regressor is given by the expression: percentage change= $100 \ (e^{\beta k \delta} -1)$, which can be interpreted as the percentage in the odds of y=1 for a δ unit change in x_k (k being the independent variables). The marginal impacts and interpretation of the coefficients are developed below.

Time variable (t)

By calculating the odds using the same methodology as the others, the odds of the goods being displayed together are 59.17% higher over time, which implies that there is a trend for displaying both labels together.

Number of manufacturing firms (nf)

If we suppose a one-unit change in the number of manufacturing firms, this corresponds to a decrease in the log-odds of y=1 of -0.07594 in the probit model, according to our estimates. Thus a change in the odds that y=1 of $e^{-.07594}$=0.92687 then the percentage change in the odds that y=1 of 100(0.92687-1)= -7.31%: i.e. the odds are 7.31% smaller.

This result validates our traditional (structural) prediction that there is a negative relationship between the number of manufacturing firms that sell their products in large supermarkets and the joint allocation of the retailer-owned brand and the branded good. According to our hypothesis the traditional or structural explanation responds to the fact that supermarkets determine the position of goods according to total shelf space allocation to product range by unit size.

Ddiscount dummy variable

If we now suppose that there is a discount or an abnormal price drop in either the supermarket or the leading brand, the dummy variable coefficient takes the value -1.25637, corresponding to a decrease in the log-odds of y=1. Substituting this value in the exponential expression for y=1 gives us 0.28469. As a result, the percentage change in the odds that y=1 of 100(0.28469-1) = -71.53%: i.e. the odds are 71.53% lower, consistent with our expectation.

As a result the probability our goods being displayed together on the shelf decreases when a supermarket cuts the product price, in line with the prediction that products are displayed separately when there is a price cut in the brands analized.

As we said in the introduction, these are pioneering results, as to our knowledge there is no previous research in this area. This means that it is not possible to make comparisons to validate these positioning strategies.

The log-specification of the number of brands

Our last model seeks to determine the relationship between the number of brands (lognb) and the following independent variables: (a) the log of the number of firms (lognf) to control for the degree of proliferation of brands per manufacturer; (b) three dummies to capture the supermarket-specific effect (DAs, DMo, DSa because Tesco is excluded); and (c) the interaction variable of our independent variables (FDAs, FDMo, FDSa).

As the coefficient of the number of firms is measured by log it corresponds to the elasticity of the number of brands in response to a marginal increase in the number of manufacturing firms.

In this specification we have excluded the discount dummy variable (Ddiscount) included in previous models because the decision about the number of brands (nb) is a strategic one for supermarkets and hence we believe that it is not determined by a particular or abnormal price variation at a particular point in time.

Table 13: Log of the number of brands for alternative estimation methods

Variables	Pooled Model	Fixed Effect Model	Random Effect Model	MLE Model
lognf	0.95923***	0.83437***	0.83516***	0.83494***
	(0.01024)	(0.00585)	(0.0585)	(0.00584)
DAs	-0.01205	-0.04209***	-0.04186***	-0.04192***
	(0.01853)	(0.00483)	(0.00484)	(0.00483)
DMo	-0.12282***	-0.01027***	-0.01043***	-0.01039***
	(0.02212)	(0.00554)	(0.00554)	(0.00553)
DSa	-0.09651	-0.02292***	-0.02312***	-0.02300***
	(0.03017)	(0.00819)	(0.00820)	(0.00818)
FDAs	0.03791**	0.01633***	0.01629***	0.01630***
	(0.01621)	(0.00408)	(0.00409)	(0.00408)
FDMo	0.08678***	-0.02757***	-0.02746***	-0.002749***
	(0.01775)	(0.00443)	(0.00443)	(0.00408)
FDSa	0.11708***	-0.00742***	-0.00737	-0.00739
	(0.02215)	(0.00600)	(0.00601)	(0.00299)
constant	0.19534)	0.33921***	0.33836***	0.33859***
	(0.12600)	(0.00616)	(0.05612)	(0.06537)
Number of Obs.	3,040	3,040	3,040	3,040
Wald Chi^2 (7)			32,097.34	
Prob> Chi^2 (9)	0,00	0,00		
F(7, 3032)	3,419.63	4,575.45 (1)		
Prob> F	0,00		0,00	
R-squared	0.8876	0.8837	0.8837	
Log-likelihood				3,995.58
LR Chi 2 (7)				7448.08

(1) F(7, 3014)

*** Significance at p=0.01; ** significance at p=0.05;   * significance at p=0.10

Table 13 shows estimates of the log-regression for the number of brands using pooled OLS, OLS for the FEM, REM and MLE models.

As we expect, there are important differences in the OLS results compared to the estimates of the other models in terms of signs and the sensitivity of the coefficients, and only three coefficients are statistically insignificant. In particular, the elasticity of the number of brands is less than 1, although it is more sensitive than that in the other models.

Looking at all the models we find that the coefficient of 'lognf' (β_1) does not satisfy the theory, as it should have a floor of 1, as we commented earlier. To find out why the models are failing, we proceed to validate the model statistically.

First, the F statistic for testing the significance of the fixed effects is 2,673.50 with 18 and 3,014 degrees of freedom (Prob> F = 0). The critical value in the table is 1.88 at 1% and 1.57 at 5%. On this basis we reject the hypothesis that the constant terms are all equal. The fit of our model increases greatly with the addition of the individual effects.

Now we then test the FEM against the REM. The Hausman test for fixed versus random effects produces a chi-squared value of 5.62 (prob>χ^2= 0.5847). The critical value in the chi-squared table is 14.07, so the null hypothesis of the random effects model is not rejected.

Next, we use the Wooldridge test for the presence of autocorrelation and the Breusch and Pagan test for heteroscedasticity to validate the REM.

The Wooldridge test for autocorrelation in panel data produces an F statistic of 3.455 with 1 and 18 degrees of freedom (Prob> F = 0.0795). The critical value in the F distribution table is 8.29 at 1% and 4.38 at 5%; the null hypothesis of no first-order autocorrelation cannot then be rejected.

The Breusch and Pagan multiplier test for heteroscedasticity in the REM produces a chi-squared of 0.00005 with a prob> F = 0, whereas the critical value in the chi-squared table is 3.84, so the null hypothesis of no heteroscedasticty is rejected.

Given that the latter test indicates the presence of heteroscedasticity, we remedy this problem by using FGLS. With the new estimates we expect a consistent value of β_1, this means $\beta_1 > 1$.

Table 14: FGLS estimates for lognb

Variables	FGLS estimates
lognf	0.95924***
	(0.01023)
DAs	-0.01205
	(0.01850)
DMo	-0.12282**
	(0.02209)
DSa	-0.09652***
	(0.02703)
FDAs	-0.09652**
	(0.01619)
FDMo	0.08678***
	(0.01772)
FDSa	0.11708***
	(0.02213)
Constant	0.19534***
	(0.01258)
Number of Obs.	3,040
Wald Chi^2 (7)	24,000.59
Prob> F	0.0000
Log-likelihood	-221.6031

*** p=0.01; ** p=0.05; *p=0.10

Even though this estimation is also inconsistent with the theory because $\beta_1 < 1$, we proceed to test the joint hypothesis of the supermarkets' coefficients and the interaction variables to find out whether they are creating noise in our regression.

For the first, we test the joint hypothesis $H_0: \beta_2 = \beta_3 = \beta_4 = 0$; H_1: coefficients $\neq 0$. The statistic chi-sq (3) =39.04 (prob > chi-sq = 0.000): these coefficients are different from zero.

On the other hand, the test for the coefficients of the interactive variables is given by $H_0: \beta_5 = \beta_6 = \beta_7 = 0$; H_1: coefficients $\neq 0$. The statistic chi-sq (3) = 41.17 (prob > chi-sq = 0.000), indicating that the inclusion of these variables is also representative.

As a last step, we estimate our specification without the interaction variables FDAs, FDMo and FDSa. These estimates are shown in Table 15, below.

Table 15: FGLS estimates of the lognb

Variables	FGLS Model
lognf	1.00044***
	(0.00660)
DAs	0.02604**
	(0.01223)
DMo	-0.03333
	(0.01216)
DSa	0.03383**
	(0.01654)
Constant	0.15469***
	(0.00998)

Number of Obs.	3,040
Wald Chi sq (4)	23,639.29
Prob> F	0.0000
Log-likelihood	-242.0493

*** p=0.01; ** p=0.05; *p=0.10

Now, $\beta_1 > 1$ and hence the coefficient is consistent with the theory. We nevertheless want to be sure that the supermarket-specific effects are statistically significant, hence we test the joint hypothesis $H_0: \beta_2 = \beta_3 = \beta_4 = 0$ H_1: coefficients $\neq 0$. As a result, the statistic chi-sq (3) = 24.85 (prob > chi-sq = 0.000). Thus we reject the null hypothesis and hence the best and most consistent specification is that shown in Table 15.

The coefficients of the dummy variable Das (0.026) and DSa are similar (0.033) and close to zero, which implies that for the basket analized the number of brands are close to that sold by Tesco. Morrisons's coefficient is negative, even though it is close to zero. These implications contradict our predictions because we posit that DAs (given its strong emphasis on own brands) should behave differently to Tesco. In the same direction, the different sign and the difference in the value of the coefficients of DMo and DSa demonstrate that these supermarkets' strategies are different in terms of the number of brands they sell.

3.8 Concluding remarks, limitations and recommendations

In this paper we have used panel data techniques to study the interactions between supermarket brands and other branded products sold by the four large UK supermarkets. To do this we have looked at the short-run interaction with a reduced number of products of mass consumption.

We estimated three regressions to capture information about relative prices, product positioning on the shelves, and a log-model about the number of brands sold by each supermarket.

For the *logistic regression of prices (P_{ob} /P_{bg})* the panel data technique that best fits our dataset is the fixed effect model, which shows positive coefficients for the independent variables time trend, number of manufacturing firms, price cuts (Ddiscount) and the dummy variables for each supermarket. The inclusion of the interaction variables marginally improves the fit of our dataset. The effects of the main variables are as follows.

The time trend coefficient t shows a positive sign and is statistically significant at 5%, although with a low coefficient (0.0016). As discussed in the hypothesis section 3.4 part a, one possible interpretation of this positive value is that the price of the supermarket brand rose by more than that of the branded good over time, which may be explained by the supermarkets pricing their own brands higher to take advantage of customer loyalty, which is consistent with the finding of Mesa *et al* (2009). Alternatively, they may be giving the signal that the own brands are as good as the leading brands because they use higher-quality ingredients, as mentioned in section 3.4.

In the case of the number of manufacturing firms (*nf*), we seek different ways to explain the positive sign of the coefficient. The most credible explanation is that competition affects each

brand to different extent. We sought an explanation in the matrix and graph of correlations, which do not however show a clear pattern of behaviour and the values between the variables are weak, hence it was not possible to infer anything from them. As a consequence our explanations are as follows.

According to our hypothesis earlier (section 3.4 a), we strongly believe that this variable (*nf*) affects the price of both labels (leading and own brand). If the effect is negative it should nevertheless impact to a lesser degree on the supermarket brand as it is more cost-related and its price cannot be cut below its floor. If the number of firms (*nf*) goes up this should increase the degree of competition and hence the price of both brands should fall such that $\mid \Delta^- Pob_{i,t} \mid < \mid \Delta^- Pbg_{i,t} \mid$ and the relative price (P_{ob}/P_{bg}) increases. On the other hand, if we assume that the number of firms impacts positively on the prices of both brands $\mid \Delta^+ Pob_{i,t} \mid > \mid \Delta^+ Pbg_{i,t} \mid$, which could be explained by the fact that the supermarkets increase $Pob_{i,t}$ in relation to $Pbg_{i,t}$ because the floor of the first is closer to the marginal cost, hence they take advantage of their market power at the retailer level by increasing in the price of their own brands more. The positive impact on $Pbg_{i,t}$ goes in the same direction as that reported in most studies so far (Gabrielsen *et al,* 2001; Bonfrer *et al,* 2004 and Bontemps *et al,* 2005, among others). In the case of the own brands, the higher prices over time are consistent with the discussion of Mesa *et al* (2009), who found that after gaining market share, prices revert to the category profit maximizing price.

The coefficients estimated to measure the supermarket-specific effects (differences among supermarkets) show that Morrisons and Sainsbury's differ from Tesco to price brands, whereas Asda is the closest to Tesco, as we predicted. Even so, we believe that the magnitude of the prices is important, and this can be explained by the low prices of branded goods considered in our basket set by the latter.

An opposite finding is related to the difference between Morrisons and Sainsbury's. The Morrisons coefficient is almost twice as high as Sainsbury's, contrary to our hypothesis of similarity between these firms. It is likely that this finding is explained by the prices of the own brands rather than those of the branded goods, as we think that Morrisons's own brands are of better quality compared to Tesco due to its historical expertise in producing high quality goods.

Morrisons and Sainsbury's development of their own brands is inferior in the categories and products sold, while their stores are of similar size. According to Morrisons, it is the only major retailer to own and operate fresh food manufacturing and processing facilities. Its operations are vertically integrated in the food category, which allows it to manufacture, distribute and retail the vast majority of its fresh meat, fresh food own-label products and dairy requirements, and process/package the fresh fruit and vegetables. Sainsbury is also a brand with a high reputation built over 140 years of service and many loyal customers.

The interaction terms given by the number of manufacturing firms per supermarket are negative and statistically signicant at 1% for all supermarkets, showing that the marginal effect of the degree of competition on the relative price is diminished when we look at each supermarket. Asda and Sainsburys' coefficients are similar. In contrast, the Morrisons coefficient is more sensitive, confirming that this supermarket uses other strategies to differentiate itself from its rivals.

On the other hand, the coefficients of the interaction terms between price cuts and the supermarket-specific effect (DiscSAs, DiscSMo and DiscSSa) are all positive but statistically insignificant.

Second, logit and probit models were estimated to determine *the placement of the products on the shelves*. We first note from the summary statistics that the supermarkets target the branded product with a 58% frequency. This high mean of our discrete variable (0.5796) validates Sayman *et al*'s (2002) argument that the supermarkets target the leading brand to influence consumers' purchase decisions. To our knowledge this model is a pioneer in this area because there is no public information about product shelf-space allocation, which discourages investigation of the issue.

Looking at our results, the best equation was given by a restrictive specification that considers time trend (*t*), number of manufacturing firms (*nf*) and price cuts (*Ddiscount*) implemented by supermarkets and a time-trend variable, which are statistically significant (the number of manufacturing firms and the time-trend variable significant at 1%). The best technique was found using the probit model due to the lower number of predicted values out of the range [0, 1] of the other regression, including the extensive form that includes the supermarket-specific effect.

The results validate our traditional prediction in the sense that there is a negative relationship between the number of manufacturing firms that sell their products in large supermarkets and joint allocation of shelf space to the products, which responds to the fact that supermarkets determine the position of goods according to the total shelf space allocated to product ranges and depending on unit size rather than for strategic reasons.

Our result shows that when there is a marginal increase in the number of manufacturing firms' brands present in the supermarket, the probability of finding the supermarket's own brand and the branded good positioned together on the shelf drops by 7.31%.

Second, the model also shows that the probability of our goods being displayed together goes down by 71.53% when a supermarket cuts the product price, in line with our prediction that

the products are displayed separately when there is a price cut. We nevertheless want to point out that this value is partially influenced by the fact that the supermarkets only sold two brands of some products, for instance milk and salt.

The other independent variable, time t, shows that the odds of the goods being displayed together rose by 59.17% over time, confirming that there is a tendency to place both labels together (next to, above or below each other).

The third model, the *log-number of brands specification* shows a low elasticity between the number of manufacturing firms and the number of brands, indicating that only a small range of brands are sold in these products. The dummy variables for Asda and Sainsbury's are similar and close to zero, indicating that they are similar to Tesco, while the coefficient for Morrisons is negative and hence its strategy goes in the opposite direction to that of Tesco.

These findings about supermarket behaviour are not generalisable because they are based on a very limited number of products (19) that the supermarkets sell. Second, when we analysed the own brands across supermarkets we assumed complete homogeneity to make them comparable, but it is clear that quality and pricing depend on many factors (chemical attributes, customers' beliefs about the goods, consumer loyalty to the store and the product), which can create abnormal changes in prices.

Further research about prices and shelf placement should continue to group products by category because the development of brands is asymmetric across categories as Oxera (2010) confirms. Following Oxera (ibid), perhaps a logical step would be to group own brands according to their level of penetration, to look at whether the behaviour of the leading brands in categories with strong manufacturer brands follows the same pattern as that of leading brands in categories with a larger number of competing brands. It would also be interesting to follow the methodologies used by Gabrielsen *et al* (2001), who estimated their model not

only by panel data but also by autoregressive first order model (AR1). Second, while collecting information about shelf space allocation is costly, we find this field exciting because it helps to increase understanding of inter- and intrabrand competition.

Annex 1

Product	Asda	Morrisons	Sainsbury's	Tesco
	Brands and number of manufacturing firms			
Baked beans	Branston, Heinz Total firms: 2	Branston, Heinz Total firms: 2	Branston, Heinz Total firms: 2	Branston, Heinz Total firms: 2
Cat food	Felix, Purina, Kitecat, Sheba Total firms: 4	Felix, Purina, Kitecat Sheba, Whiskas Total firms: 5	Felix, Purina Kitecat, Sheba, Whiskas Total firms: 5	Felix,Purina Kitecat, Sheba, Whiskas Total firms: 5
Cereal	Nestle Total firms: 1	Nestle Total firms: 1	Nestle Total firms: 1	Nestle Total firms: 1
Coffee	Nescafe, Kruger, Douwe-Egbert, Percol, illy, asda PC Kraft (3): Kenco, Birds, Tassimo Total firms 6	Nescafe Kraft (2): Kenco, Carter Noire, Douwe-Egbert, Percol, illy, Café Direct Red Mountain Total firms: 7	Nescafe Kraft (2): Kenco, Carte Noire, Douwe-Egbert, Percol, illy, Café direct, Clipper, Fair, Rocket Fuel (food brands group), Lavaza Total firms: 10	Nescafe Kraft (3): Kenco, Tassimo, Carte Noire Douwe-Egbert, Percol, illy, Red Mountain Total firms: 5
Coke	Brands: Coca Cola (2): CC, Dr Pepper , Pepsi Total firms: 2	Brands: Coca Cola (2): CC, Dr Pepper , Pepsi Total firms: 2	Coca Cola (2): CC, Dr Pepper , Pepsi Total firms: 2	Coca Cola (2): CC, Dr Pepper , Pepsi Total firms: 2
Juice	Del Monte, Don Simon, Innocent, 5 Alive, Pomegret,	Tropicana Gerber (2): Ocean Spray,	Tropicana Gerber (2): Ocean Spray,	Tropicana Gerber (3): Libbys, Ocean

	Cherrygood, V8,Tropicana, Gerber (3): Libbys, Ocean Spray, Welchs Rubicon (2): Rubicon, Sum Exotic Total firms: 10	Welchs, Innocent, Grove Total firms: 4	Welchs, Del Monte, Grove, Innocent 5 Alive, Pomegret, Princess, Rubicon V8 (Campbell) Total firms: 10	Spray, Welchs Aspall, Eager, Innocent 5 Alive, Pomegret Cherrygood, Princess V8 Total firms: 10
Mayo	Hellmanns (Unilever) Total firms: 1	Hellmanns (Unilever), Heinz Total firms: 2	Hellmanns (Unilever), Branston, Delovis , Heinz Total firms: 4	Hellmanns (Unilever), Branston Total firms: 2
Milk	Meribel, Cravendale Total firms: 2	Countrylife, Cravendale Total firms: 2	Cravendale, Rachels Total firms: 2	Cravendale Total firms: 1
Pasta	Napolitana Marshalls Total firms: 2	Napolitana, Buitoni, De Cecco Total firms: 3	Napolitana, De Cecco, Seeds of change Total firms: 3	Napolitana, De Cecco, Seeds of change Total firms: 3
Plain flours	Allison, Homepride, McDougalls Premier (1): Doves Farm Total firms: 4	McDougalls Premier (1): Allison Homepride, Doves Farm Total firms: 4	McDougalls Premier (2): Allison, Hovis, Carrs, Homepride Doves Farm Total firms: 5	McDougalls Premier (2): Allison, Hovis, Carrs, Homepride Doves Farm Total firms: 5
Sauce	Dolmio Dress Italian	Dolmio Bertolli	Dolmio Green Core (1)	Dolmio Green Core (2):

	Lloyd Grossman (Chivers) Napolitana, Seeds of Change Ragu (Knorr), Home Pride (Premier Food) Total firms: 7	(Unilever) Lloyd Grossman (Chivers) Napolitana, Seeds of Change, Ragu (Knorr) Sacla Home Pride (Premier Food) Total firms: 9	Jamie Oliver (fresh retail ventures), Lloyd Grossman (Chivers), Napolitana, Seeds of Change, Ragu (Knorr), Sacla (Sacla) Total firms: 8	Weight waslam. Bertolli (Unilever) Jamie oliver, Lloyd Grossma (Chivers), Napolitana Seeds of Change, Ragu (Knorr), Sacla (Sacla) Total firms: 9
Washing up	Fairy Total firms: 1	Fairy, Morning Fresh(Pz) Total firms: 2	Fairy, Morning fresh (Pz) Total firms: 2	Brands: Fairy, Morning Fresh (Pz) Total firms: 2
Washing power	PG (4): Ariel, Bold, Daz, Fairy Unilever (2): Persil, Surf Total firms: 2	PG (4): Ariel, Bold, Daz, Fairy Unilever (2): Persil, Surf Ecover, Draft , Surcare Total firms: 5	PG (4): Ariel, Bold, Daz, Fairy Unilever (2): Persil, Surf Ecover Total firms: 3	PG (4): Ariel, Bold, Daz, Fairy Unilever (2): Persil, Surf Total firms: 2
Tea	Brands: Café Direct, PG, Tetley, Twinings Typhoo, Yorkshire Total firms: 6	Café direct, PG, Tetley, Twinings, Typhoo, Yorkshire, Brooke Bond D (Gold Crown Foods), Builders Total firms: 8	Surcare, PG, Café Direct, Clipper (clipper), Tetley, Twinings, Typhoo Yorkshire, Dilmah Total firms: 9	PG, Café Direct (fair-trade) Clipper (clipper), Tetley Twinings, Typhoo Yorkshire Total firms: 6
Toilet tissue	Andrex, Velvet	Brands: Andrex, Velvet, Nouvelle	Andrex (Kimberley Clark) SCA (2):	Andrex (Kimberley Clark) SCA (2): Cushelle,

