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The interaction between leading drugs and pharmacy-owned labels in Chile

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Abstract: In this paper, a data panel technique to estimate a model of relative prices between large pharmacy-owned drugs and leading drugs was used. Under the assumption that dominant firm market share increases by 10%, and the other 2 (smaller ones) loss 5%, the relative prices diminish by –0.043%. The market size impacts positively (18.5%) the relative prices, implying that a larger market size the entry of more brands is encouraged, and then more competition and lower prices will be observed. This impacts the owned-brand price, which means that the leading drug price has a high degree of rigidity. For the drug specific effect – measures the drug that is targeted, the original or the leading generic – to commercialise its own brand, if the pharmacy targets the leading generic the variation of relative price between the own-brand drug and leading generic is 0.5267; which means that the owned-brand drug margin increases.

Keywords: drug markets; generic pharmaceuticals; microeconomics; competition.

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1 Introduction

It is recognised that the pharmaceutical market is characterised by a complex and asymmetric interrelationship among physicians, patients, insurance providers and reimbursement systems (Davies and Lyons, 2008, Kim, 2009). The system may be more complex when the retailer industry lacks competition and is characterised by abusive behaviours of sellers against consumers.

The price setting framework is diverse across countries. There are some operating under strongly liberalised structures, such as Canada and Chile, whereas there are others with price regulation schemes based on an upper boundary in term of profits the UK or price ceilings such as Australia and Germany (Eudrabook, 2015). Davies et al. (2008) also highlight that each European country has a different system of regulation and coverage of pharmaceuticals and differences in how the drugs are sold to hospitals and domestic consumers.

The Chilean market differs from the others mainly in three areas:

1 the therapeutic and commercial classification of the drugs

2 a liberalised system of commercialisation characterised by low barriers to introduce new drugs in a framework of a highly concentrated pharmacies market

3 a weak healthcare and reimbursement system, which implies that the medical expenses are mainly paid by the patients.

This scenario has impacted the price setting scheme in the following aspects.

First, despite a fierce race for the launch of new brands by wholesalers, the drugs average price is considered high due to the low competition among large pharmacies according to the competition agency (FNE, 2020).

Secondly, to control medical spending, the patients tend to self-medicate or follow the advice given by the seller of the pharmacy, who usually induce the purchase of the drug as a function of the premium gained for a specific brand by the pharmacy (Minsal, 2010, 2013). As a particular result of this opportunistic behaviour, it has also induced and impacted positively the entry of the large pharmacies-owned drugs, which have -in some cases- the same name as the store.

Thirdly, there is a large price dispersion caused, among others, by promotions, discounts for specific groups, different transportation costs per geographic zone and advertising costs (up to 20% total costs), which has been ratified by the authorities.

Fourthly, the three large pharmacies (80% market share in 2020) have also been punished by local authorities for collusive behaviours to fix prices (FNE, 2020), which

were ratified by the Chilean Supreme Court in 2013. This behaviour has motivated the authorities to launch different reforms to ensure low prices, such as the fixed prices strategy undertaken by a public agency.

So far, the literature is extensive respect to the entry of generics, impact evaluation of some institutional restrictions such as price regulations, hospital provision, and so on Examples are given by Reifen and Ward (2005), Terrizzi and Meyerhoefer (2020) – both with US data; Granlund and Bergman (2018) for Sweden and Izhak (2019), for Finland. On the opposite, according to our knowledge there is few research considering low regulation markets, highlighting the contribution of Balmaceda et al. (2015) and Atal et al. (2018) for the Chilean market. No more papers have been published so far.

As a result, the main motivation to carry out this research is to analyse how the prices of the pharmacies-owned brands and leading drugs (leading generics or original brands) interact in Chile. To answer this question, we estimate a pricing model by using econometric analysis models with panel data. The econometric estimation extends the literature with a new multivariable model considering a highly concentrated industry.

The paper is innovative as the dataset is not available from public sources with this level of detailed as the quantitate information used here is strategic for a firm. According to our knowledge, OECD and World Bank only publish information about health expenditure, life expectancy, population coverage and financial protection, number of doctors and nurses and so on (see for example OECD, 2021). In other words, they do not collect information with the level of detail we have, this is, therapeutical categories, number of brands, types of packaging the pharmaceutical laboratories use, among others.

As a result, the main contributions of this research are related to the detailed and specific data we have, and the model constructed from it.

2 The Chilean market

Unlike developed countries, the industry is ruled by a weak regulation to introduce and commercialise new drugs as well as some legal restrictions to sell medicines by pharmacies or other type of retailers. Only in 2008, the authority introduced a law to certify bioequivalence for generics, which has impacted the market in terms of the number of brands, market share and prices. In fact, according to the competition agency during the period 2015-2018, bioequivalent drugs had 80% market share. In spite of this policy, in 2020 the competition authority (FNE, 2020) criticised the way in which the authority rules out the regulation mainly by administrative issues such as, the lack of updated public information of the market, poor property right law to protect the entry of new brands, particularly innovative drugs.

The classification of the drugs is done according to two criteria: from the demand side and the origin (supply side). The first classification divides the drugs into three groups, direct sale drugs (over the counter, OTC), ethic drugs, which are prescribed by a physician, and intermediation drugs (demanded by health institutions). The second classification splits them into three groups, brand name drugs (original or patented), branded generics (with fantasy names) and unbranded generics. The pharmacy-owned brands fall into the second classification.

According to our knowledge, disaggregated information about the market share of different type drugs is not public for the period after 2015, which is consistent with the

way that works the Chilean market, as the information with this level of detail is not publicly available.

In fact, the competition authority (FNE) took more than 1 year to collect this information in the framework of an investigation for anticompetitive practices, which, however, is limited only to dominant brands, different from what is shown in the Table 1, where that information is more detailed (original, branded generics, brand name – patented and brand name- and unbranded generics. Anyway, FNE information shows that the branded drugs have a dominant position by total revenue -more than 90% of the market share for 2015–2019, and their physical unit market share reached around 70%, values consistent with the observed percentages above.

The available information detailed in the same classification used in this research is shown in Table 1.

Table 1 Average prices and market share according to the type of drug (2008–2012)

Classification	*Physical units market share*		*Total revenue market share*		*Average price (US$)*		
	2008	*2012*	*2008*	*2012*	*2002*	*2008*	*2012*
Original	19.1	20.6	53.1	41.3	5.96	10	12.46
Branded generics	44.6	50.9	41.0	53.5	3.86	5.65	7.48
Brand name drugs (patented + brand name)	63.7	71.5	94.1	94.8	-	-	-
Unbranded generics	36.2	28.5	5.9	5.5	0.59	0.78	1.16

Source: Minsal (2010, 2013)

On the other hand, the barriers to entry are low in comparison with those observed in Europe and US, which encourages wholesalers to introduce branded generics. The regulator has 90 days to approve the entry a new drug whereas the time between, the initial application and the approval, reaches 19 months in the US (Berger and Karst, 2017; OECD, 2019).

