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Financial incentives and physician prescription behavior

Evidence from dispensing regulations

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Abstract
In many healthcare markets, physicians can influence the volume (volume response) and the composition of the services provided (substitution response). The goal and main contribution of this paper is to empirically assess the relative importance of these two behavioral channels. Our analysis is based on the market for ambulatory care in Switzerland in which different drug dispensing regimes (banned/allowed) co-exist at the regional level but many important other features are regulated at the federal level. Dispensing creates financial incentives for physicians to sell more drugs and to substitute towards more expensive drugs thus providing an ideal setup for our empirical analysis. We combine the regional variation in the dispensing regime with comprehensive physician-level prescription data to empirically disentangle the volume and the substitution response. The estimated average effects suggest that physician dispensing increases drug costs on the order of 25% for general practitioners and 15% for medical specialists. A decomposition of this overall effect indicates that the cost increase can mainly be attributed to a volume increase, while average drug prices are not or even negatively affected in some specifications. In addition, we document substantial effect heterogeneity along the outcome distributions.

Keywords: physician agency; drug expenditures; volume response; substitution response; physician dispensing

JEL: I11, I18

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1 Introduction

Understanding physician market power, behavior, and motives – referred to as physician agency (McGuire, 2000) – is essential for assessing the efficiency of health care provision and shaping reforms. Particular interest is devoted to physicians' response to financial incentives and the closely related question, whether changing provider reimbursement such as lowering physician fees is effective in containing health care costs. Various empirical examples in the literature suggest that physicians respond to changes in the reimbursement scheme by changing the volume (volume response, see Nguyen, 1996; Yip, 1998; Gruber et al., 1999; Hadley and Reschovsky, 2006; Grant, 2009; Clemens and Gottlieb, 2014) and changing the composition of services provided (substitution response, see Van Doorslaer and Geurts, 1987; Hadley and Reschovsky, 2006) implying that imperfect physician agency is an issue.

Although it is very likely that changes in reimbursement schemes lead to both a volume and a substitution response, the relative importance of these two responses has not yet been addressed in the literature. Disentangling the volume and substitution response is important as a change in volume is likely to affect health outcomes in a different way compared to a change in the composition of services provided. Consequently, quantifying these two types of responses is relevant for shaping policies to improve efficiency in health care provision. More broadly, isolating these two behavioral channels contributes to a better understanding of physician behavior in the presence of monetary incentives. Therefore, our objective is to empirically investigate the relative importance of the volume and substitution response. To our knowledge, we are the first to disentangle these two behavioral channels in the context of physician agency.

Our analysis is based on the market for outpatient care in Switzerland where different drug dispensing regimes co-exist at the regional level.[1] Because dispensing physicians can earn a markup on drug sales that increases with the drug price, there are clear financial incentives to overprescribe or sell more expensive drugs. We exploit this setup to estimate

[1]Note that most OECD countries fully ban physician dispensing. Notable exceptions include the UK, the USA, Japan, and Switzerland of which all (partly) allow medical doctors to sell drugs.

the causal effect of dispensing on drug expenditures and subsequently decompose this overall effect into a volume response and a substitution response. The volume and the substitution response are quantified by estimating the effect of dispensing on normalized measures of the volume and the average price of prescribed drugs, respectively.

The Swiss healthcare system is well suited for an empirical analysis of physician dispensing because of the following aspects (Kaiser and Schmid, 2014). First, the regional differences in the dispensing regime are predetermined by historical differences on the cantonal (state) level. Second, drug prices as well as other important institutional features are regulated on the federal level. Third, health insurance is mandatory for the entire permanent population in Switzerland such that differences in drug prices are unlikely to be confounded by the insurance choice. Finally, only medical doctors are allowed to prescribe drugs. This feature is essential to our analysis as it implies that patients must necessarily visit a physician to obtain prescription medication. Thus, differences in access to pharmacies are unlikely to confound the analysis. We argue that this unique institutional setup combined with our rich data structure allows us to credibly identify and estimate the causal effect of dispensing.

Using doubly robust estimators (Imbens and Wooldridge, 2009), we find that annual drug costs per patient increase by more than CHF 50 (∼25%) for general practitioners (GP) and by about CHF 20 (∼15%) for medical specialists. That is, on average, GPs react more strongly than specialists to financial incentives created by the markup they earn when dispensing drugs. We proceed by decomposing these effects into a volume and a substitution response. For both GPs and medical specialists we find positive and significant effects on the drug volume but no or even weakly negative effects on average drug prices, indicating that the volume response empirically dominates the substitution response. As the impact of dispensing is potentially different in different parts of the outcome distributions, we supplement average treatment effect estimates with unconditional quantile treatment effects. Our results point to considerable effect heterogeneity in the causal effect of dispensing. This heterogeneity is even more pronounced for specialists than GPs reflecting the heterogeneous composition of this group of physicians.

Summing up, three main conclusions can be drawn from our analysis. First, GPs react more strongly than specialists to the financial incentives created by the markup they earn when dispensing drugs. Second, the volume effect empirically dominates the substitution effect. Third, there is considerable effect heterogeneity. Ignoring this heterogeneity may lead to wrong conclusions about the behavioral impact of dispensing, especially for specialists.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. In Section 3, we describe the institutional background. Section 4 discusses our identification strategy and presents the estimation approaches. In Section 5, we describe the construction of our dataset, determine common support, present descriptive statistics, and discuss our empirical results. Section 6 concludes. All figures and tables are collected in the appendix. In addition, the appendix contains an overview of the cantonal dispensing regulations and a detailed description of our dataset.

2 Related literature

While there is a large literature on physician behavior in the presence of monetary incentives (see, for instance, McGuire, 2000; Chandra et al., 2012), comparatively little is known about their prescription practices (see Lim et al., 2009, for an overview). One strand of the literature examines the prescription practices in case more than one medical alternative exists whereby the choice between generic and brand-name drugs is of particular interest (see, for instance, Hellerstein, 1998; Coscelli, 2000; Lundin, 2000). However, most of these analyses are based on countries without physician dispensing with the exception of Liu et al. (2009), Iizuka (2012), and Rischatsch et al. (2013). These authors analyze physician dispensing in Taiwan, Japan, and Switzerland, respectively, and find that physicians respond to markup differentials between generic and trade-name drugs. Regarding medical alternatives, Iizuka (2007) examines the case of anti-hypertensive drugs and finds that the prescription choices in Japan are influenced by the markup. Similarly, Park et al. (2005) and Filippini et al. (2014) find that non-dispensing physicians in South Korea and Switzerland, respectively, prescribe less antibiotics than their dispensing counterparts. In

summary, these results consistently suggest that physicians respond to financial incentives created by the drug market.

There is much less empirical work on the impact of physician dispensing on health care expenditures, prescribed drug volume, and average drug prices. The analysis conducted by Chou et al. (2003) suggests that drug expenditures per visit substantially decreased after the implementation of a dispensing ban in Taiwan. Kaiser and Schmid (2014) exploit variation in the dispensing regulation among Swiss cantons. Based on physician-level data on medical specialists, they find that dispensing considerably increases both drug and non-drug expenditures per patient. In addition, Beck et al. (2004) and Dummermuth (1993) compare aggregated cantonal expenditures and find that dispensing physicians trigger more drug expenditures per patient than non-dispensing physicians. Similar results are found for dispensing physicians in Lincolnshire (United Kingdom) by Baines et al. (1996). Finally, Rischatsch (2013) finds that dispensing physicians in Switzerland increase their own profit through the prescription of cost-inefficient drug packages, that is, costs per dose are slightly higher compared to pharmacists. Stated differently, some evidence exists that physician dispensing increases the average price of prescribed drugs.

It is worth noting that the study by Kaiser and Schmid (2014) is the closest paper to our work. Besides the different focus, our study differs with respect to the data sources and the sample selection. First, while we use data from the same data provider, we have access to a different and more comprehensive dataset, which also contains detailed information on drug prescriptions. The data used in this study consists of physicians with electronic billing, which increases the credibility and data quality. However, we have somewhat lower coverage of approximately 60% of all physicians running independent practices in Switzerland. Second, we use more years of data and, finally, we analyze the behavior of GPs *and* medical specialists. As these two groups are likely to respond differently to financial incentives, analyzing both groups increases the external validity of our results.

