Ask Your Doctor or Pharmacist! On the Effect of Self-Dispensing Physicians on Pharmaceutical Coverage

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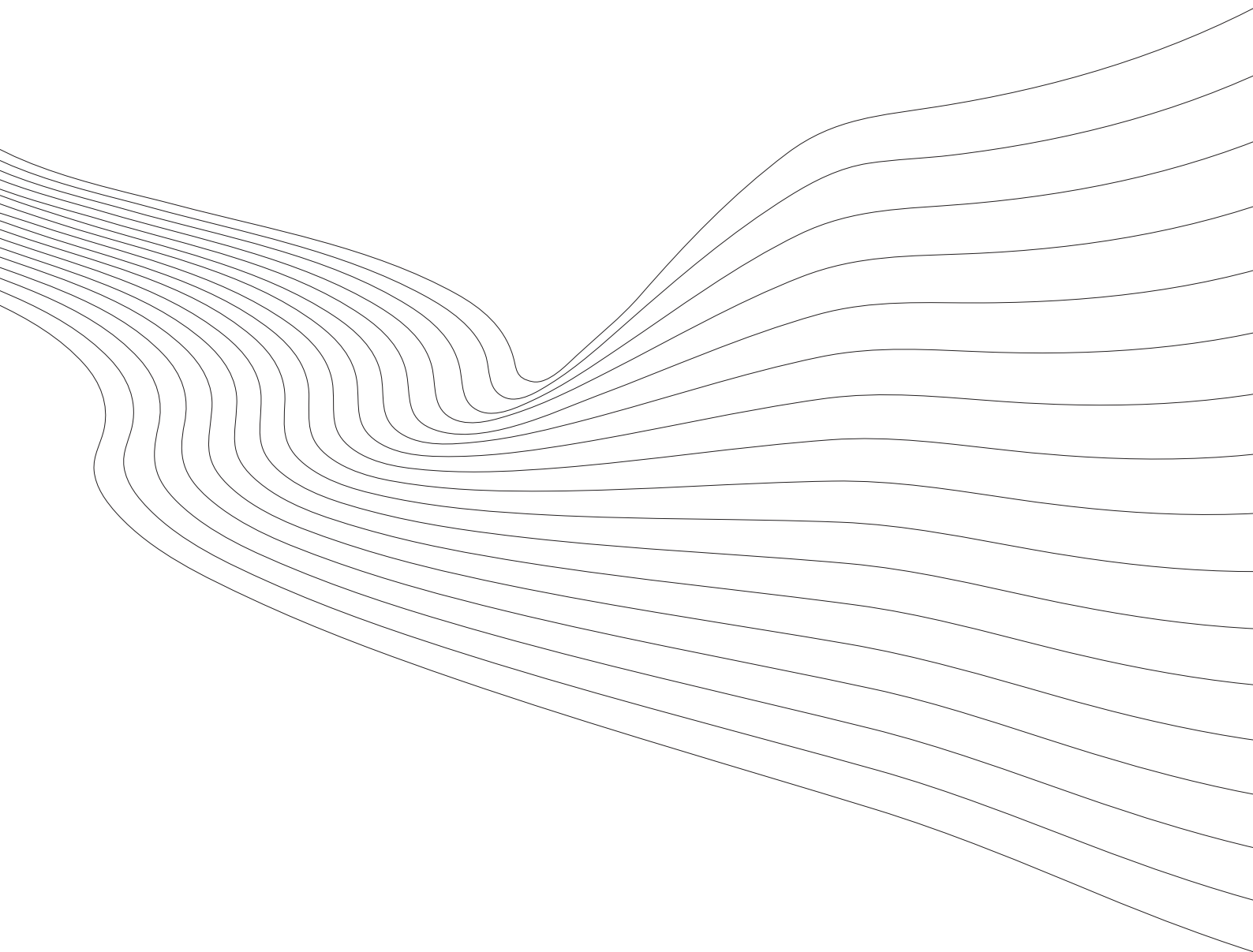
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Ask Your Doctor or Pharmacist!

On the Effect of Self-Dispensing Physicians on

Pharmaceutical Coverage

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Abstract

In most developed countries drugs are dispensed to patients through physicians and pharmacists. This paper studies the effects of allowing doctors to directly dispense drugs to patients (self-dispensation) on pharmaceutical coverage. We use a Swiss dataset in our empirical analysis because Switzerland's federalist legislation allows us to study self-dispensing and non-self-dispensing regimes alike. We add location information obtained from Google Geocoding services to our dataset in order to measure coverage based on distances. To capture a driver of long term positioning decisions, we take revenues as a proxy for a pharmacy's usage rate. We find that, ceteris paribus, self-dispensation leads to a lowered regional density of pharmacies. By matching similar pharmacies across both regimes we find that revenues are substantially lower for pharmacies under a self-dispensation regime. Pharmacies in cantons that allow physicians to dispense drugs tend to have relatively higher revenues associated with non-drugs. We suggest to organize legislation on self-dispensation at a fine grained regional level as regional typologies are the most reasonable justification for regime choice.

Keywords: pharmaceutical coverage, drug dispensation, self-dispensation, health care expenditures, GIS, Propensity Score Matching

JEL code: I18, I11, C21

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1   Introduction

In most advanced economies patients get their medicines either directly from their doctors (self-dispensation) or via a pharmacy. The discussion about the superiority of either system has long been a political debate that is particularly lifely in countries that employ both systems in parallel. The general idea of splitting prescription and sale of drugs is to prevent over-prescription or prescription of expensive drugs instead of equally effective cheaper medication (e.g. generics). However, while the separation of prescription and sale of drugs is suitable in most regions, factors such as geography or population density can justify self-dispensation. Even though self-dispensation has been shown to potentially increase general drug expenditures (Kaiser and Schmid, 2015), the aim to ensure optimal medical and pharmaceutical coverage can weigh higher than the additional costs. Though it may help particular regions to allow for self-dispensing physicians, it is obvious that a single person who pools complex competences is a second-best solution to two distinct specialists: a pharmacist with her background in chemistry and pharmacy and a doctor with her background in medicine. Thus it should be in the interest of policy makers to choose the most appropriate system given the cost and coverage situation.

However, company level economic considerations may influence coverage as well as they have the potential to systematically drive pharmacies into highly populated areas. In turn self-dispensation can drive pharmacies away from poorly covered regions that are at the brink of being attractive to them. Also, additional revenue coming from self-dispensation can be attractive to physiscians in rural areas. Consequently, the public discourse among the two main stakeholders, namely pharmacists and physicians, is driven by political lobbying and specific interests and often beclouds the true consequences of self-dispensation rules. Hence this paper intends to study whether the effects of self-dispensation on pharmacies are substiantial to a degree that influences optimal pharmaceutical coverage.

1

In our empirical analysis we make use of a pharmacy level dataset from Switzerland. Switzerland provides an ideal framework for our analysis: Swiss counties (cantons) are free in principle to choose their legislation with respect to self-dispensation and actually make use of both concepts. Hence we have heterogenous regimes within a comparatively small area. We set up a unique dataset based on multiple waves of a cross-sectional business dataset. We enrich this dataset with geospatial information which enables us to pinpoint pharmacies within Switzerland. Further we add municipality level information to the dataset to account for a pharmacy's economic environment. In our analysis of revenues we use propensity score matching (Rosenbaum, 2010) to compare similar pharmacies' revenues under different self-dispensation regimes.

