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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 respond to changes in reimbursement schemes by changing the volume (volume response) and the composition of services provided (substitution response). In this paper, we examine the relative importance of the volume and substitution response in the context of physician drug dispensing. We use data on the market for ambulatory care in Switzerland in which different dispensing regimes (banned/allowed) co-exist at the regional level. Using doubly-robust regression and semiparametric quantile treatment effect estimators, we find that dispensing increases drug costs by 52% for general practitioners and 56% for medical specialists. This increase is mainly due to a volume increase of about 56% for general practitioners and 74% for specialists. The substitution response is negative on average (around -4% for general practitioners and -20% for specialists), but not significantly different from zero for large parts of the distribution. In other words, drug dispensing causes physicians to sell more drugs but not to substitute towards more expensive drugs. In addition, our results reveal substantial effect heterogeneity along the distribution.

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

JEL: I11, I18

I. INTRODUCTION

Physicians have been shown to respond to changes in reimbursement schemes 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 by changing the composition of services provided (substitution response, see Van Doorslaer and Geurts, 1987; Hadley and Reschovsky, 2006). However, although it is very likely that (changes in) reimbursement schemes simultaneously affect both the volume and the composition of services, most of the literature analyzes the volume or the substitution response separately.[1]

We provide some of the first market-level evidence on the relative importance of the volume and the substitution response. Disentangling these two behavioral channels and assessing their relative size is important as a change in the volume is likely to affect health outcomes differently than a change in the composition of services provided. Thus, quantifying the two responses is relevant for shaping policies to improve efficiency in health care provision. More broadly, isolating these two channels contributes to a better understanding of physician behavior in the presence of monetary incentives.

We study the volume and substitution response in the context of physician dispensing regulations. Several OECD countries, including the United States, the United Kingdom, Japan, and Switzerland, (partly) allow physicians to dispense drugs (i.e., to sell drugs directly to their patients). Decomposing the volume and substitution response at the market level is challenging. First, there must be exogenous variation in the dispensing regulations that can be separated from variation in other institutional features such as drug prices and health insurance coverage. Second, disentangling the two responses generally requires detailed description-level information.

To address these challenges, we study the market for outpatient care in Switzerland. The Swiss case is well-suited for our purposes because different drug dispensing regimes

[1] Jacobson et al. (2013) is a notable exception that finds an increase in the provision of chemotherapy and a change in the mix of chemotherapy drugs administered in response to changed Medicare fees. These findings may, however, not be generalizable as the study focuses on oncologists and cancer treatments only.

co-exist at the regional level, while many other important features, most notably prices and insurance coverage, are regulated at the federal level. Another advantage of the Swiss case is that we have access to a novel and comprehensive market-level dataset on physician prescriptions. Our data contain detailed information about all prescriptions of approximately 60% of all physicians running independent practices in Switzerland. Importantly for our purposes, for each prescription, we are able to identify pharmaceutical, dosage, package size, price, as well as the defined daily dose. This information enables us to compute the days supplied and the average price per day supplied for each physician. These two variables are our main outcomes of interest and allow us to empirically disentangle the volume and the substitution effect.

Using doubly robust estimators (Imbens and Wooldridge, 2009) and controlling for a rich set of physician characteristics and local demand conditions, we first document that drug dispensing increases annual drug costs per patient on average by 52% for general practitioners (GP) and by 56% for medical specialists. We then use our volume and price measures to disentangle these overall effects into a volume response and a substitution response. For both GPs and medical specialists we find positive and significant effects on the drug volume of about 56% and 74%, while we find negative effects on average drug prices (-4% and -20%). This clearly indicates that the volume response empirically dominates the substitution response. While overall average effects provide a good starting point for understanding physician behavior, they do not allow us to study effect heterogeneity, which is particularly relevant for our market-level analysis. We therefore supplement the average effect estimates with quantile effects, estimated using the semiparametric quantile treatment effects estimator proposed by Firpo (2007). Our results show that the overall effect of dispensing on drug costs is increasing along the distribution. The quantile treatment effects for the volume response exhibit very similar patterns, which provides further evidence that the overall effect of dispensing is primarily driven by the volume response. In contrast, the price effects are not significantly different from zero at most quantiles. However, we estimate significantly negative effects at the upper tail, resulting in the negative average effects. Thus, the substitution response becomes relatively more

important at the upper tail. In summary, our quantile effect estimates reveal substantial treatment effect heterogeneity, suggesting that average effects miss a great deal. This finding is even more pronounced for specialists than for GPs, reflecting the heterogeneous composition of this group of physicians. Our findings are robust across a wide range of alternative volume and price measures.

Our paper is related to the literature studying the impact of different dispensing regulations on healthcare expenditures. 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. Beck et al. (2004) and Dummermuth (1993) compare aggregated cantonal expenditures and find that dispensing physicians in Switzerland 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). Kaiser and Schmid (2016) corroborate the earlier findings on Switzerland using more detailed physician-level data.[2] Our study also relates to the literature on physician behavior in the presence of monetary incentives (see McGuire, 2000, and Chandra et al., 2012, for two extensive overviews) and prescription practices (e.g., Hellerstein, 1998; Coscelli, 2000; Lundin, 2000; Park et al., 2005; Iizuka, 2007; Lim et al., 2009; Rischatsch et al., 2013; Iizuka, 2012; Filippini et al., 2014). However, none of the previous studies decomposes the overall effect into a volume response and a substitution response.

The remainder of this paper is structured as follows. In Section II, we describe the institutional background. Section III discusses our identification strategy and presents the estimation approaches. In Section IV, we describe the construction of our dataset, determine common support, present descriptive statistics, discuss our empirical results, and provide additional robustness checks. Section V 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] Trottmann et al. (2016) use patient-level data to analyze physician dispensing in Switzerland. Their results do, however, not allow to draw any conclusion regarding physician prescription behavior or overall health care expenditures.

II. THE MARKET FOR AMBULATORY CARE IN SWITZERLAND

The healthcare system in Switzerland can broadly be categorized as managed competition.[3] 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, insurers 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.[4] 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 doctors.[5] 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 generally corresponds to the calendar year, i.e., patients can change their insurer or health plan 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 decreases to zero once the sum of the co-payments exceeds CHF 700.[6]

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 approval 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

[3]Our summary draws on the extensive summary of the compulsory health insurance in Switzerland by Schmid et al. (2017) and on Kaiser and Schmid (2016) to whom we refer for more details on the pharmaceutical market in Switzerland.

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

[5]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 restrict the patients' provider choice in exchange for lower premiums.

[6]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, 2016, Table A.II).

Although most aspects of the Swiss pharmaceutical market are regulated on the federal level, drug dispensing rules are determined on the cantonal level, thus providing an ideal setup for analyzing the effect of financial incentives on physician prescription behavior. Most of these regulations have been in place for several decades (Table 13 provides an overview of the dispensing regulations in the 26 Swiss cantons). 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 a pharmacy. The pharmacists charges the patient the retail price plus some additional consultation fees and 2.5% VAT. In contrast to physicians, pharmacies are *never* allowed to issue prescriptions, but they can sell prescription drugs. As a consequence, doctors are the gatekeepers to the prescription drug market. That is, every patient must necessarily visit a physician to obtain prescription medication, which 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.

III. METHODOLOGY

III.A. 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. Let Y_{di} denote the potential outcome of physician i associated with dispensing status $D_i = d$. We are interested in the average treatment effect (ATE) and the average treatment effect on

the treated (ATT):

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

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

To quantify the effect heterogeneity along the outcome distribution, we supplement our average effects with quantile treatment effects. We consider 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. We note that these quantile effects provide a complete description of the distributional impact of dispensing and thus allows us to document and analyze effect heterogeneity.