3 The market for ambulatory care in Switzerland

The healthcare system in Switzerland can broadly be categorized as managed competition.[2] On the demand side, basic health insurance is mandatory for all Swiss residents. Mandatory health insurance is offered by about 60 private insurance companies, which are subject to strong regulations. First, insures cannot make profit based on mandatory insurance and mandatory insurance needs to be separated from any voluntary supplementary insurance. Second, insurance providers are obliged to accept all individuals who wish to enroll.[3] Third, health insurance providers are de facto obliged to contract with all authorized health care providers and, in particular, with all physicians running independent practices. Finally, patients can in principle freely choose their medical doctors.[4] The basic health insurance coverage is quite comprehensive and includes most ambulatory services, inpatient care, physiotherapy, prescription drugs, and old-age care. The contract period for basic health insurance corresponds to the calendar year, i.e., patients can change their insurer or insurance plans annually. Patients can freely choose between different contracts with deductible levels ranging from CHF 300 to CHF 2500. After exceeding their respective deductible level, patients face a co-payment rate of 10%, which drops to zero once the sum of the co-payments exceeds CHF 700.[5]

On the supply side, the pharmaceutical market in Switzerland is regulated on the federal level with respect to the approval and pricing of prescription drugs as well as the allowance and the pricing of all the drugs that are reimbursable by the basic health insurance. Specifically, a positive list defines all the drugs that are reimbursable by basic health insurance (list of pharmaceutical specialties). This list is adapted at least once per month and specifies, inter alia, two prices for each drug: an ex-factory price and a

[2] A rather extensive and almost up-to-date summary on the Swiss health care system is provided by the OECD (OECD/World Health Organization, 2011). For further details on the pharmaceutical market in Switzerland we refer to Kaiser and Schmid (2014).

[3] A prospective risk equalization system compensates insurers for differences in the risk profiles of their customers; see for example Van de Ven et al. (2013) for a detailed description.

[4] Health insurance providers are allowed to offer managed care contracts such as health maintenance organization (HMO) health plans and preferred provider organization (PPO) health plans that both restrict the patients' provider choice in exchange for lower premiums.

[5] Deductible levels are between zero and CHF 600 for children (aged 18 and younger). In general, the stop loss amount for children is CHF 350.

retail public price. A dispensing physician charges his patients the retail price plus 2.5% VAT such that the gross profit margin corresponds to the difference between the retail and the ex-factory price, which are both regulated on the federal level. A key feature is that the absolute markup increases with the ex-factory price such that the incentives to overprescribe increase with the drug price (Kaiser and Schmid, 2014, Table A.II).

Dispensing physicians charge patients for the medical services provided and the retail price for dispensed prescription drugs, while non-dispensing physicians only charge patients for medical services. If a physician is not dispensing, he or she issues a prescription note that entitles the patient to buy the drug at the pharmacy. The pharmacists charges the patient the retail price plus some additional consultation fees and 2.5% VAT.

Note that while pharmacies are allowed to sell prescription drugs, they *cannot* issue prescriptions. Thus, only medical doctors are allowed to issue prescriptions and every patient must visit a physician to obtain prescription medication. This institutional feature is crucial for our analysis because it mitigates concerns that the analysis is confounded by differences in the availability of pharmacies and implies that the prescription costs of dispensing and nondispensing physicians can be adequately compared.

Although most aspects of the Swiss pharmaceutical market are regulated on the federal level, drug dispensing rules are determined on the cantonal level providing an ideal setup for analyzing the effect of dispensing on physician behavior. Table VII provides an overview of the dispensing regulations in the 26 Swiss cantons. With the exception of the canton of Zürich, the regulations did not change over the course of our study period.[6] In the canton of Zürich, physicians in the cities of Zürich and Winterthur were allowed to dispense in May 2012 as the consequence of a ballot in 2008 that concluded with 53.7% affirmative votes. In all other cantons, the regulations have been in place for several decades.

[6] The cantonal electorate in Schaffhausen voted for physician dispensing in 2012 (71.5% affirmative votes). The corresponding regulation will be enacted in 2017.

4 Methodology

4.1 Identification

To describe our identification strategy, we use the potential outcomes framework (cf. Rubin, 1974). Let the indicator D_i denote the dispensing status of physician i, i.e., $D_i = 1$ for dispensing physicians and $D_i = 0$ for non-dispensing physicians. Using standard terminology, we refer to the dispensing status D_i as the *treatment*. Let Y_{di} denote the *potential outcome* of physician i associated with treatment status $D_i = d$. We are interested in the average treatment effect (ATE) and the average treatment effect on the treated (ATT):

$$\Delta = \mathbb{E}\left(Y_{1i} - Y_{0i}\right), \tag{1}$$

$$\Delta_{D_i=1} = \mathbb{E}\left(Y_{1i} - Y_{0i} | D_i = 1\right). \tag{2}$$

The ATE is relevant for assessing a policy that either bans or allows dispensing for all physicians, while the ATT is the relevant quantity for evaluating the current dispensing regime. Note that both effects coincide if we assume constant treatment effects.

The impact of dispensing is likely to be different in different parts of the outcome distributions. Quantile treatment effects are powerful tools for analyzing and summarizing such effect heterogeneity. Specifically, we are interested in quantile treatment effects (QTE) and quantile treatment effects on the treated (QTT),

$$\delta(\tau) = Q_{Y_{1i}}(\tau) - Q_{Y_{0i}}(\tau), \tag{3}$$

$$\delta_{D_i=1}(\tau) = Q_{Y_{1i}|D=1}(\tau) - Q_{Y_{0i}|D=1}(\tau), \tag{4}$$

where τ denotes the quantile index.

Without additional assumptions, both average and quantile treatment effects are not identified from our data because counterfactual outcomes are unobserved. In this paper, we achieve identification through the conditional independence assumption (CIA). Let X_i denote a vector of observable covariates that contains the characteristics of physician i,

information about his or her patients, and health care market conditions prevalent at his or her practice location. The CIA asserts that conditional on X_i, the dispensing status D_i is independent of the potential outcomes, that is, after controlling for X_i, D_i is as good as randomly assigned. Formally, the CIA reads

$$(Y_{1i}, Y_{0i}) \perp\!\!\!\perp D_i | X_i. \tag{5}$$

We also need the technical common support assumption

$$0 < p(x) < 1, \quad \forall x \in \mathcal{X}, \tag{6}$$

where $p(x) \equiv P(D_i = 1 | X_i = x)$ is the propensity score and $\mathcal{X} \subset \mathbb{R}^k$ denotes the support of X_i. Assumption (6) asserts that for every value of X_i, we can match dispensing with nondispensing physicians. In contrast to Assumption (5), Assumption (6) is testable and we assess its validity in Section 5.3. Under Assumptions (5) and (6) the average and quantile treatment effects are identified (e.g., Imbens, 2004; Firpo, 2007).

4.2 Plausibility of the conditional independence assumption

The key assumption underlying our identification strategy is the CIA. Although this assumption is fundamentally untestable, we argue that it is likely to hold in our context because of the following aspects (see Kaiser and Schmid, 2014). First, dispensing policies are predetermined on the cantonal level such that the physicians' ability to influence their treatment assignment is strongly restricted. Second, the current dispensing regulations are rooted in historical differences in cantonal health care policy. Table VII documents that most dispensing regulations have been in place for several decades. This mitigates concerns that the current regimes are endogenous outcomes of unobserved dispensing preferences. Although we cannot totally exclude the possibility that unobserved regional preferences for drug policies have a persistent impact until today, we argue that the degree of persistence necessary to threaten our design is unlikely. Third, we control for a comprehensive set of factors that affect the dispensing status and potential outcomes,

namely for physician characteristics, patient pool compositions, and healthcare market conditions in the practice location (see Section 5.1 for more details). This eliminates any bias that arises if those factors jointly affect the dispensing status and the potential outcomes. Finally, many institutional features including the positive list of prescription drugs covered by mandatory health insurance, drug prices, pharmacy markups, and health insurance regulations are determined by federal regulations and are therefore guaranteed not to confound our analysis.

