Entry liberalisation and price competition in the Portuguese over-the-counter drug market*

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Abstract

In the last two decades, many European countries have allowed Over-the-Counter (OTC) drugs to be sold outside pharmacies. This was expected to lower retail prices through increased competition. However, evidence on price reductions is scarce.
We assess the impact on OTC prices associated with the entry of supermarkets and non-pharmacy outlets in the OTC market, using a difference-in-differences strategy.
We use price data on five popular OTC drugs for all OTC retailers located in Lisbon for three distinct points in time (2006, 2010, and 2015).
We find that competitive pressure in the market is mainly exerted by supermarkets, which charge, on average, 20% lower prices than pharmacies. The entry of a supermarket among the main competitors of a retailer is associated with an average 4% to 5% decrease in prices. Additional results from a reduced-form entry model and a propensity score matching difference-in-differences approach suggest that these effects are causal.
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1 Introduction

During the last two decades, European countries have experienced a trend shift as far as the organization of the community pharmacy sector is concerned. Community pharmacy reforms usually comprise the liberalisation of entry rules for new pharmacies, the liberalisation of pharmacy ownership, and the liberalisation of Over-the-Counter (OTC) medicine distribution (OECD, 2014). This paper is devoted to the last of these components.

OTC drugs are pharmaceuticals whose purchase does not require a prescription from a physician. OTC drugs are usually not reimbursed and their pricing is free, in contrast with the highly regulated prices of reimbursed and/or prescription-only pharmaceuticals.

OTC market liberalisation implies a move from a traditional pharmacy-centred model to a multi-channel distribution model in which OTC drugs are sold outside pharmacies, namely in supermarkets, petrol stations, and other non-pharmacy outlets (hereinafter outlets). Throughout this paper, we will broadly refer to these as non-pharmacy players, as opposed to traditional pharmacies.

The rationale for OTC market liberalisation was that the entry of non-pharmacy players, combined with free OTC pricing, would lower OTC drug prices via increased competition among retailers. However, evidence of such price effects is scarce, mostly due to the lack of available OTC price data at the retailer level.

In this study we analyse the price effects of OTC market liberalisation, drawing on the Portuguese experience. In Portugal, the liberalisation of the OTC market started in late 2005 and specifically allowed OTC drugs to be sold outside pharmacies, namely in supermarkets and non-pharmacy outlets. We assess the role of supermarkets and outlets in exerting competitive pressure on their competitors. Using a difference-in-differences strategy, we estimate the impact of the entry of supermarkets and outlets on OTC drug prices. Despite the fact that pharmacies seem unable to place competitive constraints on their competitors (Stargardt et al., 2007 and Pilorge, 2016), non-pharmacy players may be able to do so if they charge substantially lower prices.

We use price data for five of the most popular OTC drugs across all retailer types (traditional pharmacies, supermarkets, and outlets) located in the municipality of Lisbon. The dataset has a panel structure and each retailer can be observed for at most three time periods, the years of 2006, 2010, and 2015. These price data were collected in face-to-face interviews at each retailer, and through the purchasing of the five OTC drugs in pharmacies who refused an interview, making this a unique dataset.

In our difference-in-differences analysis, we estimate the change in prices charged by a given retailer following the entry of a non-pharmacy player among its main competitors. We define four distinct treatment groups depending on the type of non-pharmacy player (i.e. supermarket or outlet) entering the OTC market among the main competitors of a given retailer and on the timing of entry (between 2006 and 2010 or between 2010 and 2015). The control group consists of retailers that face only traditional pharmacies amongst their main competitors during all the years covered in our dataset.[1]

According to our baseline results, retailers experiencing the entry of a supermarket among their five nearest competitors between 2006 and 2010 charge, on average, 5.3% lower prices in 2010, than the control group. This effect is maintained over time, and the same retailers charge, on average, 4.2% lower prices in 2015, compared to the control group. Retailers experiencing the entry of a supermarket among their five nearest competitors between 2010 and 2015 charge, on average, 2.6% lower prices in 2015 than the control group. Experiencing the entry of an outlet, in turn, is not associated with lower prices. We show that these results are not driven by the existence of pre-treatment trends, and that they are robust to alternative definitions of main competitors of a retailer. The causal interpretation of our findings, however, rests on the assumption that market structure is exogenous, so that exposure to treatment is random. We try to mitigate such endogeneity concerns in two ways. First, we combine propensity score matching with a difference-in-differences approach (PSM-DID) (Heckman et al., 1997, Smith and Todd, 2005). Specifically, we estimate retailer propensity scores based on pre-liberalisation levels of competitive pressure and demand faced by each retailer. We then match observations in treated and control groups based on their estimated propensity scores separately for each year and for each of the four treatments. Then we run our model specifications in this matched sample. Our PSM-DID results confirm some of the effects found using the simple DID design: retailers who face the entry of a supermarket among their five nearest neighbours between 2006 and 2010 charge, on average, 5% lower prices in 2015, compared to the control group. Overall, our results point to the existence of some long-lasting competitive effects in the OTC market, being mostly driven by supermarkets. Second, we estimate a reduced-form entry model in which the probability that a retailer faces the entry of a supermarket or outlet among its main competitors is a function of past prices of the five OTC drugs in our dataset, and we find no evidence that non-pharmacies enter the market in locations that would be more profitable.

Our findings are relevant not only to countries that have already adopted similar OTC market liberalisation reforms, but also to those that are considering implementing them in the near future. OTC market liberalisation reforms similar to the Portuguese one were implemented all over Europe during the last two decades. In 2000, Poland allowed for a limited range

[1]This is the only condition for a retailer to be classified in the control group, meaning that the control group can be composed not only of traditional pharmacies, but also of supermarkets or outlets. In robustness checks we restrict the control group to traditional pharmacies and our results are unaffected.

of OTC products to be sold outside pharmacies, namely in non-pharmacy outlets. In the following years, Denmark, Norway, Italy, Hungary, Sweden, and France adopted similar policies. Germany and the United Kingdom had already undertaken such reforms during the 1990s. Depending on which country we analyse, different types of retailers are allowed to sell OTC drugs. According to OECD (2014), the range of OTC drugs that can be sold outside pharmacies also varies across countries, with some countries imposing no restriction regarding this matter.

The fact that OTC drugs were allowed to be sold outside pharmacies implied that traditional pharmacies experienced a sudden increase in the number of competitors they face in the years following market liberalisation. Since OTC drug pricing is not regulated, one expects this increase in competition to affect equilibrium prices. That was, in fact, the rationale for OTC market liberalisation reforms: to lower prices through increased competition and consequently reduce healthcare expenditures, without harming quality, safety, and availability (Lluch and Kanavos, 2010; Stargardt et al., 2007; Morgall and Almarsdóttir, 1999).

From a theory perspective, however, the price effects of OTC market liberalisation are ambiguous. On the one hand, market liberalisation can lead to price reductions due to increased competition. On the other hand, pharmacies may try to vertically differentiate their services from non-pharmacy players through quality increases (i.e. advice from the pharmacist), while not lowering their prices.[2] OTC sales of regularly used products, such as the ones in our dataset, are simpler in this respect since they require little advice from the pharmacist. We therefore see limited scope for vertical differentiation across points of sale.