The social security system is based on a partial coverage and marginal reimbursement scheme, which means that most patients must cover the drugs cost themselves. According to OECD (2019), the total drugs expenditure in relation to health spending reached 18.3% in Japan, 16,2% in Canada, 15.3% in Spain and 12% in USA. In Latin America, Chile is in the middle with 17.3% whereas the percentage is 6.6% in Uruguay and 26.2% in Argentina.

From the consumer side, there is an abundant literature (Minsal, 2010, 2013) that discusses the particularities of the Chilean pharmacies to sell drugs. In effect, the large chains usually encourage their sellers to influence the purchase decision, inducing the demand of the high margin brands, even in cases where the physician prescribes other drugs (studied by Izhak (2019) for Finland as well). According to local law, when a physician prescribes a branded generic, the seller must sell that brand, whereas if they prescribe a generic, the seller can sell whatever drug that satisfies the medical prescription. Recently the authority informed that 85% sales require medical prescription and 18% are direct sales.

3 Literature review

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 the high cost of the healthcare system. In this context, most research is carried out with US market data. Good examples are Frank and Salkever (1997), Reiffen and Ward (2005), Saha et al. (2006) and Terrizzi and Meyerhoefer (2020), mainly addressed to answer two questions. What are the determinants of entry? How does the entry of generic drugs affect the original drug price, its market share and the degree of competition? With the expiration of patents of brand name drugs and some changes in the institutional health system (insurances, new price and bioequivalence regulation law) from the nineties, the empirical research has expanded towards other countries such as Canada, Japan, Spain and Sweden. Good examples are, Hollis (2005), Ayadi et al. (2008), Iizuka (2009) and Kim (2009). Granlund and Bergman (2018) also highlights in the last years with Swedish data. In Chile, papers by Balmaceda et al (2015) and Atal et al (2018) are strongly related to. A brief summary of these papers will be discussed in order to get information to develop a model for the data and have a strong theoretical framework.

Using a panel data technique of an the US dataset of 32 drugs that lost protection during the early eighties Frank and Salkever (1997) investigate the impact of generic entry on prices (generic and brand-name drugs). They estimate three models through fixed effect (2) and random effect. They construct a price column after transforming all items belonging to one category in a basic unity of measurement. The main finding shows that the brand-drug price rises after entry, which is accompanied by large decreases in the price of generic drugs. The net effect is a reduction in the average price of prescription for an off-patent drug. This is consistent with a consumer segmentation policy according to price-sensitivity.

Reiffen and Wards's (2005) motivation is to understand how the institutional and regulatory features affect the degree of competition in the US pharmaceutical industry. The dataset is formed by 31 drugs with monthly data for three years.

The main specification uses as a dependent variable the relative price between 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 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 10 or more competitors.

Saha et al. (2006) develop a simultaneous equations model to deal with the interaction between generic entry, price of generic drugs and market share in the US. The estimates are based on a panel dataset of 40 brand-name drugs with monthly data (July 1992, January 1998). The drugs belong to nine therapeutic classes and are produced by 20 manufacturers. The theoretical contributions of this work were the discussions about the endogeneity of the variables – entry, market share and prices-, and the use of the OLS technique to estimate regressions in this field, which yields and invalidate some inferences obtained by the research earlier about the determinants of generic competition. The most important result is given by the negative influence of generic entry on the prices ratio between generics and branded drug than go down continuously. This finding is opposite to most research carried out with the same data but different statistic methodology (Frank and Salkever, 1997).

Following this methodology, Ayadi et al (2008) applied this model with data from Tunisia. The aim was to analyse the pre-reform period of the insurance system. The dataset included 20 quarters between 2002 and 2007. This accounts for three molecules that produce nine brands (three brand names and six generics with different strengths and forms). In contrast with 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 of 31 drugs (1995–1999) sold by nine provinces and over 500 markets in Canada, Hollis (2005) focuses on the price of generic drugs that are produced by a brand name drug firm (also called 'authorised generics' or 'pseudo-generic drugs') to compete against independent generics, under the hypothesis that the entry should push the prices down because of more competition. In this country, 34.6% of the market is captured by 'pseudo-generic drugs'.

A common finding is given by 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.

Granlund and Bergman (2018) focused on measuring impact on generic prices caused by the entry of a generic using different formats such as, package size, form, or strength, which also is incorporated as independent variables in our models. They use the panel data technique, considering 1303 active substance. The main findings showed that the prices went down through different length of time depending on the substance analysed.

A paper related with the power of the pharmacist to induce demand was written by Izhak (2019) with data form Finland (like what happen in Chile). She evaluates the probability of substitution of a prescribed drug by the seller considering patients` out of pocket costs. One of her findings offer evidence that pharmacists incentives are instrumental for prescription drug cost savings.

According to our knowledge, the last paper similar than we write is due to Terrizzi et al. (2020). Using data of Prozac (antidepressant) and Zocor (control bad cholesterol), they estimate price elasticity of switching from branded to generic brands. The results show that both drugs are inelastic varying between 0.01 and 0.10.

On the other hand, there are two papers regarding this topic for the Chilean market in the last years, Balmaceda et al. (2015) and Atal et al. (2018).

Balmaceda et al. (2015) investigated the impact on prices of the bioequivalence policy. They used a dataset of 30 chronic use drugs. It was used multiple regression with prices as dependent variable and a variable to measure the entry of a bioequivalent. The main findings point out different impact on prices depending on the category analysed, which is associated to the characteristics of each market. For example, for glibenclamide and metformin drugs prices decrease whereas for fluoxetine and carvedilol, prices increase.

The second paper estimates the effects of quality regulation on market structure because of the bioequivalence policy introduced in 2008. The main findings of this research show that the bioequivalence requirement impacted negatively the number of drug products by 25%. The average drug prices went down by 10%. Finally, they show that the regulation modified sales from branded generics to innovator drugs, whereas total sales volume diminished by 20%. They affirm that any direct effect of increased price competition because of decreased scope for quality differentiation was overturned by indirect adverse effects to competition caused by drug exit.

Summing up, 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). Other models use as a dependent variable the price of either the brand name, generic drugs, or relative price between brands. These models use on the RHS, market share, the number of generic or brand name drugs, particular chemical characteristic of the drugs and institutional features of the health system.

4 Data

The dataset includes 39 categories of drugs sold by large pharmacies organised by commercial criteria, which was provided by a friendly wholesaler firm, who rejected to update the data because the Chilean competition authority is permanently investigating this industry for anticompetitive behaviour.