The remainder of the paper is structured as follows. In the second chapter we continue to dicuss the legal situation in Switzerland and provide an overview of the literature on self-dispensation. The third chapter introduces our dataset. The fourth chapter covers our methodological approach including assessment of coverage and matching. We continue to present our estimation results and finally conclude and summarize our findings. An Appendix provides further estimation diagnostics and robustness checks.

2 Literature

The following chapter consists of two subparts: The first part gives a general overview of different forms of drug dispensation in the literature. The second part focuses on self-dispensation and elaborates on the specific legal situation in Switzerland.

2.1 General Overview

The terms and conditions of drug dispensation have historically been subject to a heated debate between two professions with an academic background. Trap (1997) dates this dispute between pharmacists and doctors back to France in the 13th century. A bit earlier the German emperor Fredrick II had initiated the separation of the two professions and hence created a basis for the current system in most European countries.

Recently, several scholars studied the effects of self-dispensing physicians with particular focus on the effect of different regimes on health expenditures. In most developed countries, doctors are not allowed to sell drugs directly to their patients (Filippini, Heimsch, and Masiero, 2013). Several studies focus on Switzerland as the particular structure of the Swiss health legislation allows to study the effects of a self-dispensation regime next to the effects of a regime that prohibits self-dispensation. A recent study by Kaiser and Schmid (2015) finds that physicians in Switzerland produce higher drug expenditures than pharmacists in the order of 30% per patient. Beck, Kunze, and Oggier (2004) find higher drug expenditures in Swiss cantons that allow self-dispensation, correcting for socio-economic variables. Rischatsch and Trottmann (2009) show that self-dispensing doctors in Switzerland have a higher probability of prescribing the drug with the (most likely) higher margin compared to non-dispensing doctors. Busato, Matter, Künzi, and Goodman (2010) examine if treatment costs across medical discipline and group of drug dispensation differ for the years 2003-2007. Depending on the professional discipline, they find significant arguments both for and against lower costs for boths regimes[1]. For the most expensive treatment (non-invasive specialists) they find significant lower costs for the prescription only case. Reich, Weins, Schusterschitz, and Thöni (2012) show that an increase in the dispensing doctors' density leads to an increase in per capita health care expenditure.

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[1]They also take regimes with mixed legislation into account. See also chapter 2.2.

In a recent study commissioned by the Swiss Federal Office of Health Trottmann, Früh, Reich, and Telser (2015) examine if patients in cantons that allow self-dispensation have the same level of drug expenditures as in cantons without self-dispensation. They find, ceteris paribus, lower drug expenditures for the self-dispensation rule and a higher likelihood that patients get generics prescriptions, comparing two similar cantons, and correcting for socio-economic variables. At the same time, self-dispensation leads to higher expenditures for medical services (consultations). Overall, Trottmann, Früh, Reich, and Telser (2015) do not find differences in the level of consuming services from the compulsory health insurance in self-dispenation areas.

Internationally, most studies find self-dispensation to increase health care expenditures. Iizuka (2007) shows for Japan that the possible markup due to their right to self-dispense affects doctors in their prescription choices. Consequently they tend to over-prescribe, and, as a second effect might not choose the optimal medicine from a patient's perspective. Based on the reduction of drug expenditures in Taiwan after self-dispensation was banned Chou, Yip, Lee, Huang, Sun, and Chang (2003) claim that self-dispensation increases expenditures for medicine on a per visit basis. In a systematic review Emery, Lima, Lewis, and Sunderland (2009) examine 21 papers on the comparisons of self-dispensing doctors' and non-dispensing doctors' practices. The examined studies cover countries such as USA (6 papers) and the UK (5), followed by Zimbabwe (5), South Korea (2), Australia (1), South Africa (1), and Taiwan (1). Emery, Lima, Lewis, and Sunderland (2009) conclude that self-dispensing physicians tend to prescribe more pharmaceutical items, produce higher pharmaceutical costs, and are less likely to prescribe generics than non-dispensing doctors. Other studies focus on the aspect of federalism in health care politics (e.g. Greer and Jacobson (2010) or Uhlmann (2013)).
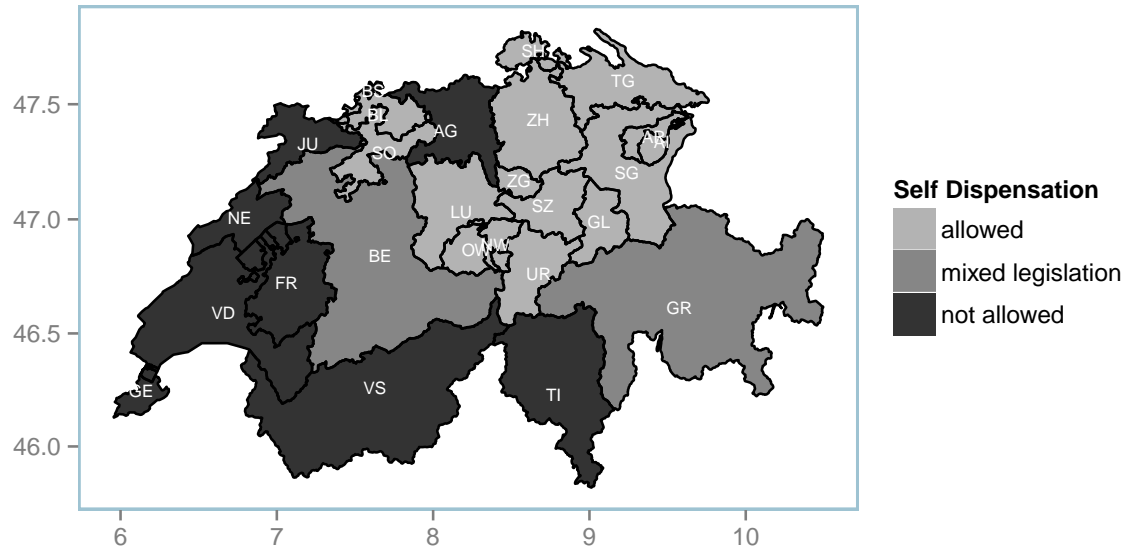
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Figure 1: Legislation by Canton

2.2 State of Legislation of in Switzerland

Switzerland is a federalist country which is structured in 26 cantons and has a long tradition of organizing many aspects of legislation on the federal level. This is also the case for the legal parameters of drug dispensation[2]. Hence different regimes can be found in Switzerland. Figure 1 shows an overview of the current legislation in all Swiss cantons.

The dark areas show cantons that do not allow physicians to dispense drugs at all. The light gray areas depict cantons that allow doctors to prescribe and hand out drugs in general. Consequently the medium shading highlights cantons that have a mixed legislation. Mixed legislation refers to a non-explicit legislation and means that the actual ruling may come down to single cases or municipality levels[3]. Because such situations can be very specific and hard to compare our empirical

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[2]The Swiss law on health care insurance states in article 37, letter 3 (Version of 1 July 2013): Die Kantone bestimmen, unter welchen Voraussetzungen Ärzte und Ärztinnen mit einer kantonalen Bewilligung zur Führung einer Apotheke den zugelassenen Apothekern und Apothekerinnen gleichgestellt sind. Sie berücksichtigen dabei insbesondere die Zugangsmgölichkeiten der Patienten und Patientinnen zu einer Apotheke.