Without additional assumptions, both average and quantile treatment effects are not identified from our data because counterfactual outcomes are unobserved. In this paper, we exploit regional variation (between *and* within cantons) in the dispensing regime and 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; see Section IV.A for a detailed description of all covariates. The CIA asserts that conditional on these observable characteristics X_i, the dispensing status D_i is independent of the potential outcomes:

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

Section III.B discusses the validity of this key condition in the context of our analysis. To obtain identification based on Assumption (5), we need the impose the following common

support assumption

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

where $p(x) \equiv P(D_i = 1|X_i = x)$ is the propensity score. Assumption (6) asserts that for every value of X_i, we can match dispensing with nondispensing physicians. Assumption (6) is testable and we address its validity in Section IV.B. Under Assumptions (5) and (6) the average and quantile treatment effects are identified (e.g., Imbens, 2004; Firpo, 2007).

III.B. Plausibility Of The Conditional Independence Assumption

The key condition 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 also Kaiser and Schmid, 2016). 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 13 documents that most dispensing regulations have been in place for several decades.[7] This mitigates concerns that the current regimes are endogenous outcomes of unobserved dispensing preferences. Although we cannot completely 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, physician training in Switzerland is centralized at a few locations at all of which dispensing was not allowed during our study period. This mitigates concerns that differences in physician training between regions with different dispensing regimes confound our analysis. Fourth, many institutional features, including the positive list of prescription drugs covered by mandatory health insurance, drug prices and markups, and health insurance regulations, are determined by federal regulations and are therefore guaranteed not to confound our

[7]The only exception is the canton of Zürich, where physician dispensing was allowed in the two largest cities within the last year of our study (May 2012). Because we have annual data, we exclude all observations of physicians that are located in these two cities in 2012.

analysis. Finally, we control for a comprehensive set of factors that are potentially related to the dispensing status and potential outcomes, namely for physician characteristics, patient pool compositions, and healthcare market conditions in the practice location (see Section IV.A for more details). This eliminates any bias that arises if those factors jointly affect the dispensing status and the potential outcomes.

III.C. Estimation

There are different approaches for estimating average treatment effects under Assumptions (5) and (6) (e.g., Imbens, 2004; Imbens and Wooldridge, 2009; Imbens and Rubin, 2015). Here we use doubly-robust regression, a method that combines regression with propensity score weighting. The main advantage of this method is that it provides better protection against misspecification than procedures relying on either the propensity score or on regression alone, because it achieves consistency under two separate sets of assumptions. Doubly robust regression is consistent if either the propensity score or the outcome model is correctly specified, or both (e.g., Wooldridge, 2007; Robins et al., 2007). 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.

The quantile treatment effects are estimated 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.[8]

2. Obtain QTE and QTT from weighted quantile regressions

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

and

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

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

IV. EMPIRICAL ANALYSIS

IV.A. Data Sources And Variables

We use 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)

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

and identifies each physician by the so-called Global Location Number (GLN). This allows us to link it to complementary data from the register of medical personnel (MedReg). This register contains personal information on each physician such 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 in the German speaking part of Switzerland. 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 (FOPH) and, in addition, to the anatomical therapeutic chemical (ATC) classification system established by the World Health Organization (WHO). Therefore, for each prescribed or dispensed pharmaceutical, we know the dosage, the package size, the ex-factory and retail prices, the active pharmaceutical ingredients, the ATC code, and the defined daily dose (DDD). Similar to Liu et al. (2009, 2012), we use the information on DDD and prices to construct volume and price measures. More precisely, we calculate days supplied (per patient) and the average price per day supplied for each physician in our data. These two measurers are our main outcomes of interest.

The health insurance data 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, as well as their health plan and deductible level. 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 *both* low healthcare expenditures and high deductibles (see Schmid, 2017). 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, 2016).[9]

IV.B. Determining Common Support

Treatment effects can only be identified and estimated for dispensing physicians for whom we observe similar non-dispensing physicians (Assumption (6)). That is, we need overlap in the covariate distributions of treatment and control units. 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.

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

Table 1 additionally shows 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.

IV.C. Descriptive Statistics

Tables 2 and 3 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. 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 and year are 196 Swiss Francs for dispensing GPs, which is 71 Swiss Francs higher than for non-dispensing GPs. This difference of 57% is exceeded by a 65% higher drug volume triggered by dispensing GPs, whereas average drug prices are 11% lower for the latter. For specialists, the percentage cost differences by dispensing status are somewhat smaller. That is, average drug costs per patient are 48% higher for dispensing than for nondispensing specialists. Nevertheless, the per-patient drug volume is 66% higher for dispensing than for nondispensing specialists, whereas average drug prices are even 18% lower for dispensing specialists.

Overall, Tables 2 and 3 suggest that physician characteristics and patient pool variables are well balanced between dispensing and non-dispensing physicians. There is one exception: 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. Nevertheless, we argue that

[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 $D_i = d \in \{0, 1\}$.

this is not a threat to our analysis. First, there is sufficient variation in the dispensing regime within rural areas (see Table 13) as well as within urban areas.[11] Second, the fraction of urban area, physician density, and population density are included as covariates in each model and are therefore able to capture potential differences in the outcomes that are related to these factors.

IV.D. 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, quantifies the overall average effect of dispensing on drug costs. The contribution of this paper is to subsequently decompose this overall effect into a volume response and a substitution response, that is, we estimate the causal effect of dispensing on days supplied per patient ('drug volume') and average price per day supplied ('drug price'). In addition, we estimate unconditional quantile treatment effects to further analyze the effect heterogeneity in the causal effect of dispensing.

We examine GPs and medical specialists separately. The covariates included in our models are essentially the same as presented in Table 1. That is, we control for individual characteristics of physicians, the composition of patients treated by a physician (age groups, type of insurance contracts, gender), and local health care market conditions (physician density, urbanity, average health status, average education levels, income per capita, etc.). Therefore, differences in these factors across cantons are captured by the included covariates. 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.

[11] Indeed, our sample contains physicians located in several cities that permit physician dispensing (e.g., Lucerne, St. Gallen, Solothurn) as well as physicians located in cities that fully ban dispensing (e.g., Bern, Basel, Aarau).

1. Average Treatment Effects. For all outcomes, we report doubly-robust estimates of the ATE and the ATT based on WLS and WPQML separately for the GPs in Table 4 and the specialists in Table 5. Before discussing these results in more detail, we would like to highlight three general findings. First, the estimated size of the selection effect, defined as the difference between the unadjusted difference and the ATT, is small and not statistically significant. This indicates that selection is a minor issue in the context of our study (conditional on the validity of the CIA). Second, the ATE and the ATT are numerically similar and not significantly different. Third, the differences between WLS and WPQML are small compared to the confidence intervals. Table 6 further demonstrates that our doubly-robust estimates are comparable to the estimates based on three alternative estimators: ordinary least squares, Poisson quasi-maximum likelihood, and inverse probability weighting. We therefore conclude that our findings are robust with respect to the choice of the econometric method. Given these general findings, we henceforth primarily focus on the estimates based on WLS and the average effects within the population of dispensing physicians (ATT).