			Charmin, Velvet Regina	Velvet Nouvelle
	Total firms: 2	Total firms: 3	Total firms: 3	Total firms: 3
Toothpaste	Colgate Glaxo (2): Aquafresh, Macleans Euthymol Total firms: 3	Palmolive-Colgate (2): Colgate, Ultrabrite Glaxo (2): Aquafresh, Macleans Unilever (2): Mentadent SR, Signal, Crest Total firms: 4	Colgate (Palmolive) Glaxo (2): Aquafresh, Macleans Unilever (2): Mentadent SR+ Signal, Crest, Euthymol Total firms: 5	Colgate (Palmolive) Glaxo (2): Aquafresh, Macleans Unilever (2): Mentadent, Signal, Crest Total firms: 4
Oil	Princess (2): Flora, Crispy Total firms: 2	Princess (2): Flora, CrispyLesieurs Total firms: 2	Princess (2): Flora, Crispy Total firms: 1	Princess (2): Flora, Crispy Total firms: 1

Annex 2

Beverage (Cola)	Coca Cola	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	44.00	42.00	44.80	43.30	39.00	42.28	2.46
Fat	0.00	0.10	0.00	0.30	0.00	0.10	0.14
Saturated fat	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sugar	11.10	10.00	11.70	10.80	9.70	10.55	0.90
Salt	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Proteins	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Carbohydrates	11.10	10.00	11.70	10.80	9.70	10.55	0.90
Sodium	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fibre	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Coffee (1tsp)	Nescafe	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	2.00	1.50		1.00		1.25	0.35
Fat	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Saturated fat	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sugar	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Salt	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Proteins	0.10	0.30		0.10		0.20	0.14
Carbohydrates	0.50		0.60			0.60	
Sodium	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fibre	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cornflakes	Kellogs	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	372.00	383.00	378.00	379.00	380.00	380.00	2.16
Fat	0.90	1.10	1.10	1.20	1.20	1.15	0.06
Saturated fat	0.20	0.30	0.40	0.40	0.40	0.38	0.05
Sugar	8.00	8.80	8.90	8.90	8.90	8.88	0.05
Salt	1.80	1.20	0.70	0.70	1.60	1.05	0.44
Proteins	7.00	7.40	7.40	7.40	7.40	7.40	0.00
Carbohydrates	8.40	8.40	8.40	8.40	8.40	8.40	0.00
Sodium	0.00	0.40	0.00	0.20	0.60	0.30	0.26
Fibre	0.00	3.00	3.00	3.00	3.00	3.00	0.00
Mayonnaise	Hellmans	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	722.00	622.00	686.00	624.00	750.00	670.50	60.76
Fat	71.90	67.20	73.00	67.90	82.20	72.58	6.92
Saturated fat	6.60	5.30		5.00	6.80	5.70	0.96
Sugar	1.30	2.60		1.90	1.30	1.93	0.65
Salt	1.50	1.40		1.20	1.50	1.37	0.15
Proteins	1.10	0.90		0.40	0.60	0.63	0.25
Carbohydrates	1.50	3.40		2.70	1.40	2.50	1.01
Sodium	0.60	0.50	0.60	0.50	0.60	0.55	0.06
Fibre	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Milk	Cravendale	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	65.00	65.00	64.00	64.00	64.00	64.25	0.50
Fat	3.60	3.60	3.60	3.60	3.60	3.60	0.00
Saturated fat	2.30	2.30	2.30	2.30	2.40	2.33	0.05
Sugar	4.70	4.70	4.70	4.70	4.70	4.70	0.00
Salt	0.10	0.10	0.10	0.10	0.10	0.10	0.00
Proteins	3.40	3.40	3.40	3.20	3.30	3.33	0.10
Carbohydrates	4.70	4.70	4.70	4.70	4.70	4.70	0.00
Sodium	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fibre	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pain Flours	Mc Douglass	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	334.00	342.00	360.00	360.00	345.00	351.75	9.60
Fat	1.30	1.30	1.30	1.30	1.30	1.30	0.00
Saturated fat	0.20	0.20	0.00	0.20	0.20	0.15	0.10
Sugar	1.40	1.50	2.00	1.50	1.40	1.60	0.27
Salt	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Proteins	10.40	10.40	9.40	9.40	10.40	9.90	0.58
Carbohydrates	70.10	70.10	78.00	71.70	70.10	72.48	3.76
Sodium	0.00	0.00	0.00	3.10	3.20	1.58	1.82
Fibre	3.20	3.20	0.00	0.00	0.00	0.80	1.60
Salt	Saxa	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fat	982.00	982.00	982.00	982.00	982.00	982.00	0.00
Saturated fat	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sugar	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Salt	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Proteins	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Carbohydrates	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sodium	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fibre	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sauce	Dolmio	Asda	Morrisons	Sainsburys	Tesco	Mean	Std. Deviation
Calories	49.00	44.00	50.00	54.00	41.00	47.25	5.85
Fat	1.40	0.60	0.30	1.20	1.40	0.88	0.51
Saturated fat	0.20	0.10	0.70	0.20	0.30	0.33	0.26
Sugar	5.90	7.60	1.50	7.20	6.10	5.60	2.81
Salt	1.20	0.10		0.90	0.70	0.57	0.42
Proteins	1.40	1.30	1.00	2.00	1.00	1.33	0.47
Carbohydrates	7.80	7.60	6.10	8.80	6.60	7.28	1.19
Sodium	0.00	0.30	0.30	0.30	0.30	0.30	0.00
Fibre	0.90	1.50	2.30	1.50	2.30	1.90	0.46

Annex 3: Interpretation of the extensive model (logit and probit model)

Number of manufacturing firms

If we suppose a one-unit change in the number of manufacturing firms, this corresponds to a decrease in the log-odds of y=1 of -0.91363 in the logit model and -0.53433 in the probit model, according to our estimates. Thus a change in the odds that y=1 of $e^{-.91363}$=0.4011, then the percentage change in the odds that y=1 of 100(0.4011-1)= -59.89% for the logit model, i.e. the odds are 59.89% lower. In the case of the probit model, $e^{-.53433}$= 0.5861, then the percentage change in the odds that y=1 of 100(0.5861-1)= -41.39%, i.e. the odds are 41.39% lower. In sum, these values validate the probabilistic hypothesis about the negative relationship between the number of brands and the joint location of the retailer-owned and the leading brand.

Ddiscount Dummy Variable

If we now suppose that there is a discount or an abnormal price drop in either the retailer-owned or the leading brand product, the dummy variable coefficients take values of -2.71659 and -1.51752 for logit and probit models which corresponds to a decrease in the log-odds of y=1 of -2.71659 and -1.51752. Changing those values in the exponential expression for y=1, gives us 0.0066 and 0.2193 respectively.

As results, the percentage change in the odds that y=1 of 100(0.0066-1)= -99.34% for the logit model, i.e. the odds are 99.34% smaller. For the probit model, the percentage change in the odds that y=1 of 100(0.2193-1)= -78.07%, i.e. the odds are 78.07% smaller.

Thus the probability of our goods being displayed together decreases when a supermarket cuts the product price, in line with our prediction that the products are displayed separately when there is a price cut.

The supermarket-specific effect

Asda: In this case the dummy variable coefficients are -2.84853 and -1.60815 for the logit and probit models, corresponding to a decrease in the log-odds of y=1 of -2.84853 and -1.60815. Changing these values in the exponential expression for y=1 gives us 0.0579 and 0.2016, respectively.

As results, the percentage change in the odds that y=1 of 100(0.0579-1) = -94.21% for the logit model, i.e. the odds are 94.2% smaller; and the percentage change in the odds that y=1 of 100(0.2016-1)= -79.84% for the probit model, i.e. the odds are 79.84% smaller.

Morrisons: The dummy variable coefficients are 1.89206 and 1.10572 for the logit and probit models and the increase in the log-odds of y=1 is1.89206 and 1.10572 respectively. Changing those values in the exponential expression for y=1, we have 6.6330 and 3.0214 respectively.

As results, the percentage change in the odds that y=1 of 100(6.6330-1) = 553.30% for the logit model, i.e. the odds are 553.3% greater. For the probit model, the percentage change in the odds that y=1 of 100(3.0214-1) = 202.14%, i.e. the odds are 202.14% greater.

Sainsbury's: In this case the dummy variable coefficients are 6.41224 and 3.59794 for the logit and probit models and the increase in the log-odds of y=1 of 6.41224 and 3.59794. The exponential expression values for y=1 are 609.26 and 36.52 respectively.

As results, the percentage change in the odds that y=1 of 100(609.26-1) = 60,826% for the logit model, i.e. the odds are 60,826% greater and the percentage change in the odds that y=1 of 100(36.52-1)= 3,552% for the probit model, i.e. the odds are 3,552% greater.

Summing up, Sainsbury's is the most aggressive supermarket of the four regarding its decisions about the joint placement of both goods, whereas Asda behaves in the opposite direction to Tesco.

The interaction variable: the number of manufacturing firms and the supermarket

In this case we are measuring the effect of increasing the number of manufacturing firms that provide their products to each supermarket that we are analysing. This coefficient involves more information than that measured separately. Now we will move to the development of the percentage change in the odds, taking into account the marginal effect for the three supermarkets estimated by the logit and probit models.

If we then consider the interaction coefficient for *Asda*, we have 0.33360 and 0.19004 for the logit and probit models. The increase in the log-odds of y=1 of 0.33360 and 0.19004. Changing these values in the exponential expression for y=1, we have 1.3960 and 1.2093 respectively.

As results, the percentage change in the odds that y=1 of 100(1.3960-1) = 39.60% for the logit model, i.e. the odds are 39.60% greater, while the percentage change in the odds that y=1 of 100(1.2093-1) = 20.93% for the ProbitModelprobit model, i.e. the odds are 20.93% greater.

If we now consider the interaction variables for *Morrisons*, we have 1.89206 and 1.10572 for the logit and probit models. The increase in the log-odds of y=1 of 1.89206 and 1.10572.

Changing these values in the exponential expression for y=1, we have 6.633 and 3.0213 respectively.

As results, the percentage change in the odds that y=1 of 100(6.633-1) = 563.3% for the logit model, i.e. the odds are 563.3 % greater. For the probit model, the percentage change in the odds that y=1 of 100(3.0213-1) = 202.13%, i.e. the odds are 202.13% greater.

Looking at the interaction variables for **Sainsbury's**, we have 0.07006 and 0.03705 for the logit and probit models and an increase in the log-odds of y=1 of 0.07006 and 0.03705. Changing these values in the exponential expression for y=1, we have 1.0726 and 1.0377 respectively.

As results, the percentage change in the odds that y=1 of 100(1.0726-1) = 7.26% for the logit model, i.e. the odds are 7.26 %, while the percentage change in the odds that y=1 of 100(1.0377-1)= 3.77% for the probit model, i.e. the odds are 3.77% .

Summary of odds ratio of Logit and Probit Model

Interaction Variables	Models	
	Logit	Probit
Discount*Asda (FDAs)	1.396	-1.2093
Discount*Morrison (FDMo)	6.633	3.0213
Discount*Sainsburys (FDSa)	1.0726	1.0377

The table above shows the summary of the interaction term. The effect of the degree of competition -measure by the number of manufacturing firms- on the endogenous variable co-location is marginal for Asda and Sainsburys and higher for Morrisons in comparison to the effect of that variable on Tesco.

Chapter 4: Leading drugs and pharmacy-owned drugs: the case of a highly liberalised industry

Abstract

We used a data panel technique to analyse how leading branded generic and original drugs and large-pharmacy-owned drugs interact in the Chilean pharmaceutical market. We estimated two models with different specifications: one for relative prices and the other for market share.

In our main model, the relative price $Pob_{i,t}/Pld_{i,t}$ is negatively affected by the degree of concentration measured by the Herfindahl Index (HHI) and positively by the pharmacies market size. However, in the case of the original drug regression, when HHI goes up the relative price decreases, implying that the increase in own-brand price is higher than that of the original drug. Thus we suggest that there are differences in magnitude that can be explained by the interaction of highly-concentrated markets at the retailer level and a strong competition caused by a large number of generics due to low barriers to entering the market that impact in different way the variation in the prices of drugs. Given the particularities of the Chilean system, we strongly believe that large pharmacies transfer their market power towards their own brands, particularly in highly concentrated markets.

In the second model, our results show a contrasting relationship between market share of both the leading drug and own drug and market size that is consistent with the identity we would expect. When market size goes up, the market share of the leading drug falls while that of own-brand drugs increases, showing that they behave as one identity. On the other hand, HHI positively affects the market share of both drugs. However, the most important finding of this model is the fact that when HHI increases by 10%, more than 90% of this higher concentration is captured by the leading and own brand drugs.

In summary, we believe that most of these results are explained by the sellers' role in inducing demand in such a way as to increase the sale of their own brands rather than of other labels.

4.1 Introduction

The pharmaceutical market is generally recognised as being characterised by a complex and asymmetric interrelationship among physicians, patients, and insurance providers and reimbursement systems (Davies and Lyons, 2008, Kim, 2009). This system may be more complex when the retail industry lacks competition and is characterised by sellers' abusive behaviour towards consumers.

Physicians prescribe a drug based on the knowledge and experience they have built up over time and are often insensitive to the entry of new drugs. Historical brand-loyalty advantages have been widely discussed in the literature; Statman (1981) and Bae (1997) point out that many physicians do not change their prescribing over time, making the entry of new brands and competition difficult. Davies *et al* (2008) additionally highlight how there is little substitution of generic drugs with branded drugs, even though they are chemically identical.

Johnson and Myatt (2003) define the market from the patients' perspective as bimodal in the sense that there are different types of consumer: those who value quality and are willing to pay a premium for a label (usually leading or patented drugs[40]), and a second group that does not care about brand names and thus prefers the cheapest drug (usually generics).

Healthcare systems and market regulations differ across countries. The US system is based on a private insurance framework; the European system is linked to the national health insurance system, whereas the UK's full health insurance coverage within a social security framework assures provision for all patients.

The price-setting framework is diverse across countries as well. There are countries in which the system is very liberal, such as Canada and Chile, and others with price-regulation schemes based on an upper profit limit (UK) or price ceiling (Australia, Brazil and Germany, Vasallo, 2010). Davies *et al* (2008) highlight how each European country has a different system of regulation and coverage of pharmaceuticals and differences in how drugs are sold to hospitals and domestic consumers.

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[40] They are also called original or brand-name drugs

The Chilean market differs from others in three main areas: (1) the therapeutic and commercial classification of the drugs; (2) a liberalised system of commercialisation characterised by low barriers to introducing new drugs in a highly-concentrated pharmacy market framework; and (3) a weak healthcare and reimbursement system, which in turn means that patients mainly pay their own medical expenses. This scenario affects Chile's price-setting scheme as follows below.

First, despite wholesalers' (whether manufacturers or importers) fierce race to launch new brands, the average price of drugs is considered high due to lack of competition among large pharmacies (Diario Oficial, 2011).

Second, to keep their medical spending down patients tend to self-medicate or follow the advice of a pharmacist, who usually induces them to purchase their own pharmacy's brand (MINSAL, 2010, Vasallo, 2010). This opportunistic behaviour has also induced and positively impacted on the entry of the large pharmacy-owned drugs, which go by fantasy names unlike the names of large supermarkets' own-brand products, which take the same name as the store.

Third, there is a wide price dispersion caused by, among other factors, promotions, discounts for specific groups, different transportation costs per geographic zone and advertising costs (Chumacero, 2010; Vasallo, 2010).

Fourth, and perhaps the most important argument to justify this research, Chile's three largest pharmacies – CruzVerde, Fasa and Salcobrand – which account for 90% of the market have been formally accused by local authorities of collusive price-fixing behaviour (Nuñez, Rau and Rivera, 2010; Quiroz and Givovich, 2009, Vasallo, 2010). While this research was progressing the pharmacies and wholesalers were being prosecuted by the competition authorities, who finally punished them with the highest penalties according to the Chilean competition laws, as confirmed by the Chilean Supreme Court in January, 2012.[41]

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[41] http://www.fne.gob.cl/2012/09/07/corte-suprema-confirma-sentencia-del-tdlc-y-aplica-multa-maxima-a-farmacias-cruz-verde-s-a-y-salcobrand-s-a-por-caso-colusion/

Based on the above points, the Chilean government requested of Parliament a thorough reform of the competition law at the beginning of 2011 to increase regulation of the industry. The main objectives are to generate more competition and to allow consumers access to direct-sale drugs (23.3 % of total sales) which are sold without the intervention of a seller. According to the authorities, increased competition may be achieved through expansion towards other types of providers, which would encourage a larger number of actors and sale locations and therefore diminish the power of the pharmacy chains (Diario Oficial, 2011).[42] In particular, the law aims to target large supermarkets, convenience stores and local stores, not only because of the number of stores located across the country but also due to the availability of shelf-space in them.

Our main intention in carrying out this research was to analyse how the prices of pharmacy-owned brands and leading drugs (leading generics or original brands) interact in Chile. To answer this question, we estimated two econometric analysis models using panel data, a pricing model and an equation to analyze the determinants of the drugs market share

So far, although the existing literature on the entry of new generic drugs and evaluation of the impact of some institutional restrictions (price regulations, hospital provision, etc.) is fairly extensive, to the best of our knowledge there is no research about little-regulated markets, such as the Chilean pharmaceutical industry, that has been conducted from countries with highly-regulated markets. Second, we refresh the research about the pharmaceutical industry with relatively up-to-date data supplied by a direct wholesaler. Third, our econometric estimation extends the literature with a new multivariable model; fourth, we investigate a market with high degree of concentration at pharmacy level.

This chapter is organised in the following way: We begin with a discussion of the Chilean pharmaceutical market (4.2), which we summarise in a literature review (4.3). Sections 4.4 and 4.5 explain the data analysis and model specifications. The methodologies used in the calculations and

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[42] Available in http://www.directoriosalud.cl/html/2011/06/la-competencia-que-se-librara-por-los-medicamentos-sin-receta/

their implications for our models are discussed in 4.6, and the results of the analysis and our conclusions are set out in sections 4.7 and 4.8.

4.2 The Chilean market

Unlike the pharmaceutical industry in developed countries, in Chile the industry is ruled by weak regulation on the introduction and commercialisation of new drugs under a sales scheme focused only on pharmacies (Vasallo, 2010). From the consumer side, insurance providers and reimbursement system are limited as they do not cover the cost of the drugs in most cases; and while the average price of drugs is low relative to other Latin countries, the competition authority considers the cost high due to the high concentration and lack of competition among pharmacies.

Drugs are classified according to demand and supply criteria. On the demand side, drugs are divided into three groups: direct-sale drugs (also called over-the-counter, or OTC); ethical drugs, which are prescribed by a physician; and intermediation drugs (used by hospitals and other health institutions). On the supply side, again there are three categories: brand-name drugs (original or patented), branded generics with fantasy names including pharmacy-owned brands, and unbranded generics.

As I show below, there are important differences in market share depending on how this is measured. Whereas original drugs hold a dominant position in total revenue with more than 50% of the market share), their market share of physical units is only 19%. This difference is explained by the combination of their higher prices and lower quantities sold in comparison to other drugs. Branded generics are commonly the leading brands in terms of physical units (44.6%), whereas unbranded drugs are at the bottom in terms of market share calculated on the basis of sales which is explained by their low prices.

According to Chile's Ministry of Health (MINSAL) the average price of drugs has increased over time, independently of the type of drug (see the last two columns in the table below). While original

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(brand-name) drug prices went up by 67.8% between 2002 and 2008, branded generics did so by only 46.4% and unbranded generics price by 32.2%.

Table 1: Market share and average prices by type of drug

Classification	Physical Units Market Share (2008)	Total Revenue Market Share (2008)	Average Price in 2002 (US$)	Average Price in 2008 (US$)
Original (patented)	19.1	53.1	5.96	10.0
Branded Generics	44.6	41.0	3.86	5.65
Unbranded Generics	36.2	5.9	0.59	0.78

Source: MINSAL, 2010

On the other hand, barriers to entry are low in Chile in comparison with Europe and the US, which encourages wholesalers (manufacturers and importers) to introduce branded generics into most drug markets. Many European countries and the US use the bioequivalence mechanism to prove that generic, branded generic or pseudo-generic drugs produced by licensed firms (Hollis, 2005) are biologically equivalent to the same, licensed drug. This technique has only been used in Chile since 2008 and mainly covers drugs with a narrow therapeutic margin such as antiepileptic and cardiology products.

According to the local regulator, MINSAL, the introduction of a drug for evaluation requires only, the submission of an application form accompanied by information about the new drug or the recommendation of any local or international agency or recognised scientific publication, regarding its therapeutic characteristics and the impact of treatment with it, and there is no requirement to prove its properties empirically. The regulator has just 90 days to approve or reject the application, whereas the time between initial application and approval can be up to 19 months in the US (Reiffen and Ward, 2003, MINSAL, 2010). Moreover, beyond the legal procedures, once a new product has been approved for sale the manufacturer has to define the production of the chemical entity, the

formulation of the bulk product (such as pills, capsules or syrup) and the packaging (Davies *et al*, 2008), which usually takes additional time.

One result of the laxer Chilean policy is systematic complaints by US firms against local producers, who argue that because of this weak regulation, copying brands is a normal activity in spite of the restrictions laid down through patents, property rights and bilateral agreements between the two countries. According to Ms Sánchez, Head of the Industrial Association of Pharmaceutical Laboratories (ASILFA, 2006), this complaint only seeks to facilitate the entry of these drugs onto the Chilean market with its huge perspective for high future growth. Today the market is largely dominated by local manufacturers: 71% of medical prescriptions are fulfilled using national medications and only 3.9% using drugs imported from the US.

Even though the Chilean market is small, the number of brands per therapeutic category is similar to that in the US. According to Bae (1997), 17.2 generic producers enter the US market on completion of the molecule patent protection compared to 18-21 Chilean producers per category. Davies and Lyons (2008) point out that the average number of generics is much lower in Europe; 2.3 in UK and 2.4 in France, with the number of therapeutic substitutes (molecules) 6.8 and 9.2 respectively.

Chile's social security system is based on a partial coverage and marginal reimbursement scheme meaning that most patients must cover the cost of their drugs themselves. According to MINSAL (2010), total drug expenditure in Chile reached US$1,200 m in 2007, of which 79% was demanded for private consumption.

In comparison with other countries, per capita annual public expenditure in 2007 reached US$139, whereas this was US$300 in Argentina and Uruguay, US$786 in Spain and US$1,939 in the US. Family drug expenditure reached 2%, with the poorest deciles spending 1.6% of their income on medicine, which is considered excessive by local authorities (WHO, 2004, IMS Health, 2010).

On the retail side, it is important to highlight the degree of competition and the role of the large pharmacies. This industry is highly concentrated, and the three large symmetric chains mentioned

earlier, which account for 90% of the market, compete aggressively against small local pharmacies with low prices and a large number of branches, flooding the market with their own brands (15.8% market share in the second term of 2010) and providing consumers with multiple services and facilities. This has negatively affected the industry, which has lost more than two thirds of its local pharmacies in the last eight years. These chains are being investigated by the Chilean competition Agency,[43] for collusive behaviour affecting the prices of 220 drugs between December 2007 and March 2008. According to the competition authority, the chains used the manufacturing firms to coordinate and control the agreement (FNE, 2010).