[3]Most cantons do have single exceptions, i.e. physicians with exceptional licenses to dispense drugs. This is the case in almost every canton and is not what mixed legislation refers to. Mixed legislation refers to a situation in which legislation varies across the entire canton. Single exception are ignored as they do not influence the aggregate effects that we study.

analysis only considers cantons that have an explicit legislation[4]. Also note that, despite the fact that several referenda took place within the observed period no regime changes that would have allowed for intertemporal comparisons within the same canton, became effective during the respective period[5]. When the cantons of Grisons and Berne are not considered, the remaining cantons clearly show clusters of regimes that can be related to their main cultural influences. The western and southern parts of Switzerland which mainly speak French respectively Italian as an official language and are mostly influenced by France and Italy are more center-oriented and homogeneous in ruling out self-dispensation. As opposed to this homogeneous legislation in the western and southern part the rest of the country, which is rather influenced by federalist Germany and Austria, does not agree with the same level of unanimity to allow doctors to dispense drugs. Figure 1 lists the cantons of Zurich and Schaffhausen as self-dispensing cantons. It is important to notice though that the three city centers of Schaffhausen, Winterthur and Zurich prohibit self-dispensation. We account for this fact and use ZIP codes to group pharmacies into the respective regime within the canton.

3   Data

The dataset used in this paper has been set up with information from multiple sources: The addresses and operating numbers of Swiss pharmacies were taken from the *RoKA* study conducted by the KOF Swiss Economic Institute on behalf of pharmaSuisse[6]. We enrich this dataset with geo location information obtained from Google's Geocoding API based on pharmacies' addresses. We use this infor-

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[4]Note that we do not consider mixed legislation as an inferior solution and rather advocate finer grained organization legislation with respect to self dispensation. Mixed legislation is excluded from our analysis only for technical reasons.

[5]A referendum to change the current legislation and allow physicians to dispense drugs was turned down in the canton of Aargau in September 2013. Further the canton of Zurich did change its legislation but the new legislation has not come into effect within the observed time span.

[6]pharmaSuisse is the association of Swiss pharmacies. pharmaSuisse commisions the cost focused *RoKA* study on a yearly basis.

mation to calculate median and average distances of pharmacies in close proximity to each other. We match the resulting dataset with municipality level information from the Swiss Federal Statistical Office (BFS). A typology of municipalities is matched using ZIP codes and unique municipality identifiers. Municipalities that cannot be matched umabigously by ZIP codes are manually looked up on Google Maps and adjusted accordingly. This additional typology information allows to classify a pharmacy's environment as a city center, agglomeration, mixed area or truly rural area. Though the BFS offers finer grained typologies with up to 22 categories, we favor the four groups mentioned above because adding municipality typologies to the dataset with the help of ZIP codes contained in pharmacies' addresses works reasonably on this level of granularity. We also match median income on municipality level to the dataset in order to control for the economic environment of a pharmacy. Table 1 shows and describes all variables contained in the final dataset.

Our sample contains all pharmacies that are subject to explicit legislation and took part in the RoKA study on regular basis. All pharmacies that are member of the pharmaSuisse association are obliged by contract to take part in the study. The fact that the *RoKA* study is actually conducted by an independent non-pharmaceutical organization makes the *RoKA* dataset a valuable basis for a scientific contribution to the ongoing public debate about self-dispensation. Currently about 77 percent of all Swiss pharmacies (1744) are affiliated with pharmaSuisse (pharmaSuisse, 2014). Thanks to response rate of 72 percent more than 57 percent of all pharmacies in the country return a questoinnaire to the KOF Swiss Economic Institute every year. Figure 2 shows the locations of RoKA participants across Switzerland. We can obviously spot densely populated city centers and agglomerations of the country's largest cities but also see elements of the Swiss topography like the Rhone Valley (south between the 7th and 8th degree of longitude) or the mountain regions of Grisons.

About 1'000 pharmacies have been taking part in the study on yearly basis. In our

7

Variable	Dataset/Provider	Description	Unit
legislation	RoKA/KOF, ETH Zurich	self-dispensation regime	categorical: (SD, NoSD)
revenue	RoKA/KOF, ETH Zurich	5 year average of yearly revenue of a pharmacy	CHF
area	RoKA/KOF, ETH Zurich	size of a pharmacy	square meters
sales area ratio	RoKA/KOF, ETH Zurich	sales area / total area	ratio
legal form	RoKA/KOF, ETH Zurich	legal form of pharmacy	categorical
pharmacist status	RoKA/KOF, ETH Zurich	is the pharmacist owner of the pharmacy?	logical
chain	RoKA/KOF, ETH Zurich	is the pharmacy part of a chain?	logical
lat	Geocoding API/Google	latitude	degree
lng	Geocoding API/Google	longitude	degree
nearest	own computation/KOF, ETH Zurich	distance to closest pharmacy	kilometers
nearest_3	own computation/KOF, ETH Zurich	average distance to 3 nearest pharmacies	kilometers
nearest_5	own computation/KOF, ETH Zurich	average distance to 5 nearest pharmacies	kilometers
grouped_types	Gemeinde Typlogien/Federal Statistical Office	type of municipality	categorical
median_income	Tax Data/Federal Statistical Office	median income	CHF

Table 1: Overview of Variables Used in the Empirical Analysis

analysis we only consider pharmacies that have returned the RokA questionnaire for at least four out of five periods between 2008 and 2012. Further, as stated before, we only analyze cantons with an explicit legislation and thus leave out all pharmacies located in Berne and Grisons. This leaves us with a total of 505 pharmacies, 376 of which are located in places that prohibit self-dispensation and 129 of which are located in places that allow physicians to dispense drugs.

Figure 3 shows the distribution of average proximity to the closest five competitors which is a focal variable to measure coverage for the remainder of this paper[7]. We

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[7]For a detailed description how distances are computed from based on pharmacies addresses
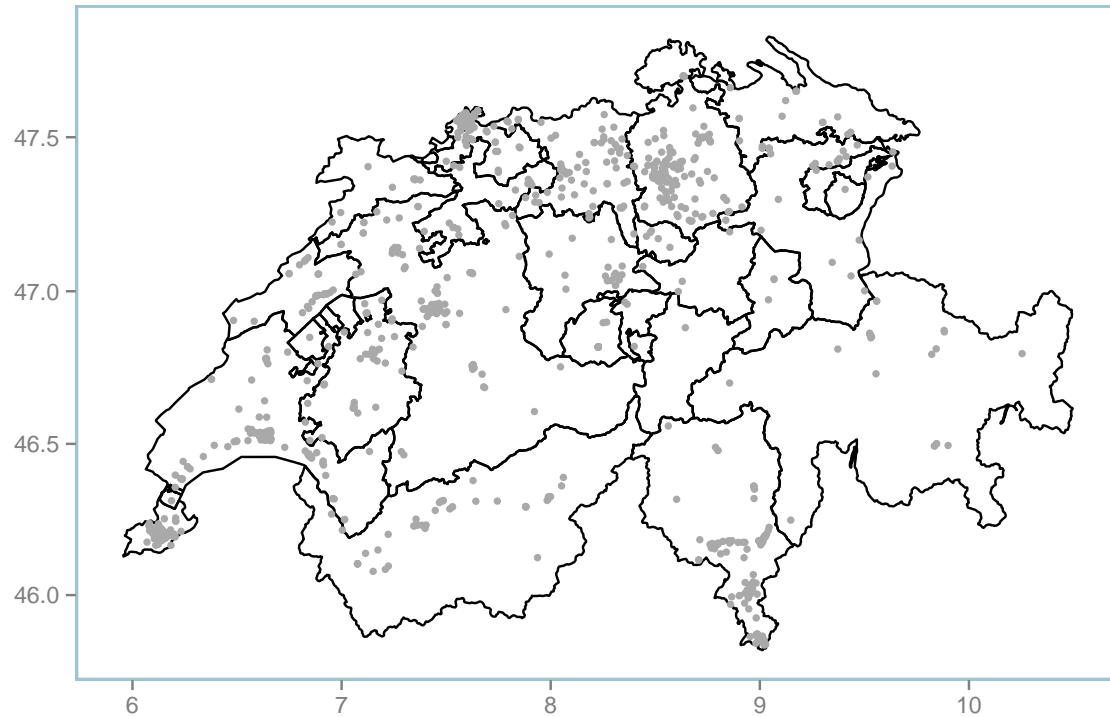
Figure 2: Pharmacies across Switzerland