Existing evidence from the empirical literature on OTC drug pricing and the effects of OTC market liberalisation in Europe is scarce, mostly descriptive, and often unable to confirm the expected downward trend in OTC prices, as pointed out in OECD (2014) and Vogler et al. (2014). Pharmacies seem unable to exert substantial competitive pressure on their competitors (Stargardt et al. 2007; Pilorge 2016). This inability may be associated with either the development of close professional relationships among pharmacists or to their use to the non-competitive environment in place prior to market liberalisation, as seems to be the case in Germany (Stargardt et al., 2007). Alternatively, it may simply mean that pharmacies do not compete in prices but rather in quality of service, location, or opening hours. There is evidence for Spain (Lluch and Kanavos, 2010), Norway (Anell 2005; Rudholm 2008), and Germany (Stargardt et al., 2007) pointing in this direction. In Portugal, traditional pharmacies located in urban areas, thus facing higher competitive pressure, were found to compete on the range

[2] At the time of the Portuguese OTC market liberalisation, several authors used the classic frameworks of Hotelling (1929) and Waterson (1993) to make predictions of the expected price outcomes of the reform (see Patrício et al., 2005; CEGEA - Centro de Estudos de Gestão e Economia Aplicada, 2005; Gomes, 2007). These predictions pointed in very different directions and the real impact of the reform was never assessed.

of services offered (Martins and Queirós, 2015). Belgian pharmacies, in contrast, do not seem to use nonprice instruments as a response to additional pharmacy entry (Schaumans and Verboven, 2008). Descriptive evidence of price reductions brought by the liberalisation process was found for both Iceland and the UK. In Iceland, pharmacies located in urban areas seem actually to be engaging in price discounts, besides competing in location and availability (Anell, 2005). As for the UK, supermarkets price OTC drugs 30% cheaper than do traditional pharmacies, according to OFT - Office of Fair Trading (2003). We contribute to this literature by focusing on competitive pressure exerted by non-pharmacy players and estimating the causal impact of OTC market liberalisation on OTC prices, rather than providing purely descriptive evidence. To our best knowledge, we are the first to make such an assessment.

Our paper also relates to a broader literature within industrial organization on the price effects following the entry of supermarkets and chain stores in general in a market previously composed of small, independent firms, as is the case of traditional pharmacies in Portugal.[3] Bennett and Yin (2018) find the entry of a retail pharmacy chain in India to lower prices charged by incumbent pharmacies by 2%. Basker (2005) studies the effect of Walmart entry on average city-level prices for a set of consumer goods and finds short-run price reductions ranging from 1.5% to 3%. Finally, Basker and Noel (2009) estimate the entry of Walmart, which charges on average 10% lower prices, to be associated with a 1-1.2% price decrease by its competitors. We contribute to this literature by providing evidence for the OTC drug market, which has not been studied in previous literature, in a developed country.

Finally, we contribute to the strand of literature applying PSM-DID in panel datasets (see, for example, Blundell et al., 2004, Polidano and Vu, 2015, and Song and Sun, 2016). We apply PSM-DID in panel data in a context with multiple treatments. To the best of our knowledge, none of the existing panel data applications of PSM-DID features such a setting.

The remainder of this paper is as follows. The next section provides some background on the Portuguese OTC market and the liberalisation process. Section 3 presents our empirical strategy and describes how we dealt with econometric challenges related to the presence of endogeneity. Our data are described in Section 4. Section 5 presents our main results and Section 6 concludes.

[3] The fact that traditional pharmacies in Portugal are independently owned results from existing pharmacy ownership restrictions, which limit the number of pharmacies that can be owned by the same agent. Therefore, there are no pharmacy chains. Restrictions of this sort are common across countries and seek to ensure a certain degree of competition in the market. More recently some organized groups of independently-owned pharmacies were created, but our data are prior to that.

2 The Portuguese OTC market

The liberalisation of OTC medicine distribution in Portugal started in 2005, following the Decree-Law n. 134/2005, published on August 16$^{\text{th}}$, which allowed non-reimbursed OTC drugs to be sold outside pharmacies. Prior to this, traditional pharmacies had a monopoly of both prescription and OTC drugs, regardless of whether they were subject to government reimbursement or not. As a result of this ruling, two new types of players entered the Portuguese OTC drug market. These were supermarkets and non-pharmacy outlets (in Portuguese, *parafarmácias*). Almost two years later the Decree-Law n. 238/2007, published on June 19$^{\text{th}}$, extended the previous ruling to government-reimbursed OTC drugs, so these could also be sold in supermarkets and outlets (though government reimbursement was conditional upon buying the drugs in a traditional pharmacy). Until today prescription drugs remain available only at traditional pharmacies and cannot be purchased either at supermarkets or at outlets. In supermarkets, by regulation, OTC drugs are not placed on the regular shelves that are freely accessible to customers. Instead, they are placed either in a closed shelf that is located behind the cashiers' check-out counter, or in a dedicated area together with other wellness products. Either way, customers who wish to purchase a given OTC drug must request it from the cashier or the employee attending to the dedicated area. Most supermarkets selling OTC drugs in Lisbon during the years we analyse belong to either one of the two biggest supermarket chains in Portugal. Moreover, we observe in our data that supermarkets belonging to these chains adopt a common price strategy, rather than store-specific prices that reflect the competitive environment faced by each store belonging to the supermarket chain. Non-pharmacy outlets are stores selling cosmetics, baby care products, vitamins and supplements, eye care products, among others. For such stores OTC drugs represented a natural expansion of their product range. Outlets can be either independently owned or part of small chains of two or three stores. In our data we observe both cases.

Non-pharmacy retailers wishing to enter the OTC market in Portugal need to apply for a licence at the National Authority of Medicines and Health Products (Infarmed IP), and satisfy specific requirements related to the storage of OTC drugs, qualification of personnel, among others. The entry of supermarkets and outlets in the OTC market took place quickly following market liberalisation.[4] According to Infarmed IP, the first entry of non-pharmacy players in the Portuguese OTC market occurred in October 2005. In the first quarter of 2009 there were over 800 non-pharmacy players in the market. In more recent years the rate at

[4]Throughout the paper, entry in the OTC market should be interpreted as the moment at which a retailer was granted a licence to sell OTC drugs. Therefore, if a supermarket had been operating in a given location since 1990, and got a license to sell OTC drugs at that location in 2011, then 2011 is its entry date in the OTC market. For supermarkets or outlets opening after OTC drugs were allowed to be sold outside pharmacies, the opening date and the date of entry in the OTC market may, but need not, be the same.

which non-pharmacy players enter the market has slowed, and by the end of 2017 there were about 1,200 non-pharmacy players in Portugal (Infarmed, IP, 2018).

According to information published regularly by Infarmed IP, the volume share of OTC drugs in the total outpatient pharmaceutical market was 16.5% by the end of 2017. The figure for the value share in the same period is 11.7%. The non-pharmacy volume share of the OTC sector in Portugal has risen continuously since market liberalisation, reaching 20.8% in 2014, reflecting the increasing importance of supermarkets and outlets as far as access to OTC drugs is concerned. From 2014 on, this share has been stable at about 20% (Infarmed, IP, 2018).

3 Methodology

3.1 Empirical Strategy

We use a difference-in-differences strategy in order to assess the price effects brought up by the liberalisation of the OTC market and consequent entry of non-pharmacy players. The liberalisation reform is, arguably, a natural experiment that generates exogenous variation in the number and type of OTC retailers in the market. We will therefore apply a treatment-effects rationale to evaluate its price effects.

The liberalisation started producing effects in late 2005, before our first round of data collection. However, the entry of both supermarkets and outlets took place gradually, meaning that different retailers will be affected by these new players at different points in time. This is the source of identification in our analysis.

More specifically, we define four distinct treatment groups, depending on the type and timing of treatment. Experiencing the entry of a supermarket or an outlet are the two types of treatment, as supermarkets and outlets may charge different prices and thus exert a different level of competitive pressure on other retailers. In addition, the entry and location decisions of supermarkets and outlets are guided by different drivers, as discussed below. A given retailer is said to have been "treated" if it experienced the entry of either a supermarket or an outlet among its main competitors. Prior to treatment, the set of main competitors of a given retailer consisted only of traditional pharmacies. Each of the treatments can take place either between 2006 and 2010 or between 2010 and 2015.[5] Formally, $I_{g(i)}$, with $g(i) = 1, 2, 3, 4$, is a

[5] In our dataset we have some retailers who already faced non-pharmacy competitors as of our first data collection round (2006). For simplicity, these retailers are disregarded throughout our analysis. In our baseline analysis, which defines main competitors as the five nearest neighbours of a retailer, this implies that 28 retailers are dropped from the estimation sample. When using radius-based measures of competition, the number of retailers excluded from the estimation sample differs.

set of binary indicators for each of the four treatments that retailer i can experience. I_1 and I_2 are indicator variables for retailers that had a supermarket and outlet, respectively, entering the OTC market among their main competitors between 2006 and 2010. Similarly, I_3 and I_4 are indicator variables for retailers that had a supermarket and outlet, respectively, entering the OTC market among their main competitors between 2010 and 2015. The control group, denoted I_0, is the set of retailers who never face supermarkets or outlets as main competitors during the entire time horizon under analysis. All treatment and control groups are mutually exclusive, and each retailer belongs to the same group throughout all time periods in which it is observed.