Chilean drugs wholesalers administrated jointly the distribution of drugs to large pharmacies for long years. This vertically integrated and centralised mechanism to control the market by wholesalers and large pharmacies was based on an on-line system which was diary filled out by chains. The idea was to control the consumer prices, the wholesaler prices and the inventories of the chains and wholesalers.

The dataset contains qualitative and quantitative information in aggregated terms, as a result it is not possible to identify sales by pharmacy.

The original dataset is expressed by total revenue (Chilean currency) and the number of products commercialised (physical quantity), that corresponds to each second quarter of the period 2012–2015. In summary, the data considers 39 commercial categories with information from four quarters, which will be transformed to therapeutic categories.

The drugs are ordered by different formats that correspond to strength/form combinations in which they are sold. A drug is formed by a family of products made from an active ingredient that can include either syrup, tablets, capsules, or pills of different doses, packed or bottled in different sizes.

As most research uses therapeutic categories in their models (Saha et al., 2006), it is used the same classification. To satisfy this, a practitioner redefined five commercial categories. Iizuka (2009) and Kim (2009) made the same work arguing that the drugs are differentiated even though they may be grouped within a same category.

After looking for groups that share similar mechanisms of action and have similar chemical structure within a category, the practitioner identified and separated the drugs belonging to five categories introducing six new groups (Analgesics – steroidal and non-steroidal anti-inflammatories, dermatological products – hair loss, skin and wrinkles – expectorants, anti-migraine products and respiratory drugs -with and without codeine). As a result, dataset is formed by 41 commercial categories, 38 originals plus three derived from the dermatological groups (See Annex 1).

After this step, it was paid attention to the existence of the original brand within each category. The identification and separation between an original and the generics were made by a member of the Chilean Pharmacist Association. As a result, there are 23 categories in which coexist the original drug and generics. To validate this information, the information was checked with that published by the local regulator.

On the other hand, following to Reiffen et al. (2003) the research was focused on brands with at least 2% of sales market share.

As a drug may be sold in different formats (strength/form combinations), it is identified the leading format of the leading brand and asked the pharmacist to transform the remaining products in a basic unit. It was carried out using therapeutic and physical criteria in such a way that the comparison is consistent across products and brands. The same methodology was also used to transform the leading generic, the original drug and the pharmacy-owned brand. Each format was also transformed to the unit of the leading product format.

Now, it was calculated the average drug price from the ratio of total revenue and total quantities. Thelimitation of constructing a variable by using average price is that this is not captured spot-prices. This transformation is widely accepted by researchers because this allows the grouping of the drugs in a straightforward way to analyse the degree of competition across formats and brands. The disadvantage is that researchers assume that drugs are homogeneous (low differentiation), and hence they are perfectly comparable in both medical (treatment or therapeutic uses) and economic terms (market limits and pricing schemes), which is refused by the technical literature because of different size effects and efficacies of one drug for different patients.

In summary, the adjusted dataset includes 41 therapeutic groups of drugs with detailed information about the branded generics, the original drug, and the retailer-owned drug. 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. The data is heterogeneous in terms of market size, prices and quantities sold.

5 Model specification

As the main motivation is related to the understanding of how the pharmacy-owned drugs interact in the markets, the model specifications differ from others, which focus on how the entry of generics impacts the original drug.

It is constructed one general equation for pricing with different specifications by considering partially five papers: Frank and Salkever, 1997, Reiffen et al., 2003, Hollis, 2005, Kim, 2009, and Granlund and Bergman, 2018. It is also considered Saha et al. (2006) because of potential problems caused by endogenous variables of our explanatory variables.

5.1 The model

The endogenous variable is the relative prices $\left(\sqrt{\text{Pob}_{i,t}}\,/\,\sqrt{\text{Pld}_{i,t}}\right)$ between the pharmacy-owned brand $\sqrt{\text{Pob}_{i,t}}$ and the leading drug $\sqrt{\text{Pld}_{i,t}}$. The unbranded generic because the market share was lower than 2%. The extensive equation initially includes five explanatory variables from the offer side. They are:

The Herfindahl Index (HHI), to control the degree of market concentration measured in total quantities and total sales.

$$\mathbf{HHIq_{i,t}} = \left\{\sum\nolimits_{j=1}^{n} (\mathbf{Sq_j})^2\right\}_{i,t} \qquad \textbf{(Total quantities)}$$

$Sq_j = q_j/TQ_{i,t}$ is the total quantities market share of the drug j belonging to the class i; q_j is the total quantities sold of the drug j belonging to the class i in the period t (1,…,4) and $TQ_{i,t} = \left(\sum_{j=1}^{n} q_j\right)_{i,t}$ is the total quantities of the class i in the period t.

The HHI in term of total sales is as follows:

$$\mathbf{HHIts_{i,t}} = \left\{\sum_{\mathbf{j=1}}^{\mathbf{n}} \mathbf{(Sts_j)^2}\right\}_{\mathbf{i,t}} \quad \mathbf{(Total\ sales)}$$

$Sts_j = (ts_j/TS_{i,t})$ is the total sales market share of the drug j belonging to the class i; ts_j is the total sales sold of the drug j belonging to the class i in the period t (1, …4) and $TS_{i,t} = \left(\sum_{j=1}^{n} ts_j\right)_{i,t}$ is the total sales of the class i in the period t.

The remaining variables are total sales to control for the market size measured in constant local currency, and 3 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 one controls the type of drug analysed (leading branded drug or the original drug).

The expectations about the relationship between the relative prices and the explanatory variables are:

5.2 Market concentration (HHI Index)

It is expected that the pharmacies and leading wholesalers set prices depending on the degree of concentration of each therapeutic category. It will be discussed the meaning of the HHI following to Davies (1978).

This approach defines the Index as HHI= $[(1 + cv^2)/n]$, where 'cv' is the coefficient of variation squared and 'n' the number of firms, cv is a pure measure of inequality in market shares. HHI can actually be interpreted as the extent to which the leader is much bigger than the other firms and hence behind H is the 'dominance' of the leader.

One of the main impacts observed for a high HHI categories is the existence of a dominant brand that conveys countervailing power against the leading pharmacies. Consequently, the wholesalers can achieve a higher wholesale price, which in turn means a higher consumer price $\sqrt{Pld_{i,t}}$. As a result, it is expected that the degree of concentration negatively impacts the relative prices $\sqrt{Pob_{i,t}}/\sqrt{Pld_{i,t}}$ and hence, the higher the HHI, the lower the relative prices will be (ceteris paribus)

The last argument deserves a deeper discussion as the chains can also take advantage by charging higher prices for the own brands without affecting negatively their demand (due to the induction of purchase observed commonly in the local market). Thus, there are two effects impacting the drug prices in the same direction.

Which effect dominates the final relative price? The impact on the leading brands to be higher as there is a double marginalisation effect given by the wholesaler and the pharmacy pricing. Thus, it is posited a negative relationship between HHI and relative prices $\sqrt{Pob_{i,t}}/\sqrt{Pld_{i,t}}$.

