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

Ana Moura[†a] and Pedro Pita Barros[b]

[a]Tilburg University, P.O. Box 90153, 5000 LE Tilburg, The Netherlands.

[b]Nova School of Business and Economics. Rua da Holanda 1, 2775-405 Carcavelos, Portugal.

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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†Corresponding author at: Tilburg University, P.O. Box 90153, 5000 LE Tilburg, The Netherlands. Tel.: +31 134 663 425.. E-mail: a.c.moura@tilburguniversity.edu.

1 Introduction

During the last two decades, European countries have extensively reformed their community pharmacy sectors. These 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. 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 refer to these as non-pharmacy retailers, as opposed to traditional pharmacies.

The rationale for OTC market liberalisation was that the entry of non-pharmacy retailers, combined with free OTC pricing, would lower OTC drug prices via increased competition among retailers (Lluch and Kanavos, 2010; Stargardt et al., 2007; Morgall and Almarsdóttir, 1999). 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 allowed OTC drugs to be sold outside pharmacies, namely in supermarkets and non-pharmacy outlets. Using a difference-in-differences (DID) strategy, we assess the impact of supermarket and outlet entry on OTC drug prices. Despite pharmacies being unable to place competitive constraints on their competitors (Stargardt et al., 2007; Pilorge, 2016), non-pharmacy players may be able to do so if they charge substantially lower prices.

We use price data for five 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 points in time, the years of 2006, 2010, and 2015. 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 DID analysis, we estimate the change in prices charged by a given retailer following the entry of a non-pharmacy among its main competitors. We define four distinct treatment groups depending on the type of entrant (supermarket or outlet) 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, compared to the control group. This effect persists over time, and the same retailers charge, on average, 4.2% lower prices than the control group in 2015. 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, compared to control group. The magnitude of these effects is larger in areas where market structure is more concentrated. Experiencing the entry of an outlet is not associated with lower prices. These results do not seem driven by existing pre-treatment trends, and are robust to alternative definitions of main competitors of a retailer. Their causal interpretation, however, rests on the assumption that market structure is exogenous, so that exposure to treatment is random. We address this concern in two ways. First, we implement a propensity score matching difference-in-differences approach (PSM-DID as in Heckman et al., 1997 and Smith and Todd, 2005), with propensity scores being a function of pre-liberalisation levels of competitive pressure and demand faced by each retailer, and obtain similar results to our baseline estimation. 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, and 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 adopted similar OTC market liberalisation reforms, but also to those considering their adoption. 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 of OTC products to be sold outside pharmacies. In the following years, Denmark, Norway, Italy, Hungary, Sweden, and France adopted similar policies. Germany and the United Kingdom had already done so during the 1990s.

Whether OTC market liberalization lowered prices via increased competition is ultimately an empirical question. In theory, pharmacies may try to vertically differentiate their services from non-pharmacies through quality increases (i.e. advice from the pharmacist), while not lowering their prices.[2] The existing empirical literature on OTC drug pricing and the effects

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

[2] Patrício et al. (2005), CEGEA (2005), and Gomes (2007) used the classic frameworks of Hotelling (1929) and Waterson (1993) to make predictions of the expected price outcomes of the reform. These predictions pointed in very different directions and the real impact of the reform was never assessed.

of OTC market liberalisation in Europe is scarce, mostly descriptive, and often unable to confirm the expected downward trend in OTC prices (OECD, 2014; 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 (Stargardt et al., 2007). Alternatively, pharmacies may not compete in prices but rather in quality and range of services, location, or opening hours (Martins and Queirós, 2015; Lluch and Kanavos, 2010; Anell, 2005; Rudholm, 2008; Stargardt et al., 2007; Schaumans and Verboven, 2008). Descriptive evidence of average price reductions after the liberalisation process was found for both Iceland (Anell, 2005) and the UK (OFT, 2003). However, neither the competitive forces leading to such outcome nor the role of non-pharmacy retailers in promoting competition have been assessed. In this paper, we focus on competitive pressure exerted by non-pharmacy retailers and estimate the causal impact of their entry in the OTC market, 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) study the entry of a retail pharmacy chain in India on the price of incumbent pharmacies. Basker (2005) studies the effect of Walmart entry on average city-level prices, and Basker and Noel (2009) estimate its effects on the competitor prices. We contribute to this literature by providing evidence for the OTC drug market in a developed country.

Finally, we contribute to the strand of literature applying PSM-DID in panel datasets (e.g., Blundell et al., 2004; Polidano and Vu, 2015; Song and Sun, 2016), by applying PSM-DID in panel data in a context featuring multiple treatments.

The remainder of this paper is as follows. Section 2 provides institutional background on the Portuguese OTC market and the liberalisation process. Section 3 presents our empirical strategy. Section 4 describes our dataset. Section 5 presents our results and Section 6 concludes.