We are interested in comparing the pre- and post-treatment price differences between the treatment groups and the control group. The regression counterpart of these differences is as follows:

$$P_{ijkt} = \beta_0 + \beta_1 T_i + \pi_{g(i)} + \delta_t + \theta_{tg(i)} + \gamma_k + \lambda_j + \varepsilon_{ijkt}, \tag{1}$$

where the dependent variable is the natural logarithm of the price charged by retailer i, located in parish j, for OTC drug k in period t.[6] The explanatory variables include indicators for retailer type (ie. whether the retailer is a traditional pharmacy, a supermarket or an outlet), in vector T_i; treatment group fixed-effects, $\pi_{g(i)}$; year fixed-effects, δ_t; treatment group-year fixed-effects, $\theta_{tg(i)}$;. drug fixed-effects, γ_k; and parish fixed-effects, λ_j. Finally, ε_{ijkt} is an error term. The price effects of OTC market liberalisation will be revealed by some of the $\theta_{tg(i)}$ estimates, namely those corresponding to the interactions between each of the treatment groups and their corresponding post-treatment periods.

Our difference-in-differences design is as flexible as possible, given that we have data for only three time periods and treatment does not occur at a specific point in time but rather over time. First, we do not restrict pre-treatment trends to be identical for the control and treatment groups. Instead, we allow for fully flexible pre-treatment trend differentials between treated and control groups. This is done by including interactions between the indicators for being treated after 2010 and the year fixed-effects, since for these treatment groups we observe two pre-treatment periods. These effects will show in the estimates for $\theta_{2010,3}$ and $\theta_{2010,4}$, and will allow testing for the parallel trend assumption. Second, we do not restrict the treatment effect to be permanent and equal to the change in price in the first post-treatment period. Instead, we allow for flexible dynamics of the treatment effect over time. That is, we include interaction terms between the indicators for being treated between 2006 and 2010

[6]In Portugal municipalities are composed of parishes. These are administrative divisions within a municipality. The number and geographic borders of the parishes of Lisbon were revised in 2012. We will use the post-2012 definition throughout our analysis, according to which there are 24 distinct parishes in Lisbon.

and the year fixed-effects, as for this treatment group we observe two post-treatment periods. These effects will be reflected in the estimates for $\theta_{2015,1}$ and $\theta_{2015,2}$.

The model is estimated using alternatively random and fixed effects at the retailer level. Note that estimating the model using fixed effects causes all retailer-specific, time-invariant regressors to be automatically dropped in the estimation. This includes T_i, $\pi_{g(i)}$, and λ_j, thus reducing equation (1) to:

$$P_{ikt} = \beta_0 + \theta_{tg(i)} + \delta_t + \gamma_k + \varepsilon_{ikt}.$$

In both the random and the fixed effects estimations, we cluster standard errors at the retailer level to account for serial correlation in the pricing decisions of each retailer.

In our baseline specification, we define the set of main competitors of retailer i as its five nearest neighbours, regardless of how far they are located. Therefore, in the baseline specification, the treatments consist of having a supermarket/outlet entering the set of five nearest neighbours between 2006 and 2010 or between 2010 and 2015. The robustness of this baseline definition of main competitors is assessed by redefining the treatments to whether retailer i experienced the entry of a supermarket or outlet within a radius of 400, 600, and 800 metres of its location. Using a radius-based treatment definition accounts for the fact that different areas have different densities of OTC retailers.

A concern is that our control group may be contaminated by the existence of second-order effects related to the entry of non-pharmacy players. That is, the fact that retailer A experiences the entry of non-pharmacy B among its main competitors causes A to lower its price (first-order effect). This, in turn, may cause retailer C, who is in the control group and has A but not B among its main competitors, to change its price as a response to the price change of A (second-order effect). As a robustness check, in order to mitigate the role of second-order effects, we restrict the control group to retailers whose main competitors are in the control group themselves. This robustness check is informative about whether our choice for the set of main competitors, and our definitions of control and treatment groups are appropriate.

Finally, there may be some heterogeneity across retailer types with respect to the price impacts of non-pharmacy entry. Since our prime interest is in the effects of entry on the pricing of pharmacies, we assess possible heterogeneous effects by estimating our models amongst pharmacies only.

3.2 Endogeneity of market structure

Our estimates from equation (1) can be interpreted as causal only if the decision of non-pharmacies to enter to OTC market in a given location and period is exogenous. While the decision of opening a supermarket or outlet is plausibly unrelated to pharmacy market structure, since OTC drugs are only a small subset of the product range offered by these players, it is more difficult to defend the exogeneity assumption when it relates to the decision of an existing supermarket or outlet to obtain a licence to sell OTC drugs. Two threats to the exogeneity assumption relate to omitted variable bias and simultaneity. We now briefly describe how we dealt with them.

There is a potential omitted variable issue in equation (1) if there are components in the error term that influence both prices charged by retailers in the market and the entry of new retailers. Using retailer fixed effects controls for all unobservables that are retailer-specific, to the extent that they are time-invariant. Therefore, we are concerned about retailer-specific, *time-variant* unobservables that can affect both entry and prices. This could be the case of demand shocks faced by certain retailers due to the natural course of urban development, gentrification of certain neighbourhoods, etc. Previous literature has dealt with the possible endogeneity of market structure by instrumenting for entry using the pre-existing market structure, though this is found to be a rather weak instrument (Basker and Noel, 2009). Therefore, we resort to an alternative approach, and combine propensity score matching with a DID approach (Heckman et al., 1997, Smith and Todd, 2005). The underlying idea of using PSM-DID is that by matching treated and untreated units on their propensity score, that is, on their probability of being treated, we make the groups more similar in terms of the observables used in the estimation of the propensity score. Thus, treatment should be random, conditional on those observables used to estimate the propensity score. The crucial assumption we are making with the use of PSM-DID is that, by achieving balancing on observables between the treated and control groups in the matched sample, it makes it more likely that such balancing also extends to unobservables, particularly time-variant unobservables, as time-invariant ones are in any case differenced out by the DID. We argue this is likely the case by checking covariate balancing between treatment and control groups in the original and matched samples, as well as by implementing two distinct PSM methods. Just like simple DID, PSM-DID yields estimates of the average treatment effect on the treated retailers. PSM is, however, a data-demanding method. Typical applications of PSM control for a large set of observables in the estimation of the propensity score. In our case we do not have many variables available to estimate propensity scores. [7] As noted by Lechner (2010),

[7]Heckman et al. (1997) has shown that models which use a richer set of covariates to estimate the propensity scores tend to be less biased. However, including more covariates also makes is more difficult to define the

one should include neither pre-treatment values of the outcome variable nor post-treatment values of independent variables in the estimation of the propensity score. We thus match retailers on the levels of competitive pressure and demand they face pre-liberalisation. Pre-liberalisation levels of competitive pressure are measured as of 2006, our first data period.[8] As for information of pre-liberalisation levels of demand faced by each retailer, we complement our dataset with information from Statistics Portugal on the resident population in the Census tract where each retailer is located. This information was collected in the 2001 Census of the population. The set of variables used to estimate the propensity score has to be such that it yields balanced treatment and control groups in terms of covariates. Since this is a demanding procedure in terms of data requirements, we categorize the two variables described above into quintiles and use these categorized variables for the matching.[9] Given our unusual setting, featuring multiple time periods and multiple treatments, we proceed as follows: using a logit model, we estimate the propensity scores separately for each of the four treatments and for each year of our data, and each treated retailer is matched to its closest untreated PSM-neighbour at each time period (thus allowing us to easily accommodate some exit that we see in the data). Therefore, for each model specification, a total of 12(=4×3) PSM procedures were carried out in order to obtain the matched sample. All PSM analyses were performed using the Stata procedure `psmatch2` by (Leuven and Sianesi, 2003). The common support condition was imposed to make sure that matches can be found for each treated retailer at each time period. Given the estimated propensity scores, we use two distinct methods for matching treated and untreated retailers. The first method is single nearest-neighbour within caliper matching with replacement, setting the caliper at 0.02.[10] The second method consists of non-parametric local linear matching, with a bandwidth of 0.8. If these two matched samples lead to similar price effects following the entry of supermarkets and outlets in the OTC market, then we have more confidence that these effects do not depend on the matching estimators used. Finally, the standard errors of the estimates need to account for the fact that the propensity score was estimated, as well as the imputation of the common support, the fact that we are matching with replacement, and possibly also the order in which treated individuals are matched. A popular approach in this setting is to use bootstrapping methods.

region of common support, as noted in Gibson-Davis and Foster (2006). There is little guidance on how to balance this trade-off. With this in mind, we opted for matching on few variables.