It is highlighted that HHI can be an endogenous variable in the relative prices specification, under the assumption that if the drug price goes down, the quantity demanded should increase as a result the market changes then HHI varies.

5.3 Market size

This variable is statistically relevant for Reiffen et al. (2003) and Hollis (2005), who argue that the market size determines the potential success of the generic drugs.

The leading wholesalers produce low substitution drug for both the practitioners and inelastic consumers because of its proven therapeutic properties and reputation. There is abundant literature highlighting that practitioners continue prescribing remedies based strongly on custom, which is explained by the mistrustfulness on the quality or therapeutic equivalence of the generics. It is reinforced because practitioners do not have direct pecuniary incentives to prescribe less expensive generic products and nor are they sensitive to the drug price.

For these reasons, it is sustained that given that the leading wholesaler is a price-setting firm, it takes advantage of the size of the market by serving the patients with the higher willingness to pay for a drug, and thus, when the market is larger, the price of these drugs increases (ceteris paribus).

In the case of competitive generics the larger market size impacts moreover negatively the drug price. For the own brand the other element that would justify lower prices is that the final price involves just one marginalisation.

As a result, the relative prices / , there are two effects operating in the same negative direction and hence, the higher the market size, the lower the relative prices.`

5.4 Prescribed drugs by physicians

It is considered a dummy variable **Dpres** to differentiate the drugs prescribed by a physician from those sold without the need of a medical prescription. As the first has low substitution in the markets this affects the prescribed drugs by increasing their prices. We then posit that the relative prices ratio $\left(\sqrt{\text{Pob}_{i,t}}/\sqrt{\text{Pld}_{i,t}}\right)$ is negatively related to this dummy.

5.5 Difference in cost

It is included a dummy variable **Dsyrup** to control differences in cost given by the way in which the drugs are commercialised (syrup, tablets, pills, capsules). It is assumed that syrup (Antihistamine and Brain and Peripheral nerve) has a higher overall cost due to the production and storage costs in comparison to the others, which should increase its final price. This variable is considered as a proxy variable to measure the differentiation across drugs.

5.6 Type of drug

A dummy variable is included to identify ‘the drug specific effect’ (called **Dtype**), to measure the drug that is targeted by the pharmacy to commercialise its own brand. As a

result, the dummy takes the value one if the pharmacy targets the leading generic or 0 the original drug. Thus, if Dtype = 1 the relative prices go up.

Summing up, it is posited initially the following model:

$$\begin{aligned} \text{Log}\{\pi_{i,t}/1-\pi_{i,t}\} = \alpha + \beta_1 HHI_{i,t} + \beta_2 \text{logsize}_{i,t} \\ + \beta_3 \text{Dpres}_{i,t} + \beta_4 \text{Dsyrup}_{i,t} \\ + \beta_5 \text{Dtype}_{i,t} + \varepsilon_{it} \end{aligned} \quad (1)$$

where i represents the drug group (pharmaceutical category), group (or drug category) i = 1,…,64 and t the period, t = 1,…,4. The variables are:

On the left side, the logistic equation Log $\{\pi_{i,t}/ (1-\pi_{i,t})\}$, where $\pi_{i,t} = \text{Pob}_{i,t}/\text{Pld}_{i,t}$,: ratio of average prices between the own-brand drug and the leading drug per category. The logistic transformation is used to prevent negative and outliers (see Saha et al., 2006).

$HHI_{i,t}$ the HHI to measure the market concentration in term of both total quantity $HHIq_{i,t}$ and total sale $HHIts_{i,t}$.

$\text{logsize}_{i,t}$ the log of the total sale per therapeutic class in the period t.

$\text{Dpres}_{i,t}$ dummy variable such that one is a medical prescription drug and 0 a direct sale drug

$\text{Dsyrup}_{i,t}$ dummy variable such that one is a drug packaged and sold in the form of a syrup and 0 others.

$\text{Dtype}_{i,t}$ 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.

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

6 Estimation methodology and its implication for our models

Methodologically speaking, the models vary from panel data (which is used in this research) to time series regression (few). The decision depends on the aim of the research and the characteristic of the data. In the same way, a common 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)

In relation to Panel Data, common techniques to analyse the impact on prices are given by random effect model (Reiffen et al., 2003; Saha et al., 2006) and fixed effect model (Frank and Salkever, 1997) under the assumption that the therapeutic categories are different in term of their medical complexity, market size and volume of sales, the barriers to entry and the distribution of generics and original drugs existent per category.

In our case, it is used the REM technique to estimate the models because of different degree of concentration of each category as there are drug categories highly competitive and other highly concentrated, which could explain for the existence of other type of entry barriers in each drug category. It is assumed the existence of unobserved heterogeneity and hence this is uncorrelated with the explanatory variables. Before estimating by REM, it is also tested by the pooling assumption and FEM technique to compare the consistency of the predictions.

In the pooling assumption therefore, it is assumed that the size of the true effects does not differ across drugs, which could be explained because of the low legal barrier. However, if is not so, the pooled coefficients do not provide reliable estimates of individual categories and hence the pooled coefficients may not even consistently estimate for the average drug.

Next, it is proceeded to check for heteroscedasticity and autocorrelation (Breusch and Pagan and Wooldridge Test respectively). Most research about panel data with heteroscedasticy 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. This technique assures statistics test more powerful if there are more cross-sectional units than number of periods, which is a characteristic of our dataset. This model also produces accurate standard error estimates.

Because our data-set considers heterogeneous drugs, the presence of heteroscedasticity is highly likely, even though it is not an important problem for a short panel. Anyway, in some point we will relax to allow heteroscedasticity by using cluster-robust inference.

The case of Autocorrelation could also be caused by a model misspecification, which yields less efficient results because of biased standard errors.

7 Results

7.1 Descriptive statistics

It is shown in this section the statistical summary of the dataset. To compare the values between the leading generic (group 1) and the original drug (group 2), it is shown the dataset disaggregated by these groups. The main variables of panel nature are shown below.

The first point pointed out is that the observations size of each group is different. Even though the number of observations is low for estimating the original drug regression, it is believed that the number is sufficient to get a good estimation.

It is observed that the mean of log $Pob_{i,t}/Pld_{i,t}$ is higher for the leading generic (lg) in comparison to the original (orig) drug [$Pob_{i,t}/Plg_{i,t} > Pob_{i,t}/Porig_{i,t}$], thus $Porig_{i,t} > Plg_{i,t}$ is consistent with the initial expectation.

HHI measured by total quantities has a higher mean and Std Dev in comparison to the Index measured by total sales, which would indicate that the 'price effect' associated to the product of (pq) is low in comparison to the quantity effect. By making a vertical comparison of HHI it is observed that this is higher for the leading drug, which can be explained by the high dominance exerted by the leading wholesaler according to the Davies expression.