On the consumer side, there is abundant literature (for example MINSAL, 2010, Vasallo, 2010) that discusses the particularities of Chilean pharmacies' sale of drugs. The large chains encourage their sellers to influence consumer's purchase decisions, inducing demand for the high-margin brands even in cases where the physician prescribes other drugs. According to local law, when a physician prescribes a branded generic the seller must provide that brand, whereas if they prescribe a generic drug the seller can sell whatever drug satisfies the medical prescription.

The law of selling drugs mentions three restrictions to how drugs must be sold: sales must only be made by pharmacies or pharmaceutical stores; drugs are divided into two categories, medical prescription drugs and direct-sale drugs; and direct-sale drugs cannot be displayed. As a consequence, many drugs are commonly recommended by the pharmacist, who thus has the power to induce the purchase of either a high-profit brand or the pharmacy-owned drug.

The direct-sale drugs list is determined by the regulatory authority, Chile's Institute of Public Health (ISPCH), taking into account criteria such as the type of treatment required to combat the illness, the degree of intoxication that the drug can cause and its reversibility, the therapeutic margin, the use of the drug and the decision to consume it without medical advice (MINSAL, 2010).

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[43] Fiscalia Nacional Economica (FNE). Avalilable in http://www.blogeconomia.uahurtado.cl/?p=103

4.3 Literature Review

The entry of generics drugs onto the market is a world-wide issue in this industry because it increases competition and helps the authorities to control the high cost of the healthcare system. In this context, most research is carried out using US market data (Grabowski and Veron1992, Bae 1997, Frank and Salkever 1997, Reiffen and Ward 2003, Saha *et al* 2006), and mainly seeks to answer two questions: What are the determinants of entry? And how does the entry of generic drugs affect the original drug price, the market share and the degree of competition? With the expiration of patents and changes to the institutional health system (which includes medical insurances, a new price regulation law) since the 1990s, empirical research has expanded towards other countries such as Canada, Japan, Spain and Sweden (Aronsson, Bergman and Rudholm 2001, Hollis 2005, Moreno, Puig and Borrel 2007, Ayadi, Chebbi and Boujelbene 2008, Iizuka 2009 and Kim 2009).

Using data on 18 drugs sold in the US, Grabowski and Veron (1992) examine the relationship between generic drug entry and the perceived profitability of the category to which they belong. They also use a model to test the price structure among generic firms in the initial period after launching the generic drug and whether the lowest-priced firms captured the largest share.

The main model uses the number of entrants measured by log as a dependent variable. The independent variables are the log of profits (measured by the percentage of the mark-up of the starting price over marginal costs at the point of entry), a proxy for advertising measured by the log of the number of years that the brand-name drug was marketed under an exclusivity contract, and a variable to control brand loyalty (a barrier to entry). The results show that profit is statistically significant and with the positive sign expected, whereas the coefficients for advertising and brand loyalty are negative but insignificant.

The second model tests prices (measured in log) against a dummy variable to control when the entry of the generic occurs, a variable to control chronic patients and a time trend variable. For the entry dummy variable, the estimates show a negative sign for six of the eighteen drugs.

Bae (1997) uses fixed and random effect techniques to look at factors that influence the speed and likelihood of generic drug entry in the US, running regressions for brand and generic drug prices. The data includes 41 drugs whose patents expired between 1987 and 1994.

In the first model, the dependent variable is the number of generic entrants, based on the assumption that entry to the market is a continuing process. The independent variables include a dummy to control for prospective profit (measured by the revenue of the brand-name drug prior to patent expiration), a variable to measure drugs that primarily treat chronic symptoms, dummy variables that divide the products into three conventional groups according to sales revenue, a time trend variable and the number of competing brand-name products (degree of competition) as a proxy variable to examine the profitability of the market.

The most important finding shows that profits negatively affect the time of entry. This means that commercially successful 'blockbuster' drugs are more likely to face generic competition than less commercially successful drugs, explained by the fact that the generic industry targets high-revenue products. The entry of generics tends to be slower for drugs with a very small or very large number of competing brands.

Using a panel data technique on a US dataset of 32 drugs that lost their patent protection during the early 1980s, Frank and Salkever (1997) investigate the impact of generic entry on the prices of generic and brand-name drugs. They estimate three models through fixed effect (2) and random effect models and construct a price column after translating all the items belonging to one category into a basic unity of measurement.

The first specification is given by generic price as a function of the number of generic producers, the brand producers' price and a time trend variable. In the second model, the number of generic producers is endogenous. It is run using the two-stage fixed effect model (FEM). In the equation estimated by random effect model (REM) they add estimators for market size and for the length of time the drug has been on the market.

The main finding shows that branded-drug prices rise after entry, accompanied by large decrease in the price of generic drugs. The net effect is a reduction in the average price of a prescription for an off-patent drug. This is consistent with a consumer segmentation policy according to the price-sensitivity to demand a drug.

Reiffen and Ward's (2003) investigate how institutional and regulatory features affect the degree of competition in the US pharmaceutical industry. Their dataset comprises monthly data on 31 drugs over 3 years.

The main specification uses as a dependent variable relative prices of generic drugs per product in the post-patent expiration period, and the price of the branded version during the year prior to patent expiration (P_{gd}/P_{bn}). The explanatory variables include a dummy for the number of generic producers, the number of chemical substitutes, revenue growth (average monthly change in revenue during the year prior to patent expiration) and a time trend variable. The main finding shows a negative impact of the number of firms on generic prices. The price moves toward marginal cost when there are ten or more competitors.

A second model uses total revenue (measured by log) as an endogenous variable and as explanatory variables, the log of average total revenue of the branded products in the year before expiration, number of visits to physicians, number of combinations of strengths of the oral form of the drug, and the percentage of patients with health insurance who are covered by a fee-for-service structure. This regression is run using two techniques, pooled regression and REM. The most interesting results indicate positive and significant coefficients for the total revenue from branded products and the number of visits paid to physicians; the estimate is negative for the number of forms and strengths.

Saha *et al* (2006) develop a simultaneous equation model to deal with the interaction between generic entry, the price of generic drugs and market share in the US. The estimates are based on a panel dataset of monthly data on 40 brand-name drugs from July 1992 to January 1998. The drugs belong to nine therapeutic classes and are produced by twenty manufacturers. Perhaps two of the major

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theoretical contributions of this work are the discussion of the endogeneity of the variables – entry, market share and prices – and the use of the ordinary least squares (OLS) technique to estimate regressions in this field, which yields and invalidates some inferences obtained earlier in the research about the determinants of generic competition.

Pooled regression and REM model are the panel data techniques used. The explanatory variables include the number of existing generic manufacturers (lagged one period), an institutional dummy variable to control for chemical restrictions imposed for the Federal Drug Association to produce some generic drugs and market size (defined as the annual dollar volume of brand sales prior to the entry of the first generic drug). They complement the latter with the dummy variable, 'blockbuster' to control for drugs with high sales. A therapeutic-class dummy variable is added to measure differences across drugs.

In the case of entry, all variables are statistically significant at 1%. The number of generic incumbents is a negative key driver of the entrance of generic drugs. Market size is also important, especially in the blockbuster drugs market, with positive signs. The dummy variable for the pricing system is negative, which in turn means that this discourages entry.

The market share of generics is positively influenced by the entry of new generics via more substitutions. Their entry intensifies competition, driving prices down, which induces consumers to switch from brand to generic drugs. There were negative impacts from the explanatory variables market size, the blockbuster dummy and regulatory restraints.

Finally, perhaps the most important result is the negative influence of generic entry on the price ratio between generics and branded drug that go down continuously. This finding is opposite to that of most research carried out using the same data but a different statistical methodology (Grabowski and Veron, 1992 and Frank and Salkever, 1997).

Aronsson *et al* (2001) look at how the market share of brand-name products is affected by generic competition in Sweden and at the impact of the reference price system on relative prices. Using long

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time-series data (100 quarterly observations from 1972 to 1996), they run regressions for 12 drugs. The general equation is estimated using a Cochrane-Orcutt technique to control for serial correlation. They also apply panel data with a FEM to control for differences across commercial presentations.

In the main model, the dependent variable is the market share of the branded drug measured by total quantity. The explanatory variables are the brand-name drug price over the generic drug price (P_{bn}/P_{gd}), a dummy variable to control for the entry of the reference prices system and a time trend variable. Aronsson *et al* found a negative relative price effect on market share for nine drugs. For the panel data, the estimate is also negative. The estimate of the institutional variable to capture the price system is statistically insignificant in the pooled regression.

The independent variables of the second model are the number of generic substitutes and a dummy variable for the institutional system. The findings show that the number of generic competitors has a significant and positive effect on relative price, whereas the introduction of regulation decreases (P_{bn}/P_g), validating the hypothesis that this provides a strong incentive for manufacturers of brand name products to lower their prices.

Ayadi *et al* (2008) apply this model using data from Tunisia to analyse the insurance system prior to the reform period undertaken in 2007. The dataset covers 20 quarters between 2002 and 2007 and three molecules that produce nine brands (three brand names and six generics of different strengths and forms). In contrast to the former paper, estimates for each molecule indicate that the relative price (P_{bn}/P_{gd}) has a positive and significant effect on the change of market share of the brand-name drug.

With yearly data from 1995to 1999 for 31 drugs sold in 9 provinces and more than 500 markets in Canada, Hollis (2005) focuses on the price of generic drugs produced by a brand-name drug firm (also called authorised generics or pseudo-generic drugs) to compete against independent generics, under the hypothesis that their entry should push the prices down due to increased competition. In this country pseudo-generic drugs capture 34.6% of the market.

The dependent variable in the main model is the brand name price, and the explanatory variables include the pseudo generic drugs' revenue share, the log of the lagged dependent variable and a vector to control the market size (total sales), the generic/brand price ratio lagged one period and the number of generic drugs. Hollis (2005) also estimated a model to measure changes in prices. The models are estimated for years 2, 3 and 4.

A common finding is that the larger the pseudo-generic share of generic sales, the higher the brand price. The log of the lagged brand-name drug price and the generic/brand price ratio, lagged one period, are positive and statistically significant for the three periods.

Moreno *et al* (2007) show the drivers of the generic entry in regulated dynamics market. They used an unbalanced panel to estimate regressions using Poisson and zero-inflated Poisson count approaches with fixed effects. The dataset is formed of Spanish quarterly data on 86 active ingredients from 1997-1 to 2005-2. The drugs include oral, non-paediatric and major prescription drugs containing only one active ingredient, for outpatients. The market is defined by the space in which imperfect substitute drugs compete.

The endogenous variable is the entry of the generic drugs. The independent variables are market size (total revenues), a dummy to control for the characteristics of the medicine' and price regulations (institutional variable), the number of incumbent generic firms, the number of substitute active ingredients, a dummy for drugs used in long-term treatments and a time trend variable.

The main finding supports the idea that the drivers of generic entry in markets with tough price regulations are similar to those in less-regulated markets. Market size and time trend have a positive impact on entry. The number of substitute active ingredients is also positive and significant at 1%, which explains why there are active ingredient markets without or with only very few generics. In contrast, the coefficients of the institutional variable to measure reference pricing system and the number of generic firms negatively affects the entry. The coefficient of the treatment is statistically insignificant.

Iizuka (2009) looks at the entry of generic drugs in Japan using a pooled regression mode with information from 2004 to 2006. This research differs from the rest due to characteristics of the Japanese pharmaceutical industry, the dataset used (micro prescriptions, whereas the others use aggregated data) and the proposed equations. The dependent variable is the number of generic drugs that can profitably enter a market. The explanatory variables come from the demand and supply sides.

From the demand side, the model includes the log of market size (brand revenue) and two variables to characterise the patients: elderly patients over 70 and chronic patients. From the supply side, the specification includes the difference in entry cost to produce drugs, the number of form strengths per molecule (under the assumption that this gives information about economies of scope in the production of a drug), the number of brand-name drugs (to capture the degree of interbrand competition) and a dummy variable to control for physicians working for research hospitals.

The results show that two variables are statistically significant with a positive sign: market size and number of formats. The coefficient of number of brands is negative and statistically significant. The other variables are not statistically significant.

Kim (2009) evaluates Korea's new regulation to control prices and combat escalating healthcare costs. The paper highlights the fact that drugs are prescribed by physicians and their decisions are influenced by complex interrelationships among patients, doctors, insurance providers and reimbursement systems (institutional factors). Unlike the healthcare system and market regulations in the US, the Korean system is similar to that of most European countries, where full health insurance is covered within a framework of social security.

Kim uses antihypertensive market data to examine the demand for pharmaceutical drugs. This market comprises five therapeutic classes of drugs. The data used include sales revenue and product launch data for 32 drugs from 2003 to 2007. The panel data approach corresponds to the FEM.

The equation uses as a dependent variable the difference in market share of a molecule, under the assumption that this is influenced by efficacy, safety or tolerability of the treatment. The explanatory

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variables are the market size of the outside good (given by the prevalence rate of hypertension), the retail price of the original drug, the market share of the molecule in a therapeutic subgroup, the original drug's age[44], the generic drug age and a dummy variable to control when a generic drug is in the market. Additionally, instrumental variables are incorporated to model the independent variables, in order to solve some endogenous problems of the drug price and its market share. The variables are the number of drugs in the same therapeutic class and the number of drugs in the same molecule.

The main findings of the model with instrumental variables show a negative price effect (which means that physicians insensitive to difference in prices), a negative impact of the Market size on the outside good. The coefficient of the original drug age is positive whereas it is negative for the generic drug age. This coefficient is used as a proxy of the drug's quality.

Summing up, there is a broad range of literature addressed to investigate the pharmaceutical industry. The research focuses mainly on the degree of competition caused by the entry of generic drugs or changes of the health institutional system (to control the increasing cost of the drugs). As the competition caused by the entry of generic drugs is a big topic in this field, the research can be divided into two groups. The first research is devoted to answer the number of generic drugs that can enter the market and the speed of entry of these drugs, where the most usual explanatory variables include the brand name price and market share for different types of drugs. Structural variables of the demand and supply are used complementarily in most models. Examples are the characterization of the patients and the degree of proliferation of strength and forms for each drug. The second group uses as a dependent variable the price of either the brand name, generic drugs or relative price between the brands. On the RHS the models include market share, the number of generic or brand name drugs, particular chemical characteristic of the drugs and institutional features of the health system.

Methodologically speaking, the models vary from Panel data to time series regression (few), which depend on the aim of the research and the characteristic of the data. In the same way, a common

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[44] It means how long the original drug has been on the market.

discussion observed especially in the last few papers is related to the problems of endogenous RHS variables, which are solved with instrumental variables (Kim, 2009) or by using simultaneous equations (Saha *et al*, 2006).

4.4 Data

We have access to a dataset of 39 categories of drugs sold by Chilean large pharmacies, which are grouped by commercial criteria, which was provided by a friendly wholesaler firm. This particular way of acquiring our data is relevant to justify the importance of this research and understand how the three large chains operated for many years. When we asked the wholesaler for further information to expand the original dataset with other months, they refused, fearing prosecution by the competition authorities.

Chilean drugs wholesalers – whether local manufacturers or importers – jointly (and illegally, according to the competition authorities) administrated the distribution of drugs to large pharmacies (90% market share) for many years, which was discovered by the competition authorities in 2009 – a couple of months after we received this dataset – following an investigation into collusive behaviour to fix prices.

This wholesalers and large pharmacies' vertically-integrated and centralised mechanism to control the market was based on an on line system that was daily filled out by the three chains. The idea was to control consumer prices, wholesaler prices and the inventories of both chains and wholesalers. According to one anonymous pharmacist belonging to one of these chains, the justification was that it allowed the control of potential deviations from the prices and inventories agreed among the large chains. They considered this system a good way of improving industry logistics. This is an on-going topic of interest in Chile as the competition authorities undertake legal procedures against them.

The context in which the pharmacy chains undertook this operation is not unusual in the country as it is also used in other industries[45], with the argument that it is a good way of controlling firms' potential deviations from market conditions such as wholesaler prices and the administration of stocks, among others.

Our dataset contains aggregated qualitative and quantitative information on Chile's three largest pharmacy chains: it is not possible to identify the individual pharmacies' sales.

The original dataset is expressed in two forms, total revenue (Chilean currency) and total number of medicaments sold (physical quantity), that corresponds to each second quarter in the period 2007-2010 (four quarters). In summary, we have 39 commercial categories with information on four quarters, which will be sorted into therapeutic categories. There is no information for some particular drugs due to the fact that they were not provided in particular periods.

Each category includes all brands; however, they are not identified in the dataset according to the Chilean classification (original, branded generics and unbranded generics). The data also include information of the manufacturers or importers (wholesalers) selling those drugs in different formats.

The drugs are also detailed by different formats that correspond to the strength/form combinations in which they are sold. A drug forms a family of products made from an active ingredient that can include syrup, tablets, capsules and pills in different doses, packed or bottled in different sizes.

For instance, aspirin is manufactured by Bayer and is only commercialised in tablets of three different strengths (300, 500 and 650 mg) in packs of 10, 20, 40, 80 and 100. The most commercially-successful are 500 mg (20 tablets) and 650 mg (10 tablets) for adults. Together these account for 79% of the market share of this medicament. In the case of the drug whose active ingredient is ibuprofen, the medication is sold in capsules, syrup or tablets of different strengths.

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[45] A good example is the distribution of electronic devices by large retailers and some groceries in the supermarket industry.

As most researchers use therapeutic categories in their models (Caves, 1991, Bae, 1997, Saha *et al*, 2006, Moreno-Torres, 2007), we follow the same line for consistency with their studies. A complete discussion about the complexity of the existing classification systems is given by Davis *et al* (2008), who argue that even though it is usual to use the formal industrial classification this is not helpful for understanding how the markets are formed.

According to the industry,[46] data classification may also be carried out using three different methods: pharmacological (therapeutic), commercial and marketing. We now discuss an example to clarify these differences. Pharmacological transformation supposes that one analgesic of 200 mg is the same as two of 100 mg; commercial classification supposes that two boxes of 100 mg tablets sold at US$5 each are equivalent to 1 box of 200 mg sold at US$9; and from the marketing point of view, the transformation is based on the idea that one 100 mg tablet is used to combat flu and one 200 mg tablet is prescribed for back pain. However, the latter may also be used to treat flu.

A practitioner helped us to redefine five commercial categories according to the therapeutic definition. Similar divisions are made by Iizuka (2009) and Kim (2009), who argue that the drugs are differentiated even though they may be grouped within a same category. Davies *et al* (2008) explain the existence of product differentiation in this market as a result of different size effects and efficacies for different patients.

After looking for groups that share similar mechanisms of action and have similar chemical structure within a category, the practitioner identified and separated drugs belonging to five categories and introduced six new groups to our dataset. The commercial categories converted to therapeutic ones are analgesics (steroidal and non-steroidal anti-inflammatory drugs), dermatological products (for hair and skin), expectorants, anti-migraine products and respiratory drugs (with and without codeine). We had a problem when we attempt to separate the own-brand drug data in each category because it was only possible to do it for the dermatological products, and hence we proceeded to work with a dataset

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[46] Information provided by Mr Yonsin Tay (manager of Alcon-Nestle, Argentina).

of 41 commercial categories, 38 originals plus 3 derived from the dermatological group (see Annex 1 for the full list).

After this step we paid special attention to the existence (or not) of the original brand in each category. The identification and separation of an original from the generics (branded and unbranded) was carried out by a member of the Chilean Pharmacist Association and found 23 categories which include both the original drug and generics. [47] To validate this information we checked it with that on the webpage of the local regulator (Public Health Institute, www.ispch.cl).

This topic is widely discussed in the literature by Aronsson (2001), Bae (1997), Caves *et al* (1991) and Frank (1997), who demonstrated that after the expiration of its patent the future of the brand-named drug is uncertain due to the entry of generics. In particular, the results show that some original brands have disappeared or their market share has strongly diminished after the drug patent's expiration. Hollis (2005) reports that in Canada manufacturers launch their own branded generics (called pseudo-generic) before the patent of their branded drugs expires to retain their market share.

We focused on brands with at least 2% of total market share. Similar methodology is used by Aronssson (2001) and Reiffen *et al* (2003). From the dataset, we firstly identified the leading brands (leading branded generics or the original drug) per category in accord with their market share, measured by total sales. As we were comparing the latter drugs with pharmacy-owned brands, we excluded brands belonging to the large pharmacies from this selection.

As a drug may be sold in different strength/form combinations, we identified the leading format of the leading brand and asked the pharmacist to help us to transform the remaining products into the basic unit of that drug using therapeutic and physical criteria in such a way that the comparison is consistent across products and brands. The same methodology was used to transform the leading generics, the original drug and the pharmacy-owned brand: each format was translated into the unit of the leading

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[47]We thank Dr Mauricio Huberman (of the Chilean Pharmacist Association) and Dr. Laigo Tay for their valuable help with this research.

product's format. The physician also identified the drugs that require a medical prescription (ethical drugs).

After translating the total sales into one homogenous unit, we calculated the average price of the drugs. Other transformations found in the literature include the average cost per unit paid by drugstores and hospitals (Grabowski and Vernon, 1992), the per-kilogram price (Reiffen and Ward, 2003), the per-gram price (Saha *et al*, 2006) and the average maintenance dose per day (Kim, 2009). We calculate average prices as the average prices obtained from the ratio of total revenue and total quantities. Taking into account the wide price dispersion observed in the Chilean industry (explained by promotions and offers, discounts for specific groups and other direct costs, as discussed by Chumacero, 2010 and Vasallo, 2010) the main limitation to constructing a variable using the average price was that these are not captured spot prices and hence the price data can contain inconsistencies. To control for this we compared historical prices, when available, informed in the pharmacy webpages[48]. In this context, this alternative method of comparison seems appropriate, as Chilean prices vary marginally over time.[49]

Is this transformation methodology a good way to understand the pharmaceutical industry and the degree of competition among brands?

The main advantage is that this type of transformation is widely accepted by researchers because it allows the grouping of drugs in a relatively straightforward way and thus analysis of the degree of competition across formats and brands. Its main disadvantage is that researchers assume that drugs are homogeneous or that there is low differentiation between them, and hence are perfectly comparable in both medical (therapeutic use) and economic terms (such as market limits and pricing schemes), which is shown to be incorrect by the technical literature due to the different size effects and efficacy of one drug for different patients. Davies *et al* (2008) discuss the definition of 'a well-defined pharmaceutical market' and the way in which prices are set.

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[48] www.fasa.cl; www.cruzverde.cl and www.salcobrand.cl
[49] see www.ine.cl

In summary, our adjusted dataset includes 41 therapeutic groups of drugs with detailed information about the branded generics, the original drug and the retailer-owned drug. From these categories we have identified 41 leading generics and 23 original drugs, which are compared with the pharmacy-owned brands. In the dataset the columns are disaggregated by the number of brands, number of manufacturers, total sales (local currency and quantity), a vector of estimated average price and the total number of strengths and forms per brand. In general this data is highly heterogeneous in terms of market size, prices and quantities sold. For example, we have nine categories with sales lower than CLP 1,000 m (US$2m) and six higher than CLP 10,000m ((US$20m).