[8]Specifically,in the specifications using the five nearest retailers as the main competitor, pre-liberalisation levels of competitive pressure are captured by the average walking time (in minutes) to the five nearest retailers in 2006. In the specifications using a radius distance to define the set of main competitors of a retailer, the pre-liberalisation level of competitive pressure is given by the number of retailers within that radius in 2006.

[9]Deciles are used for the specification using a 600-meter radius as measure of competition, as this resulted in better balancing properties in the matched sample.

[10]We tried different choices of caliper and of the number of neighbours matched. These did not change our results.

We bootstrap the entire procedure, meaning that we bootstrap retailers in the original sample, then carry out the estimation of the propensity scores and the matching procedure for each treatment and for each year, and finally estimate equation (1) in the matched sample for each of our bootstrapped samples.

The issue of simultaneity, in turn, relates to a situation in which, in addition to retailers adjusting their prices in the presence of a supermarket or outlet, we also have that supermarkets and outlets make location decisions based on the prices charged by existing retailers located in the area. In order to assess whether simultaneity might by playing a role, we assume a sequential game in which in period $t-1$ supermarkets and outlets make joint entry and location decisions for period t, taking into account (functions of) past-period prices charged by the retailers they would be competing with. Then in period t entry is realized and observed, and all players make their pricing decisions for that period taking entry as given. We have no information on the retailers that did not enter the market. Thus, we use the fact that we do observe entry in certain locations, but not in others. For this analysis, retailers are the relevant unit of observation and the prices of each of the five OTC drugs were aggregated in order to generate an OTC bundle price which is retailer-year specific. More precisely, the equation taken to the data is as follows:

$$entry^*_{ijt} = \beta_0 + \beta_1\zeta(P_{i,t-1}) + \delta_t + \lambda_j + \varepsilon_{ijt}, \qquad \varepsilon_{ijt} \sim iid\ logistic \tag{2}$$

$$entry_{ijt} = \begin{cases} 1 & \text{if } entry^*_{ijt} > 0, \\ 0 & \text{if } entry^*_{ijt} \leq 0 \end{cases}$$

where $entry^*_{ijt}$ is a latent variable representing the probability that each retailer i, located in parish j, has of experiencing the entry of a new non-pharmacy among its competitors in period t. Although we do not observe this probability, we do observe whether retailer i experienced entry of a supermarket or outlet among its main competitors at a given point in time, $entry_{ijt}$. Thus, $entry_{ijt}$ is a binary indicator taking value 1 in case retailer i located in parish j experienced the entry of a supermarket or outlet among its main competitors at time t, and value 0 otherwise. $\zeta(P_{t-1})$ is a functional form through which past prices may affect entry and location decisions by supermarkets or outlets. We estimate several model specifications which allow for ζ to be, alternatively, the price charged by retailer i located in parish j for the bundle of OTC drugs we analyse in period $t-1$ (P_{ijt-1}), and the ratio between P_{ijt-1} and the average $t-1$ price for the bundle of drugs analysed among all retailers operating in Lisbon. The remaining terms are drug, time, and parish fixed effects, as previously defined and ε_{ikt} is an error term, which is assumed to follow a logistic distribution. Since we are taking lags of price, the model is estimated using the years 2010 and 2015 only.

We estimate the model separately for the probability of retailer i experiencing the entry of a supermarket or of an outlet, and for all our alternative definitions of main competitors. If the estimates for β_1 are not statistically different from zero in these models, this suggests that the entry and location decisions by supermarkets and outlets are not affected by the prices charged by retailers operating in that location and we can rule out simultaneity.

More generally, and since our reduced-form entry model has a very specific functional form, we create bar charts of the share of retailers in each of the deciles of current and past prices for the bundle of five drugs which we analyse. If entry is in any way related to current or past price levels, then these plots should convey a non-random relationship. In particular, if we are concerned that entry may have occurred in locations which were more profitable because they had higher prices, then we expect that retailers in the highest price deciles would experience that largest shares of entry by non-pharmacies. We do this analysis separately by year and by type of non-pharmacy entrant. Similar graphs are created using deciles of resident population in order to assess whether there is any relationship between entry and demand.

4 Data

Our dataset consist of the prices of five popular OTC drugs charged by all pharmacies, supermarkets, and outlets located in the Lisbon municipality for three different time periods, 2006, 2010, and 2015.

The five OTC drugs whose prices were collected are the following: Aspirina 500mg, 20 pills, Bayer; Cêgripe, 20 pills, Jassen-Cilag Ltd.; Trifene200, 20 pills, Medinfar; Mebocaína Forte, 20 tablets, Novartis; and Tantum Verde, mouthwash, Angelini. These five medicines are some of the top-selling OTC drugs in Portugal. They are well-known brands to consumers, and often advertised in the media. These drugs tackle simple conditions such as fever and headaches (Aspirina), colds (Cêgripe), menstrual pain (Trifene200), sore throat (Mebocaína Forte), and toothache and gum swelling (Tantum Verde). None of them are subject to government reimbursement.

Price data for 2006 were collected by Simões et al. (2006), who visited each retailer in Lisbon between March and April 2006. These data were kindly made available to us, together with the key used to anonymize each retailer. We complemented these data by carrying out two additional rounds of data collection, in 2010 and 2015. Infarmed IP keeps an on-line, updated list of all active pharmacies as well as all supermarkets and outlets that are licensed to sell OTC drugs, together with the date in which the licence was granted. We examined these lists before each of the data collection rounds in order to identify the active players in the market and their exact location. Retailers were anonymized in the same way as in the 2006 data, so

that they can be followed over time.
Regarding the timing of data collection, data for 2010 and 2015 were gathered during the periods ranging from December 2010 to February 2011 and February to April 2015, respectively. Though Simões et al. (2006) visited every retailer selling the relevant OTC drugs at the time, some of them were not willing to release retail price information. When we carried out the data collection in 2010 and 2015, we purchased the drugs when the pharmacy staff did not want to release the price information. Therefore, while there are some missing price data for 2006, that does not occur for 2010 and 2015. For the last two periods of our dataset we observe prices in all retailers located in Lisbon.
Price data were complemented with indicator variables for retailer types (traditional pharmacy, supermarket or outlet) and for the parish where each retailer is located. In addition, we identified the main competitors of each retailer in each of the years under analysis. This was done using the latitude and longitude coordinates of each retailer in order determine its five nearest neighbours in each of the three time periods under analysis, as well as the competing retailers located within a 400-, 600-, and 800-meter radius from each retailer. Finally, we constructed variables indicating the number of supermarkets and outlets that each retailer faces among its main competitors.
Summary statistics of the main variables used throughout our analysis are presented in Table 1. For ease of interpretation prices are shown in euros, rather than in natural logarithms. Average prices of the drugs under analysis increased over time. Perhaps more interesting, the standard deviation of prices also increased, showing no evidence of convergence to an price equilibrium. The maximum price charged for a drug at a given point in time is often more than twice the minimum price for that drug (minima and maxima not shown in Table 1). This occurs for all time periods in our sample and motivates our analysis as it might be reflecting competition forces.
The share of supermarkets in the number of retailers in our dataset increased over time, while the share of outlets exhibits a small decline after 2010. The share of traditional pharmacies in the number of OTC retailers fell over time. The share of retailers facing a supermarket or outlet amongst their main competitors reflects these trends, as does the average number of supermarkets and outlets faced by each retailer. In our dataset we follow retailers over the three time periods for which we have data. Our dataset is unbalanced in the sense that there are retailers entering the market between each data collection round, while others exit the market. In total, 374 distinct retailers are observed in our dataset. On average, each retailer is observed for 2.24 periods. We have complete data on 221, 318, and 304 retailers, respectively, for 2006, 2010, and 2015.
In the data collection rounds of 2010 and 2015, some retailers did not have the drugs whose