Regarding the overall effect, the estimated ATT for GPs reported in the left column of Table 4 suggests that dispensing raises average drug costs per patient by CHF 65 or 52%. The estimated effects for medical specialists are very similar in relative terms, that is, dispensing raises drug costs per patient by 56%, even though the absolute effect is somewhat smaller and amounts to CHF 48 (see left column of Table 5). Our results with respect to drug costs are generally in line with the existing studies (see Kaiser and Schmid, 2016). Turning to the decomposition of this overall effect, we find a large positive and significant volume effect of 56% for the dispensing GPs. In contrast, the substitution effect of -4% is small and negative but still significant in statistical terms. In other words, dispensing increases the days supplied per patient by roughly 87 but decreases the price per day supplied by a tiny 4 cent. Regarding medical specialists, we estimate that dispensing increases the days supplied per patient by roughly 38 (74%) and decreases the average price per day supplied by 38 cent (-20%). Compared to GPs, we thus find a similar qualitative pattern though the relative effects are larger. Overall, these results

strongly suggest that the volume effect empirically dominates the substitution effect. In other words, drug dispensing causes physicians to sell more drugs but not to substitute towards more expensive drugs.

2. Quantile Treatment Effects. To examine the overall effect, the volume and substitution effect in more detail, we estimate unconditional quantile treatment effects based on the Firpo (2007)-estimator. Figure 2 displays QTE and QTT estimates for our three main outcomes both for GPs and medical specialists. Looking at Figure 2 (a), we find that the overall effect of dispensing on drug costs in the GP population is nonconstant and increasing, ranging from roughly zero at the 5%-quantile up to almost CHF 100 at the 95%-quantile. However, the effect is primarily increasing below the median and nearly constant afterwards. Regarding medical specialists, Figure 2 (b) shows a quite different pattern, that is, the overall effect of dispensing on drug costs is small positive in the lower tail up to the center of the distribution and exhibits a steep increase up to CHF 200 in the upper tail. These findings are indicative of substantial heterogeneity in the causal effect of dispensing along the outcome distribution. The results differ considerably between GPs and medical specialists, which is in line with our intuition as medical specialists are inherently a very diverse physician population.

Turning to the volume effects shown in Figure 2 (c) for GPs and in Figure 2 (d) for specialists, the QTE (and QTT) estimates exhibit very similar patterns compared to the ones shown in Figure 2 (a) and (b). In other words, we find further evidence that the overall (cost) effect of dispensing is primarily driven by the volume effect. In contrast, the causal effect of dispensing on average drug prices is roughly constant and insignificant across most quantiles. However, we estimate substantial and significantly negative effects at the upper tail. Thus, although the volume effect dominates the substitution effect in the lower parts of the distribution, the substitution effect seems to affect drug costs at the upper tail. Interestingly, the substitution response exhibits a similar pattern for GPs and medical specialists but the effect is more pronounced for specialists. This corresponds to our finding that the average substitution response is larger for the medical specialists. In any event, we find again evidence that the volume response empirically dominates the

substitution response. Furthermore, our results demonstrate that average effects miss a great deal and thus highlight the importance of examining treatment effect heterogeneity using quantile treatment effects.

3. Discussion. Given that the markup increases with the price, the negative substitution response is somewhat puzzling. Rischatsch et al. (2013) find that dispensing in Switzerland is associated with higher use of generics, but the authors do not provide any explanation for this result. One potential explanation is that dispensing physicians have better knowledge about drugs (e.g. generic market entry) than their drug prescribing peers. Although not implausible, mere knowledge does not necessarily provide incentives to dispense cheaper drugs. However, the markup increases in a step-wise fashion, that is, the absolute markup exhibits several jumps and is finally capped at CHF 240 per package. On the one hand, substituting drugs between the jumps can affect the markup much less than substitution across these jumps. Rischatsch (2013) analyzes three active pharmaceutical ingredients (API) and finds that Swiss physicians seem to optimize the markup by dispensing small packages instead of larger ones. They find that the price per dose increases by $3-5\%$, which provides some evidence that physicians indeed exploit the jumps.[12] On the other hand, the incentive for markup optimization declines with the price and vanishes at the markup cap. Thus, physicians possibly choose the less expensive drug if the options are financially similar attractive. Such a behavior would perfectly explain the negative effects depicted in Figure 2 (e) and (f) at the upper tail, that is, for the most expensive drugs. Although this provides an explanation for the estimates, the incentives for physicians to dispense less expensive drugs remain unknown.

IV.E. Robustness Checks: Alternative Volume And Price Measures

Defined daily doses (DDDs) are very appealing because one can easily calculate and aggregate drug volumes, and estimates based on such a volume measure have a direct interpretation. However, in terms of expenditures, DDDs are only available for roughly

[12] In our setup, such a behavior would have no effect on the volume, but a negative effect on the price in the lower part of the distribution as smaller packages tend to have lower ex-factory prices. However, by separately analyzing API one ignores substitutability and thus a possibility for markup optimization. Nevertheless, we find some evidence that corroborates these findings, see IV.E.2.

three fourths of all drugs in our data. Therefore, we examine the robustness of our results by considering alternative measures of drug volumes and prices.

1. Variable Construction. The alternative measures are mostly based on active pharmaceutical ingredients (API) and constructed as follows.

Price measures: we construct a 'normalized price' for each drug package by dividing the retail price per unit of the API by the lowest price in our dataset for the unit of the API. Stated differently, we determine the drug price relative to the cheapest drug with the same API.[13] The physician's average price is then calculated as the weighted average of all normalized prices using the number of all prescriptions (includes dispensing) as weights. Thus, the average price is a relative measure (relative to a scenario where the physician prescribes the cheapest drug). In addition to the average normalized price, we also compute simple average ex-factory and retail prices.

Volume measures: We construct a 'normalized volume' for each drug package by dividing each package's content in terms of API by the content of the smallest package with the same API. The physician's volume is then calculated by multiplying the number of all prescriptions (includes dispensed drugs) by the normalized volume and then aggregating over all prescriptions. Thus, the normalized volume increases if the physician dispenses or prescribes (a) an 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. One potential issue with the normalized volume measure is that it depends on the relative size of the different drug packages. We therefore also construct an index for each API running from one for the smallest package to two for the largest package. The 'volume index' is then constructed in the same way as the normalized volume measure. As a result, it exhibits basically the same desirable properties, but does not depend on the relative size of the different drug packages.

[13] This procedure takes into account that for most drugs different package sizes and dosages are available.

2. Results. We re-estimate the average effects of dispensing on drug costs per patient, drug volume per patient, and average prices using the same specification as in Section IV.D. The re-estimated effects of physician dispensing using alternative price and volume measures are reported in Tables 7, 9, and 11 for GPs and 8, 10, and 12 for specialists. We also show the corresponding quantile treatment effects in Figures 3 to 5. Regarding overall drug costs, we present overall estimates implied by the normalized volumes and price measures in the first two columns of Tables 7 and 8. While the estimates in the first column are based on all drugs, in the second column, we exclude all drugs where no DDDs are available. Finally, the third column shows estimates of the overall effect given drug costs based on ex-factory prices and actual packages for all drugs (section IV.D only considers costs of drugs where DDDs are available). The volume and substitution responses based on different volume and price measures are shown in Tables 9 (10) and 11 (12) for GPs (medical specialists).

Note that comparisons of the coefficients are difficult due to the different normalizations. Thus, we focus on the relative effects. Regarding drug costs of the GPs (specialists), we find an average effect of dispensing on the treated in the order of 40% to 52% (31% to 62%) which is driven by a positive volume effect of 52% to 55% (60% to 72%).[14] The price effect is negative and ranges from −0.5% to −11% (−0.6% to −33%) although the effect is not statistically significant for the normalized price. These results are in line with our main findings. The positive volume effect dominates the (weakly) negative price effect so that physician dispensing increases overall drug costs. The same conclusion holds for the quantile treatment effects where we find very similar pictures across normalization methods. Again, the only exception are the normalized price estimates where we find positive effects in the left tail of the outcome distribution and almost no statistically significant effect for GPs and specialists. However, this does not alter our main conclusion that the positive effect on drug costs is driven by an increase in the drug volume.