With this information we constructed columns of market share for the drugs in order to calculate the Herfindahl index, measured in terms of total quantities and total sales.

We also identified each format per drug in order to separate syrups (generally speaking, bottled drugs) from other formats (for example, tablets or capsules), because we expected this separation to give us specific information about differences in price across formats due to differences in production costs.

4.5 Model specification

As our main motivation for studying the pharmaceutical industry was to understand how pharmacy-owned drugs interact in the markets. Our specifications differ from those estimated in the quantitative literature so far.[50]

We constructed two models – one for pricing and the other for market share[51] – estimated by different specifications. We mostly take into account five papers about the pharmaceutical industry (Bae, 1997, Frank and Salkever, 1997, Reiffen and Ward, 2003, Hollis, 2005 and Kim, 2009). We also consider Saha *et al*' s (2006) discussion of the potential problems caused by endogenous variables of explanatory variables (in our case, number of products, number of existing manufacturers, prices and

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[50]Mostly focused on measuring how the entry of generics impact on the original drug in terms of price and market share (Hollis, 2005, Kim, 2009 are examples related to).

[51]It is used as a numeraire to make relative analysis.

market share). Our econometric methodology differs from that of Saha *et al* because these authors use simultaneous equations to estimate the models.

We estimated a wide range of different specifications based on linear, log-linear and logistic equations for our two theoretical models. In particular, we followed four papers for pricing estimations (Bae, 1997, Frank and Salkever, 1997, Reiffen and Ward, 2003and Hollis, 2005) and one to estimate the market share of the leading brand (Kim, 2009). We also include some elements from the Saha *et al* paper to construct our models.

The following section sums up the predictions and the models proposed initially, which are discussed separately in sections 4.5.1 (pricing) and 4.5.2 (market share) below.

4.5.1 Price Regression

In the first regression our endogenous variable is the relative prices ($Pob_{i,t}/Pld_{i,t}$) of the pharmacy-owned brand $Pob_{i,t}$ and the leading generic and original drug $Pld_{i,t}$ (leading generic and original drug). We exclude the unbranded generic because the total market share of sales for each was lower than 2%. The extensive equation initially includes five explanatory variables from the offer side. The expressions and their justifications are as follow below:

The first is the Herfindahl index (HHI), to control the degree of market concentration, which is measured by total quantities and total sales. This HHI measured by quantities is:

$$HHIq_{i,t} = \{ \Sigma_{j=1}^{n}(Sq_j)^2 \}_{i,t} \qquad \textit{(HHI in terms of total quantities)}$$

where $Sq_j = (q_j/TQ_{i,t})$ is the total market share of quantities of drug j belonging to class i; q_j is the total quantities sold of drug j belonging to class i in period t (1,…,4) and $TQ_{i,t} = (\Sigma_{j=1}^{n} q_j)_{i,t}$ is the total quantities sold of class i in period t.

The HHI in terms of total sales is as follows:

$$HHIts_{i,t} = \{\Sigma_{j=1}^{n}(Sts_j)^2\}_{i,t} \qquad \textit{(HHI in terms of total sales)}$$

Where $Sts_j = (ts_j / TS_{i,t})$ is the total market share of sales of drug j belonging to class i; ts_j is the total sales of drug j belonging to class i in period t (1, …, 4) and $TS_{i,t} = (\Sigma_{j=1}^{n} ts_j)_{i,t}$ is the total sales of class i in period t.

The remaining variables are: (b) total sales to control for market size, measured by constant local currency, and (c) three dummy variables: Dpres, Dsyrup and Dtype. The first captures information about whether or not the drug is prescribed by a physician; the second controls how the drug is packaged (syrup, tablet, others) and the third controls the type of drug that we are analysing (leading branded drug or the original drug in a category).

Our expectations about the relationship between relative prices and our explanatory variables are as follow below.

Market concentration (HHI)

We would expect that pharmacies and leading wholesalers set prices depending on the degree of concentration of each therapeutic category. Before considering the relationship between market concentration and relative prices, we discuss the meaning of the HHI following Davies (1978), who developed an alternative approach to the classical one focusing on the dimension of weights.

Davies' approach defines this index as $HHI = [(1 + cv^2)/ n]$, where cv is the coefficient of variation squared and n the number of firms. Note that cv is a pure measure of inequality in market share. In

other words, HHI can be interpreted as the extent to which the leader(s) is (are) much bigger than the other firms and hence behind the Herfindahl Index is the 'dominance' of the leader firm.

In our case, one of the main impacts observed for high HHI categories is the existence of a dominant brand with power countervailing the leading pharmacies. This allows wholesalers to achieve a higher wholesale price, which in turn means a higher consumer price $Pld_{i,t}$. As a result we would expect that the degree of concentration negatively affects the relative prices $Pob_{i,t}/Pld_{i,t}$; hence the higher the HHI, the lower the relative prices will be, *ceteris paribus* the pharmacy-owned brand price.

However, the last argument deserves deeper discussion as the Chilean pharmacy chains can also take advantage of this situation to charge higher prices for the own brands without negatively affecting their demand (due to the inducement to purchase commonly observed in the local market as was explained in section 4.2). In summary, we have two effects impacting on the drug prices in the same direction.

Which effect dominates the final relative price? We expect the effect on the leading brands to be greater, as a double marginalisation effect is created by the wholesaler and pharmacy pricing. Thus, we posit a negative relationship between market concentration (HHI) and relative prices $Pob_{i,t}/Pld_{i,t}$.

Finally, HHI can be an endogenous variable in the relative price specification, under the assumption that if the drug price goes down the quantity demanded should increase; as a result the market changes and HHI varies. However we believe that this argument is not direct in this market, as the entry decision in the pharmaceutical industry always entails some fixed cost to a firm.[52]

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[52] Good examples of where it does work are in R&D or to satisfy a legal barrier imposed for the local regulator.

Market size

We include market size, measured in Chilean real currency, as an explanatory variable to control for this effect. Bae (1997), Reiffen and Ward (2003) and Hollis (2005) find this variable statistically relevant and argue that market size determines the potential success of the generic drugs (such as pharmacy-owned drugs). Scott Morton (1999, cited by Saha *et al*, 2006) also argues that the firms are more likely to venture in large markets.

In our case, we believe that a large market size also allows each drug provider to satisfy each individual patient's need for quality-therapeutic impact/price in such a way that each provider has sufficient demand (patients) to price with different value her drug.

Leading wholesalers produce low substitution drugs for both practitioners and inelastic consumers because of their proven therapeutic properties and reputation. There is abundant literature (Statman, 1981, Bae, 1997) highlighting how practitioners continue to prescribe remedies based strongly on habit, which is explained by their mistrust of the quality or therapeutic equivalence of generics. This behaviour is reinforced by the fact that practitioners do not have direct pecuniary incentives to prescribe less expensive generic products, and nor are they sensitive to drug retail prices. On the other hand, the literature shows that patients are also insensitive to selecting or changing physicians that prescribe expensive drugs (Caves *et al*, 1991, Iizuka, 2009).

For these reasons we maintain that as a price-setting firm, the leading wholesaler takes advantage of the size of the market by serving patients who are willing to pay more for their drugs, and thus, when the market increases so does the price of these drugs (all other conditions remaining constant).

What about the fixed cost of entry?

We know that the main condition that defines entry into this industry is the fixed cost (F) rather than any legal barrier, as discussed earlier. Looking at the profit equation, $\pi = (p\text{-}c) \, q - F$, the role of F is

the key to understanding why there are different-sized markets (pharmaceutical categories), because the higher F is, the lower is π. The entry conditions require that $\pi=0$, or $(p-c)q = F$, implying that the firm must at least be able to cover the fixed cost to decide whether or to enter the market. On the other hand, when $F\rightarrow0$, the barrier is lower and the size of the market should be able to accept a large number of rivals. Under this assumption, a large market should be characterised by a large number of generics, which is consistent with our dataset.

In the case of competitive generics (such as the own-brand drug), market size moreover negatively affects price. For the own brand, the other element that would justify lower prices in relation to competition generics is the fact that the final value of this brand involves just one marginalisation due to vertical integration.

As a result, in the case of the relative prices $Pob_{i,t}/Pld_{i,t}$, there are two effects operating in the same negative direction; hence the higher the market size, the lower the relative price.

Drugs prescribed by physicians

We also consider a dummy variable, Dpres, to differentiate drugs prescribed by a physician from those sold without a medical prescription (OTC). As the first has no (or low, in the case of Chile) substitution in local markets, this affects prescribed drugs by increasing their price. We posit that the relative price ratio ($Pob_{i,t}/Pld_{i,t}$) is negatively related to this dummy.

Opportunist seller behaviour to induce demand (which could make this prediction less sensitive) is an element that we do not consider in this prediction.

In our dataset are five physician-prescribed drugs. They belong to the following therapeutic categories: dermatological products (for hair and skin), anti-obesity food and brain and peripheral nerve.

Difference in cost (syrup versus others)

We have included a dummy variable Dsyrup to control differences in cost according to how drugs are sold (as syrup, tablets, pills, capsules). We believe that syrup has a higher overall cost than the other forms due to production and storage costs, which should increase its final price. This variable can be considered a proxy variable to measure the degree of differentiation among drugs.

Among the leading brands we find two drugs sold as syrup. They correspond to the therapeutic categories antihistamines and brain and peripheral nerve.

Type of drug

We add a dummy variable to identify the drug specific effect (Dtype), to attempt to measure the drug targeted by the pharmacy (the original or leading generic) in order to sell its own brand. The dummy takes the value 1 if the pharmacy targets the leading generic or 0 for the original drug. Thus, if Dtype=1 the relative prices go up.

In sum, we initially posit the following model:

$$\text{Log } \{\pi_{i,t}/ (1- \pi_{i,t})\} = \alpha + \beta_1 HHI_{i,t} + \beta_2 logsize_{i,t} + \beta_3 Dpres_{i,t} + \beta4\, Dsyrup_{i,t} + \beta_5 Dtype_{i,t} + \varepsilon_{it} \quad (1)$$

where *i* represents the drug group (pharmaceutical category), groups i= 1,…, 64 and t the periods,
t=1,…,4. The variables are:

On the left-hand side we have the logistic equation: log $\{\pi_{i,t}/ (1- \pi_{i,t})\}$, where $\pi_{i,t} =$

$Pob_{i,t}/Pld_{i,t}$. This is the ratio of average prices between the own-brand drug and the leading

drug per category (leading branded drug and original brand) measured in Chilean currency.

$HHI_{i,t}$ is the HHI measuring market concentration in terms of both total quantity $HHIq_{i,t}$ and

total sales $HHIts_{i,t}$. The specification of the formulas for both methods is shown below.

$logsize_{i,t}$ is the log of the total sale (market size) per therapeutic class in period t measured in

real Chilean currency.

$Dpres_{i,t}$ is a dummy variable with 1 a medical prescription drug and 0 a direct sale drug

$Dsyrup_{i,t}$ is a dummy variable such that 1 is a drug packaged and sold in the form of a syrup

and 0 others (tablets, pills or capsules)

$Dtype_{i,t}$ is a dummy variable to identify the type of drug we are pegging to the own-brand drug

such that 1 is the leading generic and 0 the original drug.

$$\varepsilon_{it} \sim (0,\sigma^2)$$

Our regression uses the logistic transformation $\pi_{i,t}= Pob_{i,t}/Pld_{i,t}$, to prevent negative and outliers in

the predicted dependent variable from the linear model or log-linear specification. Saha *et al*

(2006) also use this expression. In the same way, as we are interested in the leading brands (branded

generic and original), we construct our dataset to include both type of drugs. We have 64 groups (41 leading generics and 23 original) with a maximum of 256 observations.

4.5.2 Regressions of the market share of the leading drug and pharmacy-owned drug

Our second model explores the determinants of the market shares of the leading drug and pharmacy-owned drugs, which are rivals in the same market. The leading drug is defined as that independent or national brand with top sales in terms of total quantity sold and total sales measured in Chilean currency for the four periods considered within a specific category – either the leading generic (excluding the pharmacy-owned drug) or the original drug. The number of groups was decided taking into account the top drug for each group without differentiating whether it is an original or a branded generic.

Our expectations about the relationship between market share and our explanatory variables are as follow below.

HHI (degree of concentration)

We were interested in exploring how the degree of concentration affects the market shares of the leading drug and the pharmacy-owned drug.

As we commented in the pricing specification, $HHI = [(1 + cv^2)/n]$, where cv is a measure of inequality in market share and n the number of firms. We expect a direct relationship between HHI and the market share of the leading drug because the leading drug can use its dominant position to retain or increase its market share in highly concentrated markets (and hence it affects cv, above, because of the more unequal market). In the same way, this also impacts negatively on market share of the own-brand drug as the market share for both are interlinked, i.e. when the market share of the

leading drug increases as a consequence of higher HHI, the market share of generic own-brand drug drops.

Market size

As discussed in the previous model, market size is a strong driver of entry and profitability for generics, because it allows them space in the market. Thus we expect that the bigger the market, the more numerous the number of drugs sold in it.

In the case of the leading drug, we have two opposite effects to discuss. On one hand, when the market is larger a leading drug has a strong advantage over the others due to its positioning in the minds of practitioners and patients, who assure it of a permanent demand over time. We believe that the dominant position is also an important driver to depth it and rise competitive actions to keep (at least) its market share.

On the other hand, the fact that the number of generics is higher in a larger market could negatively affect the leading drug, as patients have more chance to substitute other drugs. This hypothesis can also go in the same direction if wholesalers selling the leading drug focus on capturing the inelastic rather than the opportunistic consumer, and hence other drug sales will increase when the market is larger, as Bae (1997), Reiffen and Ward (2003) and Hollis (2005) also argue.

We expect the competitive argument to be more important and thus, when market size is greater the market share of the leading drug goes down whereas that of pharmacy-owned generics increases.

The interaction variable between market size and the market share of own-brand drugs

We also include an interaction variable which relates the degree of concentration (HHI) to market size. The coefficient of this variable shows that the marginal effect of HHI on market share increases ($\beta_3 > 0$ below) or decreases ($\beta_3 < 0$ below) when the market is larger.

As a result the general specification for the two market-share regressions (leading drug and pharmacy-owned drug) is expressed as follows:

$$MShd_{i,t} = \alpha + \beta_1 HHI_{i,t} + \beta_2 Size_{i,t} + \beta_3 HHISize_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where i is the group (therapeutic category), $i = 1,\ldots,41$, for periods $t = 1,\ldots,4$. The maximum number of observations therefore is 164. The variables are:

$MShd_{i,t}$ is the market share of the drug that belongs to class i, which is measured by total quantities sold and total sales; d is the leading drug (generic or original) and the pharmacy-owned drug. Thus, we estimate a general specification for the leading drug and the pharmacy-owned drug. The market share (MSh) of each drug is measured by the following terms:

- $MShqd_{i,t} = \{qd_{i,t}/(\Sigma_{j=1}^{n} q_j)\}_{i,t}$, $qd_{i,t}$ is the total quantity sold of drug d (leading and own brand) within class i; q_j is the total quantities of the drug j belonging to class i.

- $MShtsd_{i,t} = \{TSd_{i,t}/(\Sigma_{k=1}^{n} ts_k)\}_{i,t}$, tsd is the total sales of the drug d (leading and own brand) within class i, and ts_k is the total sales of the drug k belonging to class i.

$HHI_{i,t}$ is defined conceptually and mathematically in the same way as the earlier pricing equation. As a consequence, we have two different equations for $HHI_{i,t}$, which depend on total quantities $HHIq_{i,t}$ and total sales $HHIts_{i,t}$.

$Size_{i,t}$ is the market size of class i in Chilean real currency for the period *t*. It is measured either in log (logsize) or as a dummy variable (Dsize).

$HHISize_{i,t}$ is the interaction variable between HHI (*q* and *ts*) and market size (Size)

$$\varepsilon_{i,t} \sim \{0, \sigma^2\}$$

In sum, we calculated eight equations (four for the market share of the leading drug and four for that of pharmacy-owned drugs). The total number of therapeutic groups is 41. The drug names, total quantities and total sales are listed in Annex 1. The following table sums up these eight equations:

Table 2: Summary of the models for market share specification

Variables	HHI (degree of concentration)		Size (market size)	
Leading drug	q (total quantities)	ts (total sales)	log	dummy
Pharmacy-owned drug	q (total quantities)	ts (total sales)	log	dummy

4.6 Estimation methodology and its implication for our models

As we commented before, this topic has been widely researched and documented. Common techniques used to analyse impacts on prices are given by REM (as used by Bae, 1977, Reiffen *et al*, 2003, Saha, 2006) and FEM (see Frank *et al*, 1997and Aronsson *et al*, 2001) under the assumption that the therapeutic categories are different in terms of their medical complexity, market size and volume of sales, barriers to entry and the distribution of generic and original drugs per category. The dataset we use to estimate the price and market share models presents most of the characteristics of the literature discussed earlier.

Because our dataset shows drug categories to be highly heterogeneous, an additional argument to justify and validate application of REM is provided by the wide dispersion of the number of firms (wholesalers) and of drugs sold in the Chilean market (see descriptive analysis in the next section), even though there is a high degree of liberalisation to launch brands at the retailer level caused by the low legal barriers to entry the market.

In other words, the application of REM to estimate our models is based on the different degree of concentration of each category, as some drug categories are highly competitive and others are highly concentrated, which may be explained by the existence of other types of entry barriers in each drug category (such as, for instance, a technical barrier).

We therefore assume the existence of unobserved heterogeneity and hence this is not correlated with the explanatory variables. Before estimating using REM we also test via the pooling assumption and FEM to compare the consistency of their predictions.

In the pooling assumption we are therefore supposing that the extent of the true effects do not differ across drugs, which may be explained because of the low legal barrier to market entry in Chile. However, we know that if this is not the case, the pooled coefficients will not provide reliable estimates of individual categories and hence possibly inconsistent estimates for the average drug. Examples are provided by Reiffen *et al* (2003) (total revenue regression) and Saha *et al* (2006) (simultaneous equations model about generic entry, generic drug prices and market share).

Saha *et al* (2006) also estimates the latter equation using FEM, and Aronsson *et al* (2001) looked at the market share of brand-name products using FEM to control for differences across commercial presentations. The problem with estimating our regression using this technique is that this model is consistently estimated with $N \to \infty$ (number of groups) and over $T \to \infty$, a situation that does not satisfy our model as we have only four periods (Cameron & Trivedi, 2005).

After applying these techniques we proceed to check for heteroscedasticity and autocorrelation, following the same tests as those used in Chapter 3 of this research (the Breusch and Pagan and the Wooldridge tests, respectively). Most research about panel data with heteroscedasticity and autocorrelation suggests the need to employ either feasible generalised least squares (FGLS) or OLS with panel-corrected standard errors (PCSE) as mechanisms to solve them.

Because our dataset includes heterogeneous drugs, the presence of heteroscedasticity is highly likely even though it is not an important problem for a short panel. At a later point we allow heteroscedasticity by using cluster-robust inference.

The autocorrelation could also be caused by the misspecification of a model, yielding less efficient results due to biased standard errors.

Unlike the FGLS model used for the supermarket regressions in Chapter 3, we use the PCSE because the statistics test is more powerful if there are more cross-sectional units than periods, which is a characteristic of our dataset. This model also produces accurate standard-error estimates.

4.7 Results

As we used different dataset for our models, we show the descriptive analysis and the variance-covariance information separately below.

4.7.1 Descriptive statistics

<u>Relative prices</u>

In this section we show the statistical summary of our dataset. To be able to compare the values for the leading generic drug (group 1) and the original drug (group 2), we also separate and show the dataset disaggregated by these groups.

Table 3 summarises the main variables of panel nature for the relative prices dataset. The tables also contain separate information for the branded generic and the original drugs.

Table 3: Statistical summary of logistic of relative prices variables

Group 1: Leading branded generic

Variables	Number of Observations	Mean	Std. Dev	Min	Max
• **Logistic of relative prices**	**157**	**0.5817**	**1.5987**	**-7.1086**	**8.5808**
• **Herfindahl Index**					
Total quantities	164	0.2706	0.1809	0.033	0.75
Total sales	164	0.2409	0.1614	0.02	0.715
• **Logsize**	**164**	**7.7449**	**1.1784**	**4.4659**	**10.318**
• **Dpres**	**164**	**0.1220**	**0.3282**	**0**	**1**
• **Dsyrup**	**164**	**0.1098**	**0.3135**	**0**	**1**

Group 2: Original drug

Variables	Number of Observations	Mean	Std. Dev	Min	Max
• **Logistic of relative prices**	**87**	**0.2348**	**1.1396**	**-1.8414**	**3.4186**
• **Herfindahl Index**					
Total quantities	92	0.2455	0.1747	0.0330	0.7500
Total sales	92	0.2181	0.1497	0.0400	0.6598
• **Logsize**	**92**	**7.7454**	**1.2222**	**4.4659**	**10.318**
• **Dpres**	**92**	**0.0435**	**0.2050**	**0**	**1**
• **Dsyrup**	**92**	**0.0978**	**0.2987**	**0**	**1**

Dataset (Group 1 + Group 2)

Variables	Number of Observations	Mean	Std. Dev	Min	Max
• **Logistic of relative prices**	**244**	**0.4580**	**1.4585**	**-7.1086**	**8.5808**
• **Herfindahl Index**					
Total quantities	256	0.2615	0.1787	0.0330	0.7500
Total sales	256	0.2327	0.1574	0.0200	0.7150
• **Logsize**	**256**	**7.7454**	**1.1919**	**4.4659**	**10.318**
• **Dpres**	**256**	**0.0938**	**0.2921**	**0**	**1**
• **Dsyrup**	**256**	**0.1055**	**0.3077**	**0**	**1**

The observation size of each group is different. Even though the number of observations is low for estimating the original drug regression, we believe that it is sufficient for a good estimation.

Table 3 shows that the mean of $log\,(Pob_{i,t}/Pld_{i,t})$ is higher for the leading generic (lg) than for the original ($orig$) drug [$Pob_{i,t}/Plg_{i,t}>Pob_{i,t}/Porig_{i,t}$] which implies that $Porig_{i,t}>Plg_{i,t}$ is consistent with what we would expect.

The HHI measured by total quantities sold has a higher mean and standard deviation (Std Dev) than the index measured by total sales, indicating that the price effect associated with the product of (pq) is low in comparison to the effect of quantity. Vertical comparison of the HHI shows that it is higher for the leading drug, which can be explained by the strong dominance of the leading wholesaler, according to the Davies expression (1978).

All values for log size are similar, implying that both original and leading generic drugs interact in the top and the floor categories in term of sales.