see not only immediately that the major part of the pharmacies is under a regime that prohibits self-dispensation, but also that the distance between pharmacies has a much larger variance (28.49 vs. 16.83) in regions where self-dispensation is allowed. On average distances tend to be larger in self-dispensing regions (6.56) than in regions that do not allow self-dispensation (2.76).

The second focal variable in our research is the five year revenue average. Because the legal status of a canton is in fact time invariant in our timespan we do not consider forming a panel dataset here. Consequently pharmacies' mean revenues are averaged over five years. This aggregation of revenues over time also comes in handy inasmuch as cyclical movement is cancelled out. Figure 4 shows the density of revenues by regime.

At about 2.8 million and 2.91 million CHF respectively the sample mean does not differ significantly between both regimes[8]. Visually we can also see that

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see section 4.1

[8]The p-value (0.478516) and test statistic -0.709709 of the corresponding t-test clearly suggest to not reject the H0.
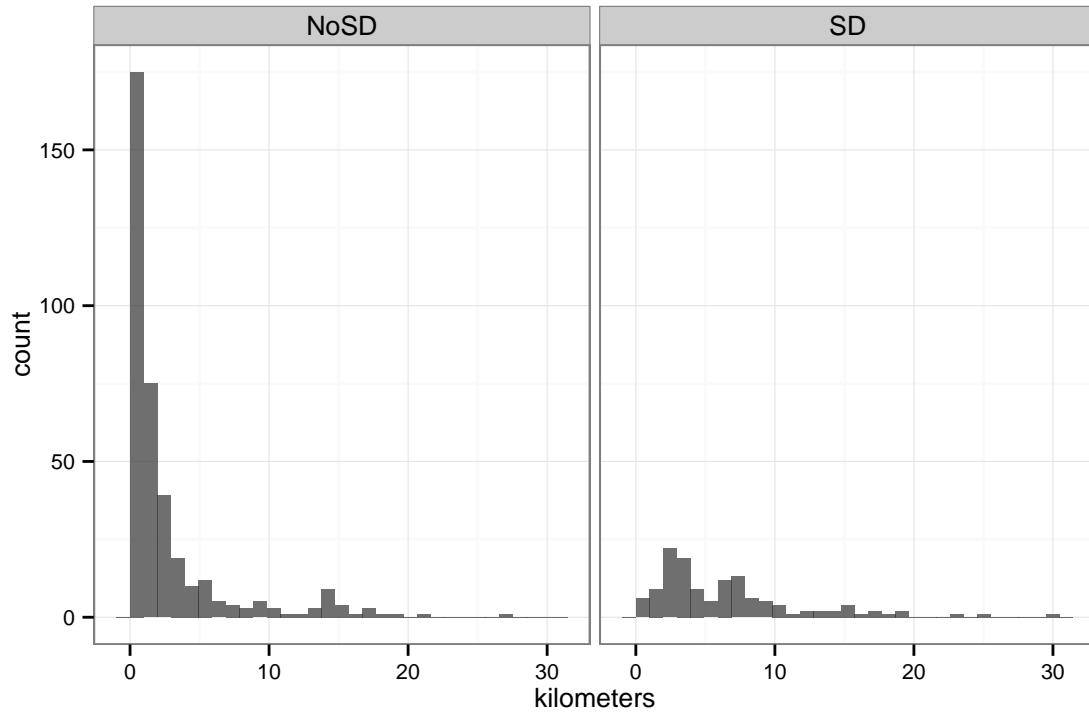
Figure 3: Average proximity to 5 closest competitors by regime
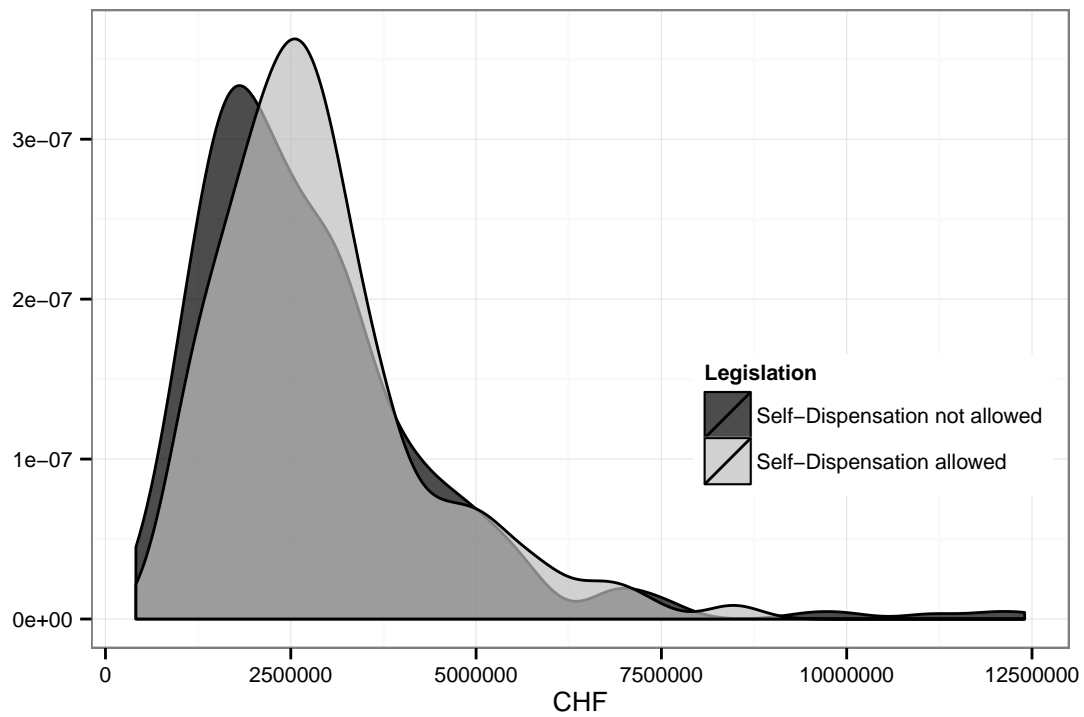

Figure 4: 5 year revenue averages by regime

both distributions are similar, though the long tail on the right is even longer

for pharmacies located in a regime that prohibits self-dispensation[9]. Intuitively, contrary effects of self-dispensation which is common in the German speaking part of Switzerland and structural inequality between the French and German speaking part of Switzerland could possibly cancel each other out and becloud the true effect of self-dispensation. In general this first naive comparison of distributions and sample means suggests that further research is needed to disentangle possible regime effects.