[3]Traditional pharmacies in Portugal are independently owned due to existing ownership restrictions which limit the number of pharmacies that an agent can own. Therefore, there are no pharmacy chains. Restrictions of this sort are common across countries and seek to ensure a certain degree of market competition. Recently, organized groups of independently-owned pharmacies were created, but our data are prior to that.

2 The Portuguese OTC market

Traditionally, pharmacies enjoyed a monopoly for selling both prescription and OTC drugs. Their monopoly for selling OTC drugs ended with Decree-Law n. 134/2005, published on August 16, which allowed the sale of OTC drugs outside pharmacies. As a result, two types of retailers entered the Portuguese OTC drug market: supermarkets and non-pharmacy outlets (in Portuguese, *parafarmácias*). Until today prescription drugs remain available only at traditional pharmacies.

In supermarkets, by regulation, OTC drugs are not are freely accessible to customers. Instead, they are placed either in a closed shelf located behind the cashiers' check-out counter, or in a dedicated area together with other wellness products. Either way, customers wishing 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 belong to either one of the two biggest supermarket chains in Portugal. We observe in our data that supermarkets belonging to these chains adopt a common pricing strategy, rather than store-specific prices that reflect the competitive environment faced by each store belonging to the chain.

Non-pharmacy outlets are stores selling cosmetics, baby care products, vitamins and supplements, 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 Portuguese OTC market must apply for a licence at the National Authority of Medicines and Health Products (Infarmed), and satisfy specific requirements related to drug storage, qualification of personnel, among others. Application by supermarket and outlet chains is done individually by each store belonging to the chain (as opposed to one licence application for all stores belonging to the chain).

The entry of supermarkets and outlets in the OTC market took place quickly following market liberalisation.[4] According to Infarmed, the first non-pharmacies entered the OTC market in October 2005. In the first quarter of 2009 there were over 800 non-pharmacy retailers in Portugal, and by the end of 2017 their number had risen to about 1,200 (Infarmed, 2018). The volume share of OTC drugs in the total outpatient pharmaceutical market was 16.5% by the end of 2017. The corresponding value share was 11.7%. The non-pharmacy volume share of the OTC sector in Portugal has risen continuously since market liberalisation, reaching 20.8% in 2014. Since 2014, this share has been stable at about 20% (Infarmed, 2018).

[4]Throughout the paper, entry in the OTC market refers to the moment at which a retailer is granted a licence to sell OTC drugs. For example, if a supermarket chain has a store in a given location since 1990 and that specific store got a license to sell OTC drugs in 2011, then 2011 is its entry date in the OTC market. If the same chain opens a new store after the sale of OTC drugs outside pharmacies is allowed, then its opening date and date of entry in the OTC market may, but need not, be the same.

3 Methodology

3.1 Empirical Strategy

We use a DID strategy to assess the price effects following OTC market liberalisation and consequent entry of non-pharmacy retailers. The liberalisation started before our first round of data collection. However, non-pharmacy entry took place gradually, meaning that each retailer experiences the entry of different types of non-pharmacies at different points in time. This is our source of identification.

We define four distinct treatment groups, depending on the type of entrant and timing of entry. 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 incumbent retailers. A 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, its set of main competitors consisted only of traditional pharmacies. Each of the two treatments can take place either between 2006 and 2010 or between 2010 and 2015. This allows us to differentiate between early and late entry.[5] The control group is composed of retailers who never face supermarkets or outlets as main competitors. 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 want to compare the pre- and post-treatment price differences between each treatment group 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. traditional pharmacy, supermarket or 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. ε_{ijkt} is an error term. The price effects of non-pharmacy entry will be revealed by the $\theta_{tg(i)}$ estimates corresponding to the interactions between each of the four treatment groups and their corresponding post-treatment periods.

[5]There are retailers who already faced non-pharmacy competitors as of our first data collection round (2006). For simplicity, these are disregarded throughout our analysis. Thus, 28 retailers are dropped from the estimation sample for the baseline analysis. When using radius-based measures of competition, the number of retailers excluded from the estimation sample differs.

[6]Portuguese municipalities are composed of smaller areas called parishes. The number and geographic borders of the Lisbon parishes were revised in 2012. We use the revised version, according to which there are 24 parishes in Lisbon.

Our DID design is as flexible as possible, given that we have data for only three time periods. 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, since $\theta_{tg(i)}$ includes interactions between the treatment groups treated after 2010 and the year fixed-effects (as for these treatment groups we observe two pre-treatment periods). The statistical significance of these coefficients informs about the plausibility of 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, since $\theta_{tg(i)}$ includes interaction terms between the groups treated between 2006 and 2010 and the year fixed-effects (as for these treatment groups we observe two post-treatment periods).