The mean of the dummy variable Dpres is higher for the generics group. As the mean is obtained from values 0 and 1, the values indicate that 12% of leading drugs are sold under medical prescription and

the remaining 88% are OTC or direct-sale drugs. In categories where there are original drugs, the value for the latter increases to 95.6%, which is consistent with the fact that the original drug faces very strong competition. Finally, the values of the dummy variable Dsyrup are similar for both groups.

The matrix of correlations between variables is shown in Figure 1, below. The scatterplot of relative prices says little about their correlation with the independent variables, as most observations are concentrated. The inverse relationship between market size (in log) and HHI implies that the larger the market, the lower the degree of concentration, indicating that the size of the market is important to generic firms as a larger market encourages the entry or existence of a greater number of brands, which is consistent with Bae (1997), Reiffen and Ward (2003) and Hollis's (2005) reports. This relationship is steeper for HHI measured by total sales. More detailed analysis is given in the model result section (4.7.2).

Figure 1: Correlation matrix for the prices model

Graphical representation of the correlation matrix
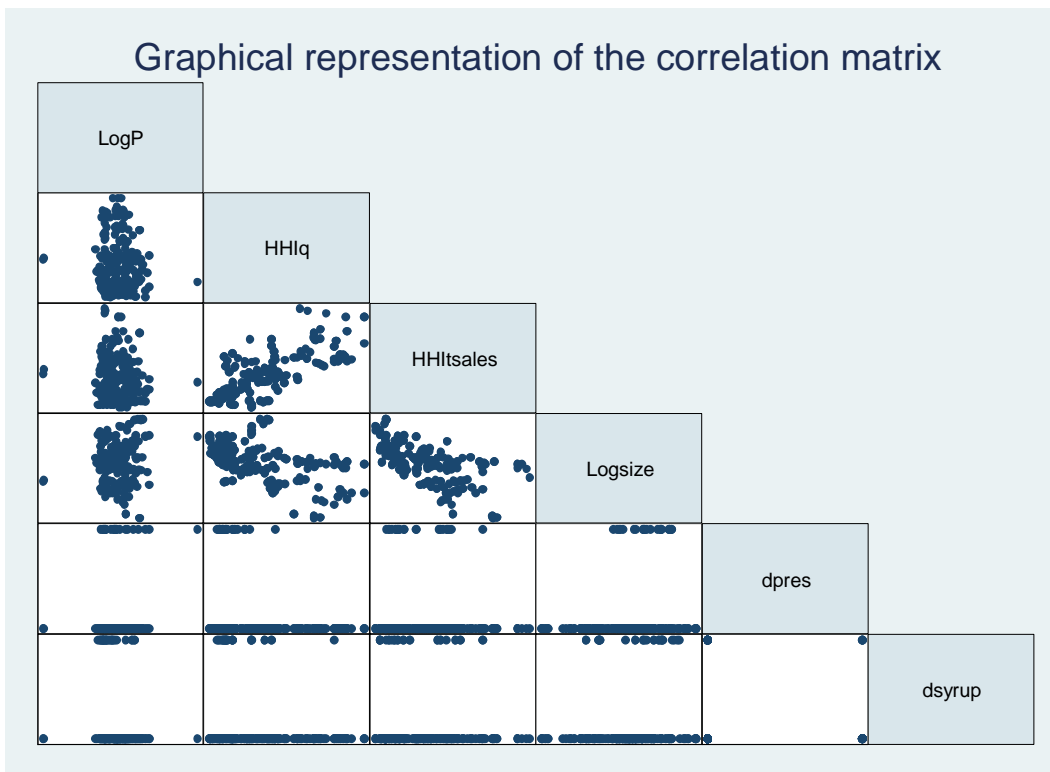
Market share (MSh) model dataset

Table 4 summarises the main variables of panel nature for the market share of the drugs. We have included information in the rows about the numbers of firms and of brands, because both can be used to understand the meaning of HHI in our equation (Davies, 1978).

Table 4: Statistical summary of the market shares of the leading and pharmacy-owned drugs (MSh)

	Mean	Std.Dev	Min	Max
• **Leading drug market share (MSh)**				
Total quantities	0.3071	0.1805	0.063	0.8595
Total sales	0.2694	01396	0.025	0.5640
• **Own brand market share(MSh)**				
Total quantities	0.2320	0.2252	0.0001	0.8640
Total sales	0.2084	0.2119	0.0030	0.8410
• **Number of drugs**	14.9817	6.7601	3	35
• **Number of firms**	7. 7622	3.0595	1	14
• **Logsize (Chilean real currency)**	7.7449	1.1784	4.4659	10.3181

The information shown above confirms the high heterogeneity of the dataset. We highlight, however, the consistency of market share values, as the market share of own-brand drugs is lower than that of the leading drug. When we look at this information horizontally we find that the number of drugs is almost twice the number of firms. The detailed information for the minimum and maximum numbers of firms and drugs is consistent with a liberalised marked, as mentioned in the introduction.

The values of market share as the mean of this indicator in total quantities sold is higher than that measured by total sales, indicating that the inferior level of the latter is due to a 'low-price effect'.

Figure 2: Correlation matrix of the market share model
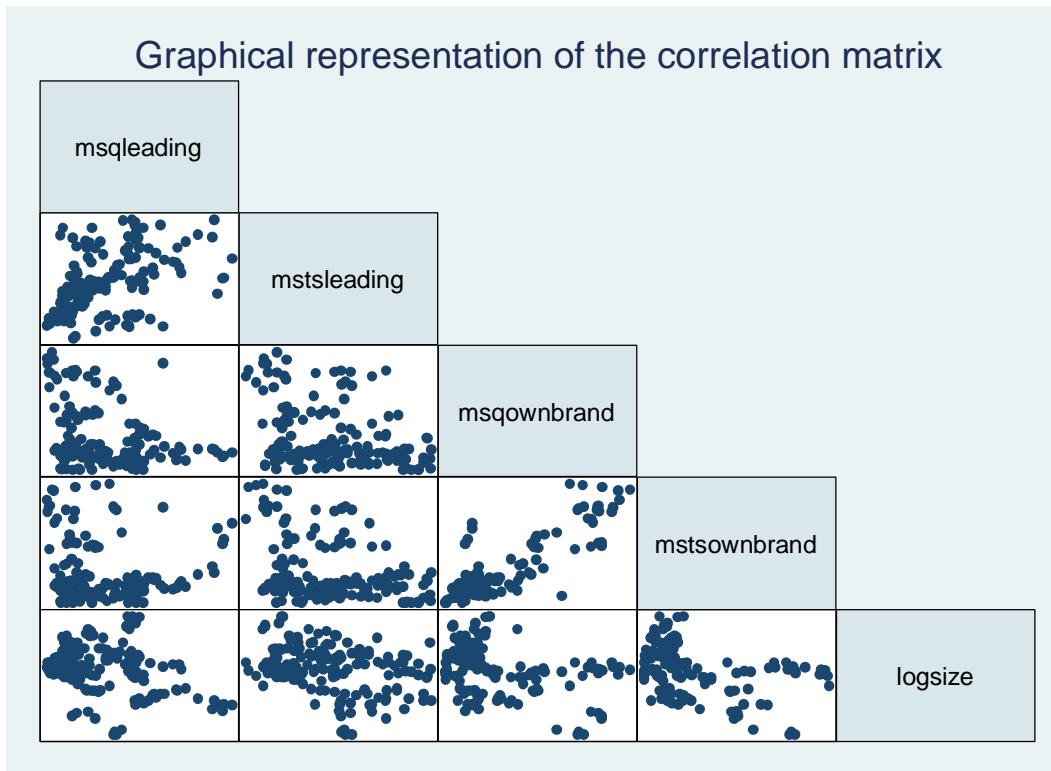
The correlation matrix above shows the inverse relationship between the market shares of the leading and the own-brand drug measured in total quantities sold, confirming the identity hypothesis posited on section 4.5.2. When measured by total sales (second and fourth columns), the figure is less clear, as there is a wide range of observations in which the points have a lower bound (almost flat).

The scatterplot of logsize against market share shows an inverse relationship; however, most observations are concentrated on the left-hand side of the figures, indicating that in small markets the concentration is high, consistent with our expectation. Few outliers are observed in this relationship. There is also a steeper slope in the scatterplot for the leading drug than for the own-brand drug. Further discussion of these scatterplots and their implications for the market share model are found in the next section.

4.7.2 Model Results

The price regression

Before estimating our regressions we plotted our variables in order to identify extreme cases (outliers) and then to study what has caused them. Below we show the key theoretical variables of our model: they are our dependent variable and two of the driver variables, market concentration (HHI) and market size. The scatterplots are shown below:

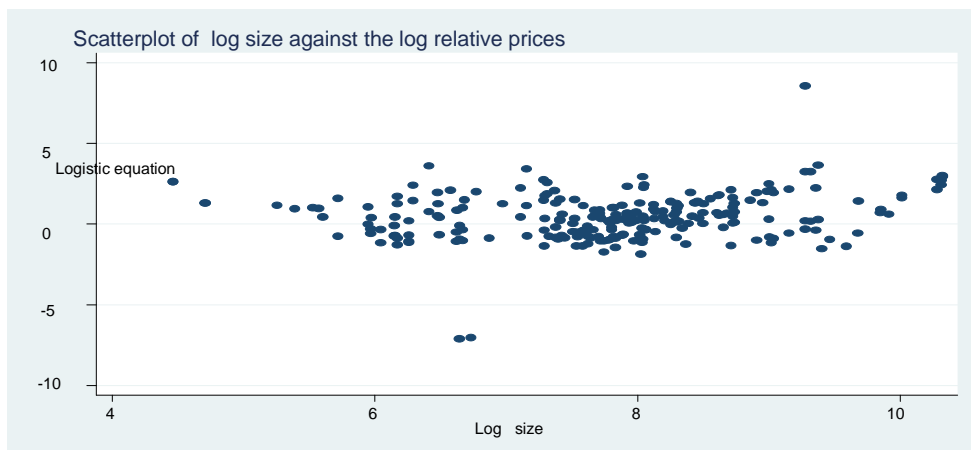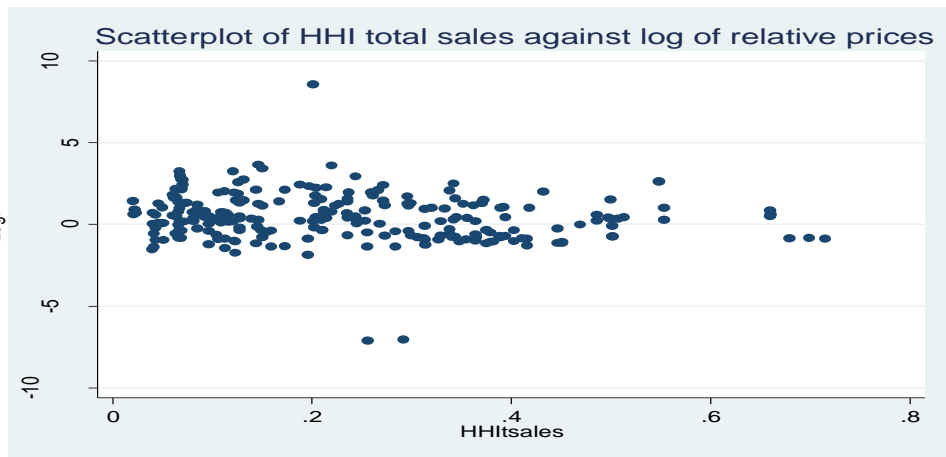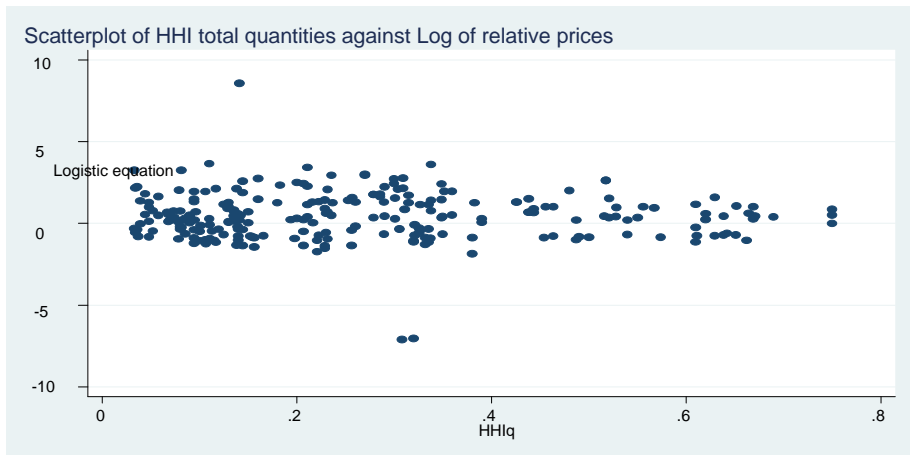**Figure 3: Scatterplots of the relevant variables**
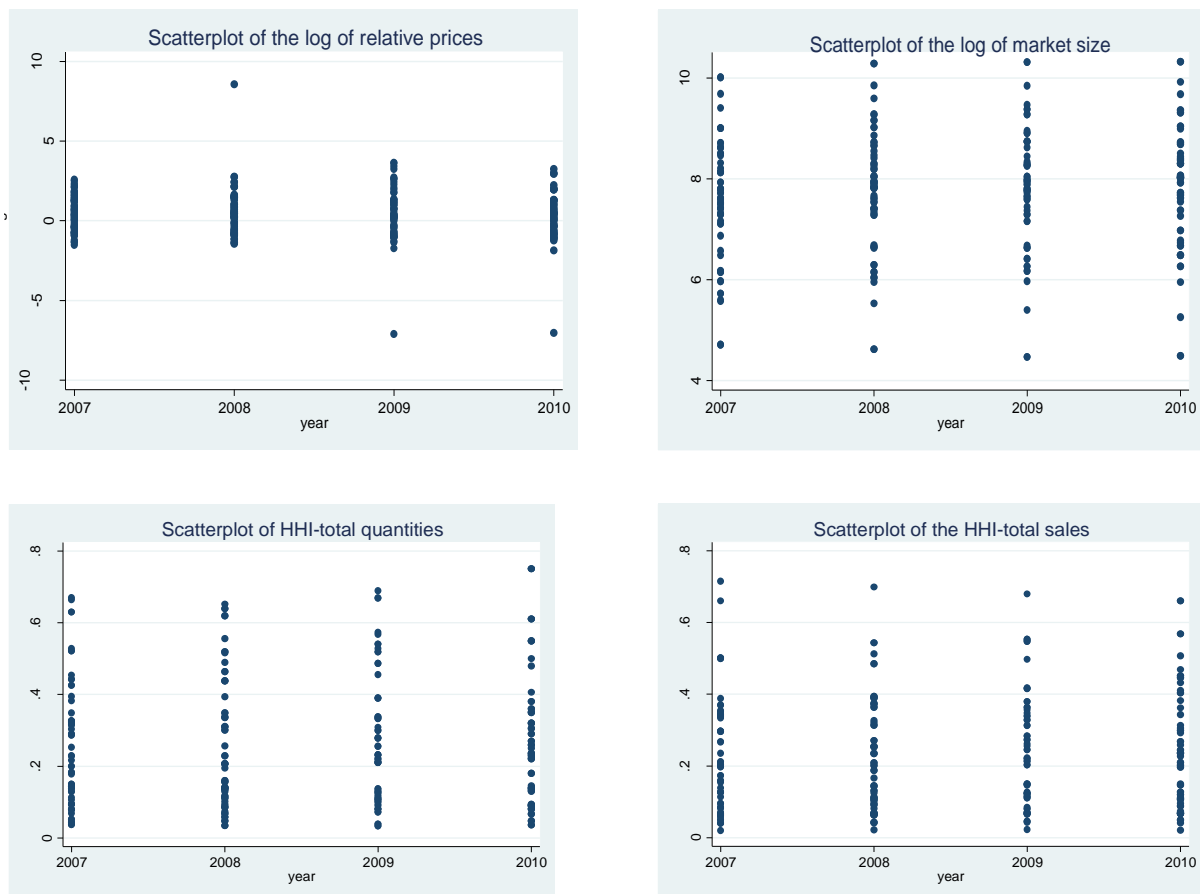
On the first row of the last figure there are some outliers,[53] and we use dummy variables in the theoretical regression to control them.

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[53] Group 8 (2008) and group 34 (2009, 2010).

On the second row are scatterplots of the HHI (quantities and total sales). Most of the observations have an upper bound of 0.4 (40% concentration), whereas the HHIq observations are more dispersed, with a significant number ranging between 0.4 and 0.8. As a consequence there is a lower degree of concentration when it is accounted for HHIts in comparison to HHIq.

We investigate whether or not it is possible to identify any objective pattern between the log of relative prices and the two key variables (HHI and logsize), as shown in the figure below:

Figure 4: Scatterplots of log of relative prices against HHI and logsize

Scatterplot of HHI total quantities against Log of relative prices

Scatterplot of HHI total sales against log of relative prices

Scatterplot of log size against the log relative prices

The graphs show that all the scatterplots have lower and upper bounds. The three outliers observed in Figure 3 are out of range in the three graphs above. As before, the scatterplot of HHIq against the log of relative prices shows values more dispersed than those in which HHIts is considered.

__Estimations of the relative prices__

The results of the three techniques (pooled, the FEM and REM) are summarised in Tables 5 and 6. We start by estimating the specification (1) of the section 4.5.1. To define the model that fits our dataset best we look first at the regression coefficients, then at the statistical tests and finally at the predicted values to check for outliers and raise mechanisms to control for them.

As we are working with two different measurements of HHI, i.e. total quantities sold (q) and total sales (ts), the results are shown separately.

To control the big difference in the market size across categories (measured in Chilean currency), we include a dummy variable (Dsize) to control for categories with high sales as an alternative variable of the logsize of equation 1. Thus, Dsize = 1 if market size > CLP10 m, otherwise Dsize = 0. For example, maximum total sales in the analgesics category exceed CLP28 m in 2009 whereas it was CLP82 m for the Vitamin A category. There are three categories with total sales of more than CLP10 m and the rest are highly dispersed. This criterion is also used by Saha *et al* (2006) to control for the blockbuster categories.

We now estimate four models of pricing considering two different measures of HHI (q and ts) and two measures of total sales on the right-hand side (log size and Dsize). In sum, we estimate 12 regressions (4 models,each using OLS-pooled and the FEM and REM techniques).

Relative price regression measured by total quantities sold

Tables 5 and 6 show that the coefficients of our key variables – degree of concentration (HHI) and market size (logsize and Dsize) – are positive and similar in five regressions without the negative relationship between HHI and the log of relative prices (P_{ob} / P_{ld}) that we predicted. The positive value of this variable for OLS (see Table 6) satisfies our expectations.

The coefficient of log size is positive for five regressions as well. In the FEM model in Table 5 this coefficient is negative. The coefficient of Dpres is also not as we predicted: we expected drugs prescribed by physicians (mainly original or leading drugs) to be negatively related to our dependent variable. The coefficient of the dummy to control the leading generic and the original drug is positive for all regressions, and thus the position coefficient of the prediction is higher when _Dtype_ =1 (generic drugs), which implies that the _log $Pob_{i,t}/Plg_{i,t}$_ > _log $Pob_{i,t}/Porig_{i,t}$_, (lg: leading generic and orig: original drug) measured by the logistic transformation, consistent with market conditions where $P_{original} > P_{generic}$.

On the other hand, when we look at how the preselected pooled model fits the dataset the F-test is statistically significant. As a result, the principal component analysis suggests that the pooling assumptions are partially satisfied for the preselected expression because this model fails in the sign of Dpres, contrary to the theory. Anyway, we have our doubts about the power of its prediction, as this technique has poor theoretical support for us as was discussed in section 4.6 about Estimation methodology, which in turn means that the pooled estimates may conceal valuable information about the drug categories that could be explained better using the REM.

Now we move to the second specification that considers HHIts as a predictor.

Table 5: Estimates of the log of relative prices

(Includes HHIq and the log size)

Logistic equation	Pooled (OLS)	FEM	REM
HHIq	0.14046	0.09116	0.22364
	(0.58779)	(1.10591)	(0.76702)
logsize	0.25820***	-0.34997	0.14251
	(0.09152)	(0.38896)	(0.14219)
Dpres	0.09814	omitted	0.13724
	(0.31955)	-	(0.56773)
Dsyrup	-0.82016***	0.34011	-0.34903
	(0.29397)	(0.58006)	(0.39359)
Dtype	0.35743*	omitted	0.32530
	(0.19300)	-	(0.33796)
constant	-1.73963	3.12228	-0.85777
	(0.80494)	(3.07999)	(1.21184)
Number of Observations	244	244	244
Wald χ-sq (k)			2.82
Prob> χsq			0.7282
F	4.00	0.39	
Prob> F	0.0017	0.7633	
R-sq overall	0.0776	0.0463	0.0694

*** Significance at p=0.01; ** significance at p=0.05; * significance at p=0.10

Table 6: Estimates of the log of relative prices

(Includes HHIq and Dsize)

Logistic equation	Pooled (OLS)	FEM	REM
HHIq	-0.38523	0.03791	0.13004
	(0.51906)	(1.24481)	(0.69948)
Dsize	1.19293***	0.84804	1.01443***
	(0.29412)	(0.47303)	(0.36090)
Dpres	0.03469	omitted	0.07959
	(0.31487)	-	(0.54758)
Dsyrup	-0.83654***	0.25823	-0.35114
	(0.28907)	(0.57253)	(0.38427)
Dtype	0.36333*	omitted	0.322153
	(0.18973)	-	(0.32744)
constant	0.28905	0.22417	0.17361
	(0.20660)	(0.29800)	(0.31915)
Number of Observations	244	244	244
Wald χ-sq (k)			9.88
Prob> χsq			0.0786
F	5.79	1.19	
Prob> F	0.0000	0.2155	
R-sq overall	0.1084	0.0337	0.0980

*** Significance at p=0.01; ** significance at p=0.05; * significance at p=0.10

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Table 7: Estimates of the log of relative prices

(Includes HHIts and the log of size)

Logistic equation	Pooled (OLS)	FEM	REM
HHIts	-0.83894	0.03791	-0.05409
	(0.74938)	(1.24481)	(0.81969)
logsize	0.17671*	-0.35185	0.009851
	(0.10367)	(0.39612)	(0.15319)
Dpres	0.12804	omitted	0.13215
	(0.31598)	-	(0.56170)
Dsyrup	-0.82466***	0.34739	-0.33374
	(0.28988)	(0.57804)	(0.39534)
Dtype	0.37981**	omitted	0.34129
	(0.19121)	-	(0.33514)
constant	-0.89204	3.15174	0.38861
	(0.92488)	(3.15761)	(1.32189)
Number of Observations	244	244	244
Wald χ-sq (k)			2.92
Prob> χsq			0.7118
F	4.26	0.38	
Prob> F	0.0010	0.7648	
R-sq overall	0.0822	0.0477	0.0730

*** Significance at p=0.01; ** significance at p=0.05; * significance at p=0.10

Table 8: Estimates of the log of relative prices

(Includes HHIts and a dummy Dsize for total sales)

Logistic equation	Pooled (OLS)	FEM	REM
HHIts	-0.90921	0.80460	-0.05409
	(0.61606)	(1.22965)	(0.81969)
Dsize	1.05944***	0.89887	1.00095***
	(0.31016)	(0.48211)	(0.37424)
Dpres	0.10018	omitted	0.06050
	(0.30489)	-	(0.53659)
Dsyrup	-0.81127***	0.23416	-0.35222
	(0.28392)	(0.56934)	(0.38470)
Dtype	0.36854*	omitted	0.32971***
	(0.18786)	-	(0.32570)
constant	0.39623*	0.15203	0.21910
	(0.20934)	(0.29641)	(0.32157)
Number of Observations	244	244	244
Wald χ-sq (k)			9.88
Prob> χsq			0.0786
F	6.15	1.28	
Prob> F	0.0000	0.2823	
R-sq overall	0.1144	0.0205	0.1008

*** Significance at p=0.01;** significance at p=0.05; *significance at p=0.10

Relative price regression measured by total sales

We now analyse the logistic equation models, considering as relevant variables HHIts (total sales) and market size (log form and Dsize). The estimates and the model statistics are shown in Tables 7 and 8.