Overall, the results in this section confirm our previous findings, emphasizing the

[14]Note that Kaiser and Schmid (2016) find an overall effect of 34% which is close to the estimates presented in the last column of Table 8. Hence, restricting the data to drugs for which DDDs are available might lead to an overestimation of the overall effect in the medical specialists population.

robustness of our main results in terms of normalization method and drugs included.

V. CONCLUSION

Physicians have been shown to respond to changes in reimbursement schemes by influencing the volume and the composition of services they provided. This paper provides some of the first market-level evidence on the relative importance of the volume and the substitution response. We investigate the physician drug dispensing regulations in Switzerland. To empirically disentangle and quantify the volume and the substitution response, we exploit the institutional setting in Switzerland, which is characterized by a combination of federal regulations and regional variation in the dispensing regime, and a novel market-level dataset on physician descriptions.

Three major conclusions can be drawn from our analysis. First, physician dispensing has a larger impact on drug costs (in absolute terms) 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 target 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 potentially 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 were available. Third, our results show that there is a lot of heterogeneity in the causal effect of dispensing within and between different types of physicians. While we are not powered to perform a detailed subgroup analysis, a further analysis of the extent and the determinants of this effect heterogeneity is certainly worth pursuing in future research.

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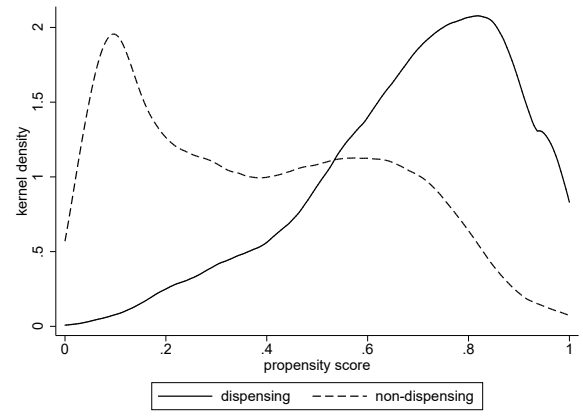
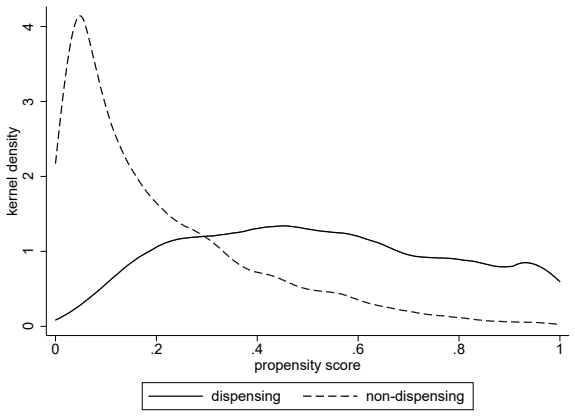
Appendix

A FIGURES AND TABLES

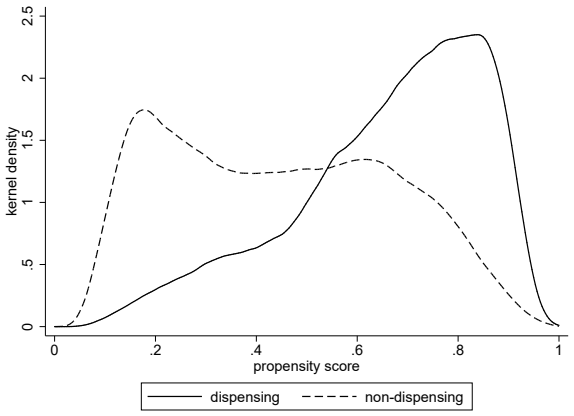
Figure 1: Kernel densities of estimated propensity scores



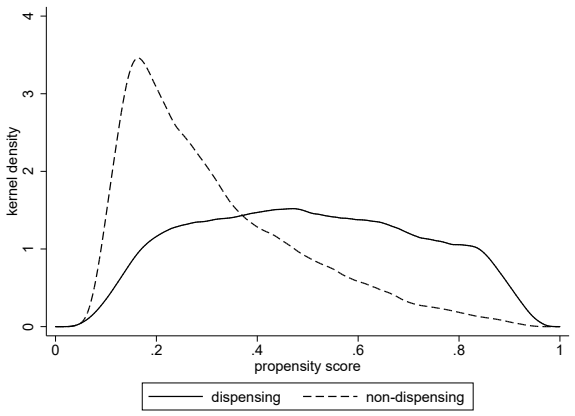
(a) General practitioners, full sample



(b) Specialists, full sample

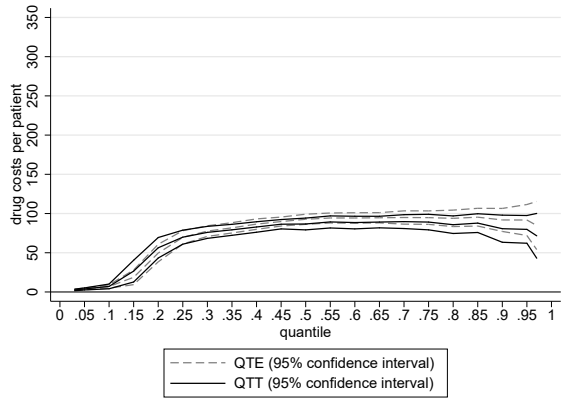


(c) General practitioners, common support sample

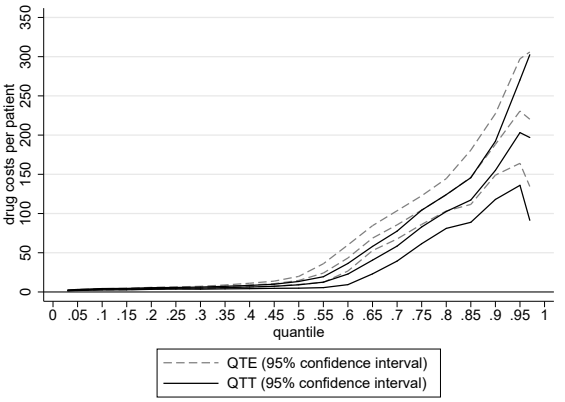


(d) Specialists, common support sample

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



(a) General practitioners, costs per patient



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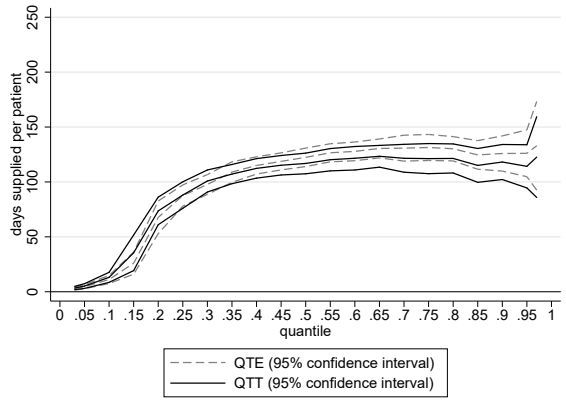
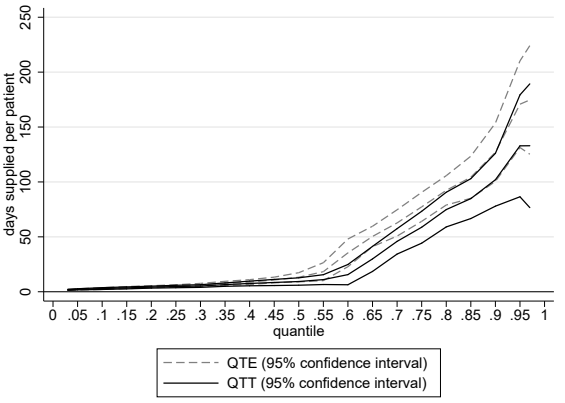