Table 1: Data descriptive statistics

Variable	2006		2010		2015	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price *Aspirina 500mg*, €	3.02	0.23	3.55	0.32	4.05	0.42
Price *Cêgripe*, €	4.30	0.21	4.91	0.40	6.13	0.69
Price *Trifene200*, €	3.33	0.24	4.06	0.38	4.21	0.44
Price *Mebocaína Forte*, €	4.68	0.26	6.07	0.62	7.62	0.67
Price *Tantum Verde*, €	4.97	0.39	5.54	0.50	6.71	0.79
Traditional pharmacy, %	98.20	13.21	88.37	32.07	83.07	37.52
Supermarket, %	0	0	3.40	18.13	9.54	29.39
Outlet, %	1.8	13.30	8.23	27.50	7.39	26.18
Distance to nearest neighbour, in km	0.305	0.22	0.320	0.29	0.321	0.25
Supermarket among 5 nearest neighbours, %	0	0	9.44	0.295	32.51	0.469
Outlet among 5 nearest neighbours, %	0	0	25.23	43.45	27.11	44.47
No. retailers	167		265		256	
Average no. drug prices observed	5		4.99		4.91	
No. retailers - prices	835		1,324		1,258	

NOTES: For each year, the two columns report the mean and standard deviation of each variable. Prices are shown in Euros. Traditional pharmacy, supermarket, and outlet are binary indicators for the type of retailer. Supermarket/outlet among 5 nearest neighbours are binary indicators for whether a retailer has a supermarket or outlet among its 5 nearest neighbours.

prices we were collecting in stock on that day. Therefore, the average number of retailer-drug observations in these two time periods is below five. In total, we have 1,110 retailer-drug observations in 2006, corresponding to the five drug prices charged by each retailer. For 2010 and 2015 we have 1,588 and 1,503 observations, respectively. In total, our sample consists of 4,196 year-retailer-drug observations.

5 Results

We start by showing the composition of our treatment and control groups, as defined in Section 3.1. Table 2 shows the number of retailers in each group for the baseline analysis, which takes the five nearest neighbours of a retailer as its main competitors.[11] Note that although retailers do not switch groups over time, the number of retailers in each group changes. Between 2010 and 2015, 6 retailers in the control group and 3 retailers who had experienced the entry of an outlet between 2006 and 2010, had exited the market. The increase in number of retailers in the control group between 2006 and 2010 reflects the missing

[11] For the radius-based measures of main competitors, Table A.1 in the Appendix shows the composition of control and treatment groups.

price data for 2006, as discussed in Section 4.

Table 2: Composition of control and treatment groups in baseline specification

Group	2006	2010	2015
Control Group, I_0	111	209	203
Treated with supermarket in 2006/10, I_1	5	5	5
Treated with supermarket in 2010/15, I_3	18	18	18
Treated with outlet in 2006/10, I_2	15	15	12
Treated with outlet in 2010/15, I_4	18	18	18
Total	167	265	256

Table 3 shows the estimates of equation (1), which uses a DID approach to assess the price effects following the entry of non-pharmacy players in the Portuguese OTC market.

From the random effects estimation results shown in column RE, we see that retailer type matters: supermarkets and outlets charge about 20% and 3.6% lower prices than traditional pharmacies, respectively. Moreover, retailers in the treatment groups do not charge statistically different prices compared to those in the control.

According to the outcome of the Sargan-Hansen test, a generalization of the Hausman test that allows for clustering in the standard errors, the fixed effects estimation is preferred to the random effects (Sargan-Hansen statistic = 36.005, with an associated p-value of 0.000). Therefore, we focus on the results from the fixed effects estimation, shown in column FE. Note that fixed effects has the advantage of accounting for all unobserved, time-invariant, retailer-specific characteristics. This is especially important in our case, as we have limited information on retailer characteristics.

The estimates of interest are the interactions between time and the treatment indicators. In general, the entry of a supermarket among the five closest competitors of a retailer i is associated with a decrease in the prices charged by i. In 2010, retailers who faced the entry of a supermarket amongst their main competitors between 2006 and 2010 charged prices that were, on average, about 5% lower than retailers in the control group. This effect lasted over time, and in 2015 this same set of retailers charged, on average, about 4% lower prices than retailers facing only traditional pharmacies among their main competitors. Retailers who faced the entry of a supermarket among their competitors between 2010 and 2015 are found to charge 2.6% lower prices than the control group in 2015. The magnitude of these effects is similar across the random and fixed effects specifications. These effects are significant at 10% significance level.[12]

[12] In order to put the magnitude of these effects into perspective, the entry of a pharmacy chain in India is associated with a 2% price decline among incumbents (Bennett and Yin, 2018), and the entry of Walmart,

Table 3: Price effects using DID and PSM-DID approaches

	Simple DID		PSM-DID	
	RE	FE	Single Neighbour	LLR
Supermarket	-0.208***			
Outlet	-0.036**			
Treated with supermarket in 2006/10	0.001			
Treated with supermarket in 2010/15	-0.003			
Treated with outlet in 2006/10	-0.002			
Treated with outlet in 2010/15	0.001			
DiD estimates:				
2010×Treated with supermarket in 2006/10	-0.050	-0.053*	-0.035	-0.024
2015×Treated with supermarket in 2006/10	-0.037	-0.042*	-0.055**	-0.049**
2015×Treated with supermarket in 2010/15	-0.021	-0.026*	-0.029	-0.023
2010×Treated with outlet in 2006/10	-0.001	-0.004	-0.005	0.001
2015×Treated with outlet in 2006/10	0.039**	0.032*	0.030	0.039
2015×Treated with outlet in 2010/15	0.003	-0.002	0.002	0.003
Pre-treatment trends:				
2010×Treated with supermarket in 2010/15	-0.028	-0.030	-0.032	-0.020
2010×Treated with outlet in 2010/15	-0.001	-0.004	-0.005	0.006
Time FE	YES	YES	YES	YES
Drug FE	YES	YES	YES	YES
Parish FE	YES	NO	NO	NO
Retailer FE	NO	YES	YES	YES
N	3,417	3,417	1,580	1,540
R^2	0.905	0.905	0.914	0.914

NOTES: Estimates based on equation (1). Column 1 uses random effects whereas column 2 uses fixed effects. Because indicators for retailer type and for the treatment groups are time-invariant, these are dropped in the fixed effects estimation. Standard errors are clustered at the retailer level. The last two columns report estimates of the PSM-DID procedure. In column 3 single neighbour matching is used, and in column 4 matching was done using local linear regression. In columns 3 and 4 standard errors were bootstrapped using 30 repetitions, drawn cross-sectionally at the retailer level in the original sample.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The entry of an outlet amongst the main competitors of a given retailer produces effects in a different direction. Having faced the entry of an outlet among the main competitors between 2006 and 2010, was associated with a price in 2015 that was, on average, about 3-4% higher than in the control group (significant at 5% and 10% in the random and fixed effects specifications, respectively).

Finally, in the last two rows of Table 3, we use the fact that retailers that were treated only after 2010 (groups I_3 and I_4) are observed for two time periods before treatment in order to assess the plausibility of the common trend assumption. In 2010, retailers that did not yet face a supermarket or outlet among their main competitors (but who would face after 2010) are found to charge similar prices to retailers in the control group. This suggests that the common trend assumption does hold in our data, though we would need more periods of data in order to make a stronger claim regarding this aspect.