As we observe above, the coefficients of our principal variables are in the direction we expect with the exception of the FEM models, whose coefficient of HHIts are more than 0 and hence contra to our predictions. This model also shows a negative relationship between logsize and logistic equation. When we try with Dsize (see Table 8 below), the HHIts is also the opposite of the sign that we posit. The FEM model results confirm our explanations (see estimation methodology section) and hence this technique is not useful for explaining our dataset.

On the other hand, the pooled and REM models (Table 7) show similar coefficients in terms of signs, but the sensitivity of the former is higher than the coefficients of the REM model. The pooled model also shows coefficients of Dsyrup and Dtype as statistically significant, and logsize is also significant at 10%. In the REM model all the coefficients are insignificant, even at 10%.

When we analyse the fit of these two models, the F-test for the pooled model is statistically significant at 1% and hence fits our dataset well. In contrast, the Wald test for the REM model is insignificant.

The alternative model estimated for OLS and REM with Dsize (Table 8) shows similar characteristics of the coefficients in terms of sign and values; however, the statistical significance of this variable is higher, at 1%. The coefficient of Dpres is different to our prediction again, whereas the coefficient of Dtype is as we predicted.

Looking at the model fit, both regressions are significant although the goodness of fit is higher for the OLS model. The R^2 is also higher for the latter model.

In sum, the dataset fits the model that includes HHIts well. We therefore use this method to select our best model. Below we evaluate which of the latter two models is the best. To complement the statistical results and bring in new information, we first check the scatterplot of the prediction. The expectation is that the predictions will move in the range [0,1] as we are using logistic transformations

of the relative prices. Then we continue to analyse the results by looking at the tests for autocorrelation and heteroskedasticity.The scatterplots of the predictions for both models are presented below.

Figure 5: Scatterplot of the prediction with different variables to measure market size
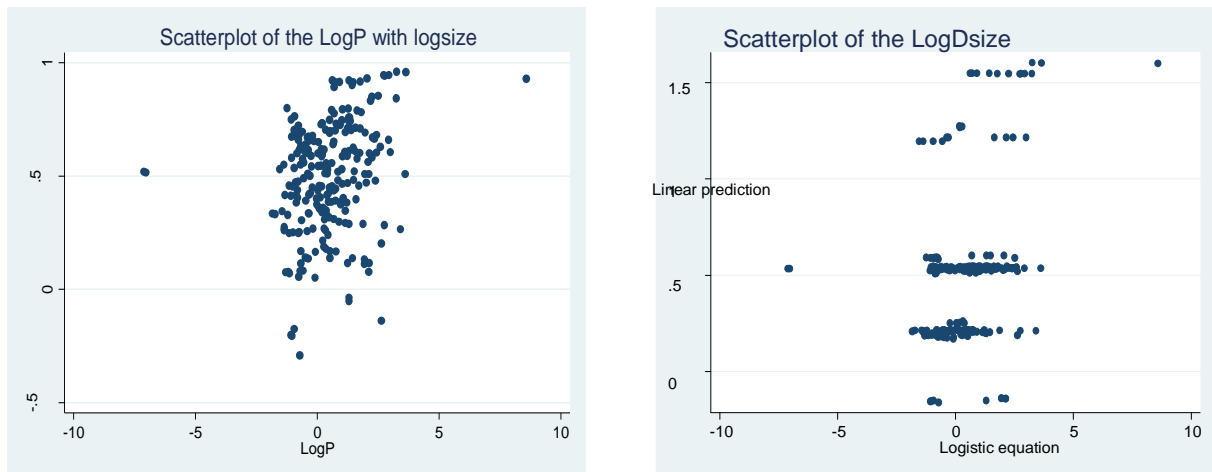
The graphs above show some predictions that are out of range (<0 or >1). We count 7 observations in the first model and 34 in the second. As a consequence, we use two different ways of attempting to controlling these outliers and hence to have an approach to the model that fits in a better way our dataset: the first is to use dummy variables to control the outliers and the second is to eliminate statistically insignificant variables except for our principal components, HHIts and market size.

The results of the first mechanism, however, are not satisfactory. We show the scatterplots for both below. Next we follow a restrictive model that considers the principal variables as predictors to explain price movement over time.

Figure 6: Scatterplot of the prediction with different variables to measure market size
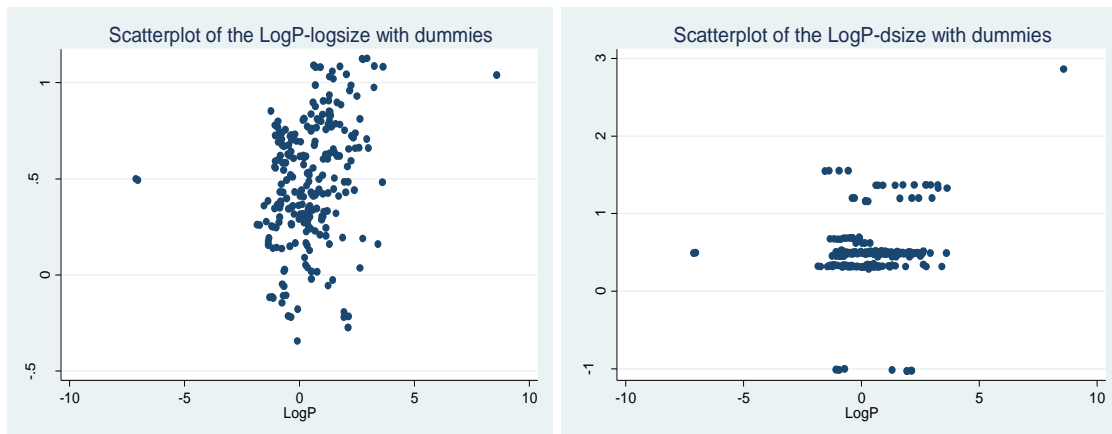
Estimates of logistic of relative prices: the restrictive model

This section presents the results from the restrictive model ($\beta_3 = \beta_4 = 0$ in equation 1). Two criteria are used to impose the last restrictions and choose the best model. They keep the principal theoretical variables and eliminating variables that have incorrect signs or are statistically insignificant. As a consequence the logistic equation regressions are now estimated against HHIts, Size (both logsize and Dsize), and the dummy variable Dtype to control the leading generic and the original drug. As before, Dsize is an alternative variable of logsize to control for market size following Saha *et al* (2006). The resulting restrictive model (1R) is as follows:

$$\textbf{Log } \{\pi_{i,t}/ (1\text{-} \pi_{i,t}) \}= \alpha + \beta_1 HHI_{i,t} + \beta_2 Size + \beta_3 Dtype_{i,t} + \varepsilon_{i,t} \qquad \textbf{\textit{(1R)}}$$

where i represents the drug group (pharmaceutical category), group i= 1,…,64 and t the period, t=1,…,4. As a result we have 256 observations. On the left-hand side is the logistic equation Log $\{\pi_{i,t}/ (1\text{-} \pi_{i,t})\}$, where $\pi_{i,t} = Pob_{i,t}/Pld_{i,t}$: this is the ratio of average prices of the own-brand drug over the leading drug (leading branded drug and original brand), measured in Chilean currency. The explanatory variables are defined as before in equation (1*)*

The following tables show the estimates for both regressions using the pooled, FEM and REM techniques.

Table 9: Estimates of Log of relative price restrictive model (logsize version)

Logistic equation	Pooled	FEM	REM
HHIts	-0.85111	0.20073	-0.41263
	(0.75298)	(1.21279)	(0.92588)
logsize	0.16055	-0.32074	0.08793
	(0.10154)	(0.39202)	(0.14893)
Dtype	0.38040**	omitted	0.34916
	(0.19205)	-	(0.33456)
constant	-0.84236	2.91058	-0.31928
	(0.91350)	(3.12639)	(1.29555)

Number of Observations	244	244	244
Wald χ-sq (k)			2.11
Prob> χsq			0.5498
F	4.27	0.40	
Prob> F	0.0059	0.6732	
R-sq overall	0.0506	0.0328	0.0464

*** Significance at p=0.01;** significance at p=0.05; *significance at p=0.10

Table 10: Estimates of Log of relative price restrictive model (Dsize version)

Logistic equation	Pooled	FEM	REM
HHIts	-0.85829	0.90488	-0.08755
	(0.62360)	(1.20242)	(0.81936)
Dsize	1.04378***	0.90749	0.98951***
	(0.31039)	(0.48053)	(0.37181)
Dtype	0.36624*	omitted	0.33116
	(0.18867)	-	(0.32568)
constant	0.30779	0.15405	0.19556
	(0.20954)	(0.15405)	(0.32196)

|			
Number of Observations	244	244	244
Wald χ-sq (k)			8.97
Prob> χsq			0.0297
F	7.33	1.85	
Prob> F	0.0001	0.1609	
R-sq overall	0.0839	0.0339	0.0781

*** Significance at p=0.01; ** significance at p=0.05; significance at p=0.10

The tables show that the coefficients of HHIts for the FEM models are the opposite to those predicted. The F tests are also statistically insignificant. This technique is therefore not good for explaining the interaction between the variables, which agrees with our previous theoretical analysis.

The coefficients for the pooled and REM models are similar for both restrictive equations. The model that fits in a better way the dataset is the Dsize version (Table 10). In this model this variable is statistically significant, at 1% with both techniques. The individual coefficients are more sensitive for the pooled estimation. In particular, we pay attention to the coefficient of HHIts due to its high value, which is little credible for us, while the value of this coefficient using the REM is more consistent with our expectations. We now work in two directions to decide what model to follow.

We look at the scatterplots of the prediction to check for outliers, and then we apply the Breush Pagan Lagrange Multiplier (LM). The null hypothesis is that the variance across categories is zero, implying no panel effect.

Figure 7: Scatterplots of the predictions (Restrictive model)
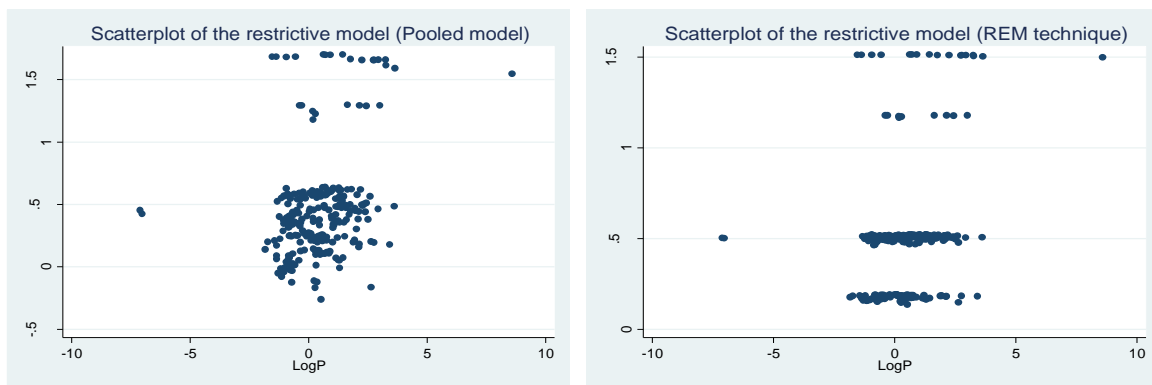
The scatterplot in Figure 7 shows the persistence of outliers that are out of range for both techniques and hence we are unable to make a decision from the graphs. Next, we apply diagnostic tests to the regressions in order to find the best model.

The Breush Pagan test gives a Chi-sq of χ^2 (1) = 137.09 (Prob $>\chi^2$ = 0.0000), confirming that the null hypothesis is rejected, and we conclude that therefore the REM is the appropriate model for our dataset. In other words, with this result there is evidence of significant differences across drug

categories, confirming our theoretical discussion about the REM as the most suitable technique for estimating our model.

Although we know that the serial correlation is not a problem in micro panels with a small number of periods we test for it anyway using the Woodridge test (H_0: no first-order autocorrleation). The F test is $F(1, 60) = 7.267$, Prob>F = 0.0091, and hence we reject the null hypothesis and confirm the existence of autocorrelation.

To remedy the latter problems, we estimate the regression using panel-corrected standard errors (PCSEs) as discussed in section 4.6 on the estimation methodology for these models..To look at the differences between branded generics and original drugs we estimated the models separately. The table (see Annex 2) shows that the PCSE coefficients are significant at 1% for the whole dataset; however, the most important thing about this estimate is that the regression gives the same result as the OLS-pooled regression (see Table 9), with differences in the statistical significance of the coefficients of HHIts and the intercept (constant), which are insignificant in the OLS-pooled model shown in Table 9. We also pay attention to the coefficients for the group, which are also too high or too sensitive for us.

We firstly believe that this unsatisfactorily result is due to the small number of periods in the estimation. This is confirmed by Hoechle (2007), who, based on a paper by Beck and Katz (1995), highlights how the PCSE method gives imprecise estimates if the T/N [54] ratio is small, which is the case in our dataset. The argument is as follows: For finite samples, properties of the PCSE estimator are poor when the panel's cross-sectional dimension N is large compared to the time dimension T. We thus return to the REM estimates as the best model. The results of these estimates for both the complete dataset and each group are shown below.

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[54] T is the number of periods and N the number of observation

Table 11: REM Estimates of Logistic equation restrictive model (best estimates)

Logistic equation	Dataset (1)	Leading generics (2)	Original drugs (3)
HHIts	-0.08755	-0.29487	1.59142**
	(0.37181)	(1.12668)	(0.76397)
Dsize	0.98951***	1.42604**	0.34189
	(0.37181)	(0.56542)	(0.26182)
Dtype	0.33116	-	-
	(0.32568)	-	-
constant	0.19556	0.52721	-0.09501
	(0.32196)	(0.35878)	(0.30072)

Number of Observations	244	157	87
Wald χ-sq (k)	8.97	7.64	5.02
Prob> χsq	0.0297	0.0219	0.0811
R-sq overall	0.0781	0.0724	0.0087

*** Significance at p=0.01; ** significance at p=0.05;* sign. at p=0.10

The coefficients of the estimates are consistent with our predictions (except for the value of HHIts for the original drugs, which we discuss later). In the same way, the coefficients of the dataset estimates are less sensitive than those of the leading generics.

How can we interpret the negative coefficient of HHIts of Table 11?

To understand the logic of this variable we simulate an industry comprising one dominant and two symmetric small firms in terms of size whose market shares change. If Firm 1's market share increases by 10% the others each lose by 5%; thus there are two opposite effects of HHI.

First, by applying the HHI formula developed in section 4.5.1 $-\Delta$HHIts$= \Delta^+ 0.01 + \Delta^-(0.0025)2 = 0.005$ –, HHIts increases by 0.005. Second, by considering this value in regression (1), the effect on the log of relative prices will be negative and equal to (-0.08755)(0.005)= -0.00043775, which in turn implies that the logistic of relative prices drops by -0.043775%. This is consistent with our prediction. This fall can be explained by a fall in $Pob_{i,t}$ or a raised $Pld_{i,t}$

Due to the lack of literature about HHI as an independent variable in relative price equations we use Davies's definition of HHI, mentioned in 4.5.1 (recall that HHI= $\{(1 + cv^2)/ n\}$), to analyse the role of the number of firms[55] as an inverse determinant of HHI such that the results are comparable with the literature.

On one hand, taking into account the formula mentioned above the negative coefficient in regressions (1) and (2) in Table 11 implies that the relationship between HHIts (given a higher n, ceteris paribus) and the log of relative prices is consistent with the results obtained by Frank and Salkever (1997) and Reiffen and Ward (2003).

On the other hand, the counterintuitive positive coefficient of HHIts in column (3) deserves more attention, as the positive value implies that the higher the HHIts (less competition), the higher the log of relative prices. Thus if $Pob_{i,t}$ is constant, $Porig_{i,t}$ should fall, or if $Porig_{i,t}$ is constant, $Pob_{i,t}$ should rise. In the same way, a third explanation is given by changes of different magnitudes in prices, where the positive impact is higher for the own brand ($\Delta Pob_{i,t} > \Delta Porig_{i,t}$). Which impact is more sensitive? Davies's equation is also used to analyse the consistency of this prediction. If n goes down, this implies that HHIts increases and hence, according to the positive coefficient of the original drug, the log of relative prices should increase.

In the case of Chile's pharmacological industry, we believe that the third alternative makes more sense because the largest pharmacies take advantage of their dominant position (the three of them having captured 90% of the market) increasing $Pob_{i,t}$ into a larger magnitude than that of the increase in the original drug price. In fact, we maintain that $Porig_{i,t}$ also goes up because the wholesaler targets patients with great willingness to pay; however, as their average prices are much higher than those of generics, including own-brand drugs, the margin for big price increases is reduced.

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[55] The number of firms (n) is usually used as an explanatory variable in other research.

Put mathematically, if the initial relative price is $Pob_{i,t}/Porig_{i,t}$, and if the own-brand price increases by 10% and the original price does so by 5%, now the relative price goes up by (1.1)/(1.05)=1.0476; i.e. an increase of 4.76%.

Is the firm size important as a predictor of the log of the relative prices?

As we know from Davies's equation, size of firm is captured by *cv* in HHI. We have not yet discussed the role of the dominant drug in the market. If HHIts goes up because the dominant drug gains a greater share of the market (the market is more unequal, i.e. cv is higher), we should expect a different impact on the log of relative prices depending on whether the pharmacy-owned or the independent leading drug has the leading market share. If the log of relative prices increases (*ceteris paribus*) this may be explained by a higher drug price on the numerator or a lower price on the denominator, and vice versa.

Next, looking at the summary of the statistics of the drugs market share, the own-brand drug has a high market share of the market (23.2% in quantity and 20.8% in money). The leading drugs correspond mostly to generics, which in turn suggest that the original drug has a lower market share of the market. The own-brand drug dominates the original drug in market share. Another argument that maintains this line of thinking is the way in which the Chilean large-pharmacies operate, with the pharmacist playing a strong role in inducing demand for own-brand drugs. We believe that when an original drug interacts in the market with the own-brand drug the seller induces demand for the latter and hence its price goes up because of a higher HHIts, which is consistent with the coefficient in regression (3).

Sign of the 'Dsize' dummy variable

The coefficient of Dsize is positive for all equations and statistically significant for our main regression (see first column of Table 11) and the generics model. We therefore think that this direct relationship between Dsize and the log of relative prices in our dataset reflects the idea that a larger

market size encourages more firms (mainly generics) to enter the market. With increased competition, the prices of all drugs should go down. On the other hand, as the pharmacy-owned drug is more cost-related, its cost provides a long-term floor for the price of any generic drug and the lower prices affect the relative price $Pob_{i,t}/Porig_{i,t}$ on the denominator on a larger scale, hence the log of relative price increases. An important antecedent that justifies this explanation is the large number of brands provided in Chile, which varies between 18 and 21 per category. However, this average is strongly influenced by the biggest categories which include a maximum of 35 drugs.

Looking at the differences among the whole dataset and the separated groups, the coefficient of the leading generics is the highest, which may be explained mathematically by a lower fall on the denominator (the leading generic, $Plg_{i,t}$) respect to the fall of this value in the other regressions. How can this be interpreted? We believe that the leading drug price has a degree of rigidity (is less elastic) in comparison to the others and so its price goes down, but only marginally (ceteris paribus), which is consistent with the fact that the leading generic wholesaler takes advantage of its market power in a short period and thus applies a higher margin (price higher than marginal cost) respect to that of their rivals even when it faces fierce competition. In other words, when a successful blockbuster generic suffers less from competition, if its price goes down the drop is much smaller than that of its rivals. Frank and Salkever (1997) also use this argument to explain that competition caused by a new generic drug creates a considerable drop in the average price of generic drugs.

Finally, the lower coefficient of the original drug shows its high substitution, given a greater number of generics firms due to a larger market. In fact, as we commented before, most of the drugs in the dataset are generics, which are provided in a large number of formats due to the low legal barriers to entry in the Chilean market (*Official Newspaper*, 2011. Discussed in section 4.2). In the same way, as sellers play an active role in their clients' decisions it is highly likely that they take advantage of these higher prices to recommend the purchase of generics, particularly their own brands.

Dtype dummy variable

The coefficient of the Dtype dummy variable is positive, even though it is statistically insignificant. Thus when Dtype =1 (leading generics, lg) the log of relative prices intersects at a higher value on the y- axis in comparison to the value obtained when Dtype=0 (original drug), which in turn means that the logistic expression of relative prices $Pob_{i,t}/Plg_{i,t}>Pob_{i,t}/Porig_{i,t}$, and hence necessarily $Porig_{i,t}>Plg_{i,t}$.

As we are investigating the difference between the estimates for the leading generic and the original drug (which is equivalent to comparing the two groups of drugs), we use the Wald test to evaluate the differences between these nested models,[56] imposing the restriction on the coefficient of the Dtype dummy variable β_3=0 (in a regression model, restricting a parameter to zero is accomplished by removing the predictor variables from the model). The $\chi^2(1) = 1.03$ (prob>χ^2=0.3092), the null hypothesis is not rejected.

Market share regressions

Given that the leading and pharmacy-owned drugs are part of the same industry, we now investigate the relationship between the market share of each, with two market variables: the size and the degree of the concentration of the industries. As explained in section 4.5.1, we define the leading drug as the,original or generic (not pharmacy-owned) blockbuster drug on the market in terms of total quantity sold and total sales measured in Chilean currency. This definition differs from that used for the construction of the dataset for pricing regression, for which the original and the branded generic drug prices were compared with the price of the pharmacy-owned drug. In sum, we want to know whether or not the market shares of these drugs follow the same pattern when they interact with our explanatory variables.