(c) General practitioners, volume per patient



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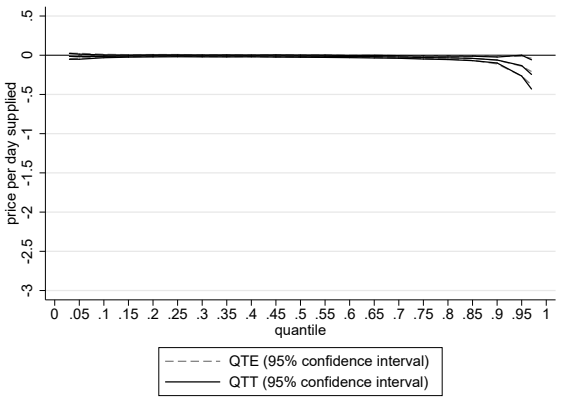
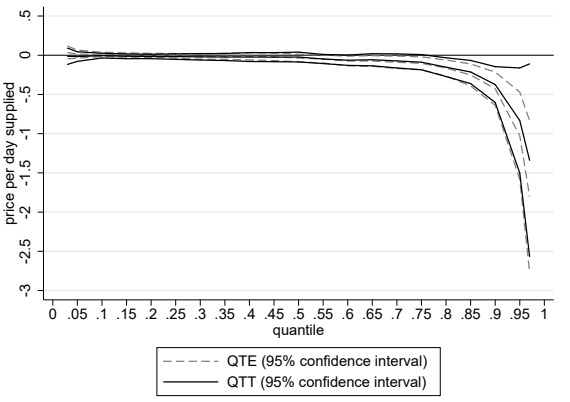
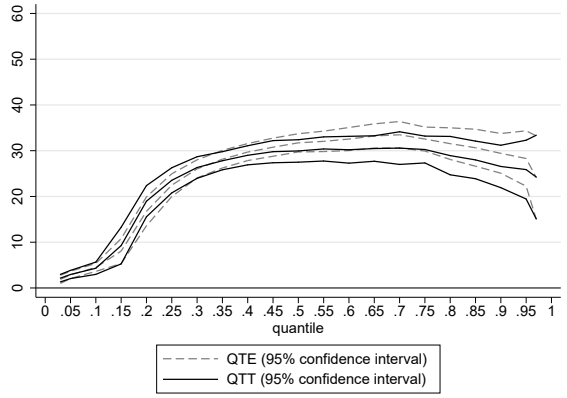


(e) General practitioners, average drug price

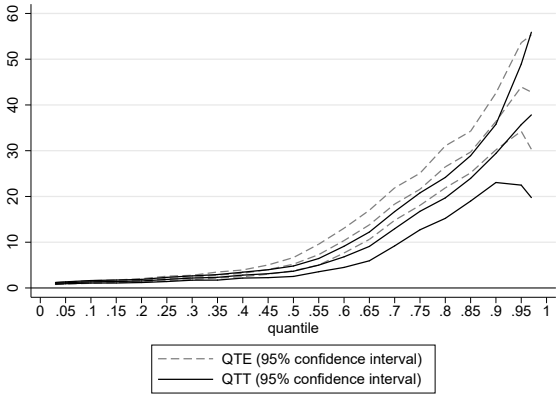


(f) Specialists, average drug price

Figure 3: Quantile treatment effects using different measures of drug costs



(a) General practitioners, normalized



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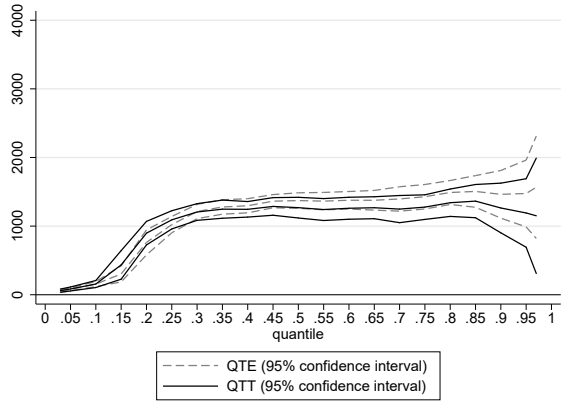

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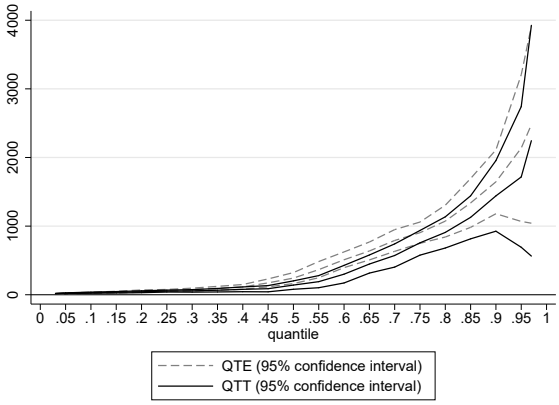

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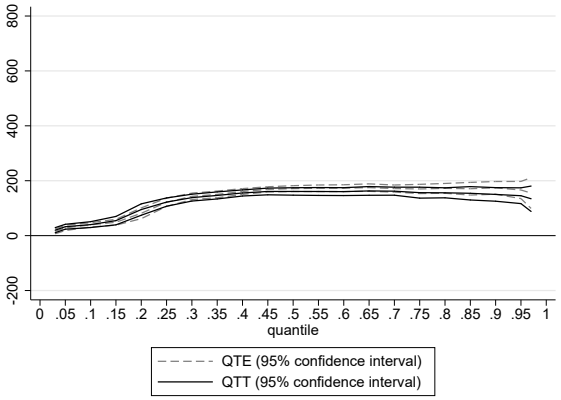
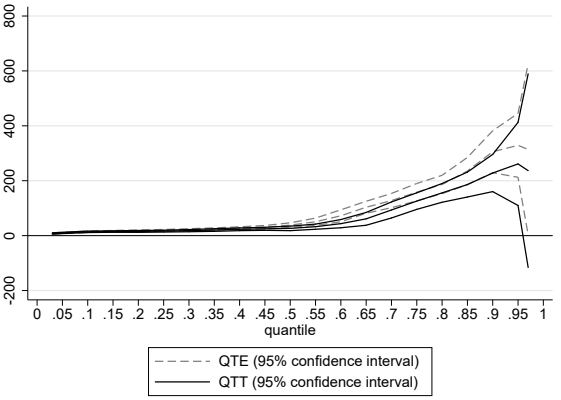
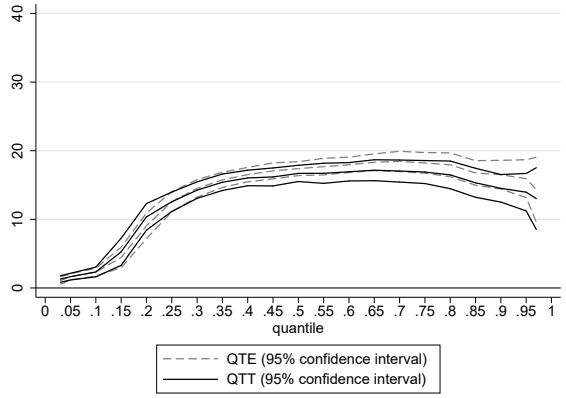