Equation (1) is estimated using alternatively random-effects and fixed-effects at the retailer level. In both estimations, we cluster standard errors at the retailer level to account for serial correlation in retailer pricing decisions.

In our baseline specification, we define the set of main competitors of a retailer as its five nearest neighbours, regardless of how far they are located. Therefore, the baseline treatments consist of having a supermarket or outlet entering the set of five nearest neighbours between 2006 and 2010 or between 2010 and 2015. In robustness checks we redefine the set of main competitors of a retailer to include all retailers located within a radius of 400, 600, and 800 metres of its location.

Entry is expected to have stronger effects in areas where market structure is more concentrated, i.e. closer to a monopoly. In the limit, with price competition and undifferentiated products one single entrant can drive monopoly prices down to marginal cost. We assess this hypothesis by restricting our sample to the most spatially isolated retailers. Furthermore, there may be heterogeneous price responses to non-pharmacy entry across retailer types. Since our prime interest is in the effects of entry on the pricing of pharmacies, we estimate our models amongst pharmacies only. Finally, our control group may be contaminated by second-order effects related to the entry of non-pharmacies. 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 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). In order to mitigate this concern, 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 adequate.

3.2 Endogeneity of market structure

Our estimates from equation (1) can only be interpreted as causal if the entry and location decisions of non-pharmacies are exogenous. The decision of opening a supermarket or outlet in a given location is plausibly unrelated to pharmacy market structure, as OTC drugs are a only small subset of their product range.[7] However, it is more difficult to defend the exogeneity assumption when an existing retailer belonging to a chain applies for a licence to sell OTC drugs, while other retailers belonging to the same chain do not.

One potential threat is the existence of *time-varying*, retailer-specific, unobservables that affect both prices charged by incumbent retailers and entry. 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 instrumented for entry using pre-existing market structure, though this is a rather weak instrument (Basker and Noel, 2009). We use an alternative approach, and combine propensity score matching with our DID design (Heckman et al., 1997; Smith and Todd, 2005). The underlying idea is that by matching treated and untreated retailers 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. We estimate the propensity score as a function of the level of competitive pressure and demand retailers face prior to the liberalisation reform (additional technical details are discussed in online Appendix B).

Another potential threat is that, 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 address this concern, 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) $t-1$ 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 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 are aggregated in order to generate an OTC bundle price which is retailer-year specific. The precise equation

[7] In the particular case of supermarket chains, OTC drugs seem to correspond to a small share of total sales. For example, in 2014 the supermarket chain with the largest OTC sales value was Pingo Doce with M€ 8.3 nationwide (Infarmed, IP, 2015). Its total sales value was M€ 3,234 (Jerónimo Martins SGPS SA, 2015). At the time OTC drugs were available at 74 of a total of 380 stores existing Pingo Doce in Portugal. Assuming stores are symmetric, on average, OTC drugs amount to 1.3% of total sales value per store.

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 retailer i, located in parish j, experiences the entry of a non-pharmacy among its competitors in period t. Although we do not observe this probability, we observe whether a retailer experienced non-pharmacy entry 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 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. ε_{ikt} is a logistically-distributed error term. Since we take 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 an outlet, and for all our alternative definitions of main competitors. If the estimates of 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 driven by the prices charged by retailers operating in that location.

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 points in time, 2006, 2010, and 2015.

The five OTC drugs 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 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).

Price data for 2006 were collected by Simões et al. (2006), 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 keeps an on-line, updated list of all active pharmacies as well as all supermarkets and outlets that are licensed to sell OTC drugs. We examined these lists before each data collection round in order to identify the active retailers in the market and their exact location. Price data for 2010 and 2015 were gathered between December 2010 and February 2011 and between February and April 2015, respectively.

Though Simões et al. (2006) visited every OTC retailer at the time, some of them were not willing to release price information. This results is some missing price data for 2006. When we carried out the data collection in 2010 and 2015, we purchased the drugs when the pharmacy staff did not want to release their prices. Therefore, in these two periods we observe prices for 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. We identify the main competitors of each retailer in each time period using their latitude and longitude coordinates. Summary statistics of the main variables used throughout our analysis are shown in Table 1. For ease of interpretation prices are shown in euros, instead of 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 equilibrium.

The share of supermarket retailers in our dataset increased over time, while the share of outlets exhibits a small decline after 2010. The share of retailers facing a supermarket or outlet amongst their five nearest neighbours reflects these trends. In our dataset we follow retailers over the three time periods for which we have data. Our dataset is unbalanced because there are retailers entering and exiting the market between each data collection round. 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 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.