4.3 Estimation

4.3.1 Average treatment effects

There are different approaches for estimating average treatment effects under Assumptions (5) and (6). Here we employ 'doubly-robust' regression, a method that combines regression with propensity score weighting. The main advantage of the doubly robust regression is that it achieves consistency under two separate sets of assumptions, i.e., it is consistent if *either* the propensity score *or* the outcome model is correctly specified, *or* both (e.g., Wooldridge, 2007; Robins et al., 2007). Doubly robust regression thus provides better protection against misspecification than standard procedures relying on either the propensity score or on regression alone. This estimator is explicitly recommended by Imbens and Wooldridge (2009) because of its good performance in situations where covariate distributions differ between the treatment and control group (cf. Section 5.3). Estimation proceeds in four steps:

1. Estimate the propensity score using parametric logit models and compute the predicted probabilities $\hat{p}(X_i)$.

2. Construct propensity score weights $\lambda(X_i) = \left(\frac{D_i}{\hat{p}(X_i)} + \frac{1-D_i}{1-\hat{p}(X_i)}\right)$ for the ATE and $\lambda_{D_i=1}(X_i) = \left(D_i + \frac{\hat{p}(X_i)}{1-\hat{p}(X_i)}(1-D_i)\right)$ for the ATT.

3. Choose parametric models for the mean functions of the treated and non-treated physicians, $m(X_i, \beta^1)$ and $m(X_i, \beta^0)$ for the ATE and $m(X_i, \beta^1_{D_i=1})$ and $m(X_i, \beta^0_{D_i=1})$

for the ATT. The coefficients of the mean functions are obtained as the solutions of the following inverse probability weight augmented moment conditions:

$$\sum_{i:D_i=d} \hat{\lambda}(X_i)\left[Y_i - m(X_i,\hat{\beta}^d)\right]X_i = 0, \quad \text{for} \quad d \in \{0,1\}, \tag{7}$$

$$\sum_{i:D_i=d} \hat{\lambda}_{D_i=1}(X_i)\left[Y_i - m(X_i,\hat{\beta}^d_{D_i=1})\right]X_i = 0, \quad \text{for} \quad d \in \{0,1\}. \tag{8}$$

4. Estimate the ATE and ATT as follows

$$\hat{\Delta} = \frac{1}{N}\sum_i m\left(X_i,\hat{\beta}^1\right) - m\left(X_i,\hat{\beta}^0\right)$$

$$\hat{\Delta}_{D_i=1} = \frac{1}{N_1}\sum_{i:D_i=1} m\left(X_i,\hat{\beta}^1_{D_i=1}\right) - m\left(X_i,\hat{\beta}^0_{D_i=1}\right),$$

where $N_1 = \sum_i D_i$ is the number of treated physicians.

In our empirical analysis, we consider two different mean functions $m(\cdot,\cdot)$: a linear model in which case (7) and (8) become weighted least squares (WLS) estimators, and an exponential model in which case (7) and (8) are the weighted Poisson quasi-maximum-likelihood estimator (WPQML); see, e.g., Wooldridge (2007) for more details.

4.3.2 Quantile treatment effects

We estimate the QTE using the semiparametric estimation approach proposed by Firpo (2007). Estimation proceeds in two steps:

1. Construct the propensity score weights $\hat{\lambda}(X_i)$ and $\hat{\lambda}_{D_i=1}(X_i)$ as described before.[7]

2. Obtain QTE and QTT from weighted quantile regressions

$$\left(\hat{\delta}(\tau),\hat{Q}_{Y_{0i}}(\tau)\right) = \arg\min_{\delta,Q}\frac{1}{n}\sum_{i=1}^{n}\lambda(X_i)\rho_\tau\left(Y_i - D_i\delta - Q\right)$$

[7] In this paper, the weights are constructed based on the same parametric propensity score estimates as used for the average effects.

and

$$\left(\hat{\delta}_{D_i=1}(\tau), \hat{Q}_{Y_{0i|D_i=1}}(\tau)\right) = \arg\min_{\delta,Q} \frac{1}{n}\sum_{i=1}^{n} \lambda_{D_i=1}(X_i)\rho_\tau\left(Y_i - D_i\delta - Q\right),$$

where $\rho_\tau(u) = u(\tau - \mathbb{1}\{u < 0\})$ is the check function.

5 Empirical analysis

5.1 Data sources and variables

We exploit physician-level data on drug prescriptions for the years 2008-2012. The data is provided by the operator of the nationwide database of Swiss health insurers (Sasis AG) and identifies each physician by the Global Location Number (GLN). We are therefore able to link it to complementary data from the register of medical personnel (MedReg). This register contains personal information on each physician, as the dispensing permission indicator (treatment indicator D_i) and the practice location. Additionally, we observe gender, nationality, age, experience, and the medical specialty of each physician.

Our data includes prescriptions triggered by self-employed GPs and specialists who deliver outpatient care in private practices. For each prescription, we observe the gross drug costs and identify the prescribing physician as well as the pharmaceutical (*pharmacode*). The drug costs are either direct costs induced by dispensing physicians or indirect costs originating from prescriptions filled in pharmacies. Using the identifier for the pharmaceutical, we are able to merge each prescription to the list of pharmaceutical specialties provided by the Federal Office of Public Health. The list includes dosages, package sizes, and retail prices, which allows us to construct normalized volume and average price measures as described in Section 5.1.1.

The health insurance data at hand further contains information on the physicians' pool of patients, which allows us to control for differences in patient compositions. In particular, we observe the patients' residence, age, gender, and their model of insurance, i.e., cost-saving health plans and deductible levels. Knowing the patients' residence, we

additionally control for location-specific heterogeneity by exploiting municipality level averages provided by the Swiss Federal Financial Administration (SFFA), the Swiss Federal Statistical Office (SFSO), and the Swiss Household Panel (SHP). Using these data sources, we observe the population density, the share of foreigners, urbanity, the unemployment rate, mean education levels, income per capita, physician density, the share of individuals with very good, good, average, and bad self-reported health status, and the mean Body Mass Index (BMI). As physicians draw patients from different municipalities, we control for a physician's average patient composition by weighted averages over municipalities. The weights correspond to the number of patients within each municipality.

There are two types of drug costs that are not part of our data. First, we do not observe out-of-pocket expenditures that are not reported to the insurers. In all likelihood this is only the case for patients with low health care expenditures and high deductibles (see Schmid, 2015). Second, there are some over-the-counter products that do not require prescriptions and, therefore, cannot be linked to a physician. Their relevance, however, is limited because only few of the drugs covered by mandatory health insurance are over-the-counter products (Kaiser and Schmid, 2014).[8]

5.1.1 Volume and price measures

To decompose the overall effect into a volume and price effect, we need a volume (price) measure that is independent of the price (volume). The definition of these two dependent variables is thus a central issue. Regarding volume, we have to take into account that for most drugs different package sizes and dosages are available. In addition, drugs can be offered by several producers in case generic versions exist. Therefore, we base our analysis on the active pharmaceutical ingredient (API) and proceed as follows. First, we determine the smallest package per API and divide afterwards each package's content in terms of API by the content of the smallest package with the same API. In other words, we express the package volume in terms of the smallest package, which we refer to as 'normalized volume'. Second, the volume on the *pharmacode level* is constructed by

[8]Examples include painkillers with low dosage or certain herbal products.

multiplying the number of prescriptions (includes dispensed drugs) on the physician level by the corresponding normalized volume. Finally, we aggregate these figures to obtain the total volume for each physician and divide this volume by the number of patients. The normalized volume increases if the physician dispenses or prescribes (a) and additional drug package or (b) the package content in terms of API increases. However, it does *not* increase if the physician decides, for instance, to dispense two small packages instead of one large package as long as the two choices are equal in terms of the API content.

Our price measure is constructed as follows. First, we calculate the price per unit of the API using the retail price and, in turn, divide it by the lowest price in our data for this API. Stated differently, we determine the drug price relative to the cheapest drug with the same API. We refer to this relative price as 'normalized price'. Second, to construct the physician's average price, we calculate the weighted average of all normalized prices using the number of prescriptions (includes dispensing) as weights. Thus, the average price is a relative measure (relative to a scenario where the physician prescribes the cheapest drug) and does not depend on the volume.