All values for the log size are similar, which implies that both drugs (original, leading generic) interact on the top and the floor categories.

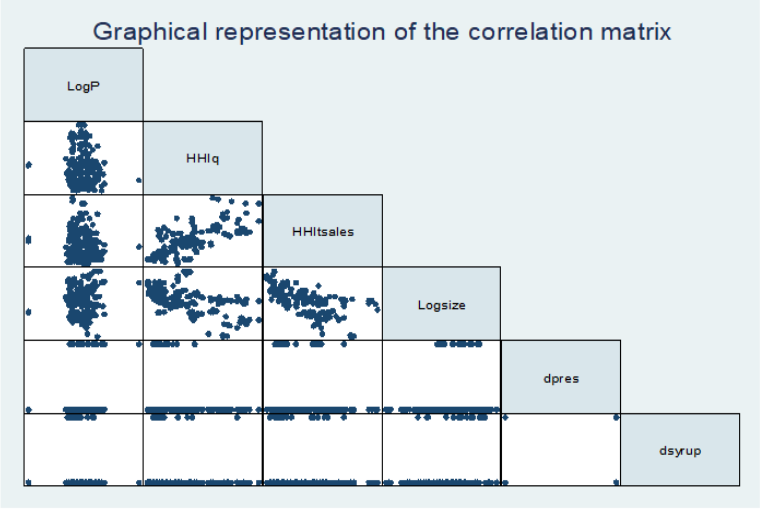
The mean of the dummy variable Dpres is higher for the generics group. As the mean is obtained from values 0 and 1, the values indicate that 12% of the leading drugs are sold under medical prescription and the remaining 88% correspond to OTC drugs or direct sale drugs. In categories where there are original drugs the latter value increases to 95.6%, which is consistent with the fact that the original drug actually does face a fiery competition. Finally, the values of the dummy variable Dsyrup for both groups is similar.

Table 2 Statistics summary for the log of relative prices equation

Group 1: Leading branded generic	*Number of observations*	*Mean*	*Std. dev*	*Min*	*Max*
Variables					
Logistic of relative prices	157	0.5817	1.5987	–7.1086	8.5808
HHI					
Total quantities	164	0.2706	0.1809	0.033	0.750
Total sales	164	0.2409	0.1614	0.020	0.715
Logsize	164	7.7449	1.1784	4.466	10.318
Dpres	164	0.122	0.3282	0	1
Dsyrup	164	0.1098	0.3135	0	1
Group 2: Original drug	*Number of observations*	*Mean*	*Std. dev.*	*Min*	*Max*
Variables					
Logistic of relative prices	87	0.2348	1.1396	–1.8414	3.4186
HHI					
Total quantities	92	0.2455	0.1747	0.033	0.750
Total sales	92	0.2181	0.1497	0.040	0.659
Logsize	92	7.7454	1.2222	4.466	10.32
Dpres	92	0.0435	0.205	0	1
Dsyrup	92	0.0978	0.2987	0	1
Dataset:	*Number of observations*	*Mean*	*Std. dev.*	*Min*	*Max*
Variables					
Logistic of relative prices	244	0.458	1.4585	–7.1086	8.5808
HHI					
Total quantities	256	0.2615	0.1787	0.033	0.750
Total sales	256	0.2327	0.1574	0.020	0.715
Logsize	256	7.7454	1.1919	4.466	10.32
Dpres	256	0.0938	0.2921	0	1
Dsyrup	256	0.1055	0.3077	0	1

The correlation matrix between variables as showed in Figure 1. The scatterplot for relative prices says few things about its relation with the independent variables. Secondly, it is important to note the inverse relationship between market size (in log) and HHI which implies that the larger the market size, the lower the degree of concentration, that would indicate that the size of the market is important for the generic firms as a higher market size encourages the entry or existence of a higher number of brands which is consistent with Reiffen and Ward (2005) and Hollis (2005).

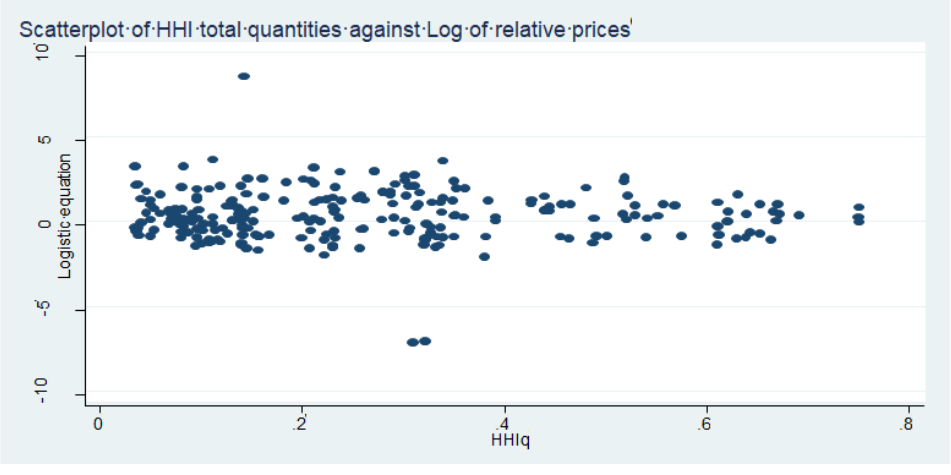
Figure 1 Correlation matrix (see online version for colours)



7.2 Model results

First, it is tried to find out 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 an example, in the Figure 2 shows the case of relative price against HHI. Looking at the graphs, we observe that all scatterplots are lower and upper bounded. As before, the scatterplot of HHIq against log of relative prices shows values more dispersed than that in which HHIts is considered.

Figure 2 Scatterplots of log of relative prices against HHI (see online version for colours)



7.3 Estimations of logistic of relative prices

The results of the three techniques are summarised in Tables 3 and 4. It was started estimating the specification (1). To define the best model that fits the dataset it was proceeded to look at the regression coefficients, the statistical tests, and finally the predicted values to check for outliers and raise mechanism to control for them.

As the model uses two different measurements of HHI – total quantities and total sales – the results are showed separately.

To control the big difference in the market size across categories, it was included Dsize to control for categories with high sales as an alternative variable of the logsize of the equation 1. Thus, Dsize = 1 if market size > ch$10.000 (million), otherwise Dsize = 0.

As a result, it is estimated four models of pricing, considering two different measures of HHI (q and ts) and two measures of total sales on the RHS (log size and Dsize). In sum, it is estimated 12 regressions (4 models foreach technique).