(e) General practitioners, drug costs in CHF

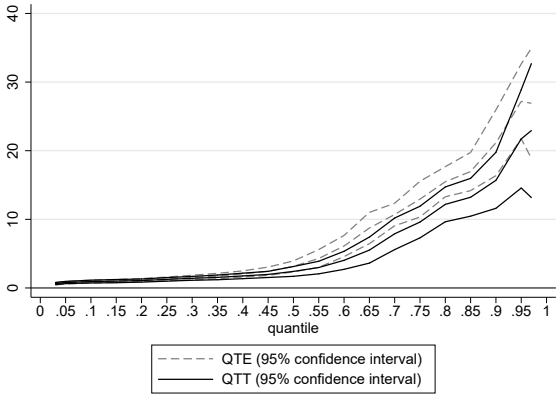


(f) Specialists, drug costs in CHF

Figure 4: Quantile treatment effects using different measures of drug volumes



(a) General practitioners, normalized



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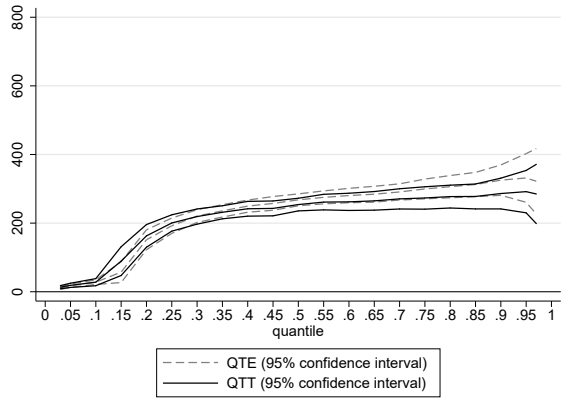

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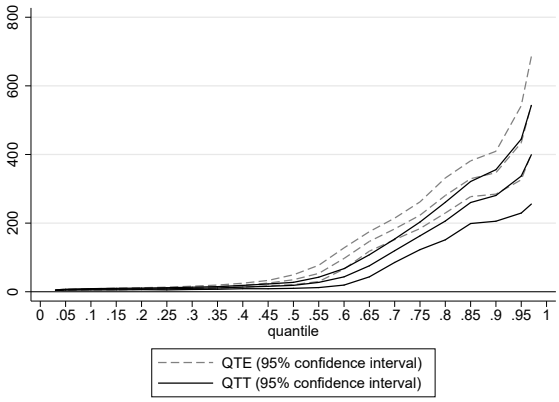

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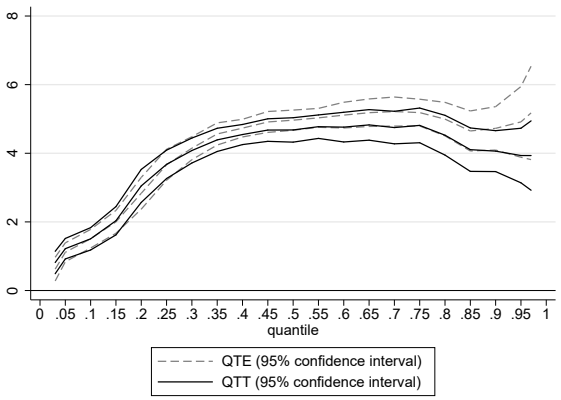
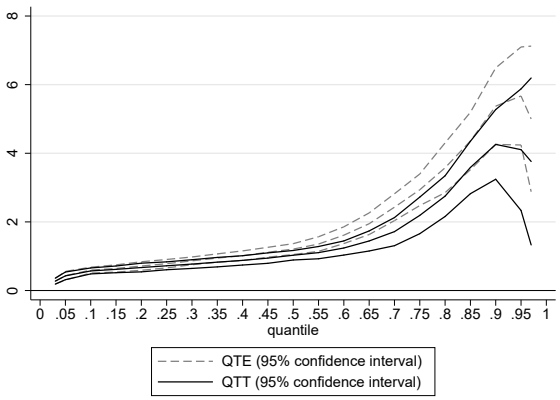
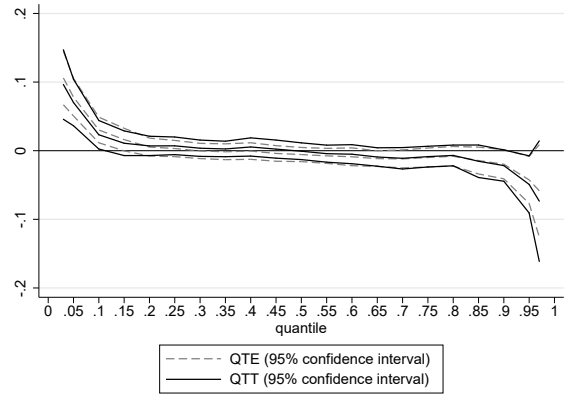


(e) General practitioners, volume index



(f) Specialists, volume index

Figure 5: Quantile treatment effects using different measures of drug prices



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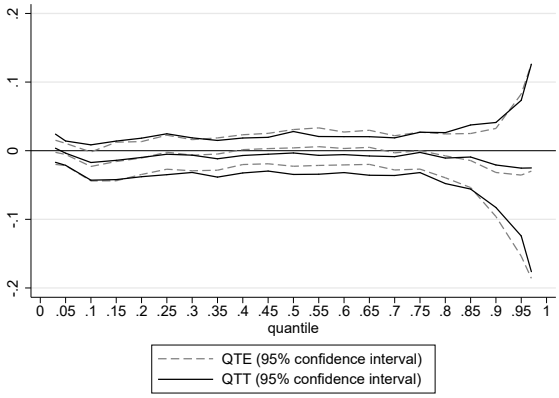

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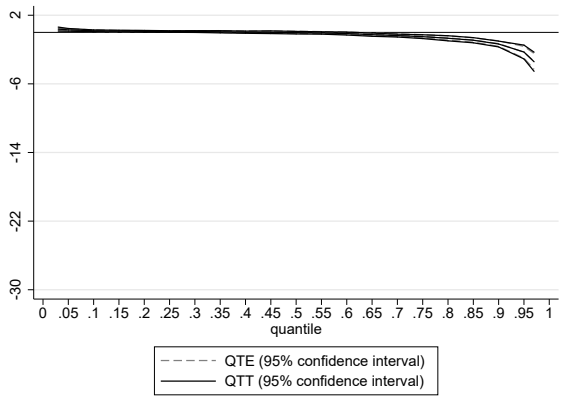
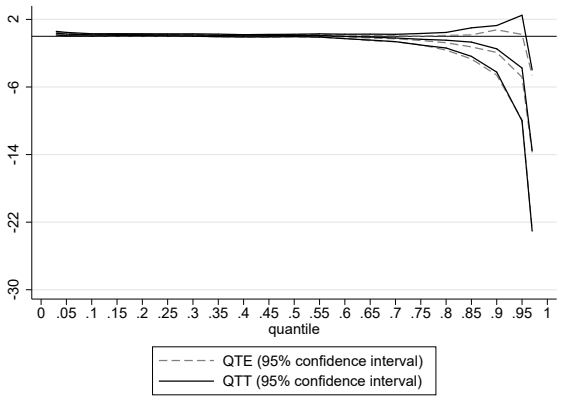
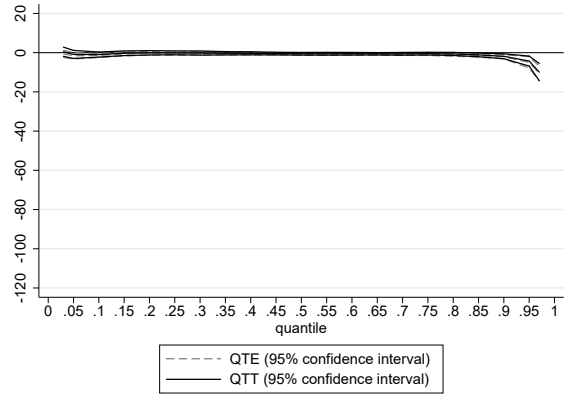