Table 1: Summary 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 retailer type. Supermarket/outlet among 5 nearest neighbours are binary indicators for whether a retailer has a supermarket or outlet among its 5 nearest neighbours.

5 Results

Table 2 shows the composition of the treatment and control groups when defining the five nearest neighbours of a retailer as its main competitors.[8] Although retailers do not switch groups over time, the number of retailers in each group varies over time due to market entry and exit. The increase in the number of retailers in the control group between 2006 and 2010 also reflects the missing 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	111	209	203
Treated with supermarket in 2006/10	5	5	5
Treated with supermarket in 2010/15	18	18	18
Treated with outlet in 2006/10	15	15	12
Treated with outlet in 2010/15	18	18	18
Total	167	265	256

[8]Table A.1 in the online Appendix shows the composition of control and treatment groups for the radius-based measures of main competitors.

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 RE uses random-effects and column FE uses fixed-effects. Standard errors are clustered at the retailer level. Columns 3 and 4 report estimates of the PSM-DID procedure using single neighbour matching and local linear regression, respectively. Standard errors in columns 3 and 4 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 DID estimates of equation (1) are shown in Table 3. The results for the random-effects estimation (column RE) show that retailer type matters: supermarkets and outlets charge about 20% and 3.6% lower prices than traditional pharmacies, respectively. Retailers in the treatment groups do not charge statistically different prices compared to those in the control. According to the Sargan-Hansen test, a generalization of the Hausman test that allows clustering in the standard errors, the fixed-effects estimation is preferred to the random-effects (Sargan-Hansen statistic = 36.005, p-value=0.000). Therefore, we focus on the results in column FE, which have the advantage of accounting for all unobserved, time-invariant, retailer-specific characteristics.

In general, the entry of a supermarket among the five closest competitors of a retailer is associated with a price decrease. 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 persists over time, and in 2015 this same set of retailers charged, on average, about 4% lower prices than retailers in the control group. Retailers who faced the entry of a supermarket among their competitors between 2010 and 2015 charged 2.6% lower prices than the control group in 2015.[9]

The entry of an outlet amongst the five closest competitors of a retailer produces effects in the opposite direction. Retailers who faced the entry of an outlet among their main competitors between 2006 and 2010 charged a 3-4% higher price in 2015, compared to the control group. Finally, in the last two rows of Table 3, retailers treated only after 2010, who are observed for two time periods before treatment, inform about the plausibility of the common trend assumption. The estimated coefficients are not statistically significant, suggesting that the common trend assumption is plausible in our setting, though we would need more periods of data in order to make a stronger claim on this matter.

The last two columns of Table 3 present the PSM-DID results using single 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. The remaining effects are no longer statistically significant. These 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 (see Table A.4 in the online Appendix).[10]

[9] To help putting 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, which charged on average 10% lower prices, is 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).

[10] The results using radius measures are rather unstable. 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 because 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.

The results are also robust to restricting the sample to traditional pharmacies (Table A.3 in the online Appendix). Their magnitudes and significance are stronger amongst retailers who were most spatially isolated in 2006 (Table A.2 in the online Appendix).[11] Finally, our results remain unchanged when restricting the control group to retailers whose main competitors are in the control group themselves, suggesting very limited second-order effects (Table A.5 in the online Appendix).

The results of our reduced-form entry model do not support the claim that supermarkets and outlets make entry decisions based on the prices charged by retailers already operating in that area, since the estimate of β_1 in equation (2) is never statistically significant (Table A.6 in the online 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, and because 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. We do this analysis separately by year and by type of non-pharmacy entrant. 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. However, we find no such patter (see Figure A.1 in the online Appendix). A similar analysis using deciles of resident population instead of price deciles yields again no clear pattern (see Figure A.2 in the online Appendix).

6 Concluding remarks

We study price competition in the OTC drug market following entry liberalisation, using data from Portugal. Entry liberalisation allowed supermarkets and outlets to sell OTC drugs. Their entry represented an increase in competitive pressure 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 retailers 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

[11] We also run our model amongst the least isolated retailers as of 2006. We find few significant effects and of a very small magnitude, suggesting that all the action originates from retailers who enjoyed some degree of market power before facing entry (results available upon request).

supermarkets are able to significantly impact the pricing decisions of their competitors: a retailer experiencing the entry of a supermarket among its main competitors lowers its price by 4-5%. This effect persists over time and its magnitude is stronger amongst retailers who likely enjoyed some degree if market power prior to experiencing entry. The ability of supermarkets to impact the prices charged by incumbent retailers likely originates from the fact that supermarkets charge 20% lower prices for the set of drugs we analyse. This lower prices might be due to economies of scale in the distribution chain of supermarkets, 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 non-pharmacies. A more inelastic demand can result from pharmacies having a monopoly on 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. The OTC drugs we analyse are regularly used products and require little advice from the pharmacist, which limits scope for vertical differentiation across points of sale. Nevertheless, if pharmacies adjust along the quality dimension our estimates can be seen as a lower bound. Regarding search costs and habit formation, the benefits of searching in the drug market are higher for expensive drugs and regular purchases (Sorensen, 2000), and this is not the case of OTC drugs.