4 Empirical Strategy

Studying the effects of self-dispensing physicians on adequate pharmaceutical coverage makes us investigate two major aspects: First we use distances to measure pharmaceutical coverage itself. Second to get an idea of a pharmacy's usage rate we take pharmacies' revenues as an indicator for a pharmacy's business activity. Consequently we regard usage of a pharmacy as an important channel through which a canton's pharmaceutical coverage is influenced[10].

4.1 Measuring Coverage

We measure coverage in a particular region by computing the distance of a pharmacy to all other pharmacies in that region. The distance itself is computed from the geo locations of all pharmacies[11]. With the respective longitude and latitude of two points distances can be computed using the Great Circle Distance. Simple trigonometric procedures that assume the earth to be spherical can already produce reasonable results. Considering an equatorial axis and a flat-

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[9]The two sample KS-Test rejects the H0 at the 10 percent level just narrowly (p.value: 0.1097735).

[10]Note that we also prefer revenue over profit as an indicator because we suspect smaller measurement error due to the fact that revenue is directly reported from the *RoKA* online survey. As opposed to profit that would have to be computed from different variables and thus would add up measurement errors of all variables used in the computation.

[11]See also section 3.

tening factor computation of distances get more complex but can account for an ellipsoid earth model. The pioneering approach of Vincenty (1975) suggests an iterative procedure which became the basis of many of today's state-of-the art procedures. However, we use an approximation suggested more recently by Meeus (1999) which produces very accurate results and does not rely on iteration[12]. Approxmiation requires to set constants for the flattening factor f and equatorial radius r. The values of these constants ultimately depend on the selected ellipsoid model. Choosing the World Geodetic System Standard WSG84 (NIMA, 2000) implies the following values:

$$r = 6378.137 \tag{1}$$

$$f = 1.0/298.257223563 \tag{2}$$

Following Meeus (1999) we can compute the distances $d_{i,j}$. We use these distances to measure a region's pharmaceutical coverage as follows. Suppose,

$$D = \begin{pmatrix} 0 & d_{1,2} & \cdots & d_{1,n} \\ d_{2,1} & 0 & \cdots & d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n,1} & d_{n,2} & \cdots & 0 \end{pmatrix},$$

where the j-th column is a vector of distances from the j-th pharmacy to all pharmacies in the sample. Hence, the diagonal elements of the matrix D are obviously zero as they contain the distance from a pharmacy to itself. In order to construct a metric for coverage we use the distance matrix D to aggregate the distance of the c closest pharmacies to the j-th pharmacy. Suppose that d_j is a sorted sequence of the values of the j-th column of D:

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[12]The Meeus distance is implemented in several R packages. We chose the implementation provided by *sp* (Bivand, Pebesma, and Gomez-Rubio, 2013), (Pebesma and Bivand, 2005) because of its use of C++. Using C++ considerably speeds computation of our 500×500 distance matrix up.

$$d_j = \langle d_{j,1}, d_{j,2}, \cdots, d_{j,n} \rangle, \quad where \quad d_{j,1} \leq d_{j,2} \leq \cdots \leq d_{j,n}$$

Then, we can easily compute the average distance to the c closest pharmacies to obtain a pharmacy level coverage metric C_j. Note that $k = 1$, is left out as the first element of d_j is always zero:

$$C_j = \frac{1}{n} \sum_{k=2}^{c} d_{k,j}$$

We can further generalize our coverage indicator by:

$$C_j = f(d_j, k), \quad where \quad k = \langle 1, 2, 3, \cdots, c \rangle.$$

Typically we use the median or the mean as a function to aggregate the truncated vector of distances. For example if $c = 5$ was set, we would obtain the average respectively the median distance of the j-th pharmacy to the five closest competitors[13].

In a second step we continue to investigate what drives pharmacy level coverage on the regional level. We estimate the following simple model to get an idea of the most important driving forces:

$$C_j = \alpha + \gamma l_j + X'\beta + \epsilon, \quad where \tag{3}$$

l_j is a logical variable that indicates whether self-dispensation is allowed in a particular canton. X contains a set of control variables including the size of a pharmacy in square meters, a dummy variable that indicates whether a pharmacy is part of a chain. We also account for a pharmacy's revenue, median income in

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[13]Appendix 6 covers robustness checks for variations of c.

the municipality and the type of municipality (city centers, agglomerations, rural etc.).

4.2 Matching Pharmacies under Different Regimes

Still finding an effect of legislation on coverage as described above raises the question of causality. As discussed before, self-dispensation is meant to moderate insufficient pharmaceutical coverage – particularly in rural regions. Though improving coverage in these regions is clearly desired, self-dispensation potentially affects pharmacies in regions with sufficient coverage, too. Hence we study whether legislation affects pharmacies revenues to a degree that changes pharmacies' behavior in a way that causes undesired effects[14].

In order to understand coverage better, we study the causal effect of legislation on pharmacies' revenues. Revenue can be seen as a proxy for a pharmacy's usage rate and thus is closely linked to pharmaceutical coverage in the long run. The effect of legislation on revenues can be evaluated in a treatment / control setup. Such setups stem from controlled studies and are widely used in evaluation econometrics and have often been described in the literature. In this chapter we borrow the treatment / control terminology from this strand of literature to conveniently describe our identification strategy. In our case being treated refers to being located in a canton that allows physicians to dispense drugs. In turn being assigned to the control group refers to being under a regime that prohibits self-dispensation. Thus, on the individual level the effect τ of legislation can be regarded as the difference in revenue between both regimes:

$$\tau = Y_{i1} - Y_{i0} \quad where,$$

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[14]In this case undesirable refers to situations that [1] increase health expenditure costs due to over-prescription induced by physicians, [2] that only provide second best coverage for the patient in which optimal coverage (physician and pharmacist) would be possible and [3] situations that lead to over-coverage in populated areas and thinning out in less populated areas.

Y_{i1} denotes the revenue of pharmacy i under treatment $l = SD$ while Y_{i0} denotes the revenue of pharmacy i when it is not treated $l = NoSD$. Because we cannot observe counterfactuals for a single pharmacy we aim at comparing similar pharmacies under different regimes. In randomized studies this comparison is straightforward because treatment and control subjects are interchangeable. In observational studies, however, treatment and control units are hardly balanced in their pre-treatment properties and cannot be interchanged freely.

Thus, in order to identify what is called the Average Treatment Effect on the Treated (ATT) we follow a well established causal model brought up by Rubin (1974). Sekhon (2011) describes this model framework and its extensions in greater detail and provides an implementation to compute the ATT τ defined as:

$$\tau|(l = SD) = E[E[Y_i|X_i, l = SD] - E[Y_i|X_i, l = NoSD]|l = SD]$$

Following Rosenbaum and Rubin (1983), the identification of the ATT basically relies on the assumptions that assignment into treatment is unconfounded given a set of covariates and that there is a positive probability of being treated for all observations[15]. In order to account for the distribution of multi-dimensional pre-treatment properties we use a propensity score matching (PSM) approach. As opposed to a straight forward exact matching on pharmacies' properties, PSM represents similarity between pharmacies by a single individual level probability of being treated (propensity score). Thus PSM avoids an issue known as curse of dimensionality when trying to classify finite samples into a large number of different bins.