(c) General practitioners, normalized (DDD)

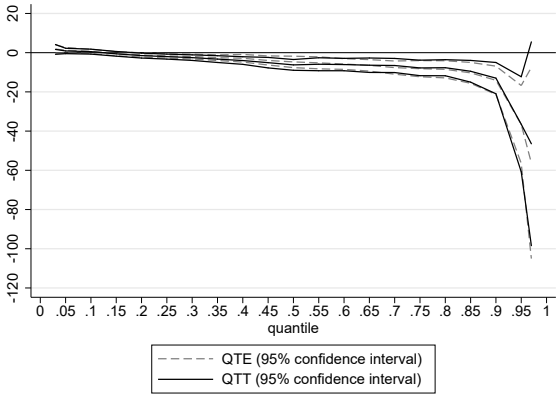


(d) Specialists, normalized (DDD)

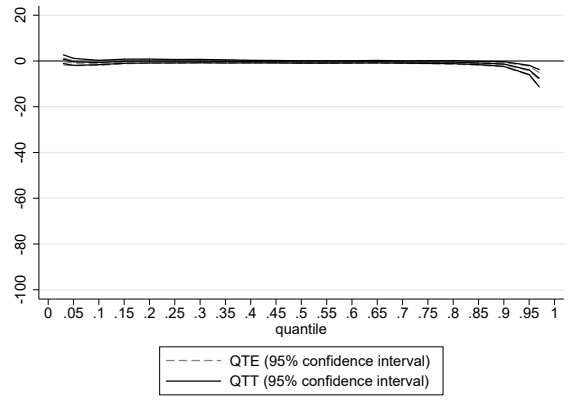
Figure 5 (Continued): Quantile treatment effects using different measures of drug prices



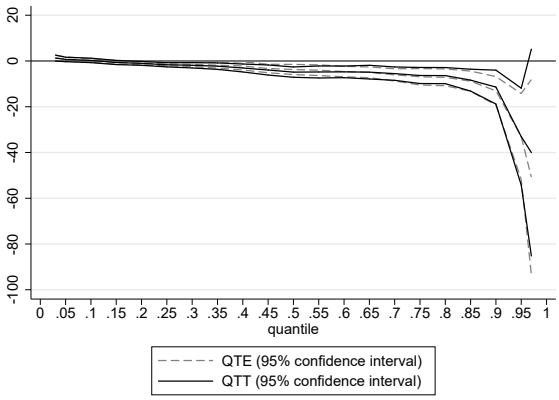
(e) General practitioners, retail price (CHF)



(f) Specialists, retail price (CHF)



(g) General practitioners, ex-factory price (CHF)



(h) Specialists, ex-factory price (CHF)

Table 1: 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	−0.070	−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	0.041
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	−0.062	−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	0.094
Share with deductible of CHF 2000	0.107	0.083	0.159	0.073
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	0.024
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	−0.019
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			0.151	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	12941	7859
# treated obs. (dispensing)	10936	9262	5642	4940

Notes: CS sample refers to the common support subsample (Section IV.B). Detailed definitions of the variables can be found in Table 14. obs.: observations.

Table 2: General practitioners' descriptive statistics (2008-2012)

	Nondispensing		Dispensing	
	Mean	Std. Dev.	Mean	Std. Dev.
Drug prescriptions				
Costs per patient	124.330	150.306	195.514	122.974
Volume (days supplied) per patient	155.686	155.592	257.468	159.450
Average drug price (per day supplied)	0.919	1.248	0.814	0.560
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 14. Std. Dev.: Standard Deviation.

Table 3: Specialists' descriptive statistics (2008-2012)

	Nondispensing		Dispensing	
	Mean	Std. Dev.	Mean	Std. Dev.
Drug prescriptions				
Costs per patient	85.949	187.704	127.071	218.567
Volume (days supplied) per patient	51.357	86.568	85.403	123.111
Average drug price (per day supplied)	1.877	4.182	1.534	1.590
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	51.235	8.649	50.620	7.980
Work experience	15.939	8.529	15.599	7.683
Patient pool variables				
# patients	783.142	811.729	1076.456	930.581
# visits	2051.342	1779.419	2705.850	1864.862
# visits per patient	4.651	4.086	3.975	3.270
Patients' average age	49.556	10.429	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 14. Std. Dev.: Standard Deviation.

Table 4: 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	71.18***	3.60	57.25	101.78***	4.58	65.38	−0.11***	0.03	−11.44
Average treatment effect									
Weighted least squares	68.45***	4.11	55.06	90.31***	4.77	58.00	−0.04**	0.02	−4.74
Weighted PQML	68.50***	3.56	55.10	91.64***	4.01	58.86	−0.04*	0.02	−4.66
Average treatment effect on the treated									
Weighted least squares	64.56***	4.74	51.93	86.58***	6.61	55.61	−0.04**	0.02	−4.46
Weighted PQML	66.66***	4.18	53.61	89.07***	5.19	57.21	−0.04**	0.02	−4.31

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 5: 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	41.12***	8.36	47.85	34.05***	4.37	66.30	−0.34***	0.08	−18.27
Average treatment effect									
Weighted least squares	53.71***	7.59	62.49	42.21***	3.67	82.19	−0.37***	0.08	−19.72
Weighted PQML	50.69***	6.80	58.97	41.41***	3.41	80.63	−0.37***	0.08	−19.80
Average treatment effect on the treated									
Weighted least squares	48.21***	7.88	56.09	38.17***	3.75	74.33	−0.38***	0.11	−20.04
Weighted PQML	46.02***	7.10	53.54	37.72***	3.39	73.46	−0.41***	0.13	−21.65

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 6: Causal effects estimated with OLS, PQML, and IPW (2008–2012)

General practitioners	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	71.18***	3.60	57.25	101.78***	4.58	65.38	−0.11***	0.03	−11.44
Average treatment effect									
Least squares	68.20***	3.41	54.86	90.00***	4.03	57.81	−0.05*	0.03	−4.98
PQML	69.03***	3.37	55.52	91.50***	4.16	58.77	−0.04*	0.03	−4.85
IPW	72.92***	3.94	58.65	96.92***	4.49	62.25	−0.05**	0.02	−5.71
Average treatment effect on the treated									
Least squares	67.98***	3.82	54.68	90.22***	4.79	57.95	−0.05*	0.02	−5.10
PQML	69.18***	4.03	55.64	91.13***	5.24	58.53	−0.05**	0.02	−5.13
IPW	67.34***	3.94	54.16	91.77***	5.20	58.95	−0.05***	0.02	−5.84
Specialists	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	41.12***	8.36	47.85	34.05***	4.37	66.30	−0.34***	0.08	−18.27
Average treatment effect									
Least squares	54.32***	7.46	63.20	42.94***	3.71	83.61	−0.39***	0.08	−20.78
PQML	51.43***	6.88	59.84	41.73***	3.36	81.26	−0.38***	0.08	−20.48
IPW	57.00***	8.28	66.32	44.26***	4.03	86.17	−0.36***	0.08	−19.26
Average treatment effect on the treated									
Least squares	50.92***	7.24	59.25	40.59***	3.58	79.04	−0.42***	0.11	−22.15
PQML	47.91***	6.55	55.74	38.89***	3.33	75.72	−0.41***	0.11	−21.96
IPW	42.85***	8.06	49.85	34.58***	3.94	67.33	−0.35***	0.09	−18.47