We find no clear ability of outlets to impact prices of existing retailers, as both the sign and significance of the estimated coefficients vary depending on the model specification.

The Portuguese government announced its intention to liberalise the OTC market a few months before Decree-Law 134/2005 was passed. We cannot completely rule out that pharmacies adopted strategies other than pricing to prevent entry of non-pharmacy retailers. Nevertheless, the fact that entry of non-pharmacies took off quickly after liberalisation, combined with pharmacies not being used to operate in a competitive environment, leaves less scope for such strategic behaviour.

The number of traditional pharmacies in the Lisbon municipality has been steadily declining over time. Exit of traditional pharmacies cannot be directly linked to the liberalisation of the OTC market, as the share of OTC drugs on total pharmacy revenue is probably too small to produce such an impact. Instead, it is more likely a consequence of the overall economic environment and the squeezing of pharmacy margins on prescription drugs (Barros, 2012). Our results are specific to retailers operating in the Lisbon municipality, and to the set of drugs and years we analyse. Nevertheless, our study contributes to a deeper understanding of how competition takes place in retail pharmaceutical OTC markets in general. Based on our results, OTC market liberalisation reforms can be successful at bringing competition forces into play and lowering OTC drug prices, though this crucially depends on the characteristics of the entrants. In particular, price reductions may not occur in rural areas, where the entry of supermarkets takes place on a smaller scale.

References

A. Anell. Deregulating the pharmacy market: the case of Iceland and Norway. *Health Policy*, 75:9–17, 2005. doi: https://doi.org/10.1016/j.healthpol.2005.01.020.

P.P. Barros. Pharmaceutical market reforms in Portugal under the memorandum of understanding. *Eurohealth*, 18(1):33–36, 2012.

E. Basker. Selling a cheaper mousetrap: Wal-Mart's effect on retail prices. *Journal of Urban Economics*, 58(2):203–229, 2005. doi: https://doi.org/10.1016/j.jue.2005.03.005.

E. Basker and M. Noel. The evolving food chain: competitive effects of Walmart entry into the supermarket industry. *Journal of Economics and Management Strategy*, 18(4):977–1009, 2009. doi: https://doi.org/10.1111/j.1530-9134.2009.00235.x.

D. Bennett and W. Yin. The market for high-quality medicine: retail chain entry and drug quality in India. [cited in November 2018], 2018. URL `https://dornsife.usc.edu/assets/sites/1018/docs/chainentry.pdf`.

R. Blundell, M. Costa Dias, C. Meghir, and J. van Reenen. Evaluating the employment impact of a mandatory job searching program. *Journal of the European Economic Association*, 2 (4):569 – 606, 2004. doi: https://doi.org/10.1162/1542476041423368.

Centro de Estudos de Gestão e Economia Aplicada (CEGEA) . A situação concorrencial no sector das farmácias [competition in the retail pharmacy sector]. Technical report, Commissioned by Autoridade da Concorrência (Portuguese Competition Authority), October 2005. URL `http://www.concorrencia.pt/SiteCollectionDocuments/Estudos_e_Publicacoes/Outros/03_Farmacias_Final_2005.pdf`.

C.M. Gibson-Davis and M.E. Foster. A cautionary tale: Using propensity scores to estimate the effect of food stamps on food insecurity. *Social Service Review*, 80(1):93–126, 2006. doi: https://doi.org/10.1086/499416.

M. Gomes. The liberalization of the retail market of non-prescription medicines. Master's thesis, Universidade do Porto, Porto, 2007. URL `http://repositorio-aberto.up.pt/bitstream/10216/7417/2/Manuel%20Gomes.pdf`. [cited in November 2018].

J.J. Heckman, H. Ichimura, and P.E. Todd. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64 (4):605–654, 1997. doi: https://doi.org/10.2307/2971733.

H. Hotelling. Stability in competition. *The Economic Journal*, 39:41–57, 1929. doi: https://doi.org/10.2307/2224214.

Infarmed, IP. Vendas de medicamentos não sujeitos a receita médica fora das farmácias, jan-dez 2014, 2015. URL `http://www.infarmed.pt/documents/15786/1085388/MNSRM_201412.pdf`.

Infarmed - Autoridade Nacional do Medicamento e Produtos de Saúde . Vendas de medicamentos não sujeitos a receita médica fora das farmácias, jan-dez 2017, 2018. URL `http://www.infarmed.pt/documents/15786/2210525/janeiro+a+dezembro/`.