Note that Ling et al. (2002) and Liu et al. (2009, 2012) use defined daily doses (DDD) and the anatomical therapeutic chemical classification system established by the World Health Organization (WHO) to take into account that for many diseases several drugs with different API exists. However, the WHO Collaborating Centre for Drug Statistics Methodology (2011) states clearly that DDD do generally not reflect therapeutic equivalence and, therefore, it is usually not valid to use DDD to compare costs across different drugs. Nevertheless, we examine the robustness of our results by analyzing volume and price measures based on DDD in Section 5.6.

5.2 Data restrictions

Importantly, there is only variation in the dispensing regulations in the German speaking part of Switzerland. The Italian and French speaking cantons completely prohibit dispensing.[9] As our empirical strategy relies on cross-sectional variation in the dispensing

[9] Note that there are some exceptions in regions where the pharmacy density is low, see Table VII.

rule, this feature implies that we cannot control for language regions. In view of the ample evidence about culture-specific heterogeneity in health-care expenditures and consumption, an analysis based on the whole of Switzerland would likely be confounded by unobserved cultural differences. As a consequence, we restrict our analysis to the German speaking area.

As discussed in Section 3, dispensing was allowed in the cities of Zürich and Winterthur in May 2012. Because we have annual data, we exclude all observations of physicians that are located in these two cities in 2012.

5.3 Determining common support

Treatment effects can only be estimated for dispensing physicians for whom we observe similar non-dispensing physicians. That is, we need overlap in the covariate distributions of treatment and control units. We define this common support condition in terms of the propensity score and drop observations with a very low (close to 0) or very high (close to 1) propensity score. This is achieved using the approach proposed by Crump et al. (2009). Their methodology is purely data driven, does not depend on outcome variables, and requires a first-step estimation of the propensity score, denoted by $\hat{p}(x)$. In the second step, treatment effects are estimated using the common support sample of observations with $\hat{p}(x) \in [\hat{\alpha}, 1 - \hat{\alpha}]$ only, where the cutoff parameter $\hat{\alpha} \in [0, 1/2]$ is chosen optimally such that average treatment effects can be estimated most precisely. Using the algorithm of Crump et al. (2009), we estimate $\hat{\alpha} = 0.103$ ($\hat{\alpha} = 0.096$) for GPs (specialists) and drop 17% (31%) of the observations. Figure 1 shows the estimated propensity scores for the full samples of GPs and specialists as well as for their common support samples. In contrast to the full samples, the common support samples, i.e., panels (c) and (d), do no longer exhibit probability mass at the boundary points 0 and 1. This means that it is no longer the case that for some covariate values, the treatment status is (almost) perfectly predicted.

Table I additionally illustrates the impact of the cutoff parameter on the normalized

difference of covariate means by dispensing status.[10] This difference is more convenient than t-statistics because an increase in the sample size does not systematically affect the normalized difference (Imbens and Wooldridge, 2009). For GPs as well as specialists, the normalized differences are significantly lower in the common support samples, which shows that the covariate distributions are indeed more balanced.

5.4 Descriptive statistics

Tables II and III show the descriptive statistics for the common support samples of GPs and specialists. These samples consist of 3918 GPs and 3488 specialists, most of whom are observed in each of the years 2008 to 2012, leading to panels of 16291 and 12799 observations, respectively. To take differences in the number of patients into account, the dependent variables drug costs and drug volume are measured in per-patient terms. The third outcome of interest, the average drug price, does not require an adjustment to the number of patients.

Average drug costs per patient are 56 Swiss Francs higher for dispensing GPs than for non-dispensing GPs. This difference of almost 26% is reflected by a 28% higher drug volume triggered by dispensing GPs, whereas average drug prices are not significantly different for the two groups. For specialists, the percentage differences by dispensing status are somewhat smaller. That is, average drug costs per patient are 10% higher for dispensing than for nondispensing specialists. The per-patient drug volume is 25% higher for dispensing than for nondispensing specialists, whereas average drug prices are approximately 2% lower for dispensing specialists.

The average physician characteristics and further patient pool variables are very similar for dispensing and non-dispensing physicians. The characteristics of the local health-care markets show that dispensing physicians are less often located in urban regions than their nondispensing colleagues. That is, physician density, the fraction of urban area, and the population density are on average lower for dispensing physicians. Apart from these

[10] Normalized differences are computed as $(\bar{x}_{j1} - \bar{x}_{j0})/\sqrt{\hat{V}_{j1} + \hat{V}_{j0}}$, where $\bar{x}_{jd}$ and $\hat{V}_{jd}$ are the sample mean and the sample variance of the subsamples with $D_i = d \in \{0, 1\}$.

differences in urbanity, the covariates seem to be well-balanced across dispensing status.

5.5 Causal effects of dispensing

In this section, we report estimates of the causal effect of dispensing on physician behavior. The first outcome variable of interest, drug costs per patient, has been studied before by Kaiser and Schmid (2014) and allows us to quantify the overall effect of dispensing on drug costs.[11] The main contribution of this paper is to subsequently decompose this overall effect into a volume response and a substitution response. This is achieved by estimating the causal impact of dispensing on normalized volume and average drug prices respectively.

Our analysis is carried out separately for GPs and medical specialists. The covariates included in our models are essentially the same as in Table I. We additionally include year fixed effects as we have pooled data for the years 2008-2012 and exclude the number of patients as well as the number of visits as two of our outcomes are per patient measures. To compute standard errors and confidence bands, we employ the block bootstrap to account for the potential serial correlations within clusters (i.e., physicians observed for more than one year) and the uncertainty associated with the first-step estimation of the propensity score. For all outcomes we report doubly-robust estimates of the ATE and the ATT based on WLS and WPQML as well as estimates of the unconditional QTE and the QTT based on the Firpo (2007)-estimator.

5.5.1 General practitioners

The estimated average effects reported in the left column of Table IV imply that dispensing raises a physicians' drug costs per patient by CHF 51 or 23% (WLS) and CHF 55 or 25% (WPQML) within the population of dispensing GPs (ATT). In the overall population (ATE), the estimated causal effects are slightly higher: CHF 57 or 26% (WLS) and CHF 58 or 27% (WPQML). The differences between WLS and WPQML are rather small compared to the confidence intervals, suggesting that our results are robust with respect to the choice

[11] Recall that Kaiser and Schmid (2014) use a different dataset and different samples (Section 2).

of the mean function. Furthermore, since the ATE and the ATT are not significantly different, we cannot reject the hypothesis of no average treatment effect heterogeneity. Finally, a comparison with the unadjusted difference allows us to compute the size of the selection effect (selection effect = unadjusted difference - ATT). The estimated selection effect is small and not statistically significant, indicating that selection is a minor issue in the context of our study (conditional on the validity of the CIA assumption).

Figure 2 displays QTE and QTT estimates for our three main outcomes. Looking at Figure 2 (a), we find that the overall effect of dispensing on drug costs is nonconstant and hump-shaped, ranging from below CHF 20 at the 5%-quantile up to over CHF 80 at the median. These results are indicative of substantial heterogeneity in the causal effect of dispensing along the outcome distribution.

Turning to the decomposition of the overall cost effect, we find a positive and significant volume effect of 22% (WLS) respectively 25% (WPQML) for the treated and 25% (WLS) respectively 26% (WPQML) for the overall population and a small and insignificant effect on average drug prices. These results strongly suggest that the volume effect empirically dominates the substitution effect. In other words, drug dispensing causes GPs to sell more drugs but not to substitute towards more expensive drugs. The QTE and QTT estimates reported in Figure 2 (c) and (e) confirm this result. The QTE estimates for the normalized volume exhibit a hump-shaped pattern, which is very similar to the one depicted in Figure 2 (a). While the causal effect of dispensing on average drug prices is roughly constant and insignificant across most quantiles, we estimate substantive and significantly positive effects at the lower tail and significantly negative effects at the upper tail. Thus, although the volume effect dominates the substitution effect in the center of the distribution, the latter effect tends to be much more important at the tails where the former effect is smallest.