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. Standard errors are block bootstrapped on the physician level using 250 replications. OLS: Ordinary least squares. PQML: Poisson quasi-maximum likelihood. IPW: Inverse probability weighting. Coef.: Coefficient. S.E.: Standard Error.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: General practitioners' average effects using different measures of drug costs

	Normalized			Normalized (DDD)			Drug costs in CHF		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	24.99***	1.19	58.52	1138.40***	68.80	49.97	133.45***	6.43	56.06
Average treatment effect									
Weighted least squares	22.54***	1.27	52.78	1012.82***	77.41	44.46	127.56***	6.91	53.58
Weighted PQML	22.97***	1.13	53.79	1012.70***	76.93	44.45	128.54***	5.68	54.00
Average treatment effect on the treated									
Weighted least squares	21.19***	1.85	49.63	914.09***	98.39	40.12	119.20***	8.56	50.07
Weighted PQML	22.15***	1.33	51.87	930.06***	96.59	40.82	123.35***	6.09	51.82

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 8: Specialists' average effects using different measures of drug costs

	Normalized			Normalized (DDD)			Drug costs in CHF		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	9.61***	1.24	56.95	394.35**	157.19	33.47	55.97***	19.45	31.53
Average treatment effect									
Weighted least squares	11.70***	1.13	69.31	491.09***	150.72	41.68	67.07***	18.73	37.78
Weighted PQML	11.55***	1.07	68.43	505.88***	144.51	42.93	67.01***	16.42	37.75
Average treatment effect on the treated									
Weighted least squares	9.96***	1.52	59.03	514.19***	154.10	43.64	55.45**	21.85	31.24
Weighted PQML	10.50***	1.09	62.18	520.11***	154.54	44.14	60.21***	19.63	33.92

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 9: General practitioners' average effects using different measures of drug volumes

	Normalized			Normalized (DDD)			Volume index		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	13.87***	0.61	61.25	228.12***	11.93	61.62	4.04***	0.17	59.98
Average treatment effect									
Weighted least squares	12.68***	0.76	55.98	209.91***	11.90	56.70	3.83***	0.20	56.89
Weighted PQML	12.89***	0.58	56.90	211.39***	10.99	57.10	3.87***	0.17	57.50
Average treatment effect on the treated									
Weighted least squares	11.85***	0.99	52.30	196.99***	15.19	53.21	3.51***	0.28	52.17
Weighted PQML	12.32***	0.70	54.39	202.51***	12.69	54.71	3.63***	0.21	53.94

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 10: Specialists' average effects using different measures of drug volumes

	Normalized			Normalized (DDD)			Volume index		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	5.82***	0.74	59.04	95.56***	11.81	66.98	1.60***	0.16	60.59
Average treatment effect									
Weighted least squares	7.16***	0.78	72.72	121.18***	11.38	84.94	1.87***	0.14	70.49
Weighted PQML	7.05***	0.66	71.57	117.69***	9.93	82.49	1.87***	0.12	70.70
Average treatment effect on the treated									
Weighted least squares	5.96***	0.82	60.49	101.90***	11.69	71.42	1.62***	0.15	61.20
Weighted PQML	6.34***	0.63	64.33	102.10***	10.97	71.56	1.69***	0.13	63.77

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 11: General practitioners' average effects using different measures of drug prices

	Normalized			Normalized (DDD)			Retail price (CHF)			Ex-factory price (CHF)		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	−0.01	0.01	−0.54	−1.06***	0.33	−15.35	−2.50***	0.81	−5.14	−2.01***	0.64	−6.21
Average treatment effect												
Weighted least squares	−0.01	0.01	−0.65	−0.93***	0.23	−13.40	−2.14***	0.69	−4.39	−1.67***	0.59	−5.13
Weighted PQML	−0.01	0.01	−0.64	−0.89***	0.20	−12.80	−2.12***	0.69	−4.35	−1.65***	0.59	−5.07
Average treatment effect on the treated												
Weighted least squares	−0.01	0.01	−0.48	−0.79***	0.21	−11.42	−1.48**	0.59	−3.04	−1.16**	0.52	−3.56
Weighted PQML	−0.01	0.01	−0.46	−0.75***	0.19	−10.85	−1.41**	0.57	−2.90	−1.09**	0.50	−3.37

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 12: Specialists' average effects using different measures of drug prices

	Normalized			Normalized (DDD)			Retail price (CHF)			Ex-factory price (CHF)		
	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean	Coef.	S.E.	% of mean
Unadjusted difference	−0.03**	0.01	−1.74	−2.38***	0.68	−23.17	−12.68***	2.90	−17.20	−10.76***	2.75	−19.97
Average treatment effect												
Weighted least squares	−0.02	0.01	−0.92	−2.97***	0.86	−28.95	−13.35***	3.55	−18.10	−11.66***	2.87	−21.63
Weighted PQML	−0.01	0.01	−0.85	−2.61***	0.83	−25.47	−13.39***	3.38	−18.16	−11.63***	2.96	−21.57
Average treatment effect on the treated												
Weighted least squares	−0.01	0.01	−0.63	−3.24***	1.24	−31.61	−13.77***	4.43	−18.67	−12.13***	3.95	−22.51
Weighted PQML	−0.01	0.01	−0.59	−3.40***	1.24	−33.15	−14.69***	5.31	−19.93	−12.99***	4.83	−24.10

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

B DRUG DISPENSING REGULATION

Table 13: 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 (2016)
[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 SUPPLEMENTARY MATERIAL: VARIABLE DEFINITIONS AND CONSTRUCTION

Table 14: Variable Definitions and Construction

Variable Name	**Description/Construction**	**Aggregation**	**Source**
drug costs per patient	Annual gross drug costs per patient 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
days supplied, per patient	a physician's annual prescribed (and dispensed) drug volume per patient in terms of days supplied based on defined daily doses		WHO, Sasis AG, SL
price per day supplied	average price per day supplied by a physician based on defined daily doses and the ex-factory price of the drug package		WHO, Sasis AG, SL
normalized volume, per patient	a physician's annual prescribed drug volume per patient in terms of standardized packages based on the active pharmaceutical ingredient. Section IV.E.1 outlines the construction of the variable in detail.		Sasis AG, SL
normalized price	the annual average drug price over all prescriptions issued by a physician, based on standardized packages based on active pharmaceutical ingredient and ex-factory prices. Section IV.E.1 outlines the construction of the variable in detail.		Sasis AG, SL
volume index, per patient	a physician's annual prescribed drug volume per patient in terms of standardized package sizes between one (smallest package) and two (largest package) based on active pharmaceutical ingredients. Section IV.E.1 outlines the construction of the variable in detail.		Sasis AG, SL
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

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Table 14 – *Continued from previous page*

Variable Name	**Description/Construction**	**Aggregation**	**Source**
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
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

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Table 14 – *Continued from previous page*

Variable Name	**Description/Construction**	**Aggregation**	**Source**
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
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, SL: List of Pharmaceutical Specialties, WHO: World Health Organization