Our results are broadly robust to defining the treatment to facing the entry of a supermarket or outlet within a radius of 400, 600, and 800 meters. The opening of a supermarket leads to lower average OTC prices. The magnitude and significance of these effects differs from that of the baseline estimates, though some effects persist. The full set of results for these robustness checks is shown in the first three columns of Table A.3 in the Appendix.[13]

Furthermore, our results are robust to restricting the control group to retailers whose main competitors are in the control group themselves. The magnitudes and significance levels obtained are similar to those of the baseline analysis, suggesting very limited second-order effects. Also, our results are unchanged when restricting the sample to traditional pharmacies (see Table A.2 in the Appendix).

We now address the endogeneity concerns introduced in Section 3.2, and report the results from the PSM-DID estimation are reported in the last two columns of Table 3. Column 3 reports the results using single neighbour matching, whereas column 4 reports those using local linear regression. In many, but nor all, our PSM estimations we are able to achieve a decently balanced sample in terms of the covariates, and we thus assume that balance was achieved also in terms of unobservables.[14] It is worth bearing in mind that while asymptotically the

which charged on average 10% lower prices, was associated with a 1-1.2% price decrease by its competitors (Basker and Noel, 2009) and a short-run average city-level price decrease in the range of 1.5-3% (Basker, 2005).

[13]The results using radius measures are rather unstable, which is not surprising. Recall that we exclude from our analysis retailers that had experienced entry before our first round of data collection. Thus, a longer radius means that more retailers will be excluded from the analysis on the grounds that they had already been treated before our first round of data collection. This produces changes not only in the sample used for estimation, but also in the composition of treatment groups.

[14]For the sake of brevity, and since 12 PSM procedures are carried out for each of the models we estimate, we do not show the results of covariate balancing tests or graphs of the common support condition. These are available as supplementary material upon request from the authors.

estimates produced should be independent of the matching method, this is not the case in smaller samples. In particular, nearest neighbour estimates may be the least biased, but are also less precise. Nonparametric methods, such as local linear regression, in turn, may be more biased, but have higher precision (Gibson-Davis and Foster, 2006). Looking at the PSM-DID estimates using nearest neighbour matching and local linear regression, retailers who experienced the entry of a supermarket between 2006 and 2010 charge between 4.9% and 5.5% lower prices in 2015, compared to the control group (significant at 5%). The remaining effects are no longer statistically significant. The loss of statistical significance may be a result of the smaller estimation samples used, as for each treated retailer we select only one matched untreated retailer. Alternatively, it may be due to the larger standard errors obtained with bootstrapping. We also carried out the PSM-DID analysis using the radius-distance treatment definitions. The results of these analyses can be found in the last 6 columns of Table A.3 in the Appendix. Here as well, they resemble the results obtained from the simple DID.

Next, we report the results of our reduced-form entry model. When allowing the entry of supermarkets and outlets in a given location to be a function of past prices charged by the players operating in that location, we find no evidence supporting the claim that supermarkets and outlets make entry decisions based on the prices charged by retailers already operating in that area. In none of our model specification is the marginal effect associated with β_1 in equation (2) statistically significant (results reported in Table A.5 in the Appendix). This is quite natural for supermarkets, whose location is often pre-determined and OTC drugs are just added to the range of products already sold in existing locations.

Finally, the bar charts of the share of retailers in each decile of current and past price who experienced entry of non-pharmacy players among their five nearest competitors do not convey a clear relationship. In particular, the share of retailers experiencing entry is not larger for higher deciles of current or past prices. A similar analysis using deciles of resident population instead of price deciles yields again no clear pattern (see Figures A.1 and A.2 in the Appendix).

6 Concluding remarks

In this paper we study competition in the OTC drug market and the price effects following entry liberalisation, using data from Portugal. After entry liberalisation, new types of players other than traditional pharmacies are allowed to sell OTC drugs. In the market under analysis, these players consisted of supermarkets and outlets. The change in market structure represented an increase in competition faced by traditional pharmacies. While existing literature finds price competition among pharmacies to take place on a very small scale, the extent to which non-pharmacy competitors are able to place competitive constraints on their competitors is a topic that, to our best knowledge, has not yet been fully addressed in the literature.

Using unique price data at the retailer level for three distinct points in time, we show that non-pharmacy players, namely supermarkets, are able to somewhat constrain the pricing decisions of their competitors. This ability likely originates from the fact that non-pharmacy players do charge lower prices for the set of drugs we analyse. The magnitude of these differences is large, especially in the case of supermarkets, which charge, on average, 20% lower prices than traditional pharmacies. Outlets are found to charge, on average, 3.6% lower prices than traditional pharmacies. The fact that supermarkets charge much lower prices than both pharmacies and outlets might be reflecting the existence of economies of scale in their distribution chain, more efficient practices regarding stock management and logistics, and stronger bargaining position when engaging in price negotiations with suppliers. Alternatively, traditional pharmacies may be able to charge higher prices if they face a more inelastic demand than outlets and supermarkets. A more inelastic demand can result from the fact that pharmacies have a monopoly on selling prescription drugs, but may also arise if consumers value quality (i.e. the advice from the pharmacist) over price differences, or if they exhibit some degree of habit formation and search costs are high relative to its benefits. In order to analyse differences in the elasticity of demand across types of players in the OTC market, we would need quantity data at the retailer level, which we lack. However, some of these aspects can be discussed. Regarding quality of service, if pharmacies indeed adjust along this dimension, then our estimates of the price effects following the entry of non-pharmacies can be seen as a lower bound. With regard to search costs and habit formation, Sorensen (2000) notes that the benefits of searching in the drug market are higher for expensive drugs and regular purchases, and this is not the case of OTC drugs.

We obtain the price effects associated with the entry of either a supermarket or an outlet amongst the main competitors using a difference-in-differences approach with four distinct treatment groups. Treatment groups differ in the type of treatment (having a supermarket or outlet entering the OTC market amongst the five main competitors) and the timing of the treatment (between 2006 and 2010 and between 2010 and 2015). Retailers whose main competitors are always traditional pharmacies are our control group. According to our baseline findings, retailers that had a supermarket entering the OTC market among their five nearest neighbours between 2006 and 2010 were charging, on average, 5.3% lower prices in 2010, as compared to the control group. The effect is maintained over time and in 2015 these retailers were charging prices that were 4.2% lower than those charged by the control group. These results suggest that the liberalisation process caused a long-lasting decrease in prices through the entry of supermarket players, who are able to place competitive constraints on their competitors. More recent entry by supermarkets (i.e. after 2010) leads to price reductions of a lower magnitude, about 2.6%. We show that our results are not driven by the existence of pre-treatment trends, and that they are somewhat robust to alternative measures of competitive pressure, based on the entry of a supermarket or outlet within a given radius of a retailer. While statistical significance is often lost, some effects show consistently in our results. In addition, results from the estimation of a reduced-form entry model and the use of a propensity score matching difference-in-differences approach help to rule out concerns related to simultaneity and omitted variable bias from our analysis. This gives us confidence that we are capturing the causal effects of non-pharmacy entry on the pricing decisions of existing retailers.

Given that the intention to liberalise the OTC market was announced by the Portuguese government a few months prior to its implementation, one cannot completely rule out the possibility that traditional pharmacies adopted a strategy (other than pricing) aimed at preventing entry of non-pharmacy players. Nevertheless, the fact that entry of non-pharmacy players took off quickly after liberalisation, combined with pharmacies not being used to operate in a competitive environment, leaves less scope for such strategic behaviour by pharmacies.

In our dataset we observe that the number of traditional pharmacies in the Lisbon municipality has been steadily declining over time. However, exit of traditional pharmacies cannot be directly linked to the liberalisation of the OTC market. Instead, it is more likely a consequence of the overall economic environment and the squeezing of pharmacy margins on prescription drugs (Barros, 2012), rather than of the liberalisation of the OTC market. Indeed, the share of OTC drugs on total pharmacy revenue is likely too small to produce such an impact. In any event, we do not study entry and exit of pharmacies in this paper due to the fact that: i). the opening of a pharmacy is subject to licensing by the Portuguese government, and that there are restrictions on the minimum population to be served by the new pharmacy; and ii). our data have long gaps between the periods we observe, not allowing timely observation of entry and exit of players in the market.