5.5.2 Specialists

In Table V, we report the ATE and ATT estimates for the medical specialists. The results indicate that there are significant positive cost effects for the overall population, CHF 27

or 17% (WLS) and CHF 26 or 16% (WPQML), while the average effects for the dispensing specialists are not significant. This corroborates the earlier findings by Kaiser and Schmid (2014), although the effects reported here are somewhat smaller. The differences between WLS and WPQML are small relative to the standard errors. However, the QTE and QTT estimates in Figure 2 (b) show small positive effects in the lower tail up to the center of the distributions and much larger effects in the upper tail. These results are indicative of substantial effect heterogeneity, which corresponds to our intuition as medical specialists are inherently a very diverse physician population.[12] Table V further reports the average causal effects of dispensing on the volume per patient and the average price. The results indicate that there is a significantly positive volume response ranging from around 30% for the treated up to over 35% for the overall population, while there is no substitution response as measured by the effect on average prices. The QTE estimates in Figures 2 (d) and (f) confirm these findings. Similar to the corresponding estimates of overall cost effects, the volume effects are positive and increasing along the distribution, while there are no significant distributional effects on average prices.

On the whole, our findings suggest that the causal effect of dispensing on drug costs is less pronounced for specialists than for GPs. Nevertheless, we find clear evidence that the volume response empirically dominates the substitution response. Furthermore, our results highlight the importance of analyzing effect heterogeneity along the outcome distributions using quantile treatment effects.

5.6 Robustness checks

Here we examine the robustness of our results by applying alternative measures of drug volumes and prices that are not based on the API. We construct normalized volumes and normalized prices using DDD as defined by the World Health Organization. Using data from the WHO Collaborating Centre for Drug Statistics, we are able to link the DDD to approximately 63% of the prescriptions in our initial data. In terms of the costs, the

[12] For instance, invasive medical specialists' drug cost per patient are CHF 43 (102) while their non-invasive counterparts exhibit per patient drug cost of CHF 395 (881) (standard deviations in parentheses). In contrast, GPs have on average drug cost per patient of CHF 249 with a standard deviation of 189 implying that this group is much more homogeneous.

prescriptions for which DDD are available account for 72% of the overall drug costs in our data. Using this subsample and the normalizations based on DDD, we re-estimate the average effects of dispensing on the drug volume per patient and the average drug price using the same specification as in Section 5.5.

The re-estimated effects of physician dispensing on volumes and prices are reported in Table VI. The positive and highly significant effects on drug volume per patient are similar in percentage terms to the previous results based on API (Tables IV and V). In particular, the effects in percent are almost identical for GPs, whereas they increase by approximately one fourth for specialists. The coefficients itself are different because the normalizations are based on DDD instead of API. The price effects turn out to be significantly negative when using DDD. For GPs, we find effects of approximately -8%. For specialists, the estimates range from -23% (ATE) to -35% (ATT). However, recall that DDD do generally *not* reflect therapeutic equivalence (Section 5.1.1). Nevertheless, these results confirm our finding that higher drug costs of dispensing physicians are driven by an increased volume that dominates the impact of drug prices.

6 Conclusion

Physicians are in many cases able to influence the volume and the composition of the services they provide. The extent and relative importance of these two behavioral channels both depend on the financial incentives faced by the physician. We study the case of drug dispensing regulations in Switzerland, which provide clear financial incentives to sell more drugs (volume response) and more expensive drugs (substitution response). To empirically disentangle and quantify these two responses, we exploit the unique institutional setting in Switzerland, which is characterized by a combination of federal regulations and regional variation in the dispensing regime (banned/allowed).

Our findings can be summarized as follows. First, the physician dispensing has a larger impact on drug costs for GPs than for specialists. Second, the volume response empirically dominates the substitution response. In other words, the permission to dispense drugs causes physicians to sell more drugs but not necessarily to sell more expensive drugs.

Third, we find substantial heterogeneity in the impact of dispensing along the outcome distributions. From a policy perspective, the most relevant insight of our paper is the relative importance of the volume response, indicating that policies that regulate the volume are likely to be more effective than price regulations for containing healthcare costs.

There are some limitations to our analysis. First, dispensing physicians face additional financial incentives that are unobserved. For instance, they might receive kick backs or discounts on the ex-factory price. Second, we cannot quantify the impact of dispensing on health outcomes. Both issues could be tackled if more detailed data was available. Finally, our results show that there is a lot of heterogeneity in the causal effect of dispensing within and between different types of physicians. A further analysis of the determinants of this effect heterogeneity is certainly worth pursuing in future research.

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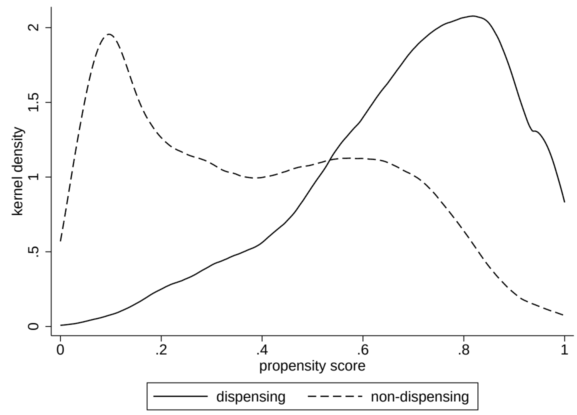
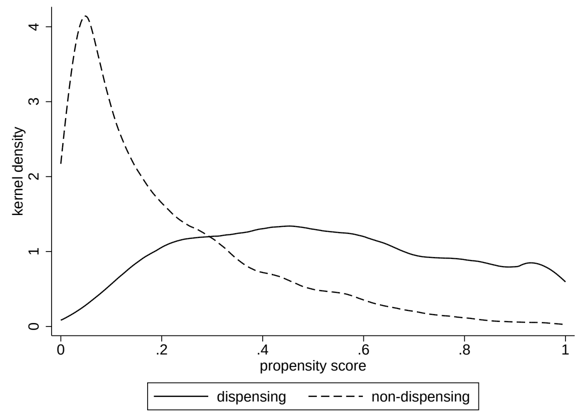
Appendix

A Figures and tables

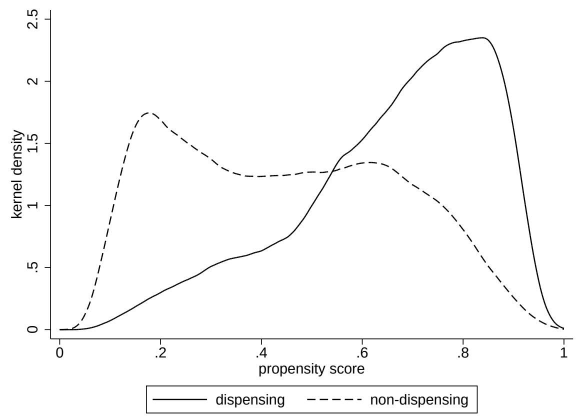
Figure 1: Kernel densities of estimated propensity scores