Table 3 Estimates of the log of relative prices (include 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	0.3253
	–0.193	-	–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	0.39	
Prob> F	0.0017	0.7633	
R-sq. overall	0.0776	0.0463	0.0694

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

7.4 Logistic of relative prices regression measured by total quantities

Looking at Tables 3 and 4, it is observed that the coefficients of the'key variables' – degree of concentration (HHI) and the market size (logsize and Dsize) – are positive and similar for 5 regressions and contrary to the initial predictions since it is expected a negative relationship between HHI and the log of relative prices $Pob_{i,t}/Pld_{i,t}$. The positive value of this variable for OLS (in Table 4) satisfies the expectation.

The coefficient of log size is positive for 5 regressions as well. For the FEM model Table 3 this coefficient is negative. The coefficient of Dpres also is different to our prediction as it was expected that the drug predicted by physicians 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, 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 org: original drug) measured by the logistic transformation, which is consistent with market condition where $P_{original} > P_{generic}$.

Table 4 Estimates of the log of relative prices (include HHIq and the Dsize)

Logistic equation	*Pooled (OLS)*	*FEM*	*REM*
HHIq	–0.38523	0.0371	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	0.32215
	–0.18973	-	–0.32744
Constant	0.28905	0.22417	–0.17361
	–0.20660	–0.29800	–0.31915
N. of observations	244	244	244
Wald χ-sq (k)			9.88
Prob> χsq			0.786
F	5.79	1.19	
Prob> F	0	0.2155	
R-sq overall	0.1084	0.0337	0.098

Note: *** Significance at p = 0.01; ** significance at p = 0.05; * significance at p = 0.10.

On the other hand, when it is looked at how the pre-selected pooled model fits the dataset, F-test for OLS model is statistically significant. As a result, the principal component analysis suggests the pooling assumptions are partially satisfied for the pre-selected expression because this model fails in the sign of Dpres, which is contrary to the theory. Anyway, there is a doubt about the power of its prediction as this technique has a poor theoretical support, which in turn means that the pooled estimates may conceal valuable information about the drug categories that could be explained in a better way by using REM technique.

Now, the second specification that considers HHIts as a predictor is shown in Table 5.

Table 5 Estimates of the log of relative price (include 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	-	–0.5617
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
N. of observations	244	244	244
Wald χ-sq. (k)			2.92
Prob> χ-sq.			0.7118
F	4.26	0.38	
Prob> F	0.001	0.7648	
R-sq. overall	0.0822	0.0477	0.073

Note: *** Significance at p = 0.01; ** significance at p = 0.05; * significance at p = 0.10.

7.5 Logistic of relative prices regression measured by total sales

Now, it is analysed the Logistic equation models by considering as relevant variables HHIts and market size (log form and Dsize). Tables 5 and 6 summarise the estimates and the model statistics.

As it is observed above, coefficients of the principal variables are in the direction expected, except for the FEM models. The coefficient of HHIts > 0 and hence, contrary to the predictions. This model also shows a negative relationship between logsize and Logistic equation. When it was used Dsize Table 6, the HHIts also showed the opposite sign. Therefore, the FEM model is not good to explain the dataset.

The Pooled and REM models Table 5 show similar coefficients in term of signs but the sensitivity of the first is higher than those of the REM model. The Pooled Model also shows coefficients of Dsyrup and Dtype statistically significant. The logsize is significant at 10% as well. In the case of the REM model all coefficients are insignificant even at 10%.

When it is analysed the fit of these two models, the F-test for pooled model is statistically significant at 1% and hence it fits in a good way our dataset. In contrast, the wald test for the REM model is insignificant.

The alternative model estimated for OLS and REM with Dsize Table 6 shows the same characteristics of the coefficients, however, the statistical significance of this variable is higher. The coefficient of Dpres is different to our prediction again, whereas the coefficient of Dtype is that was predicted.

Table 6 Estimates of the log of relative price (include HHIts and a Dsize)

Logistic equation	*Pooled (OLS)*	*FEM*	*REM*
HHIts	–0.90921	0.80460	–0.05409
	–0.61606	–1.22965	–0.81969
Dsize	1.05944***	0.89887	1.00909***
	–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
N. of observations	244	244	244
Wald χ-sq. (k)			9.88
Prob > χ-sq.			0.0786
F	6.15	1.28	
Prob > F	0	0.2823	
R-sq. overall	0.1144	0.0205	0.1008

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

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 in a good way the model that includes HHIts. Now, it is evaluated which of the latter two models is the best. In order to complement the statistic results and have new information it is checked the scatterplot of the prediction. The expectation is that the predictions move in the range [0, 1] as we are using the logistic transformation of the relative prices. Then, the results are analysed by looking at the Test for autocorrelation and heteroskedasticity. As a consequence, it was counted seven outliers in the first model and 34 in the second. It is used two alternative ways to attempt controlling those outliers and hence to have an approach to the best model. The first is by considering dummy variables to control them and the second is by eliminating statistically insignificant variables excepting our principal components HHI_{ts} and market size.

As the results were not satisfactory for the first mechanism it was followed a restrictive model that considers the principal variables as predictors to explain the prices movement over time.

7.6 Estimates of logistic of relative prices: the restrictive model

In this section is showed the results of the restrictive model $\beta_3 = \beta_4 = 0$ in equation (1). Two criteria are used to impose the later restrictions and get the best model. They are, to keep the principal theoretical variables and to eliminate variables with incorrect signs or

those statistically insignificant. The Logistic equation regressions are now estimated against HHIts, Size (both logsize and Dsize), and Dtype to control the leading generic and the original drug. As a result, the restrictive equation (1R) is as follows:

$$\text{Log}\{\pi_{i,t} /1-\pi_{i,t}\} = \alpha + \beta_1 HHI_{i,t} + \beta_2 Size + \beta_3 Dtype_{i,t} + \varepsilon_{i,t} \quad (1R)$$

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, the logistic equation Log $\{\pi_{i,t}/(1-\pi_{i,t})\}$, where $\pi_{i,t} = Pob_{i,t}/Pld_{i,t}$, (ratio of average prices between the own-brand drug and the leading drug per category). The explanatory variables are defined as before in equation (1)

Table 7 show the estimates for both regressions, by pooled, FEM and REM techniques.

Table 7 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
	–0.9135	–3.12639	–1.29555
N. of observations	244	244	244
Wald χ-sq. (k)			2.11
Prob > χ-sq.			0.5498
F	4.27	0.4	
Prob > F	0.0059	0.6732	
R-sq. overall	0.0506	0.0328	0.0464

Note: *** Significance at p = 0.01;** significance at p = 0.05; *significance at p = 0.10.

As it is observed above, the coefficients of HHIts for the FEM models are opposite to the prediction. The Wald tests are also statistically insignificant. As a result, this technique is not good to explain the interaction between our variables.