As usual in natural experiment settings, our results are specific to retailers operating in the Lisbon municipality, and to the set of drugs and years we analyse. Nevertheless, our study makes a contribution to a deeper understanding of how competition takes place in retail pharmaceutical OTC markets in general, drawing on the Portuguese experience. Based on our results, OTC market liberalisation reforms can be successful at bringing competition forces into play and lowering OTC drug prices. This may not occur in rural areas, where the entry of non-pharmacy players takes place on a smaller scale.

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A Appendix

Table A.1: Composition of control and treatment groups in radius-based specifications

Radius	Group	2006	2010	2015
400 m	Control Group, I_0	139	237	226
	Treated with supermarket in 2006/10, I_1	5	5	5
	Treated with supermarket in 2010/15, I_3	6	6	6
	Treated with outlet in 2006/10, I_2	15	15	13
	Treated with outlet in 2010/15, I_4	12	12	12
	Total	177	275	262
600 m	Control Group, I_0	96	196	190
	Treated with supermarket in 2006/10, I_1	9	9	8
	Treated with supermarket in 2010/15, I_3	12	12	12
	Treated with outlet in 2006/10, I_2	18	18	14
	Treated with outlet in 2010/15, I_4	12	12	12
	Total	174	247	236
800 m	Control Group, I_0	70	171	170
	Treated with supermarket in 2006/10, I_1	9	9	7
	Treated with supermarket in 2010/15, I_3	8	8	8
	Treated with outlet in 2006/10, I_2	22	22	18
	Treated with outlet in 2010/15, I_4	10	10	10
	Total	119	220	212

NOTES: The table shows the number of retailers included in the estimation sample, for each of the radius used to define the set of main competitors of a retailer. The lower number of retailers in the control group in 2006 is a consequence of missing price data for that year, as discussed in Section 4. In addition, the number of retailers used changes with the length of the radius. Recall that we exclude from our analysis retailers which had experienced entry before our first round of data collection. Thus, a longer radius means that more retailers will be excluded from the analysis because they had already been treated before our first round of data collection.

Table A.2: Results from estimating equation (1) among pharmacies only

	400m radius	600m radius	800m radius	5 nearest neighbours
DID estimates:				
2010×Treated with supermarket in 2006/10	-0.076***	-0.022	-0.037	-0.049
2015×Treated with supermarket in 2006/10	-0.038*	-0.038*	-0.030	-0.044*
2015×Treated with supermarket in 2010/15	-0.025	-0.010	-0.045*	-0.028*
2010×Treated with outlet in 2006/10	-0.006	-0.002	0.007	0.005
2015×Treated with outlet in 2006/10	0.015	0.012	0.009	0.028
2015×Treated with outlet in 2010/15	0.035*	0.005	-0.007	-0.004
Pre-treatment trends:				
2010×Treated with supermarket in 2010/15	-0.040	0.002	-0.038	-0.027
2010×Treated with outlet in 2010/15	0.011	-0.000	-0.012	0.000
Time FE	YES	YES	YES	YES
Drug FE	YES	YES	YES	YES
Parish FE	NO	NO	NO	NO
Retailer FE	YES	YES	YES	YES
N	3,170	2,765	2,372	3,035
R^2	0.912	0.909	0.914	0.911

NOTES: Estimates based on the fixed effects estimation of equation (1) among traditional pharmacies only. Columns 1 to 3 take the main competitors of retailer i as being all retailers located within a radius of 400, 600, and 800 meters, respectively. Column 4 takes the main competitors if retailer i as being its 5 nearest neighbours. Standard errors are clustered at the retailer level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A.3: Results from DID and PSM-DID estimations using radius-based measures of competition

	Simple DID			Single neighbour			Local Linear Regression		
	400m radius	600m radius	800m radius	400m radius	600m radius	800m radius	400m radius	600m radius	800m radius
DiD estimates:									
2010×Treated with supermarket in 2006/10	-0.079***	-0.026	-0.042	-0.053*	-0.007	-0.045	-0.053**	-0.014	-0.047
2015×Treated with supermarket in 2006/10	-0.037	-0.036*	-0.028	-0.010	-0.027	-0.036*	-0.010	-0.027	-0.044
2015×Treated with supermarket in 2010/15	-0.024	-0.008	-0.043**	0.009	-0.001	-0.039*	0.008	-0.001	-0.047*
2010×Treated with outlet in 2006/10	-0.025	-0.002	0.005	0.010	0.017	-0.003	0.011	0.026	-0.006
2015×Treated with outlet in 2006/10	-0.005	0.017	0.012	-0.024	0.025	0.016	0.024	0.030	0.009
2015×Treated with outlet in 2010/15	0.036*	0.007	-0.005	0.060**	0.004	-0.015	0.060*	0.004	-0.022
Pre-treatment trends:									
2010×Treated with supermarket in 2010/15	-0.044	-0.001	-0.043	0.020	0.013	-0.051	0.021	0.013	-0.054
2010×Treated with outlet in 2010/15	0.007	-0.004	-0.017	0.040*	0.012	-0.029	0.040*	-0.012	-0.032
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Drug FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Parish FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
Retailer FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	3,567	3,147	2,754	990	1,430	1,350	990	1,380	1,350
R^2	0.904	0.902	0.906	0.903	0.912	0.926	0.903	0.913	0.932

NOTES: Estimates based on the fixed effects estimation of equation (1). There are three vertical blocks in the table, corresponding to a simple DID estimation, a PSM-DID estimation using single neighbour matching, and a PSM-DID estimation using local linear regression. In each of the three vertical blocks, the first column shows the price effects of the entry of supermarkets and outlets within 400m, whereas the second and third columns use radii of 600 and 800m. Standard errors are clustered at the retailer level in the simple DID estimation. For single neighbour matching and local linear regression, standard errors are bootstrapped using 30 repetitions, drawn cross-sectionally at the retailer level in the original sample. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A.4: Results from estimating equation (1) among retailers whose competitors are all in the control group

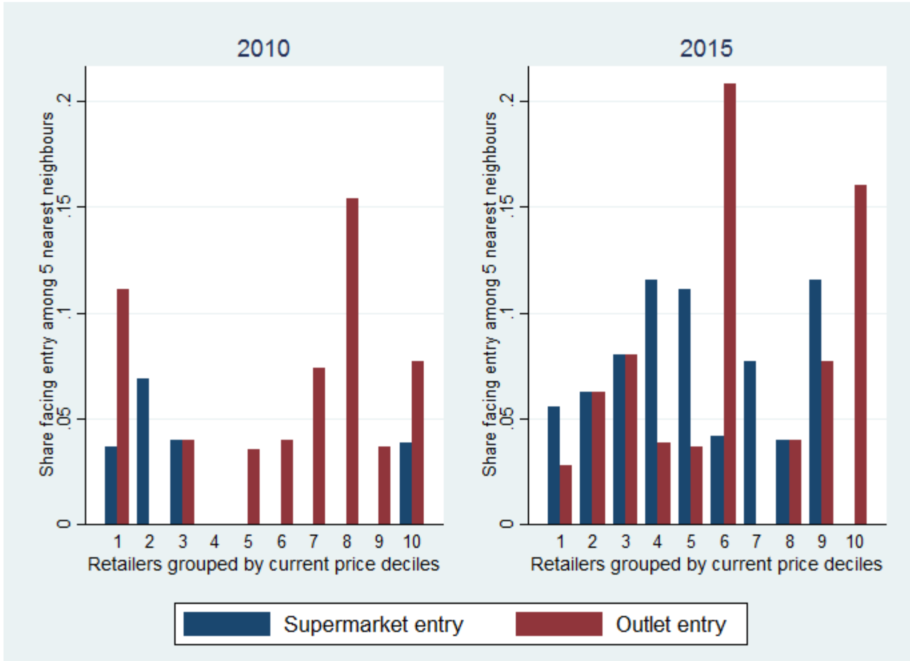
	400m radius	600m radius	800m radius	5 nearest neighbours
DID estimates:				
2010×Treated with supermarket in 2006/10	-0.077***	-0.024	-0.049	-0.049
2015×Treated with supermarket in 2006/10	-0.038	-0.035*	-0.035	-0.046*
2015×Treated with supermarket in 2010/15	-0.024	-0.008	-0.051*	-0.029*
2010×Treated with outlet in 2006/10	-0.022	0.001	-0.002	0.000
2015×Treated with outlet in 2006/10	0.005	0.017	0.005	0.029
2015×Treated with outlet in 2010/15	0.036*	0.007	-0.013	-0.006
Pre-treatment trends:				
2010×Treated with supermarket in 2010/15	-0.041	0.001	-0.049	-0.027
2010×Treated with outlet in 2010/15	0.010	-0.001	-0.013	-0.000
Time FE	YES	YES	YES	YES
Drug FE	YES	YES	YES	YES
Parish FE	NO	NO	NO	NO
Retailer FE	YES	YES	YES	YES
N	2,962	2,049	1,681	1,712
R^2	0.866	0.849	0.843	0.892