To answer this question we first estimate, for both brands, a specification that measures the interaction between market share and two explanatory variables – the degree of market concentration (measured

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[56]One model is considered nested in another if the first model can be generated by imposing restrictions on the parameters of the second.

by HHI as before) and market size (Size). On the left-hand side of the regression, market share (MSh) is estimated for both the leading brand and the pharmacy-owned drug against our predictors, thus we estimate four equations.

Methodologically, we start by plotting the main graphs of this dataset including the scatterplots of all the variables and the relationships between variables.

Figure 8: Scatterplot of market share for both brands (total quantities and total sales)
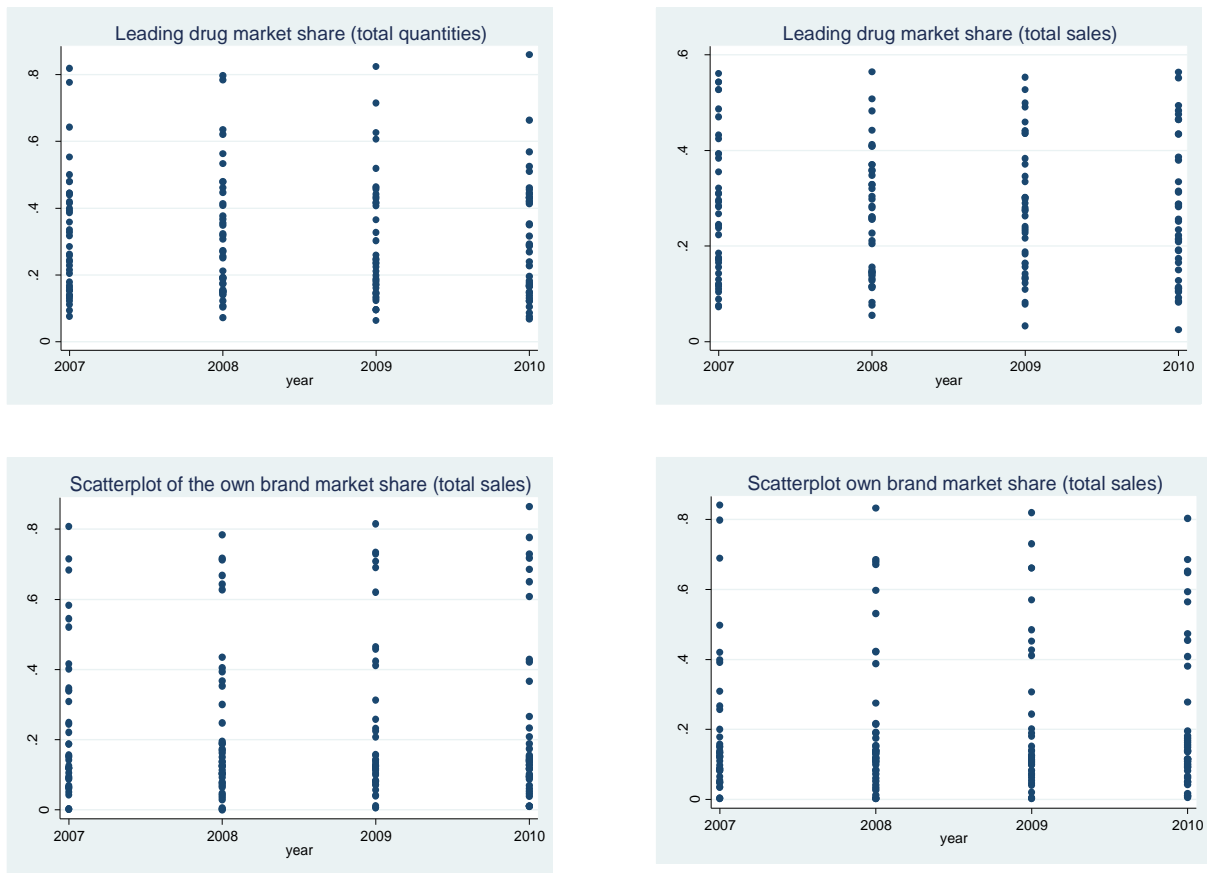

As we see in the first row above, the market shares of the leading drugs are mostly distributed and concentrated at values lower than 0.5. From the market share measured by total quantities we nevertheless find few observations over the value 0.6, which moreover is the upper bound for market share in terms of total sales. The scatterplot of the own-drug market share (second row) shows that most observations correspond to values lower than 0.2, even though there are some drugs in which the

market is dominated for this brand (in some particular cases, the market share of own-drugs is more than 80%).

In the graph below we show six scatterplots. On the first row, we show the relationship between the market shares of the two types of drug. The horizontal axis is the market share of the pharmacy-owned brand, and the market share of the leading drug is on the vertical axis. A line of best fit is included in both graphs. The negative slope of both graphs shows the opposite relationship between market shares of both drugs and hence the market share relationship behaves as one identity: if the own-brand drug captures a higher market share than that of the leading drug drops.

Figure 9: Scatterplot of relatonships between variables
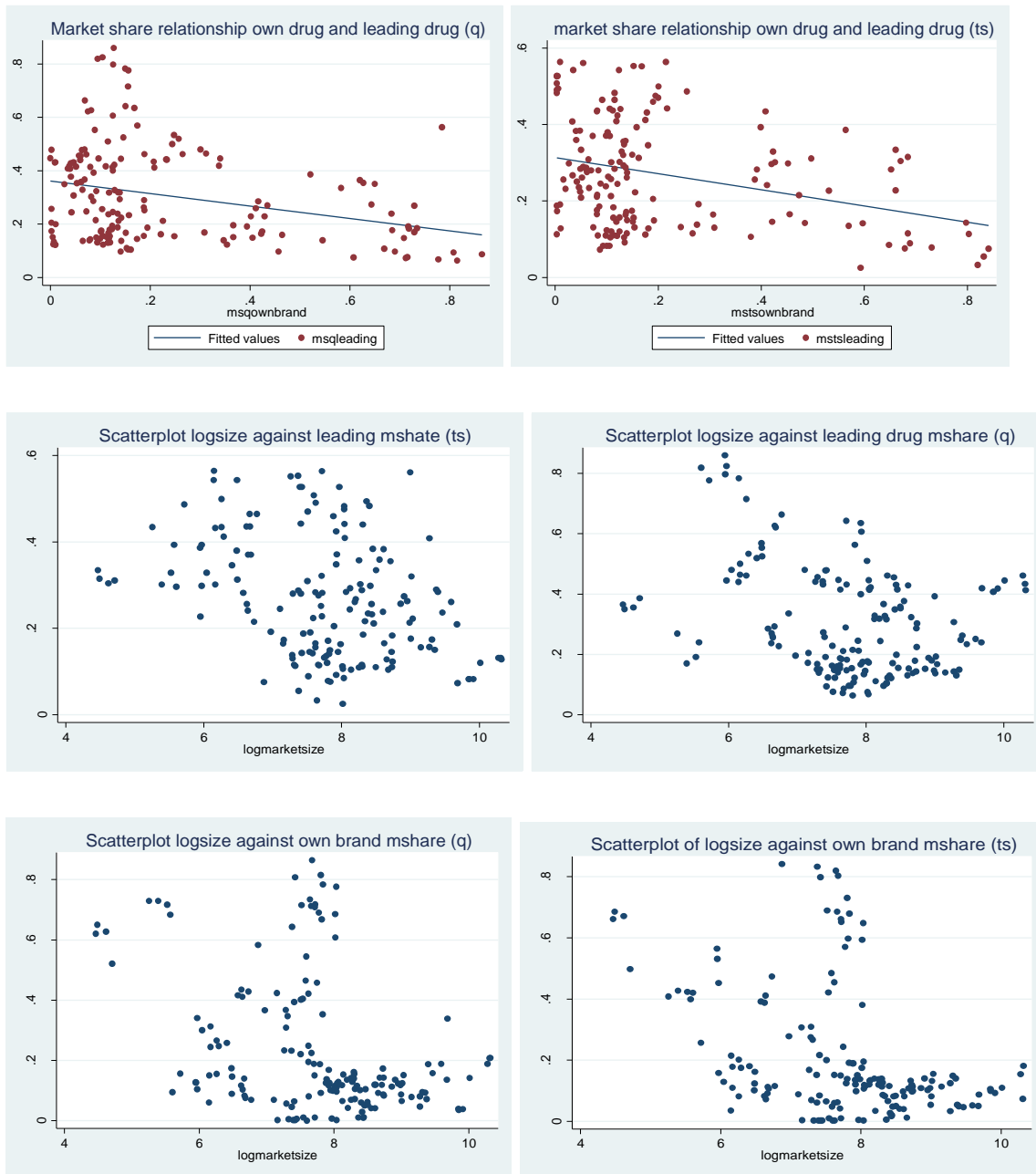
The second row presents a scatterplot of the relationship between logsize and market share of the leading drug. This relationship has a lower bound for q and total sales. Graphically, it is possible to separate the observations into two ranges. For the first range of observations, it is possible to draw a line with a steep negative slope (the limit is the log market size = 8), whereas for the second, the lower bound is almost completely flat.

On the last row above, the scatterplot of logsize is presented with the market share of the own-brand drug. As before, this relationship has a lower bound which can be divided in two ranges. Unlike the leading brand, we observe a strong positive slope in the points until logsize =6 (first range), and then a completely flat range of data closer to zero.

The mathematical representation of this type of scatterplot is given by a logistic equation of the following form **logistic (x/1-x) = α + β (1/ y)**, and hence by replacing our variables in this equation we obtain the following equation:

$$\textbf{\textit{Logistic [mshd/ (1- mshd)] = α + β (1/ logsize)}}$$

As before, d is the leading and the own-brand drug; msh = market share. Given this expression, we also proceed to estimate a regression considering this representation for our theoretical model and then compare it with our initial specification. In sum, we also estimate the following model:

$$\textit{Logistic } \{MSd_{i,t}/ (1\text{-} MSd_{i,t}) \}= \alpha + \beta_1(1/logsize_{i,t}) + \beta_2 HHI_{i,t} + \varepsilon_{i,t} \qquad \textbf{(3)}$$

where i is the group (therapeutic category) i= 1,…,41, for periods t =1,…,4. The maximum number of observations is therefore 164. The variables and techniques used to estimate this equation are discussed in the following section.

Estimates of the drug market share regression (FEM and REM models)

We start estimating two versions of the general linear model (equation 2 in section 4.5.2) by including HHIq and HHIts respectively as predictors. The models are estimated using the FEM and REM techniques, even though the REM should be the best technique for us (as discussed in section 4.6) where an inconsistent estimation showed that the FEM is not good for a short panel dataset. We then proceed to estimate the logistic specification (equation 3) above and compare the results with the first market-share regressions.

Tables 12 and 13 include the equations with the principal predictors (HHI and logsize) and an extensive model that includes the interaction variable between our two explanatory variables (see equation 2). Even though we maintain that the drug categories should behave randomly due to their different market sizes and degrees of concentration, we consider the Hausman test analysis to define between the FEM and the REM estimations.

We follow the same steps with specification (3) and then compare the resultant models.

The market share (MSh) linear specification

As a first approach to the model's evaluation, we observe that the coefficient signs for two basic equations are the same (see Tables 12 and 13) considering the FEM and REM techniques. The FEM coefficients are more sensitive than those of the REM models for both estimations. Statistically, there is a difference only in the significance of logsize (HHIq as a predictor). While this coefficient is statistically significant at 1% for the FEM, it is significant at 10% for the REM. Finally, all models are significant at 1%, with little differences in the value of R^2.

When we move to the model incorporating the interaction variables HHIqsize and HHItssize there is a marginal increase in the value of both R^2 and χ^2 statistics respectively. The main disadvantage of the extensive regression is that there is a drop in the statistical significance of the coefficients for all regressions, which discourages us from considering these equations as the best model. As a result, we analyse the basic model, including only the principal variables HHI and logsize, in detail.

Table 12: Estimates of the leading drug market share in terms of total quantities (linear specification)

MSh	FEM (a)	FEM (a) + interaction variable	REM (a)	REM (a) + interaction variable
logsize	-0.08958***	-0.11412**	-0.03301*	-0.02372
	(0.03424)	(0.05223)	(0.01863)	(0.03272)
HHIq	0.46080***	0.01753	0.42498***	0.62447
	(0.11164)	(0.72000)	(0.09166)	(0.58368)
HHIqsize	-	0.06080	-	-0.02702
	-	(0.09756)	-	(0.07808)
constant	0.87624***	1.06568***	0.44779***	0.37542
	(0.26834)	(0.40591)	(0.15591)	(0.26117)

Number of Observations	164	164	164	164
Wald χ-sq (k)			33.32	33.26
Prob> χsq			0.0000	0.0000
F	12.46	8.39		
Prob> F	0.0014	0.005		
R-sq overall	0.1979	0.1894	0.2300	0.2349

Table 13: Estimates of the leading drug market share in terms of total sales

MSh	FEM (b)	FEM (b) + interaction variable	REM (b)	REM (b) + interaction variable
logsize	-0.05286*	-0.11604**	-0.02865*	-0.05550**
	(0.02812)	(0.03648)	(0.01605)	(0.02209)
HHIts	0.39728***	-0.90860*	0.30306***	-0.44338
	(0.09049)	(0.50419)	(0.08080)	(0.43220)
HHItssize	-	0.18192***	-	0.10250*
	-	(0.06915)	-	(0.05803)
constant	0.58316***	1.06940***	0.41834***	0.62715
	(0.22469)	(0.28687)	(0.13582)	(0.17984)

Number of Observations	164	164	164	164
Wald χ-sq (k)			28.35	32.11
Prob> χsq			0.0000	0.0000
F	14.89	12.58		
Prob> F	0.0000	0.0000		
R-sq overall	0.1170	0.1299	0.1092	0.1178

*** Significance at p=0.01; ** significance at p=0.05; * significance at p=0.10

Now we test the FEM versus the REM. We call equation (a) to the specification including HHiq (Table 12) and equation (b) to the specification with HHIts as a predictor (Table 13). For specification (a), the Hausman test for fixed versus random effects gives a chi-squared value of 3.90 (prob>χ^2= 0.1420), so the null hypothesis of the REM is not rejected. The Hausman test for specification (b) including HHIts yields a chi-squared value of 7.21 (prob>χ^2= 0.0271). As the p-value is in the range [0.01, 005] we have doubt if reject the null hypothesis. However, we solve this problem by restricting the statistical significance of the model at 1% and the null hypothesis of the REM is not rejected.

The market share logistic specification

As before, the logistic model (specification 3) shown in Tables 14 and 15, below, are estimated including HHIq (Table 14, eq. c) and HHIts (Table 15, eq. d) respectively.

This equation for market share measured by total quantities sold fits our dataset better. The sign of the coefficient for both regressions is the same. In the case of the logistic model including HHIq, the independent variables show statistically significant coefficients. The coefficient of HHIq is positive, so the higher the HHIq, the higher the relative market share of the leading drug, as we expected. The positive sign of the inverse of logsize is also satisfactory for us (logsize moves in the opposite direction), as we would expect a larger market to encourage the entry of generics and hence increase competition; as a consequence the leading drug should lose market share.

Next we carry out a diagnostic test. The Hausman test for fixed versus random effects yields a chi-squared (2) value of 2.87 (prob>χ^2= 0.2383) for regression (c): the null hypothesis of the REM is not rejected, while the Haussman test for regression (d) yields a chi-squared value of 10.08 (prob>χ^2= 0.0065); the null hypothesis of the REM is rejected and hence the best estimation is given by the FEM model.

Table 14: Estimates of the logistic equation for the leading drug market share (total quantities)

Logistic equation	FEM Results (c)	REM Results (c)
(1/logsize)	24.20861**	10.31739**
	(9.64008)	(5.05445)
HHIq	1.57918**	1.56706***
	(0.62883)	(0.50651)
constant	-4.57660	-2.73208
	(1.26740)	(0.64345)

Number of Observations	164	164
Wald χ-sq (k)		21.53
Prob> χsq		0.0000
F	7.24	
Prob> F	0.0000	
R-sq overall	0.1624	0.1857

Table 15: Estimates of the logistic equation for the leading drug market share (total sales)

Logistic equation	FEM Results (d)	REM Results (d)
(1/logsize)	19.59320**	10.78396**
	(7.56990)	(4.55352)
HHIts	1.89960***	1.38461***
	(0.48740)	(0.44113)
constant	-4.19092	-2.89921
	(0.97628)	(0.58029)

Number of Observations	164	164
Wald χ-sq (k)		25.83
Prob> χsq		0.0000
F	15.10	
Prob> F	0.0000	
R-sq overall	0.0900	0.0828

*** Significance at p=0.01; ** significance at p=0.05;

* significance at p=0.10

So far we have four estimations for the market share of the leading drug panel considering the Hausman Test results. We sum up these results below.

Table 16: Summary of the Hausman Tests for the leading drug regressions

Model and LHS variable	Total quantities		Total sales	
	FEM	**REM**	**FEM**	**REM**
Market share equation		√		√
Logistic equation		√	√	

Note: it is considered the statistical significance at 1%

Market share of pharmacy-owned drug

We follow the same procedures as for the analysis of the leading drug, estimating the linear model and the logistic model to find the market share of both brands. In order not to repeat what we did for the leading drug step by step, all the results and interpretation tables, diagnostic tests and analysis are to be found in Annex 3.

Below we summarise the results obtained for the own-brand drug market share specifications.

Table 17: Hausman Tests Summary for the pharmacy-owned drug regressions

Model and LHS variable	Total quantities		Total sales	
	FEM	**REM**	**FEM**	**REM**
Specification (2): market share linear regression	√			√
Specification (3): logistic equation	√			√

Note: We consider statistical significance at 1%

The Hausman test results shown in Tables 16 and 17 indicate a coincidence in the leading drug and own-drug regressions: the REM estimation for the market-share specification measured by total sales. These results are as expected, given the nature of our dataset, and confirm the use of the technique (as justified in section 4.6) for our estimation methodology and its implication for our models. We therefore proceed to evaluate these two regressions using different diagnostic tests: we test for the presence of autocorrelation using the Wooldridge test and for heteroscedasticity with the Breusch and Pagan test to validate the REM for both regressions.

For the leading drug market share, the Wooldridge Test for autocorrelation in panel data yields a test $F(1, 40) = 1.724$ (Prob> F = 0.1966). The critical value in the F distribution table is 4.08, so the null hypothesis of no first-order autocorrelation is not rejected.

The Breusch and Pagan multiplier test for heteroscedasticity yields $\chi^2 = 168.42$ (prob>χ^2=0.000). The critical value in the χ^2 table is 3.84, so the null hypothesis of no heteroscedasticity is rejected.

For the own-brand regression, the Wooldridge test for autocorrelation in panel data yields a test; $F(1, 40) = 64.522$ (prob> F = 0.0000). The critical value in the F distribution table is 4.08, so the null hypothesis of no first-order autocorrelation is rejected. The Breusch and Pagan multiplier test for heteroscedasticty in the REM yields $\chi^2 = 189.70$ with a prob>$\chi^2 = 0.0000$, so the null hypothesis of no heteroscedasticity is rejected, so we go on to estimate the model using PCSE.

Estimates and results analysis for PCSE and REM models

The estimates are shown in the following table. We also present the REM results for comparison with the PCSE estimates.

Table 18: PCSE estimates of the market share linear regression for leading and pharmacy-owned drug

MSh (total sales)	Leading drug		Pharmacy-owned drug	
	PCSE	REM	PCSE	REM
logsize	-0.04040***	-0.02865**	0.00142	0.01073
	(0.00327)	(0.01605)	(0.00602)	(0.01875)
HHIts	0.03330	0.30306***	0.86905***	0.64674***
	(0.04131)	(0.08080)	(0.05897)	(0.08744)
constant	0.57429***	0.41834	-0.01202	-0.03056
	(0.02926)	(0.13582)	(0.05626)	(0.15682)
Number of Observations	164	164	164	164
Wald χ-sq (k)	175.82	28.35	689.04	61.47
Prob> χsq	0.0000	0.0000	0.0000	0.0000
R-sq overall	0.1344	0.1092	0.4314	0.4278

*** Significance at p=0.01; ** at p=0.05; and * at p=0.10

What do the coefficients imply about how market share interacts with market size and HHI?

According to the last table, the model that fits our dataset in a better way corresponds to the pharmacy-owned drug in both estimation techniques. The PCSE technique nevertheless increases the overall significance of both regressions measured by Wald χ^2 statistic and the value of R^2. The individual analysis follows below.

Market size: logsize variable

Looking at individual coefficients, the logsize is statistically significant for the leading drug regression, whereas this is not in the case for the own-brand drug using either technique. Similarly, the PCSE estimate is less sensitive than the REM estimate for the own brand. The opposite is true for the leading drug.

The opposite signs of the logsize coefficient for both drug regressions validate our hypothesis that this variable affects the leading drug and the competitive own-brand drug in different ways. Thus a bigger market encourages more competition with the leading drug losing market share, which is partially captured by the pharmacy-owned drug.

For the REM technique, the coefficients show that if the market size doubles the leading drug loses 2.8% market share and the own-brand market share increases by 1.07%. The PCSE logsize coefficient is more sensitive for the leading drug as the market share diminishes by 4% when the size doubles, whereas the own-brand drug only captures 0.1% of market share.

These results are consistent with our expectations and are similar to those of Bae (1997), Reiffen and Ward (2003) and Hollis (2005). Thus they validate the fact that market size is an important determinant of the success of a generic drug.

Degree of concentration (HHIts)

The positive sign of this coefficient for all the regressions confirms our expectation. It is also consistent with Saha *et al*'s (2006) findings, which show that the entry of new generics causes greater competition (HHIts goes down) and increases market share.

The HHIts coefficient for the leading drug regression, measured by PCSE, is now insignificant and much less sensitive than that of the REM model, while this coefficient is statistically significant at 1%

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for both own-brand regressions. Both coefficients are highly sensitive; however, the PCSE estimation increases the sensitivity in 20% respect to that of the REM technique.

The sum of the coefficients (HHIts) for both drugs according to PCSE and REM models deserves more attention. In effect, the sum of both coefficients for REM technique is equal to 0.3031+0.6467=0.9498, whereas it is 0.90235 for the PCSE. Thus when HHI increases by 10%, more than 90% of this higher degree of concentration is captured by only two brands, the leading and the own brand.

The HHIts coefficient is much higher for the own-brand drug. In the PCSE model, the coefficient is 0.87, which implies that if Δ^+ HHIts=0.1, 87% of this increase is captured by this brand whereas 3.3% goes to the leading drug. The values are more moderate for the REM technique, whose HHIts coefficient for the leading brand shows that it captures 30% of the higher degree of concentration whereas the own brand captures 64%.