While the propensity score would be known in a randomized study it is estimated most of the time in practice. The propensity score is defined as the conditional

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[15]The second property is often referred to as *overlap*, because also observations which are in fact untreated have a positive probability of being treated given their pre-treatment properties. Formally overlap can be expressed as $0 < P(l = SD) \leq 1$. The bundle of both assumptions, unconfoundedness and overlap, is often referred to as strong ingorability. In order to obtain the ATT, this assumption can even be further relaxed to just assuming mean independence.

probability of being treated given a set of covariates Z. In our case the probability of being located in a canton that allows physicians to dispense drugs is formally defined as

$$P(l = SD|Z) = \Lambda(Z'\gamma) \quad where$$

Λ is the cumulative distribution function of a logit and γ is a vector of coefficients. Hence we can use a standard probit model to estimate the conditional probability that a particular pharmacy is under a self-dispensation regime given Z [16].

Rosenbaum and Rubin (1983) have shown that treated and untreated observations with the same propensity score have the same distributions for all covariates Z. Z contains information on pharmacies pre-treatment properties such as size of the pharmacy in square meters, the ratio of sales area to a pharamcy's total area, whether a pharmacy belongs to a chain, its legal form, the ownership status and the type of municipality a pharmacy is located in. We chose a caliper of .2 standard deviations and allow for ties and replacement in our basic matching setup[17].

5   Estimation Results

This section presents the results of the estimations described in the previous section. First we show how legislation affects the actual coverage measured by the mean distance of a pharmacy to its five closest competitors. Besides we illustrate our findings using graphical heatmaps for examplary regions. In addition to studying coverage itself, we give a closer insight to pharmacies' revenues under self-dispensation as revenue can be seen as a proxy for a pharmacy's usage rate and thus is a channel that influences long run coverage in a particular region.

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[16]Often a logistic distribution is used instead of a Normal. Estimation results of the underlying logit model are similar most of time as distributions mostly differ in their tails.

[17]Appendix 6 discuss some matching diagnostics and robustness to modifications to the basic setup.

	Average Proxmity Nearest 5 (OLS)
intercept	4.249 (1.298)**
legislation (ref: NoSD)	4.041 (0.434)***
five year average revenue in million CHF	0.668 (0.318)*
squared five year average revenue	−0.057 (0.031)
size in square meters	−0.000 (0.002)
chain (ref: FALSE)	−0.611 (0.381)
type of region: agglomeration (ref: center)	0.398 (0.442)
type of region: tertiary (ref: center)	7.048 (0.575)***
type of region: rural (ref: center)	5.623 (1.714)**
median income in 2011 in the municip. in 1000 CHF	−0.081 (0.030)**
R^2	0.381
Adj. R^2	0.370
Num. obs.	505
RMSE	3.772

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2: Estimation Results: Coverage Model

We present the average treatment effect on the treated (ATT) for pharmacies' revenues located in a canton that allows physicians to dispense drugs.

5.1 Coverage

Table 2 shows the OLS estimation results of equation 3 presented in section 4[18]. Our main variable of interest, namely *legislation* has a significant and comparatively strong effect. The average proximity of the five closest pharmacies is 4.04 kilometers larger in cantons that allow self-dispensation. The size of the effect suggests that comparisons of both regimes outside city centers strongly contribute to this result.

As stated before we use revenue to proxy a pharmacy's usage rate. Table 2 shows that revenue and coverage do not have a linear relationship. In general, for every 1 million CHF in own revenue, pharmacies tend to be located about 0.67 kilometers further away from the group of competitors in closest proximity. This effect reverses for the most active pharmacies, but decreases in effect size. This is perfectly reasonable because in general newcomers would not move too close to

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[18]Regression outputs were created using the texreg R packages (Leifeld, 2013).

a well established competitor - except for regions with extremely high customer frequency. Still though the largest pharmacies are usually located within city centers that naturally contain more pharmacies because of their high population density. Pharmacies must also be regarded as retailers and hence the most active pharmacies are situated in prime locations within city centers.

When controlling for revenue, the actual size of the pharmacy measured in square meters does not have a significant effect on coverage. Being part of a chain reduces the distance to the closest competitors as chains tend to move to city centers and pursue market shares more systematically and aggressively. The chain indicator is not significant though when controlling for revenues as chains tend to have higher revenues on average.

Regional typology plays an important role in our analysis of coverage. As described in section 3 we group municipalities into four types. In our regression we use city centers as the reference type. While we cannot observe a significant difference for urban agglomerations the effects for the remaining types are substantial and significant. The average proximity to the five closest competitors is 7.05 kilometers larger in tertiary regions and more than 5.62 kilometers larger in rural regions than in city centers. Obviously this does not come as a suprise but shows the importance of controlling for this typology in order to study the effects of self-dispensation. Finally, the wealth of a municipality does have a negative effect on the distance between pharmacies, indicating that the density of pharmacies in Switzerland is higher in wealthier regions. Per 1000 CHF in median taxable income the average proximity of the five closest competitors decreases by 80 meters.

In addition to estimations we studied coverage visually. Heatmaps as examplary shown in figure 5 can provide an intuitive comparison: The heatmap on the left side shows distances between pharmacies in the city centers of the canton of Fribourg where self-dispensation is prohibited and the figure in the right facet shows the city centers of the canton of Lucerne where self-dispensation is allowed. The example compares only the distance of pharmacies within city centers. The city centers of

18
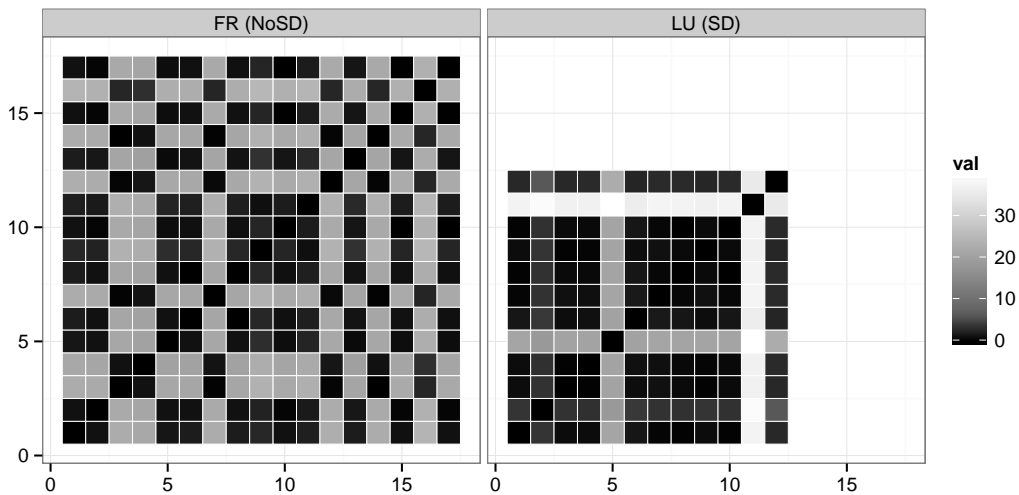
Figure 5: Heatmap Comparison

Lucerne and Fribourg can be considered topographically similar. In both facets every square represents the distance between a pair of pharmacies. Hence the diagonal (from the bottom left corner to the upper right corner) of a heatmap represents the distance of a pharmacy to itself. Dark shades of grey indicate close distances, in turn lighter shades indicate greater distance. We can not only see that fewer pharmacies are located in the city centers of Lucerne, the heatmaps also indicate that pharmacies in Lucerne's city centers are closer to each other and tend to be in the same place. This could be an indication that pharmacies need to act more as retailers of non-drugs under a self-dispensation regime and thus tend to crowd in regions with high customer frequency.