Jerónimo Martins SGPS SA. Preliminary sales report, 2015. URL `https://www.jeronimomartins.com/wp-content/uploads/com/2016/en/com_20160112_1_en.pdf`.

M. Lechner. The estimation of causal effects by difference-in-difference methods. *Foundations and Trends in Econometrics*, 4(3):165 – 224, 2010. doi: https://doi.org/10.1561/0800000014.

M. Lluch and P. Kanavos. Impact of regulation of community pharmacies on efficiency, access and equity. Evidence from the UK and Spain. *Health Policy*, 95:245–254, 2010. doi: https://doi.org/10.1016/j.healthpol.2009.11.002.

L. Martins and S. Queirós. Competition among pharmacies and the typology of services delivered: the Portuguese case. *Health Policy*, 119:640–7, 2015. doi: https://doi.org/10.1016/j.healthpol.2015.03.001.

J.M. Morgall and A.B. Almarsdóttir. No struggle, no strength: how pharmacists lost their monopoly. *Social Science and Medicine*, 48:1247–1258, 1999. doi: https://doi.org/10.1016/S0277-9536(98)00424-9.

Office of Fair Trading (OFT) . The control of entry regulations and retail pharmacy services in the UK. Technical report, 2003.

Organisation for Economic Co-operation and Development (OECD) . Competition issues in the distribution of pharmaceuticals. contribution from Ms Sabine Vogler, March 2014. URL `http://search.oecd.org/officialdocuments/displaydocumentpdf/?cote=DAF/COMP/GF(2014)6&docLanguage=En`.

M. Patrício, M. Luz, and R. Espírito Santo. O impacto da liberalização da venda de medicamentos não sujeitos a receita médica fora das farmácias. Unpublished manuscript, 2005.

C. Pilorge. Monopole officinal et concurrence en prix pour la délivrance des médicaments non remboursables: l'exemple français. *Revue Économique*, 67:1057–1084, 2016.

C. Polidano and H. Vu. Differential labour market impacts from disability onset. *Health Economics*, 24(3):302 – 317, 2015. doi: https://doi.org/10.1002/hec.3017.

N. Rudholm. Entry of new pharmacies in the deregulated Norwegian pharmaceuticals market - Consequences for costs and availability. *Health Policy*, 87:258–263, 2008. doi: https://doi.org/10.1016/j.healthpol.2007.10.016.

C. Schaumans and F. Verboven. Entry and regulation: evidence from health care professions. *RAND Journal of Economics*, 39(4):949–972, 2008. doi: https://doi.org/10.1111/j.1756-2171.2008.00045.x.

A.P. Simões, A.T. Paquete, F. Fernandes, F. Lourenço, and M. Araújo. O impacto da liberalização do mercado dos medicamentos não sujeitos a receita médica. Unpublished manuscript, 2006.

J.A. Smith and P.E. Todd. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1):305 – 353, 2005. doi: https://doi.org/10.1016/j.jeconom.2004.04.011.

Y. Song and W. Sun. Health consequences of rural-to-urban migration: evidence from panel data in China. *Health Economics*, 25(10):1252 – 1267, 2016. doi: https://doi.org/10.1002/hec.3212.

A.T. Sorensen. Equilibrium price dispersion in retail markets for prescription drugs. *Journal of Political Economy*, 108(4):833–850, 2000. doi: https://doi.org/10.1086/316103.

T. Stargardt, J. Schreyögg, and R. Busse. Pricing behaviour of pharmacies after market deregulation for OTC drugs: The case of Germany. *Health Policy*, 84:30–38, November 2007.

S. Vogler, K. Habimana, and D. Arts. Does deregulation in community pharmacy impact accessibility of medicines, quality of pharmacy services and costs? evidence from nine European countries. *Health Policy*, 117(3):311–327, September 2014.

M. Waterson. Retail pharmacy in Melbourne: Actual and optimal densities. *Journal of Industrial Economics*, 41(4):403–419, 1993. doi: https://doi.org/10.2307/2950600.

Online Appendix

A Additional Tables of Results

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 because 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.