On the other side, the coefficients for pooled and REM models are similar for both restrictive equations. The model that fits in a better way the dataset is given by Dsize version Table 8, where this variable is statistically significant at 1% for both techniques. The individual coefficients are more sensitive for the Pooled estimation. In particular, it is put attention to the coefficient of HHIts due to its high value, which is little credible theoretically speaking. On the opposite, the value of this coefficient by REM technique is more consistent with the theoretical intuition.

Table 8 Estimates of log of relative price restrictive model (Dsize version)

Logistic equation	*Pooled*	*FEM*	*REM*
HHIts	–0.85111	0.90488	-0.08755
	–0.75298	–120.242	
Logsize	0.16055	0.90749	0.98951***
	–0.10154	–0.48053	-0.37181
Dtype	0.38040**	omitted	0.33116
	–0.19205	-	-0.32568
Constant	–0.84236	0.15405	0.19556
	–0.9135	–0.15405	-0.32196
N. of observations	244	244	244
Wald χ-sq. (k)			8,97
Prob. > χ-sq.			0,0297
F	4.27	1.85	
Prob. > F	0.0059	0.1609	
R-sq. overall	0.0506	0.0339	0.0781

Note: *** Significance at p = 0.01;** significance at p = 0.05; *significance at p = 0.10.

Now, the research follows in two directions to decide what model to choose.

First, it is looked at the scatterplots of the prediction to check for outliers and secondly, it is applied Breush Pagan lagrange multiplier (LM) to decide between them. The null hypothesis is that the variance across categories is zero which implies no panel effect.

The findings point out the persistence of outliers out of range for both techniques and hence, it is not possible to take any decision from the graphs. Next, diagnostic tests to the regressions in order to get the best model are applied.

The Breush Pagan test gives a Chi-sqr. of χ^2 (1) = 137.09 (Prob. > χ^2 = 0.0000), which confirms that the null hypothesis is rejected and conclude that REM is the appropriated model to fit the dataset. In other words, with this result there is evidence of significant differences across drug categories and therefore confirms the theory about the REM as the best technique to estimate the model.

Although it is known that the serial correlation is not a problem in micro panels with few numbers of periods, it is tested by using the Woodridge test ($\sqrt{H_o}$: no first-order autocorrelation). The F test is F (1, 60) = 7.267, Prob > F = 0.0091, and hence reject the null hypothesis and conclude the existence of autocorrelation.

To remedy the latter problems, it was estimated the regression by PCSEs. In order to look at differences between the branded generic and original drugs it is estimated the model separately, as shown in Annex 2. As it can be observed there, the PCSE coefficients are all significant at 1% for the complete dataset. However, the most important thing of this estimates is that the regression gives the same result as the OLS-pooled regression (see Table 7), with differences of the statistical significance of the coefficients of HHIts and constant, which are insignificant for the OLS-pooled model seen in Table 7. The coefficients for group are also too high or sensitive.

To remedy the latter problems, it is estimated the regression by PCSEs. To look at differences between the branded generic and original drugs the models are run separately. The most important result of this estimates is that the regression gives the same result as the OLS-pooled regression (see Table 7), with differences of the statistical significance of the coefficients of HHIts and constant, which are insignificant for the OLS-pooled model. The coefficients for group are also too high or sensitive.

Firstly, this unsatisfactorily result is yielded for the reduced number of periods. It is confirmed by Hoechle (2007), who highlights that PCSE method gives imprecise estimates if the ratio T/N is small, which happens in the dataset. The argument is as follows. For finite sample properties of the PCSE estimator are poor when the panel's cross-sectional dimension N is large compared to the time dimension T. Therefore, the REM estimates are the best models. The results of these estimates for the complete dataset as well as each group are shown in Table 9.

Table 9 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
N. of observations	244	157	87
Wald χ-sq. (k)	8.97	7.64	5.02
Prob > χ-sq.	0.0297	0.0219	0.0811
R-sq. overall	0.0781	0.0724	0.0087

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

The coefficients of the estimates are consistent with the predictions (except the value of HHIts for the original drugs). In the same way, the coefficients of the dataset estimates are less sensitive than those of the leading generics.

7.7 How is the negative coefficient of HHIts interpreted (Table 9)?

To understand the logic of this variable, it is simulated an industry composed by three firms (one dominant and two symmetric small firms) in which there is a change in market share. Then, if Firm 1 market share increases by 10%, the other 2 loss 5% each one, then there are two opposite effects on HHI.

First, by applying the formula of HHI, ΔHHIts= Δ^{+} 0.01 + Δ–(0.0025)2 = 0.005. i.e., HHIts increases by 0.005. Second, by considering this value in regression (1), the impact in 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 the prediction. This fall can therefore be explained by either a fall in $Pob_{i,t}$ or by a higher $Pld_{i,t}$.

Due to the lack of literature about HHI being an independent variable on the relative price equation, it is used Davies's definition of HHI [recall HHI = $\{(1 + cv^2)/n\}$] to analyse the role of the number of firms 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 9, implies that the relationship between HHIts (given a higher n, all other ceteris paribus) and the log of relative prices is consistent with the results obtained by Frank et al (1997) and Reiffen and Ward (2005).

On the other, the counterintuitive positive coefficient of HHIts in column (3) deserves more attention, as the positive value implies that the higher HHIts (less competition), the higher the log of relative prices. Thus, if $Pob_{i,t}$ is constant then $Porig_{i,t}$ should fall, or if $Porig_{i,t}$ is constant, $Pob_{i,t}$ should rise. A third explanation is given by changes in prices in different magnitude, where the impact is higher in the numerator ($\Delta^+ Pob_{i,t} > \Delta^+ Porig_{i,t}$). What impact is more sensible? Davies's equation is also to analyse the consistency of this prediction. Suppose that n goes down, it implies that HHIts increases and hence, according to the positive coefficient of the original drug, the log of relative prices should increase.

The third alternative has more sense, because the largest pharmacies take advantage of its dominant position increasing $Pob_{i,t}$ in a larger magnitude than the magnitude of the increase in the original drug price. In fact, it is sustained that $Porig_{i,t}$ also goes up because the wholesaler targets its brand to patients with high willingness to pay, however, as their average prices are much higher than those of the generics, included the own brand drugs, the margin to increase prices in a high magnitude is reduced.

Put it mathematically, if initially the relative prices is $Pob_{i,t}/Porig_{i,t}$, then if the own brand price increases by 10% and the original one by 5%, now the relative price goes up by (1.1)/(1.05)=1.0476, i.e., an increase by 4.76%.

7.8 Is it important the size of the firms as a predictor of the log of relative prices?

Now, it will be discussed the role of a dominant drug in the market. If HHIts goes up because of a higher market share of the dominant drug (the market is more unequal, i.e., cv is higher), it should be expected a different impact on the log of relative prices depending on which drug is the leading in term of market share (the pharmacy-owned drug or the independent leading drug). If the log of relative prices increases (ceteris paribus) it could be explained by a higher drug price on the numerator or a lower price on the denominator. If the impact is negative, the contrary happens.