Though pairwise visual comparisons do give interesting additional insights it is difficult to find a comprehensive set of pairs. Switzerland is a heterogenous country in many aspects. Its four official languages, the cultural influence from Italy, France and Germany as well its undeniably unique own culture along with a topographically diverse landscape make it difficult to draw exact matches across all dimensions.

19

5.2 Usage (Revenue)

As described in section 4.2 we study the effects of legislation on pharmacies revenues in addition to coverage in order to understand usage of existing pharmacies. Because of the multi-faceted diversity described in the previous section we use propensity score matching to conveniently condition pharmacies revenues on a set of various pre-treatment properties.

	ATT_Revenue	ATT_High_VAT_Ratio
ATT	-503409.4	0.08250038
SE	273393	0.02998645
statistic	-2.594	3.986
p.value	0.009486	6.709e-05
N	505	405
N_treated	129	109
dropouts	0	0
total_matches	165	126
caliper	0.2	0.2

Table 3: Average Treatment Effects on the Treated (ATT)

Table 3 displays the ATT estimations of legislation for two revenue related variables: the left column shows the estimation results for total revenue. The right column shows the results of an additional estimation of the ATT on revenue with products which are sold at a higher VAT (of 8%)[19].

Though VAT is relatively low in general in Switzerland, drugs are sold at a lowered rate. Hence categories of VAT are good indicators of the portfolio of products of a pharmacy and give hints about a pharmacies strategical direction. At about -503'409 CHF the effect of legislation on total revenue can be considered substantial and highly significant. Though the actual effect size varies with modifications of the logit model, choice of the caliper as well as further matching configurations such as avoiding ties or replacement, we can observe a meaningful negative effect

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[19]Note that the basis of the additional computation is not as solid as the ATT estimations for total revenue. While total revenue ATTs are based on five year averages of total revenue, revenues by VAT categories are only available for 2012 and are thus based on a single year only. Though results should be interpreted with additional caution, the results are reasonable and inline with previous thoughts following our visual analysis.

on a robust basis. Following Austin (2011) we chose a caliper of 0.2 standard deviations which has turned out to be a reasonable bandwidth also in our case. Of 505 pharmacies 129 are located in a canton that allows physicians to dispense drugs. Using matching with replacement our ATT estimation leads to 165 matches. The right column shows the ATT for the ratio of revenue with high VAT products (i.e. non-drugs) to total revenue. The higher the ratio, the more non-drug products are sold relatively. Again the treatment effect of legislation is substantial and significant: The ratio is about 0.08 higher for pharmacies under a self-dispensation regime. This substantial increase in the relative amount of non-drugs sold can be interpreted as a hint that pharmacies seem to employ side-stepping strategies or to favor a drugstore business approach under a self-dispensation regime.

6 Conclusion

In this paper we contribute to the debate about drug dispensation which is particularly lively in countries that allow both, physicians and pharmacists, to dispense drugs. We study the effects of self-dispensation on pharmacies based on data from Switzerland. Switzerland can be considered an ideal model case as its legislation is organized on cantonal (county) level and hence provides the opportunity to study different regimes in a relatively small area. The starting point for our research is the idea that optimal coverage from a patient's perspective means that both, pharmaceutical and medical expertise are available in close proximity. Hence legislation that influences coverage of pharmacies or doctors potentially leads to a sub-optimal coverage situation in which both expertises are combined in one person as opposed to two distinct experts in their respective fields.

We find that, ceteris paribus, the density of pharmacies is substantially lower in cantons that allow physicians to dispense drugs. Though improving general medical and pharmaceutical coverage in scarcely populated areas has been the initial impetus of the legislation, we find influences of self-dispensation on pharmacies

21

in other, more populated regions of the same canton, too. Total revenues are substantially lower for pharmacies under a self-dispensation regime compared to similar pharmacies in cantons that prohibit drug dispensation by physicians. In line with these observations we also find that the share of revenues made with non-drugs is substantially higher in cantons that allow self-dispensation. This indicates a side-stepping strategy respectively a shift towards a more drug store oriented business. In the sense of Kaiser and Schmid (2015) and other studies described in section 2 a general replacement of pharmacies through physicians would lead to higher health expenditures due to physicians' incentive to over-prescribe. For the specific case of Switzerland our findings gain further relevance for future debates as pharmacies have just gained new rights lately: To moderate low medical coverage, pharmacies will be allowed to offer additional services such as vaccination that have formerly belonged to the domain of physicians solely.

However, when debating both dispensing regimes policy makers should not only consider potential additional health expenditures but also weigh in the importance of a two way coverage from a patient's perspective as well as the implications to the pharmaceutical and medical professions. It is safe to say that allowing physicians to dispense drugs in regions which are so scarcely populated that pharmacies as retail businesses cannot survive helps to improve pharmaceutical coverage and thus can be considered a Pareto improvement. On the other hand we consider legislation on cantonal level as too coarse – even though cantons are relatively small counties in international comparison. The benefits of self-dispensation are dependent on regional typologies rather than counties. We conclude that the right to dispense drugs should be organized more specifically according to type of a municipality.

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Appendix A: Estimation of Propensity Scores

Table 4 shows the estimation results of the logit model we fitted to estimate the propensity scores used in our matching. While several properties, namely legal form and pharmacist status are basically balanced across treatment and control group, a set of variables that we expected to differ actually differs. The proximity indicator which also indicates the degree of competition and thus should influence revenues is not balanced across both groups. Also median taxable income of the muncipality a pharmacy is located in differs significantly as well the size of a pharmacy in square meters. As expected typology of the municipality is unbalanced as well. In practice matching based on the propensity score does not entirely balance out differences between treatment and control group with respect to all properties but greatly improves our comparison[20]. Appendix C gives further insights to effectivity of our propensity score matching. Note that our results improve when we use a logit model instead of a probit model to estimate propensity scores which indicates particular relevance of the tails of the distribution.

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[20]Zhao (2005) finds in simulation study that poor estimates of the coefficients due to bi-modal error terms have little influence on ATT estimates. Though the effect size may be under- or overstimated, these findings increase the trust in our general results

	Propensity Score Estimation (Logit)
Intercept	−8.385 (1.138)***
Type of Region: urban (ref: center)	1.308 (0.300)***
Type of Region: tertiary (ref: center)	−0.994 (0.524)
Type of Region: rural (ref: center)	−0.142 (1.111)
Size in sqm	0.003 (0.001)**
Legal form sole prop. (ref: stock corporation)	0.589 (0.363)
Legal form KG (ref: stock corporation)	0.981 (0.677)
Legal form GmbH (ref: stock corporation)	0.970 (0.546)
Legal form co-operation (ref: stock corporation)	−1.731 (1.176)
Pharmacist status co-owner (ref: owner)	−0.413 (0.550)
Pharmacist status administrator (ref: owner)	0.360 (0.342)
average median income in the municipality	0.000 (0.000)***
average distance to 5 closest compet.	0.252 (0.033)***
AIC	418.316
BIC	473.235
Log Likelihood	-196.158
Deviance	392.316
Num. obs.	505

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 4: Statistical models

Appendix B: Robustness

The following appendix section discusses the robustness of our ATT estimation results to several ceteris paribus specification changes: number of matches, omission of the proximity variable, using different numbers of pharmacies to compute average proximity. While the ATT estimations are basically robust to the modifications above, the results are sensitive to not accounting for municipality income. This is expected as leaving municipality income out of the propensity score estimation would lead to many matches between the pharmacies in the cantons of Zurich and Ticino. The substantial differences in wealth and structure between these two regions are likely to have a larger effect on pharmacies than the contrary effect of legislation. Table 5 shows the ATT estimation results for the basic setup for different number of matches.