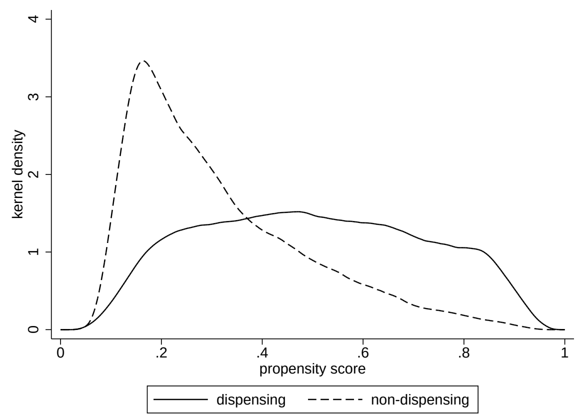
(a) General practitioners, full sample



(b) Specialists, full sample

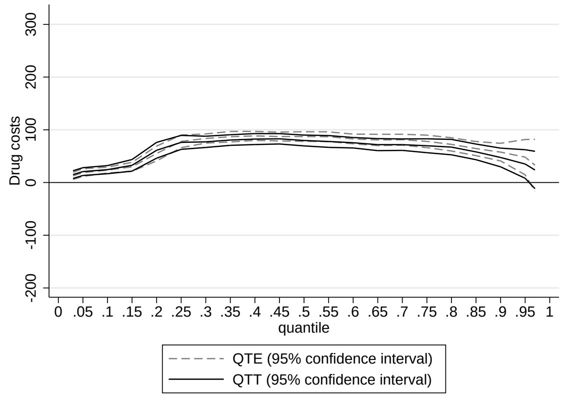


(c) General practitioners, common support sample

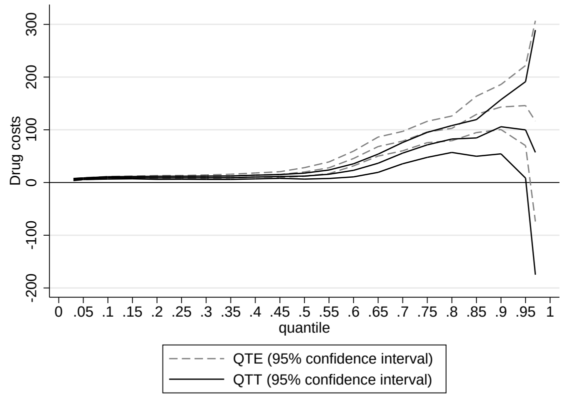


(d) Specialists, common support sample

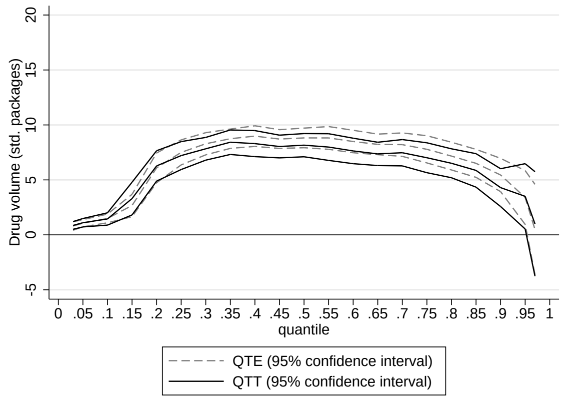
Figure 2: Quantile treatment effects of dispensing, 2008-2012



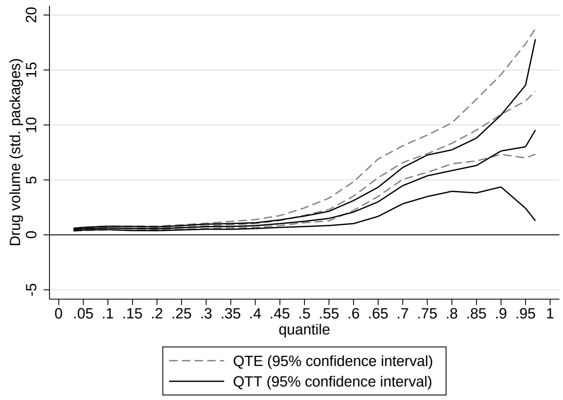
(a) General practitioners, costs per patient



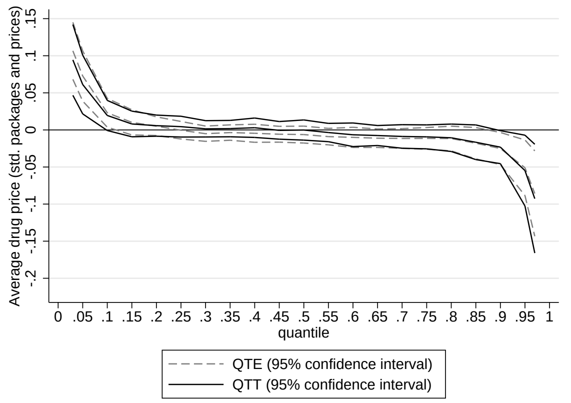
(b) Specialists, costs per patient



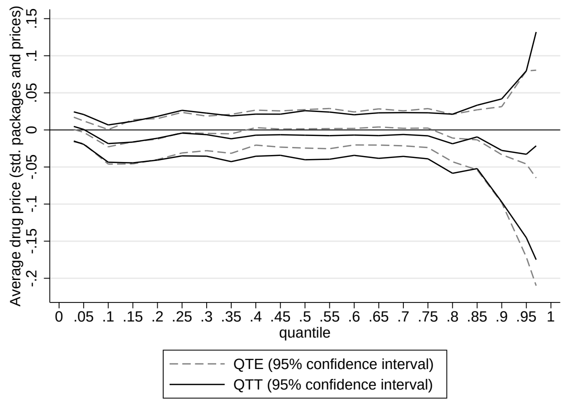
(c) General practitioners, volume per patient



(d) Specialists, volume per patient



(e) General practitioners, average drug price



(f) Specialists, average drug price

Table I: Normalized differences of covariate means (2008-2012)

	General Practitioners		Specialists	
	Full sample	CS sample	Full sample	CS sample
Physician characteristics				
Female	−0.144	−0.106	−0.028	0.002
German nationality	0.046	0.026	0.119	0.069
Other foreign nationality	0.012	0.008	−0.018	−0.004
Age	−0.076	−0.037	−0.126	−0.052
Work experience	−0.017	−0.008	−0.069	−0.030
Patient pool variables				
# patients	0.304	0.229	0.340	0.238
# visits	0.266	0.213	0.324	0.254
Patients' average age	−0.021	0.002	0.023	−0.002
Cases aged >80 years	−0.017	0.010	0.060	0.042
Cases aged 66-80 years	0.122	0.091	0.064	0.020
Cases aged <25 years	−0.012	−0.028	−0.015	0.001
Cases of men	0.173	0.126	−0.061	−0.030
Share with deductible of CHF 500	−0.017	0.020	−0.182	−0.109
Share with deductible of CHF 1000	0.077	0.058	0.104	0.068
Share with deductible of CHF 1500	0.157	0.100	0.204	0.095
Share with deductible of CHF 2000	0.107	0.083	0.159	0.072
Share with deductible of CHF 2500	−0.078	−0.054	−0.003	−0.004
Share of children with deductibles	0.050	0.023	−0.014	−0.012
Share with insurance model HMO	0.086	0.032	0.178	0.153
Share with insurance model PPO	0.156	0.113	0.176	0.090
Share with insurance model TelMed	0.091	0.066	0.103	0.092
Characteristics of the local healthcare market				
Physician density	−0.502	−0.330	−0.429	−0.109
Share with very good health	0.053	0.011	0.069	0.025
Share with good health	0.025	0.027	0.029	0.004
Share with fair health	−0.109	−0.063	−0.143	−0.043
Share with chronic health problems	−0.096	−0.036	−0.218	−0.076
Share that needs medication	−0.067	−0.019	−0.206	−0.062
Average body mass index	0.282	0.193	0.253	0.124
Share of immigrants	−0.251	−0.173	−0.083	−0.020
Fraction of urban area	−0.470	−0.330	−0.431	−0.227
Net income per capita	0.156	0.003	0.138	0.026
Unemployment rate	−0.371	−0.245	−0.311	−0.187
Share of medium educated	0.405	0.284	0.249	0.034
Share of high educated	−0.300	−0.253	−0.344	−0.151
Population density	−0.473	−0.337	−0.414	−0.199
Type of physician				
GP II: practice diploma	−0.052	−0.026		
GP III: pediatrist	−0.069	−0.070		
gynecologist			0.152	0.065
angiologist			−0.027	−0.014
cardiologist			0.026	0.007
invasive specialist			0.086	0.029
psychiatrist			−0.240	−0.108
other type of specilist			−0.073	−0.045
Trimming and # obs.				
alpha		0.103		0.096
# control obs. (non-dispensing)	8646	7029	12943	7859
# treated obs. (dispensing)	10936	9262	5642	4940

Notes: CS sample refers to the common support subsample (Section 5.3). Detailed definitions of the variables can be found in Table VIII. obs.: observations.