Despite this difference, the high coefficient of the own brand is a clear demonstration that the power of the seller to induce demand in Chile lies mainly in expanding the sale of the pharmacy-owned drug, affecting the relative share of the leading drug when the market is more concentrated.

In the Davies equation, the sign and magnitude of this coefficient for the own-brand drug shows that the inequality in market share goes up with the degree of concentration increases. From the perspective of competition policy this is highly worrying, not only because sellers' opportunistic behaviour induces demand and changes patients' preferences, even in the case of prescribed drugs, but also because of the implications for the elimination of market competition and development in the long run.

Just as health policy is sensitive to what happens in the drugs market, the recent intervention by the authorities to include other retailers such as large-supermarkets, convenience stores and local stores in the sale of drugs is widely justified by our results; this policy should not only generate more competition but also bring to an end large pharmacies' opportunistic promotion of their own brands, as well as the existence of incentives to introduce new drugs.

4.8 Concluding remarks

With this research we have updated the literature in this field by investigating a highly liberalised market at the retailer level. Given the wealth and breadth of our dataset, we have constructed two quantitative models on relative prices and drugs market share (leading drugs and pharmacy-owned drugs). Our main results are outlined below.

For the model about relative price of the own brand and the leading drug $Pob_{i,t}/Pld_{i,t}$, our regression indicates that the degree of concentration in total sales measured by the Herfindahl Index (HHI) impacts negatively the relative prices, which is consistent with the findings obtained by Frank and Salkever (1997) and Reiffen and Ward (2003). In other words, we find that when the degree of concentration goes up the prices of the leading drug and the own brand go up by different percentages, $\Delta\%^{+}Pob_{i,t} < \Delta\%^{+}Pld_{i,t}$ and hence relative prices fall. One explanation for this is that the leading wholesaler has strong market power due to a low substitution and therefore can increase wholesale prices, and hence consumer prices, without negatively affecting demand. The higher concentration is also exploited by pharmacies by charging a higher margin.

This coefficient is reversed when we estimate the model for the original drug: when prices increase as a consequence of a more concentrated market, the difference in magnitude is higher for the own-brand drug, $\Delta\%^{+}Pob_{i,t} > \Delta\%^{+}Porig_{i,t}$. The mean of the logistic prices is lower for the original drug, which in turn means that $Pob_{i,t} \ll Porig_{i,t}$ and hence there is little roominess to increase the price of the original drug compared to an increasing of prices of the own-brand drug.

The size of the firm is also important in explaining the signs of the HHI coefficient. We strongly believe that the largest pharmacies have significant power in the Chilean market because they have not only 90% of the market share overall but their own-brand drugs also have a high market share due to demand induced by sellers.

The market size coefficient is also positive for all equations and statistically significant for our logistic equation, particularly for the generics model. We therefore think that this direct relationship means that a larger market encourages more firms (mainly generics) because of the low barriers to entry such as low legal barriers and low fixed costs. With greater competition, prices go down. On the other hand, as the pharmacy-owned drug is more cost-related in comparison to other drugs, its cost provides a long-term floor for the price of any generic drug. The price of the other drugs is therefore more elastic and hence drops on a bigger scale; as a result, the relative price increases. Frank and Salkever (1997) also use this argument to explain that the competition caused by a new generic drug results in a large decrease in the price of existing generics. Another possible reason, discussed earlier, for the drop in the price of generic drugs that accompanies the introduction of a new drug is Chile's weak regulations; when a commercially successful drug appears it is rapidly copied by rivals and the prices drop. Thus the leading drug can only maintain its initial market share for a short time.

In spite of this last argument, we believe that the price of the leading drug has a degree of rigidity with respect to that of the other drugs, so on average its price drops only marginally (*ceteris paribus*), which is consistent with the fact that the leading generic wholesaler takes advantage of its market power in the short term to apply a higher margin than its rivals, given a constant marginal cost. On the other hand, the results of the equations for the market share of total sales agree with our predictions. The model is more robust for the pharmacy-owned drug dataset.

Looking at the individual coefficients, the logsize is statistically significant for the leading drug regression but not for the own-brand drug.

The different signs of the logsize coefficient for both drug regressions validate our hypothesis that this variable affects the leading drug and the competitive drug (own brand drug) in opposite ways, which means that in practice both drugs behave as one identity: when the market share of the leading drug decreases, that of the own brand increases. For example, using the REM, the coefficients show that if the market size increases by 100% the leading drug loses 2.8% of its share in the new market while the own brand's market share increases by 1.07%. These results are consistent with our expectations

and go in the same direction as Bae (1997), Reiffen and Ward (2003) and Hollis's (2005) findings, validating the hypothesis that market size is an important determinant of the success of a generic drug, under the assumption of low fixed costs.

When we look at the impact of HHI on market share we obtain a surprising result: the sum of the coefficients is equal to 0.9498 in the REM, whereas it is 0.90235 in the PCSE, thus when the HHI increases by 10%, more than 90% of this higher concentration is captured by the leading brand and the own brand.

In terms of competition policy there are two matters for concern: the fact that sellers today induce demand for particular drugs and seek to change patients' preferences; and the sustainability of the markets in the long run given the implications of the coexistence of increasing numbers of competitors. Those arguments validate the recent reform that seeks to allow other retailers (such as large supermarkets, convenience stores and local stores) to sell drugs, which can positively affect the degree of competition and stop large pharmacies' opportunistic behaviour inducing demand for a specific (and mainly their own) brand.

However, we used an aggregate dataset, which means that we cannot identify the sales distribution per pharmacy. This can result in an additional problem in the case of the pharmacy's own brand because we are supposing that the own brands across pharmacies are completely homogenous.

Another important problem with our dataset is that it corresponds to a period during which the large pharmacies were involved in collusive behaviour to fix prices, and hence the prices of the brands analysed may be influenced by that behaviour.

Finally, our prices were constructed as average prices, which do not allow us to identify spot prices, including price cuts or any discounts over time. In addition, as the drugs are produced and sold in different strengths and formats we had to transform the data into a homogenous measurement in order to have a common unity, which could bias our results. This has been widely discussed in the literature due to the different impacts that a particular drug can have on different patients (See, for example,

Davis *et al, 2008)*, which in turn means that it is not the same a Pharmacological transformation than

a commercial classification as was discussed in section 4.4 (about "data").

Annex 1

Classes	Market Share leading drugs	
	Total quantities	**Total Sales**
1	Kitadol	Kitadol
2	Diclofenaco	Lertus
3	Trio-val	Trio-val
4	Dercos	Dercos
5	Neutrogena	Neovadiol
6	Liftactiv	Liftactiv
7	Aerious	Aerious
8	Xenical	Xenical
9	Abrilar	Abrilar
10	Dinaflex	Dinaflex
11	Clotrimazol	Fittig
12	Infor	Infor
13	Migranol	Migranol
14	Listerine	Listerine
15	Hipoglos	Hipoglos
16	Flemex	Flemex
17	Calorub	Dolorub
18	Elcal-d	Elcal-d
19	Disfruta	Disfruta
20	Ciruelax	Ciruelax
21	Polivitamin	Trivitana
22	Descong. Bufocar	Descong. Bufocar
23	Manteca Cacao	Manteca Cacao
24	Ensure	Ensure
25	Naturalist	Sacarina
26	Clearblue	Clearblue
27	Venastat	Daflon
28	Garden Light Cromo	Garden Light Cromo
29	Agua Oxigenada	Bialcol
30	Melipass	Melipass
31	Pharmaton	Pharmaton
32	Somazina	Somazina
33	Predual	Predual
34	Egogyn	Egogyn
35	Bilaxil	Bilaxil
36	Num-Zit	Num-Zit
37	Bbdent	Bbdent
38	Ezetrol	Ezetrol
39	Loperamida	Loperamida
40	PPG	PPG
41	Retinol	Retinol

Annex 2

Estimates of Logistic equation restrictive model for complete panel data, branded generic and original drugs.

(Panel-Corrected Standard Errors -PCSEs)

Logistic equation	PCSEs dataset	PCSEs leading generic	PCSEs original
HHIts	-0.85829***	-0.67077**	-1.14949***
	(0.27913)	(0.28350)	(0.39000)
Dsize	1.04378***	1.22641***	0.73205***
	(0.18097)	(0.35755)	(0.19990)
Dtype	0.36624***	-	-
	(0.09312)	-	-
constant	0.30779***	0.60940***	0.40143***
	(0.04471)	(0.07515)	(0.05380)
Number of Observations	244	157	87
Wald χ-sq (3)	38.13	23.99	18.58
Prob> χsq	0.0000	0.0000	0.0001
R-sq overall	0.0839	0.0738	0.0755

*** Significance at p=0.01; ** Significance at p=0.05

Annex 3: Pharmacy-owned drug market share regression

The linear equation

The estimates of the equation for the market share of the pharmacy-owned drug with different HHI are shown in the tables below.

In the quantity regression, the signs of the coefficients are the same and are as expected, except for the REM extensive regression (last column), where the signs are the opposite to our predictions and statistically insignificant even at 10%.

In the FEM extensive model the values are statistically insignificant even though the signs of the coefficients are consistent with our predictions.

The Hausman Test for the basic equation yields a chi-squared (2) value of 11.19 (prob>χ^2= 0.0037), so the null hypothesis of the REM is rejected and thus the FEM provides the best estimation, contrary our justification of the best technique given by REM for this pharmaceutical dataset in the estimation methodology section.

The Wald test for total sales market share model is significant for all regressions (p values=0.000). All coefficients are similar and consistent with our predictions. The contribution of the interaction term HHItssize is marginal with respect to the basic model.

The statistical significance of HHIts is high for all regressions, whereas the logsize is only significant for the FEM regressions.

The Haussman test yields a chi-squared value of 7.88 (prob>χ^2= 0.0194). With statistical significance at 1%, the null hypothesis of the REM is not rejected and hence REM provides the best estimation.

Estimates of the pharmacy-owned drug market share in terms of total quantities

MSh	FEM	FEM +interaction variable	REM	REM + interaction variable
logsize	0.05772**	0.04198	0.01418	-0.01750
	(0.02320)	(0.03539)	(0.01758)	(0.02840)
HHIq	0.39165***	0.10715	0.45959***	-0.17656
	(0.07564)	(0.48790)	(0.07151)	(0.45692)
HHIqsize	-	0.03903	-	0.08670
	-	(0.06611)	-	(0.06148)
constant	-0.32106*	-0.19947***	-0.00221	0.24343
	(0.18180)	(0.27506)	(0.144106)	(0.22518)
Number of Observations	164	164	164	164
Wald χ-sq (k)			41.39	43.67
Prob> χsq			0.0000	0.0000
F	15.95	10.69		
Prob> F	0.0000	0.0000		
R-sq overall	0.0578	0.0820	0.3188	0.3451

Estimates of the pharmacy-owned drug market share in terms of total sales

MSh	FEM	FEM + interaction variable	REM	REM + interaction variable
logsize	0.05943**	0.10334***	0.01073	0.02977
	(0.02927)	(0.03856)	(0.01875)	(0.02538)
HHIts	0.59310***	1.50086***	0.64674***	1.16036**
	(0.09418)	(0.53303)	(0.08744)	(0.47334)
HHItssize	-	-0.12646*	-	-0.07055
	-	(0.07311)	-	(0.06385)
constant	-0.39477*	-0.73277**	-0.03056	-0.17855
	(0.23384)	(0.30328)	(0.15682)	(0.20571)
Number of Observations	164	164	164	164
Wald χ-sq (k)			61.47	62.67
Prob> χsq			0.0000	0.0000
F	19.89	14.48		
Prob> F	0.0000	0.0000		
R-sq overall	0.2082	0.1001	0.4278	0.4396

*** Significance at p=0.01; ** at p=0.05; * at p=0.10

The logistic equation

The results of the logistic equation are shown in the tables below. The main conclusion obtained from the signs of the coefficients is that they are all consistent with our predictions except for the sign of (1/logsize) in the REM equation, which we proceed to exclude, preselecting the FEM equation for this specification even though this technique is not satisfactory for us.

Next, we check the results for total sale market share. The signs of the coefficient are those we posited and are significant for all regressions. The goodness of fit, measured by R^2, is higher in the REM model even though when it is measured by the F and χ^2 both are significant at 1%.

Given that the logistic regression results for total sales are consistent with our predictions for the two techniques, we proceed to the Hausman test. This yields a chi-squared value of 4.89 (prob>χ^2= 0.0866) and so the null hypothesis of the REM is not rejected at 1%.

Estimates of the logistic equation for the own-brand drug market share (total quantities)

Logistic equation	FEM Results	REM Results
(1/logsize)	-26.91546*	1.01874
	(15.47081)	(8.99756)
HHIq	1.21208	2.16923**
	(1.00917)	(0.86095)
constant	1.52316	-2.43842
	(2.03398)	(1.15662)

	FEM	REM
Number of Observations	164	164
Wald χ-sq (k)		7.46
Prob> χsq		0.0240
F	2.00	
Prob> F	0.1400	
R-sq overall	0.0317	0.1957

*** Significance at p=0.01; ** at p=0.05; * at p=0.10

Estimates of the logistic equation for the own-brand drug market share (total sales)

Logistic equation	FEM Results	REM Results
(1/logsize)	-19.62568*	-0.55473**
	(11.82757)	(8.00787)
HHIts	2.71174***	2.68703***
	(0.76154)	(0.70933)
constant	0.09113	-2.42921**
	(1.52539)	(1.03444)

Number of Observations	164	164
Wald χ-sq (k)		16.42
Prob> χsq		0.0003
F	6.56	
Prob> F	0.0020	
R-sq overall	0.0004	0.1469

*** Significance at p=0.01; ** at p=0.05; * at p=0.10

Chapter 5: Conclusions, limitations and recommendations

We have written three independent papers to understand the interaction between own brands that take the same name as the store and leading branded goods. The main results are explained in the following paragraphs.

The first paper theoretically models the entry of the own brand to the market through the backward vertical integration of an unbranded product of low quality, and then, it supposes that the retailer chooses the level of quality that maximizes its profits by selling it together with a high-quality branded good. As a consequence, the model expands the knowledge about how the own-brand goods affect the outcome of the large retailers, the manufacturers of the branded goods, and the consumers.

Under the first framework, the after integration solution shows that the impact on the price of the branded product is ambiguous as it depends on the values taken by the production cost and the products' inherent quality. When the own-brand production cost moves towards zero and the inherent quality of the own brand is greater than 25% of that of the branded good, the price goes up. In contrast, if the percentage is lower than 25% the own brand negatively affects the price of the branded good. The wholesale price of that label moves according to the same rules discussed. The model also shows that the quantity of the branded product always decreases after integration.

In the case of the retailer-owned brand the impact also varies depending on the values of the production cost and the products' inherent quality. That is, if production cost moves towards zero, the price falls if the own brand is a low quality label (takes any value in the range $[0, ¼]$) while the price goes up for any quality higher than that observed in the last range. In contrast when production cost moves towards the upper bound $(c \rightarrow ½)$ the price always goes down. The total quantity of the own brand increases after integration under the rule $c/s < 1/2$, between production cost and quality, and hence the market shre of this label goes up.

On the other hand, when the retailer decides the quality of its own brand (endogenous quality), the model points out that the growth of the variety of products that takes the name as the store has a more

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flexible quality-production cost restraint in comparison with that of the "vertical integration solution" where the retailer acts as a mere distributor selling an unbranded good of low quality. As a result, the retailers can expand the variety of own brands towards a greater variety of products. Our result validates the opinion of The Institute of European and Comparative Law (2008), which sustains that the own-brands can grow until an average structural upper boundary of a 45% market share.

In spite of its expansion, the most competitive manufacturers can enjoy a dominant position by producing goods that the retailer could only produce inefficiently.

In terms of the branded product, we observe that the impact of higher inherent quality of the retailer-owned brand negatively affects the price of the branded good, as both labels become close substitutes for each other in comparison to the initial situation where the quality of the own brand was exogenous (high differentiation). This means that the degree of competition increases with the quality of the own brand. The model also shows that the total production of the branded good is not altered, which can be explained by the argument that this brand is demanded by consumers with high willingness to pay for it. In the same way, the model shows that the wholesale price decreases and hence the manufacturer's profit always falls as the quality of the own brand rises, consistent with the argument that the retailer improves its negotiation capacity with the private manufacturer when it sells an own brand that is a close substitute for the manufacturer's label, which always forces the wholesale price of the branded product down.

The fact that the retailer defines the quality of its own brand could positively impact its price by 50%, which is explained by its higher quality for a constant production cost.

Alternative explanations about why a retailer gives its name to a brand must also be sought in other areas. One of these reasons discussed in chapter 2 is that the retailer sells different own brands with different qualities in order to serve consumers with different tastes. At the same time, this strategy also avoids that consumers associate the quality of these goods with reputation, and hence it is part of a strategy to segment the market.

We also believe that the findings of Berges-Sennou (2004, 2006) are important to back up our finding, who argue that the launching of the retailer-owned brands not only strengthens brand competition, but competition amongst retailers (horizontal differentiation), which in turn means that the seller uses these brands to gain a greater market share, or to satisfy consumers that prefer to buy goods in one place. The latter argument is relevant when the retailer has a big proportion of loyal consumers. For switching consumers, this strategy is also important since the retailer can satisfy different types of consumers (Berges-Sennou, 2006) and attract them to its stores. Another alternative is given by the argument made by Gabrielsen *et al* (2007), who have pointed out that low quality goods are used to impose unilateral contracts or some restraints on manufacturers.

A limitation of our model that should be considered for future research is that we modelled assuming linear price contracts, which can be unrealistic in the sense that slotting allowances are common in the retailer industry. As we affirm at the end of this paper, we believe that the assumption used does not invalidate our results as Gabrielsen *et al* (2007) argue that the introduction of the own brand goes in the same direction as the slotting allowance, and hence the final effect is the same. The assumption about the monopolist retailer can be discussed as well, however we believe that in small markets, it is possible to observe this type of structure. When we tried to expand the model by considering other retailers and other goods, it was difficult to manipulate the equation due to complex equations.

The other two papers are of quantitative analysis. The first is about large supermarkets in the UK, and the other one is about large pharmacies.

First, we constructed our own database for ***the UK supermarket*** in order to analyse the interaction between the supermarket-owned brands and the branded products for a basket of 19 products sold by the four large supermarkets (Asda, Morrisons, Sainsburys and Tesco). The dataset was collected over 40 weeks from October 2 2008 to Thursday July 2 2009.

We used panel data techniques to look at the determinants of the relative price of the own brand and the branded good, the product allocation on the shelves, and a log-model about the number of brands they sell.

The estimates of the relative price model found positive coefficients for the independent variables: time trend, number of manufacturing firms (degree of competition), abnormal price cuts (discounts) and dummy variables to control differences in the development of own brands and pricing in each supermarket. We also included interaction variables between our variables, which marginally improved the fit of our regressions. The coefficients estimated to measure "Supermarket specific effects" show that three supermarkets differ from Tesco, Asda being the closest one, as was predicted. A contradictory finding is related to the difference between Morrison and Sainsbury's. The Morrison coefficient is almost twice as high as the Sainsbury's coefficient, which is contrary to our hypothesis of similarity between both firms. It is likely that the explanation behind this finding is given by prices of the own brands rather than prices of the branded good, since we think that Morrison's own brands have a higher quality due to its historical expertise in producing high quality goods.

Comparisons between our model and the existing literature must be made carefully, as the models are different and the timing is associated to short term competition, which differs from the literature, which in general, uses monthly or quarterly data.

The second model aimed to determine *the product allocation on the shelves*. We used models for the discrete dependent variable estimated (Logit and Probit models). We assumed that the supermarkets target the leading brand to influence the consumers purchase decisions, following a paper by Sayman *et al* (2002). The high mean of our discrete variable (0.5796) validates the Sayman *et al*'s view.

According to our knowledge this model is a pioneer in this area because there is no public information about product allocation on the shelves, which discourages investigation about this issue.

The best model estimated was by Probit Modeling, due to a lower number of predicted values out of range [0, 1] in comparison to those obtained by the Logit Model. The finding validates our predictions in the sense that there is a negative relationship between the number of brands and the joint allocation of the products. As a result, when there is a marginal increase in the number of firms, the probability to put the goods together drops by 7.31%. Secondly, the model also shows that when there is a discount, the odds are 71.53% smaller.

We want to point out that these findings are restrictive to make inference about supermarket behaviour because they are based on a very limited number of products (19) the supermarkets sell, and hence we estimate that following this model is perfectly replicable to test other products categories.

Second, we work with a ***Chilean dataset about large pharmacies***. The Chilean market is attractive for research because it is different to others, mainly because it is highly liberalized due to low barriers to introduce new drugs into a highly concentrated pharmacy market framework. Under this panorama, the sellers induce demand for drugs, which has been considered by the competition authorities as an abuse of market dominance. We believe that our results validate this issue, and hence they are a significant contribution to support the apprehension of the local authorities.

To understand how their brands interact with the branded drugs we estimated two models, one for relative prices and another for market share. In order to do that we had real micro-data, that was provided by a friendly wholesaler.

We proceeded to work with a dataset of 41 commercial categories, where we identified 41 leading generics and 23 original drugs that corresponds to each second quarter in the period 2007-2010 (four quarters).

In our pricing model, the relative price between the own generic and the leading drugs (original and branded generic) is affected negatively by the degree of concentration (measured by the Herfindahl Index, HHI) and positively by market size. However, in the case of the original drug regression, when HHI goes up, the relative price decreases, which implies that the increase in own brand price is higher than that of the original drug. Thus we sustain that there are differences in magnitude that can explain such impacts, which are caused by the interaction of highly concentrated markets at the retailer level and a high number of generics due to low barriers to enter the market, that impact the variation in the price of drugs in different way.

The market share regressions show a contrasting relationship between market share and market size, which is consistent with previous research. When the market size goes up, the leading drug loses market share, whereas the own brand increases its market share, thus they behave as an identity. On the other hand, the degree of concentration (HHI) positively impacts the market share of both drugs.

At the end of this paper we discuss the implication of our results for the competition policy, as they are consistent with the way in which they operate. As we commented before, these pharmacies have been punished by the local authorities due to collusive behaviour s in order to fix prices. If we add the paternalistic (or abusive) way used to deviate demand, and hence the negative impact on social welfare, we validate the reforms proposed by the Chilean government to increase the degree of competition.

Three important limitations of this research are related with data. First, we used an aggregate dataset, which means that we cannot identify the sales distribution per pharmacy. This can result in an additional problem in the case of the pharmacy's own brand because we are supposing that the own brands across pharmacies are completely homogenous. Second, the dataset corresponds to a period during which the large pharmacies were involved in collusive behaviour to fix prices, and hence the prices of the brands analysed may be influenced by that behaviour. Finally, our prices were constructed as average prices, which do not allow us to identify spot prices, including price cuts or any discounts over time. In addition, as the drugs are produced and sold in different strengths and formats we had to transform the data into a homogenous measurement in order to have a common unity, which could bias our results.

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