Table 6 shows estimation results that do not account for the average median income of a municipality. Without narrowing the caliper, the ATT still remains very robust. When narrowing the caliper of .1 leads to more dropouts, results

Matches	ATT	SE	statistic	p.value	dropouts	total_matches	caliper
1	-503409.35	273392.95	-2.594	0.009486	0.00	165	0.20
2	-353809.73	228895.62	-1.906	0.05659	0.00	275	0.20
3	-332220.62	215823.49	-1.811	0.0701	1.00	396	0.20
4	-409057.56	201097.50	-2.085	0.03706	10.00	489	0.20
5	-492896.27	181278.87	-2.408	0.01606	20.00	557	0.20

Table 5: Baseline estimation robustness for different matches

become partly insignificant. Still for all estimations a substantial negative ATT can be observed.

Matches	ATT	SE	statistic	p.value	dropouts	total_matches	caliper
1	-444781.12	251002.62	-2.339	0.01935	2.00	174	0.20
2	-361676.44	197508.37	-1.977	0.04806	5.00	286	0.20
3	-377480.89	188293.67	-2.013	0.04409	8.00	396	0.20
4	-327855.70	186027.56	-1.684	0.09216	12.00	490	0.20
5	-325005.95	177530.96	-1.583	0.1134	17.00	581	0.20
1	-466259.67	245873.66	-2.369	0.01782	8.00	168	0.10
2	-336255.01	184279.61	-1.768	0.07712	14.00	268	0.10
3	-317789.02	172044.46	-1.61	0.1075	19.00	363	0.10
4	-212695.23	167673.06	-1.024	0.3056	26.00	434	0.10
5	-271812.07	149737.31	-1.228	0.2196	35.00	491	0.10

Table 6: Modified estimation robustness for different matches

Yet in the standard setup which includes incomes, narrowing the caliper to .1 standard deviations does not lead to insignificant ATTs. Table 7 shows the baseline estimation using a narrower caliper of .1 standard deviations.

Matches	ATT	SE	statistic	p.value	dropouts	total_matches	caliper
1	-496349.15	272711.46	-2.539	0.0111	1.00	164	0.10
2	-475082.26	210240.18	-2.402	0.01632	13.00	249	0.10
3	-368151.64	181521.62	-1.809	0.0704	23.00	330	0.10
4	-368391.26	166290.82	-1.648	0.09934	36.00	385	0.10
5	-350878.00	157075.31	-1.53	0.1259	40.00	457	0.10

Table 7: Baseline estimation robustness for different .1 caliper

Appendix C: Matching Diagnostics

This subsection of the appendix discusses metrics to empirically assess the suitability of the propensity matching applied in this paper. Figure 6 shows the density of
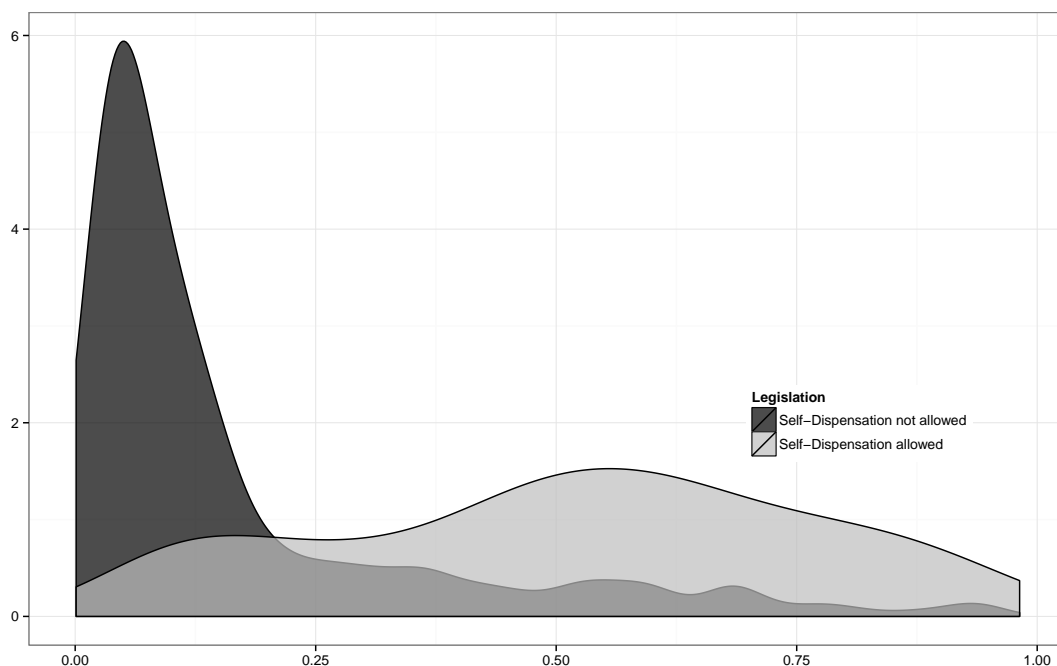
Figure 6: Densities of Propensity Scores by Treatment and Control Group

the estimated propensity scores by treatment and control group. We can clearly see that the bulk of the propensity scores belonging to the control group is relatively low and has smaller standard deviation, while the propensity score for the treated observations is lower and has a much larger variance. Figure 6 also shows that there is considerable overlap between both distribution which is an important assumption for propensity score matching.

The matching R package (Sekhon, 2011) provides a convenient way to test the means and distributios of all covariates before and after matching. We perform such a test in order to assess the effectivity of our matching approach in practice. The following output shows detailed variable by variable comparisons: Table 8 shows means of both treatment and control group before matching. Table 9 shows means and the p-values of the t-test for equal sample means after matching. We can clearly see that matching helped to level differences in means between the treatment and control group.

	mean_treat_before	mean_control_before	t_test_p.value_before
agglomeration	0.58	0.19	0.00
mixed	0.10	0.11	0.66
rural	0.02	0.01	0.53
size	243.70	204.83	0.00
solecorp	0.30	0.30	0.88
KG	0.04	0.04	0.94
GmbH	0.08	0.05	0.26
coop	0.01	0.04	0.01
co-owner	0.08	0.09	0.71
admin	0.47	0.47	0.93
income	47617.83	42547.74	0.00
nearest_5	6.58	2.76	0.00

Table 8: Comparison of means before matching

	mean_treat_after	mean_control_after	t_test_p.value_after
agglomeration	0.59	0.62	0.53
mixed	0.10	0.04	0.06
rural	0.02	0.00	0.16
size	244.18	242.42	0.93
solecorp	0.30	0.27	0.60
KG	0.04	0.04	0.88
GmbH	0.08	0.11	0.44
coop	0.01	0.01	1.00
co-owner	0.08	0.13	0.19
admin	0.47	0.46	0.90
income	47649.22	48604.04	0.28
nearest_5	6.44	5.65	0.20

Table 9: Comparison of means after matching