Table A.2: Results from estimating equation (1) among the most spatially isolated retailers in 2006

	5 Nearest Neighbours	400m Radius	600m Radius	800m Radius
DID estimates:				
2010×Treated with supermarket in 2006/10	-0.059*	-0.099***	-0.059**	-0.058**
2015×Treated with supermarket in 2006/10	-0.058**	-0.074***	-0.049**	-0.043**
2015×Treated with supermarket in 2010/15	-0.057**	-0.047	-0.038	-0.040*
2010×Treated with outlet in 2006/10	-0.009	-0.054***	-0.050**	-0.001
2015×Treated with outlet in 2006/10	0.021	-0.018	-0.017	0.028
2015×Treated with outlet in 2010/125	-0.069*	0.076*	0.020	-0.070
Pre-treatment trends:				
2010×Treated with supermarket in 2010/15	-0.054	-0.008	-0.038	-0.033
2010×Treated with outlet in 2010/15	-0.036*	-0.005	0.034	-0.035***
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	873	884	868	738
R^2	0.919	0.921	0.912	0.921

NOTES: Estimates based on the fixed effects estimation of equation (1) among retailers located in areas where market structure is more concentrated. Column 1 takes the main competitors if retailer i as being its 5 nearest neighbours. The sample was restricted to retailers whose walking time (in minutes) to their fifth competitor is above the sample median in 2006. Columns 2 to 4 take the main competitors of retailer i as being all retailers located within a radius of 400, 600, and 800 meters, respectively. The samples were restricted to retailers whose number of competitors within the relevant radius in 2006 is below the sample median for the relevant radius distance. Standard errors are clustered at the retailer level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

Table A.3: 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.4: 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.5: 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.6: 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. $*p < 0.10, **p < 0.05, ***p < 0.01$.

B Details on the PSM-DID procedure

We use a propensity score matching difference-in-differences approach to address the possible endogeneity of market structure (Heckman et al., 1997; Smith and Todd, 2005). The underlying intuition for this approach is that by matching treated and untreated retailers on their propensity score, that is, 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 the 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).

Below, we detail the more technical aspects regarding our implementation of PSM-DID.

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. While 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, including more covariates also makes is more difficult to define the region of common support (Gibson-Davis and Foster, 2006). There is little guidance on how to balance this trade-off. As noted by Lechner (2010), 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. With this in mind, and given that we do not have many variables available to estimate propensity scores, we opted for matching on few variables.

Specifically, we match retailers based on measures of 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. 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. 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.

We categorize the two variables used to estimate the propensity score into quintiles and we used the categorized variables for the matching.[12] 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. Then, we match each treated retailer 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 treatments $\times$3 time periods) PSM procedures were carried out in order to obtain the matched sample. Finally, we run our model specifications in this matched sample.

The common support condition was imposed to ensure 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.[13] The second method consists of non-parametric local linear matching, with a bandwidth of 0.8.[14] While asymptotically the estimates obtained 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). Therefore, 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.

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. 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.

We check covariate balancing between treatment and control groups in the original and matched samples. 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 here. In many, but nor all, of our PSM estimations we are able to achieve a decently balanced

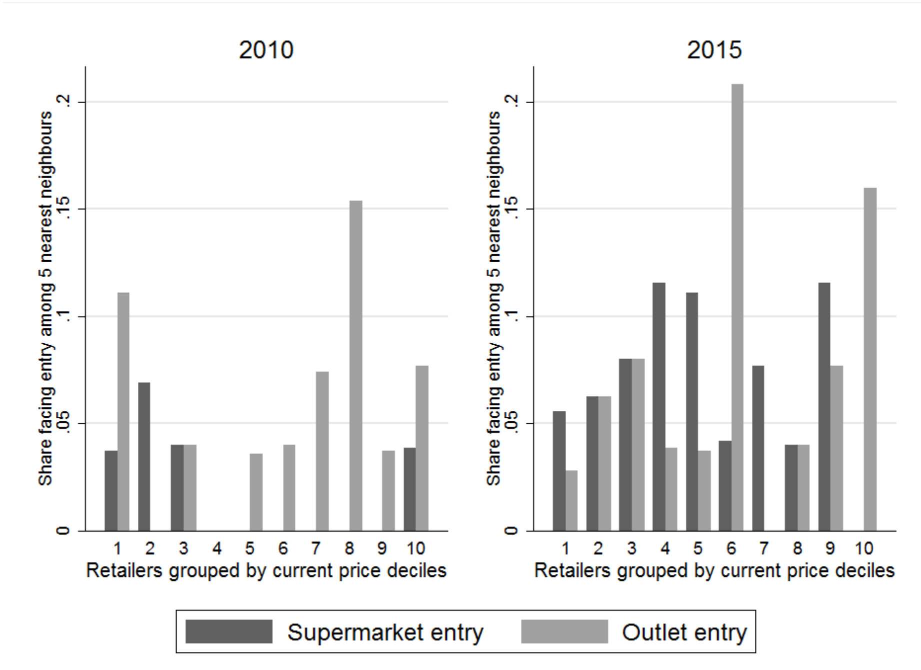
[12]Deciles are used for the specification using a 600-meter radius as measure of competition, as this resulted in better balancing properties in the matched sample.