Table II: General practitioners' descriptive statistics (2008-2012)

	Nondispensing		Dispensing	
	Mean	Std. Dev.	Mean	Std. Dev.
Drug prescriptions				
Costs per patient	217.611	220.889	273.989	156.149
Volume (std. packages) per patient	20.983	20.213	26.829	15.616
Average price (std. packages and prices)	1.852	0.440	1.840	0.246
Physician characteristics				
Female	0.271	0.445	0.208	0.406
German nationality	0.060	0.238	0.069	0.254
Other foreign nationality	0.012	0.107	0.013	0.113
Age	52.136	8.686	51.679	8.523
Work experience	16.601	9.211	16.494	8.837
Patient pool variables				
# patients	923.446	581.994	1109.383	565.168
# visits	3788.582	2321.423	4482.523	2296.373
# visits per patient	4.404	2.008	4.210	1.514
Patients' average age	44.412	15.882	44.444	13.431
Cases aged >80 years	0.115	0.098	0.116	0.077
Cases aged 66-80 years	0.207	0.118	0.221	0.105
Cases aged <25 years	0.222	0.300	0.211	0.258
Cases of men	0.407	0.120	0.426	0.101
Share with deductible of CHF 500	0.160	0.091	0.163	0.082
Share with deductible of CHF 1000	0.023	0.017	0.025	0.014
Share with deductible of CHF 1500	0.054	0.036	0.059	0.031
Share with deductible of CHF 2000	0.009	0.010	0.010	0.009
Share with deductible of CHF 2500	0.028	0.025	0.026	0.019
Share of children with deductibles	0.009	0.015	0.009	0.013
Share with insurance model HMO	0.047	0.078	0.050	0.076
Share with insurance model PPO	0.287	0.129	0.306	0.118
Share with insurance model TelMed	0.030	0.034	0.033	0.035
Characteristics of the local healthcare market				
Physician density	3.371	1.641	2.551	1.872
Share with very good health	0.190	0.062	0.191	0.072
Share with good health	0.646	0.067	0.649	0.077
Share with fair health	0.141	0.048	0.137	0.049
Share with chronic health problems	0.372	0.072	0.369	0.067
Share that needs medication	0.409	0.075	0.406	0.081
Average body mass index	24.430	0.734	24.641	0.815
Share of immigrants	0.209	0.072	0.191	0.071
Fraction of urban area	0.318	0.186	0.242	0.136
Net income per capita	75.945	8.880	75.981	10.279
Unemployment rate	2.703	0.683	2.454	0.748
Share of medium educated	0.510	0.044	0.525	0.033
Share of high educated	0.213	0.046	0.197	0.042
Population density	0.091	0.924	−0.332	0.853
# observations	7029		9262	

Notes: Based on the common support subsample and averaged across the period 2008-2012. The variables are measured annually on the physician level. Detailed definitions of the variables can be found in Table VIII. Std. Dev.: Standard Deviation.

Table III: Specialists' descriptive statistics (2008-2012)

	Nondispensing		Dispensing	
	Mean	Std. Dev.	Mean	Std. Dev.
Drug prescriptions				
Costs per patient	160.610	454.424	176.655	321.059
Volume (std. packages) per patient	9.421	16.633	11.767	15.610
Average price (std. packages and prices)	1.664	0.431	1.637	0.400
Physician characteristics				
Female	0.293	0.455	0.295	0.456
German nationality	0.110	0.313	0.142	0.349
Other foreign nationality	0.018	0.133	0.017	0.131
Age	51.236	8.650	50.620	7.980
Work experience	15.939	8.530	15.599	7.683
Patient pool variables				
# patients	783.126	811.721	1076.456	930.581
# visits	2051.245	1779.284	2705.850	1864.862
# visits per patient	4.651	4.086	3.975	3.270
Patients' average age	49.551	10.437	49.529	8.636
Cases aged >80 years	0.055	0.065	0.059	0.063
Cases aged 66-80 years	0.189	0.147	0.193	0.140
Cases aged <25 years	0.121	0.164	0.122	0.121
Cases of men	0.355	0.206	0.346	0.201
Share with deductible of CHF 500	0.175	0.070	0.166	0.057
Share with deductible of CHF 1000	0.029	0.021	0.031	0.019
Share with deductible of CHF 1500	0.074	0.049	0.080	0.047
Share with deductible of CHF 2000	0.013	0.014	0.014	0.013
Share with deductible of CHF 2500	0.038	0.033	0.037	0.029
Share of children with deductibles	0.005	0.013	0.005	0.009
Share with insurance model HMO	0.051	0.059	0.066	0.071
Share with insurance model PPO	0.254	0.122	0.269	0.105
Share with insurance model TelMed	0.035	0.041	0.040	0.042
Characteristics of the local healthcare market				
Physician density	3.173	0.972	2.987	1.414
Share with very good health	0.187	0.044	0.189	0.051
Share with good health	0.650	0.050	0.650	0.060
Share with fair health	0.139	0.039	0.137	0.039
Share with chronic health problems	0.374	0.054	0.368	0.052
Share that needs medication	0.412	0.061	0.406	0.065
Average body mass index	24.518	0.707	24.641	0.689
Share of immigrants	0.207	0.054	0.206	0.044
Fraction of urban area	0.309	0.137	0.269	0.105
Net income per capita	79.328	11.553	79.780	12.828
Unemployment rate	2.676	0.534	2.536	0.521
Share of medium educated	0.514	0.034	0.515	0.020
Share of high educated	0.216	0.042	0.207	0.038
Population density	0.173	0.719	−0.017	0.624
# observations	7859		4940	

Notes: Based on the common support subsample and averaged across the period 2008-2012. The variables are measured annually on the physician level. Detailed definitions of the variables can be found in Table VIII. Std. Dev.: Standard Deviation.

Table IV: General practitioners' causal effects of dispensing, 2008-2012

	Costs per patient			Volume per patient			Average drug price		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	56.38***	5.48	25.91	5.85***	0.48	27.86	−0.01	0.01	−0.64
Average treatment effect									
Weighted least squares	56.80***	5.76	26.10	5.32***	0.65	25.35	−0.01	0.01	−0.75
Weighted PQML	57.92***	4.62	26.61	5.53***	0.45	26.35	−0.01	0.01	−0.74
Average treatment effect on the treated									
Weighted least squares	50.75***	8.11	23.32	4.70***	0.91	22.42	−0.01	0.01	−0.54
Weighted PQML	55.08***	5.27	25.31	5.19***	0.56	24.75	−0.01	0.01	−0.52

Notes: The estimation sample consists of 16291 observations from the years 2008-2012 that lie in the common support subsample. The outcomes are measured annually on the physician level. Standard errors are block bootstrapped on the physician level using 250 replications. PQML: Poisson quasi-maximum likelihood. Coef.: Coefficient. S.E.: Standard Error. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table V: Specialists' causal effects of dispensing, 2008-2012

	Costs per patient			Volume per patient			Average drug price		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	16.05	15.35	9.99	2.35***	0.58	24.90	−0.03**	0.01	−1.64
Average treatment effect									
Weighted least squares	26.56*	14.88	16.54	3.51***	0.62	37.23	−0.01	0.01	−0.83
Weighted PQML	26.20**	13.11	16.31	3.38***	0.52	35.92	−0.01	0.01	−0.76
Average treatment effect on the treated									
Weighted least squares	17.71	18.15	11.03	2.66***	0.79	28.28	−0.01	0.01	−0.64
Weighted PQML	20.60	15.95	12.83	2.98***	0.53	31.68	−0.01	0.01	−0.60

Notes: The estimation sample consists of 12799 observations from the years 2008-2012 that lie in the common support subsample. The outcomes are measured annually on the physician level. Standard errors are block bootstrapped on the physician level using 250 replications. PQML: Poisson quasi-maximum likelihood. Coef.: Coefficient. S.E.: Standard Error. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table VI: Robustness check (volume and substitution response based on DDDs)

	General practitioners						Specialists					
	Volume per patient			Average drug price			Volume per patient			Average drug price		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	96.37***	10.22	28.04	−0.75**	0.35	−11.36	41.59***	9.22	30.27	−1.80**	0.76	−18.37
Average treatment effect												
Weighted least squares	88.99***	10.36	25.90	−0.61**	0.24	−9.18	63.60***	8.40	46.30	−2.65***	0.99	−27.00
Weighted PQML	90.77***	9.37	26.42	−0.57***	0.21	−8.66	60.15***	7.03	43.79	−2.28**	1.00	−23.26
Average treatment effect on the treated												
Weighted least squares	79.91***	14.66	23.26	−0.47**	0.20	−7.08	51.80***	9.09	37.71	−3.24**	1.51	−33.11
Weighted PQML	85.74***	10.29	24.95	−0.44**	0.18	−6.70	51.22***	8.17	37.29	−3.38**	1.46	−34.51

Notes: The estimation sample consists of 16291 (12799) observations for GPs (specialists) from the years 2008-2012 that lie in the common support subsample. The outcomes are measured annually on the physician level. Prescriptions of pharmaceuticals without information on DDDs are excluded. Standard errors are block bootstrapped on the physician level using 250 replications. PQML: Poisson quasi-maximum likelihood. Coef.: Coefficient. S.E.: Standard Error. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Drug dispensing regulation