NOTES: Estimates based on the fixed effects estimation of equation (1) among retailers whose competitors are all in the control group. Columns 1 to 3 take the main competitors of retailer i as being all retailers located within a radius of 400, 600, and 800 meters, respectively. Column 4 takes the main competitors if retailer i as being its 5 nearest neighbours. Standard errors are clustered at the retailer level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

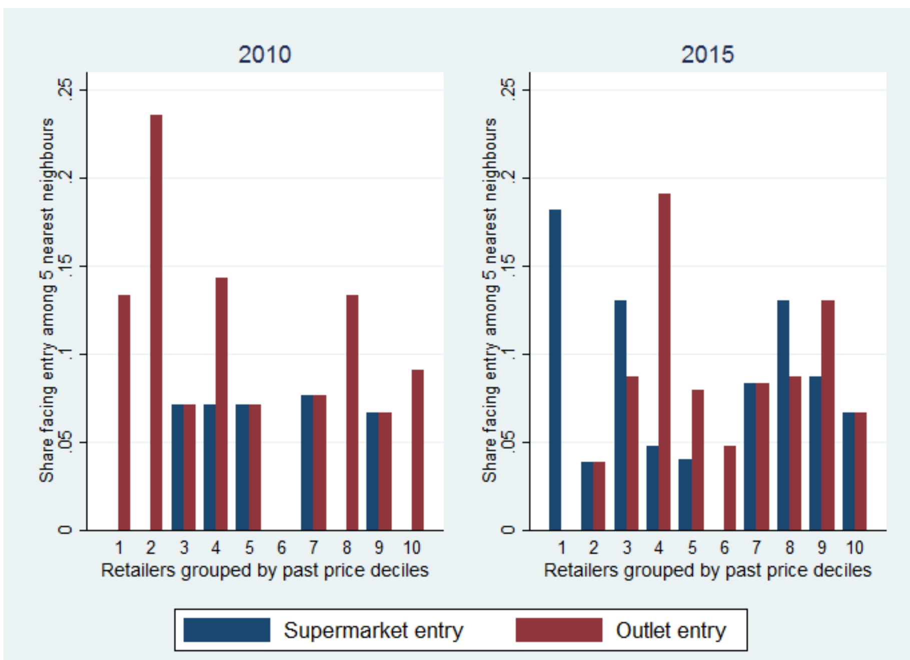
Table A.5: Results from the estimation of the reduced-form entry model

Main Competitors	$\zeta(P_{t-1})$ specification	Supermarket	Outlet
5 Nearest neighbours	P_{it-1}	-0.238	0.288
5 Nearest neighbours	P_{it-1} relatively to average market price	-0.358	0.141
400m radius	P_{it-1}	-0.317	0.499
400m radius	P_{it-1} relatively to average market price	-0.661	0.127
600m radius	P_{it-1}	0.251	1.066
600m radius	P_{it-1} relatively to average market price	0.112	0.966
800m radius	P_{it-1}	0.416	-0.839
800m radius	P_{it-1} relatively to average market price	0.286	-0.947

NOTES: Marginal effects of β_1 from RE logit estimation of equation (2), with dependent variable being an indicator for facing the entry of a supermarket (column 1) and an outlet (column 2). There are four panels, each corresponding to an alternative definition of main competitors of retailer i. In the top panel, the main competitors of a retailer are its five nearest neighbours. In the second, third, and fourth panels the competitors of a retailer are the retailers located within a 400, 600, and 800-meter radius, respectively. In each of the panels, the first row tests whether retailer i facing the entry of a supermarket/outlet among its main competitors depends on the prices it charged in the previous period, $\zeta(P_{t-1}) = P_{it-1}$. The corresponding figures can be interpreted as the percentage-point change in the probability of facing entry associated with a 1% higher OTC bundle price in the previous period. The second row tests whether it depends on the lagged prices of retailer i relatively to the average bundle price in the city of Lisbon. The corresponding figures can be interpreted as the percentage-point change associated with a 1-unit increase in the independent variable. Recall that our estimation sample differs according to how we define the set of main competitors of retailer i, so that a different number of observations is used to obtain each estimate shown on the table. Standard errors are clustered at the retailer level. $*p < 0.10, **p < 0.05, ***p < 0.01$.



(a) By current price deciles



(b) By past price deciles

Figure A.1: Share of retailers facing entry of non-pharmacies among the 5 nearest neighbours, by price deciles

NOTES: In the top panel, retailers were grouped into deciles according to their current price for the bundle of five OTC drugs considered in our analysis. In the bottom panel, retailers were grouped into deciles according to their past price for the bundle of five OTC drugs considered in our analysis. In all the four plots the vertical axis indicates the share of retailers in each decile who faced the entry of a supermarket or outlet among their five nearest neighbours. We see that entry of supermarkets and outlets took place along all current and past price deciles in both 2010 and 2015l, with no clear pattern.

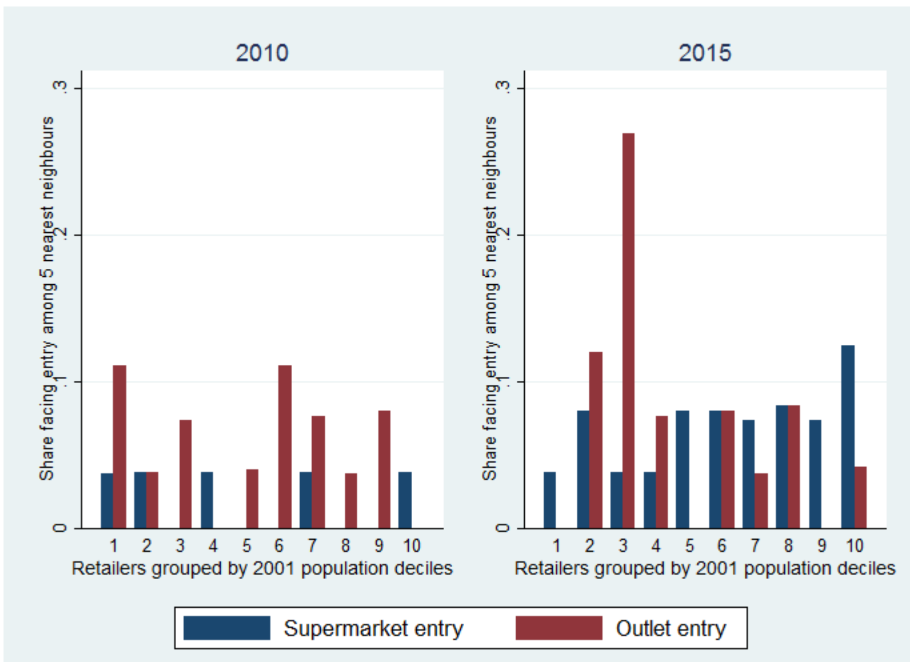


Figure A.2: Share of retailers facing entry of non-pharmacies among the 5 nearest neighbours, by population deciles

NOTES: In order to create this figure, retailers were grouped into deciles according to their 2001 level of demand, as measured by the resident population in the Census tract where they are located. In all the four plots the vertical axis indicates the share of retailers in each decile who faced the entry f a supermarket or outlet among their five nearest neighbours. We again see that entry of supermarkets and outlets took place along all population deciles in both 2010 and 2015, with no clear pattern.