[13]Different choices of caliper and of the number of neighbours matched did not change our results.

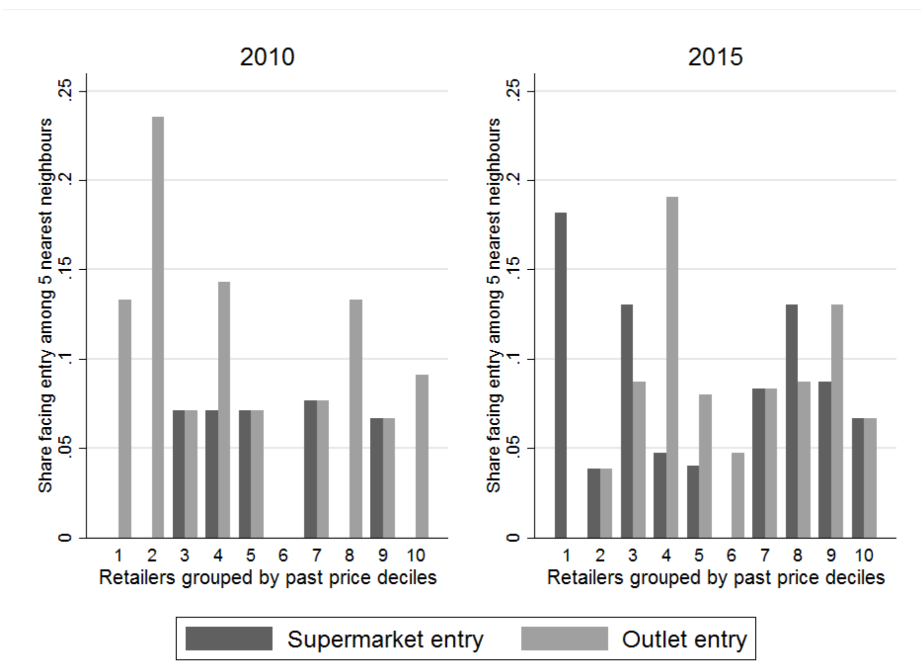
[14]Different choices of bandwidth did not alter our results.

sample in terms of the covariates, and we thus assume that balance was achieved also in terms of unobservables.

Overall, the results of the PSM-DID are in line with those from the simple DID, though several effects lose statistical significance. 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.



(a) By current price deciles



(b) By past price deciles

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

NOTES: In the top panel, retailers are grouped into deciles of their current price for the bundle of five OTC drugs considered in our analysis. In the bottom panel, retailers are grouped into deciles of 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 2015, with no clear pattern.

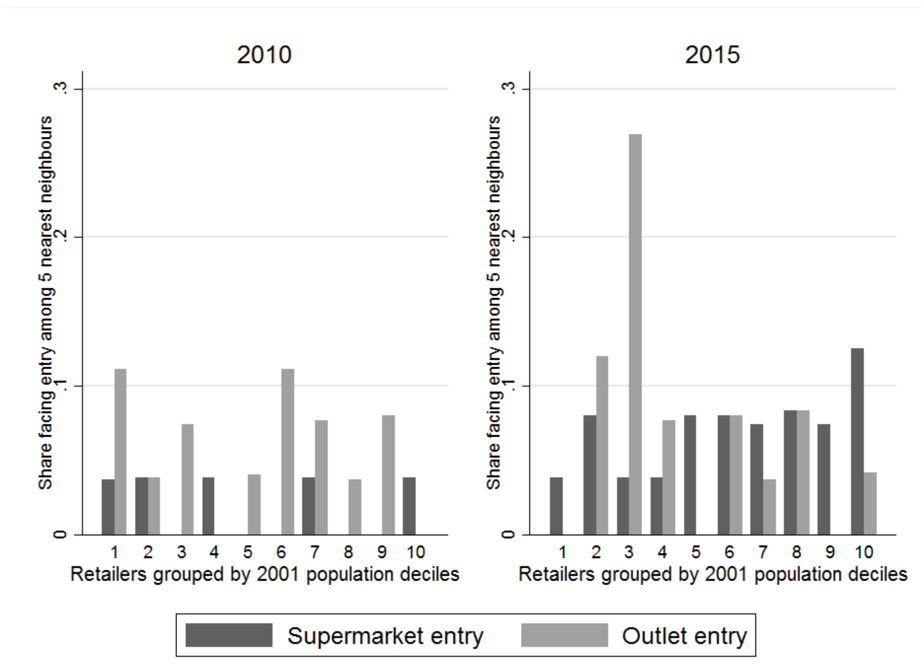


Figure A.2: Share of retailers facing entry of non-pharmacies among the 5 nearest neighbours, by population deciles

NOTES: In order to create this figure, retailers are grouped into deciles of 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.