Next, looking at the summary statistics of the drug market share, there is a high own-brand drug market share (23.2% and 20.8% for quantities and sales respectively). At the same time, the leading drugs are formed mostly by generics, which in turn imply that the original drug has a lower market share. As a consequence, when it is compared what happens between the own brand and the original drug, the first is the dominant. Other argument that sustains this line of thinking is the way of how the large pharmacies operate, where the pharmacy seller plays a strong role to induce demand of its own brand. As a result, when an original drug interacts with the own-brand drug, the seller induces the demand for the latter and hence its price goes up because of a higher HHIts.

7.9 Sign of the dummy variable Dsize

The coefficient of Dsize is positive for all equations and statistically significant for the main regression and the generics model. This direct relationship between Dsize and the log of relative prices observed in our dataset reflects the idea that a larger market encourages more firms (mainly generics). As a result of more 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 run floor for the price of any generic drug. As a consequence, the lower prices affect, on a larger scale, the drug on the denominator, and hence the log of relative price increases. An important antecedent that justifies this explanation is the big number of brands provided in Chile, which varies between 18 and 21 per category. However, this average is strongly influenced by 'the largest categories', where the maximum number of drugs is 35.

When it was looked at the differences among the whole dataset and the separated groups, the coefficient of the leading generics is the higher, which mathematically could be explained by a lower fall on the denominator (the leading generic, $Plg_{i,t}$ respect of the fall of this value in the other regressions. How can this be interpreted? It is believed that the leading drug price has a degree of rigidity respect to the others, so its price goes down but only marginally (all other ceteris paribus), which is consistent with the fact that the leading generic wholesaler takes advantage of her market power in a short period, and thus applies a higher margin respect to their rivals even when it faces a fiery competition. In other words, as a successful blockbuster generic suffers less from a higher competition, thus if its price goes down, the drop is much lower than that observed in the remaining rivals. This argument is also brought out by Frank and Salkever (1997) to explain that the competition, caused by a new generic, yields a 'large' decrease in the generics average price.

Finally, the lower coefficient of the original drug would show its high substitution, given a bigger number of generics firms due to a larger market. In fact, as it was commented before most of the drugs in the dataset corresponds to generics, which are also provided in a big number of formats due to low legal barriers to entry.

7.10 Dtype dummy variable

The coefficient of the Dtype is positive, even though it is statistically insignificant. Thus, when Dtype = 1 (leading generics, lg) the log of relative prices intersects in a higher value 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 $Porig_{i,t} > Plg_{i,t}$.

As it is relevant to know about whether or not there is any difference between the estimates of the leading generic and the original drug (which is equivalent to compare the two groups of drugs), it is used the Wald test to evaluate the difference between these nested models, by imposing the restriction to the coefficient of the Dtype dummy variable $\beta_3 = 0$. The $\chi^2(1) = 1.03$ ($Prob>\chi^2 = 0.3092$), then the null hypothesis is not rejected.

8 Concluding remarks

With this research is updated the literature in this field by considering a highly liberalised market at the retailer level. Given the wealth of the dataset, it was constructed a theoretical model on relative prices about leading drugs and the pharmacy-owned drug. The main results are as follows.

The key regression indicates that the degree of concentration measured by HHI in total sales impacts negatively the relative prices $Pob_{i,t}/Pld_{i,t}$ finding that is consistent with the results obtained by Frank and Salkever (1997) and Reiffen and Ward (2005). In other words, when the degree of concentration goes up, the prices of both drugs go up in different percentage, $\Delta\%^{+}\ Pob_{i,t} < \Delta\%^{+}\ Pld_{i,t}$) and hence, the relative prices fall. An explanation to sustain this argument is that the leading wholesaler has a strong market power due to a low substitution and hence, it can increase wholesale prices and hence the consumer prices without affecting negatively the quantity demanded. The higher concentration is also exploited by the pharmacy that charges a higher margin as well.

This coefficient is opposite when it was estimated the model for the original drug. So, when prices increase as a consequence of a more concentrated market the difference in magnitude is higher for the own brand drug, $\Delta\%^{+}\ Pob_{i,t} > \Delta\%^{+}\ Porig_{i,t}$. In fact, looking at Statistics Summary it is observed that the mean of logistic prices is lower for the original drug, which in turn means that $Pob_{i,t} << Porig_{i,t}$ and hence the space to increase original drug prices is low in comparison to what happens with the own brand.

The size of the firms is important to explain this sign. Following Davies's HHI equation, it is raised the role of the dominant firm. Under this context, it is believed that the largest pharmacies have a big market power because not only they have 80% market share but also a high market share of their own drugs due to demand induced by the seller.

The market size coefficient is also positive for all equations and statistically significant for the Logistic equation and particularly, for the generics model. This direct relationship reflects the idea that a larger market encourages more firms (mainly generics) because of lower barrier to entry (such as legal barriers and low fixed costs). As a result of more competition, the prices go down. On the other hand, as the pharmacy-owned drug is more cost related, its cost provides a long run floor for the price of any generic drug, and thus the price of the others is more elastic and hence they go down in a larger scale, as a result the relative prices increase. This argument is also brought out by Frank and Ward (1997) to explain that the competition, caused by a new generic, yields a 'large' decrease in the price of the existent generics. Other argument discussed earlier that could explain this large decrease in generics prices is given by the weak regulation existent so far, and hence when appears a commercially successful drug, it is rapidly copied by rivals and prices go down. Thus, the leading drug can keep its market share only in the short run.

In spite of this last argument, the leading drug price has a degree of rigidity respect to the others, so its price goes down in average but only marginally (all other ceteris paribus), which is consistent with the fact that the leading generic wholesaler takes advantage of her market power in the short run to apply a higher margin respect to their rivals given a constant marginal cost.

9 Conclusions

Given that the seller induces demand changing the customer preferences, which in turn impacts negatively the competition and hence, the long-term sustainability of markets. This argument validates the reforms implemented that seeks to expand the sale of drugs toward other retailers and to undertake a fixed-price strategy since impact positively competition and reduce the opportunistic behaviour undertaken by large pharmacies.

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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

Annex 1 (continued)

Classes	*Market share leading drugs*	
	Total quantities	*Total sales*
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	–0.2835	-0.39
Dsize	1.04378***	1.22641***	0.73205***
	–0.18097	–0.35755	–0.1999
Dtype	0.36624***	-	-
	–0.09312	-	-
Constant	0.30779***	0.60940***	0.40143***
	–0.04471	–0.07515	–0.0538
Number of observations	244	157	87
Wald χ-sq. (3)	38.13	23.99	18.58
Prob.> χ-sq.	0	0	0.0001
R-sq. overall	0.0839	0.0738	0.0755

Note: *** Significance at p = 0.01; ** significance at p = 0.05.