Table VII: Physician Dispensing Regulations (1820–2012)

Canton	Initial dispensing regulation (year of enactment)[1]	Regulation 2008-2012 (year of enactment)[2]
Zurich	allowed (1854)	banned in the cities Zurich and Winterthur until 2012, otherwise allowed (1951)
Bern	allowed (1865)	banned in communities where at least two pharmacies guarantee emergency supply, otherwise allowed (1984)
Lucerne	unknown[4]	allowed (1981)
Uri	allowed (1823)	
Schwyz	allowed (1878)	
Obwalden	allowed (1955)	
Nidwalden	allowed (1973)	
Glarus	allowed (1953)	
Zug	allowed (1912)	
Fribourg	unknown[4]	banned (1943)[3]
Solothurn	allowed (1857)	
Basel-Stadt	banned (1879)[3]	banned (1960)
Basel-Landschaft	allowed (1865)	
Schaffhausen	allowed (1856)	banned in communities with more than two pharmacies (i.e. Schaffhausen and Neuhausen), otherwise allowed (1970)
Appenzell A. Rh.	allowed (1865)	
Appenzell I. Rh.	allowed (2000)	
St. Gallen	unknown[4]	allowed (1979)
Graubünden	allowed (1848)	banned in communities where at least one pharmacy guarantees emergency supply, otherwise allowed (1985)
Aargau	banned (1919)[3]	
Thurgau	allowed (1850)	
Ticino	unknown[4]	banned
Vaud	banned (1810)[3]	
Valais	banned (1896)[3]	
Neuchâtel	banned (1984)	
Genève	unknown[4]	banned (2006)
Jura	unknown[4]	banned (1990)[3]

Notes: This table is an updated version of Table A.I. of Kaiser and Schmid (2014)
[1] Before any regulation existed, physician dispensing was generally allowed.
[2] Where no changes are mentioned, the regulation in 2012 corresponds to the initial regulation.
[3] Exceptions depend on the availability of pharmacies.
[4] Cantonal authorities and archives did not provide any information.

C Variable definitions and construction

Table VIII: Variable Definitions and Construction

Variable Name	Description/Construction	Aggre-gation	Source
drug costs	Annual gross drug costs resulting from prescriptions of a physician, including direct costs induced by dispensing as well as indirect costs originating from prescriptions filled in pharmacies.		Sasis AG
drug volume	a physician's annual prescribed drug volume in terms of standardized packages. Section 5.1.1 outlines the construction of the variable in detail.		Sasis AG
average drug price	the annual average drug price over all prescriptions issued by a physician, based on standardized packages and prices. Section 5.1.1 outlines the construction of the variable in detail.		Sasis AG
drug costs per patient	drug costs/# patients		Sasis AG
drug volume per patient	drug volume/# patients		Sasis AG
dispensing status, D_i	=1, if physician runs a dispensary in his practice, =0 otherwise.		MedReg
female	=1 if physician is female, =0 if physician is male		MedReg
German nationality	=1 if physician has German nationality, =0 otherwise		MedReg
other foreign nationality	=1 if physician has foreign nationality other than German, =0 otherwise		MedReg
age	current year - year of graduation from medical school + 26, where 26 is the average age at graduation		MedReg
work experience	current year - year of attainment of specialty title		MedReg
# patients	the total number of patients who come to the physician's office in a calendar year		Sasis AG
# visits	the total number of visits to the physician's office in a calendar year		Sasis AG
# visits per patient	# visits/# patients		Sasis AG
patients' average age	sum of patients' age/# patients		Sasis AG
cases aged $> 80y$	# visits by patients aged above 80/# visits		Sasis AG
cases aged $66 - 80y$	# visits by patients aged btw. 66-80/# visits		Sasis AG
cases aged $< 25y$	# visits by patients aged below 25/# visits		Sasis AG
cases of males	# visits by male patients/# visits		Sasis AG
share with deductible of CHF X	The share of patients with deductibles of CHF X = 500, 1000, 1500, 2000, or 2500 per year. The ordinary deductible for adults is CHF 300 per year.		Sasis AG
share of children with deductibles	The share of children patients with non-zero deductibles. The ordinary deductible for children aged younger than 18 years is CHF 0.		Sasis AG

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Table VIII – *Continued from previous page*

Variable Name	Description/Construction	Aggregation	Source
share with insurance model HMO	The share of patients with an HMO (Health Maintenance Organization) health insurance plan.		Sasis AG
share with insurance model PPO	The share of patients with a PPO (Preferred Provider Organization) health insurance plan.		Sasis AG
share with insurance model TelMed	The share of patients with a TelMed health insurance plan (insurance plan where the patient has to call a consultation hotline before seeing a doctor).		Sasis AG
physician density	The physician density is the total number of physicians per 1000 inhabitants in a municipality.	1	MedReg, SFSO
share with very good health	The share of the population who self-report very good health in the region.	2	SHP
share with good health	The share of the population who self-report good health in the region.	2	SHP
share with fair health	The share of the population who self-report fair health in the region.	2	SHP
share with chronic health problems	The share of the population who self-report chronic illness or long-term health problems in the region.	2	SHP
share that needs medication	The share of the population who self-report the need for medication for everyday functioning in the region.	2	SHP
average body mass index	The average Body Mass Index in the region. It is calculated from the self-reported body weight and height.	2	SHP
share of immigrants	percentage of non-Swiss citizens in the permanent resident population of a municipality	1	SFSO
fraction of urban area	percentage of urbanized acreage relative to total acreage of a municipality	1	SFSO
net income per capita	average net income per-capita (2008) in 1,000 Swiss francs in municipality	1	SFFA, SFSO
unemployment rate	percentage of unemployed in total workforce in municipality	1	SFSO
share of medium educated	percentage of vocational and secondary school graduates relative to total adult population in municipality	1	SFSO
share of high educated	percentage of college and university graduates relative to total adult population in municipality	1	SFSO
population density	log of population in 1000 per square kilometre in municipality	1	SFSO
GP I: general internal medicine	reference group. =1 if GP has a diploma in general internal medicine, =0 otherwise		Sasis AG
GP II: practice diploma	=1 if GP has a practice diploma (German: praktischer Arzt), =0 otherwise		Sasis AG
GP III: pediatrist	=1 if GP has a diploma in pediatrics, =0 otherwise		Sasis AG

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Table VIII – *Continued from previous page*

Variable Name	**Description/Construction**	**Aggregation**	**Source**
non-invasive specialist	reference group. =1 if specialty includes dermatology, venereology, specialty for allergies and immunology, endocrinology, pneumology, nephrology, neurology, hematology, gastroenterology, oncology, physical medicine and rehabilitation, specialty for infectious diseases, tropical medicine, metabolic pathology and neuropathology, =0 otherwise		Sasis AG
gynecologist	=1 if gynecologist, =0 otherwise		Sasis AG
angiologist	=1 if angiologist, =0 otherwise		Sasis AG
cardiologist	=1 if cardiologist, =0 otherwise		Sasis AG
invasive specialist	=1 if specialty is surgery, pediatric surgery, ophthalmology, orthopaedy, vascular surgery, urology, jaw and facial surgery, plastic surgery, or hand surgery, =0 otherwise		Sasis AG
psychiatrist	=1 if psychiatrist, =0 otherwise		Sasis AG
other type of specialist	=1 if specialty is anesthetics, radiology, industrial medicine, pathology, pharmaceutical medicine, radio-oncology, intensive-care specialty, nuclear medicine, clinical pharmacology and toxicology, genetics, or other non-classified specialty, =0 otherwise		Sasis AG

Aggregation 1: For each physician i, we compute a weighted average across municipalities. The share of visits at physician i's office attributable to people living in these municipalities is used as a weight.

Aggregation 2: For each physician i, we compute a weighted average across regions. The share of visits at physician i's office attributable to people living in these regions is used as a weight. Note: the SFSO divides Switzerland into 106 so-called mobility regions.

Data Sources: Sasis AG: nationwide operator of the insurance claims database of Swiss health insurers, MedReg: federal register of medical professionals, SFSO: Swiss Federal Statistical Office, SHP: Swiss Household Panel, SFFA: Swiss Federal Finance Administration