

Rents for Pills: Financial Incentives and Physician Behavior

Tobias Müller ^{*1}, Christian Schmid ^{†2}, and Michael Gerfin ^{‡3}

¹University of Bern

²CSS Institute for Empirical Health Economics

³University of Bern

October 30, 2020

Abstract

We analyze how a recent regime-change in self dispensing impacts the prescription decisions of physicians in two large Swiss cities. The regime-change introduced financial incentives into the prescription decisions, because physicians were now allowed to dispense drugs at their on-site pharmacy and earn a mark-up on each prescription. Using detailed physician-, patient- and product-level claims data from a large health insurer, we find that dispensing leads to significant increases in drug spending per patient by up to 15%. Our analysis is indicative that dispensing operates through two main channels: *a*) physicians increase the number of packages prescribed to patients which is compatible with a package size channel and *b*) physicians switch to more profitable brands implying a cherry-picking response. On the other hand, our findings suggest that the financial rewards inherent in dispensing do not alter the dosage-decisions of doctors nor do they result in practice style changes. Overall, our results show that dispensing induces physicians to engage in rent-seeking behavior resulting in avoidable costs for the health care system.

JEL Classification: D01, C21, I11

Keywords: Rent-seeking, Physician agency, Prescription behavior, Drug expenditures

*First author. Schanzenekstrasse 1, 3001 Bern, Switzerland, email: tobias.mueller@vwi.unibe.ch

†Tribtschenstrasse 21, 6002 Luzern, email: christian.schmid@css-institut.ch

‡Schanzenekstrasse 1, 3001 Bern, email: michael.gerfin@vwi.unibe.ch

1 Introduction

When decision-makers have different knowledge and pursue different objectives, agency issues likely arise. In health economics, the interaction between physicians and patients has received particular attention: because patients lack medical expertise, they delegate medical decision-making to their physicians. If physicians act as perfect agents, monetary incentives should play no role in determining medical treatment as the only goal of physicians reduces to assist their patients to demand the quantities of various types of care that patients would have chosen if they had access to the same information and knowledge as the doctors (Pauly, 1980). Economists have long questioned the “perfect agent” hypothesis and argued that physicians’ treatment decisions are influenced by factors beyond their patients’ needs. In a seminal contribution, Ellis and McGuire (1986) formalize this idea by specifying physicians’ utility as a function of both patient benefit and physician income so that doctors may be willing to trade off some patient benefit for a higher income. For example, physicians might schedule unnecessary follow-up treatments or favor more generously reimbursed interventions (e.g. surgeries) to reach their income goals despite little medical benefits for the patient. Moreover, they show that depending on the reimbursement system in place, imperfect agency may lead to the over- or underprovision of medical care: while fee-for-service payment schemes are prone to result in the provision of excessive care, prospective payment systems (capitation) incentivize physicians to ration treatments and therapies. These theoretical predictions have led to a large and growing body of empirical work providing evidence that financial considerations systematically influence physician behavior (see e.g. McGuire, 2000, 2011; Johnson, 2014, for surveys of this literature).

Much less attention has been paid to situations where two or more treatment alternatives are available that provide identical benefits to patients but differ in the financial reward to the physician. One example for this case are pharmaceuticals. When several drugs with the same active ingredients are available for a particular diagnosis, physicians may increase their income by choosing a more expensive brand without changing treatment and patient benefit at all. In this case, physicians engage in a classic rent-seeking behavior. Furthermore, if patients are insured they have little financial incentive to curb physicians’ rent-seeking activities. This paper analyzes the role of rent-seeking behavior among physicians that are allowed to sell prescription drugs through their own practice pharmacy in the Swiss outpatient sector.

We exploit a recent regime-change in drug dispensing giving physicians the opportunity to prescribe and sell drugs to their patients at their doctors offices. Importantly, the change in the regulation introduced financial incentives into the drug prescription decisions of physicians enabling them to increase their income by directly selling drugs to their patients. A question that immediately arises in this context is how these financial

incentives influence the prescription behavior of physicians. One can easily imagine that the introduction of monetary incentives negatively affects the propensity of physicians to act as perfect agents for their patients: First, physicians might choose drugs no longer based only on efficacy or safety reasons but also to earn the markups on them. Second, physicians might overprescribe pharmaceuticals as each additional unit increases their income. Third, they might opt for the more profitable drugs imposing unnecessary additional costs on the health care system without generating improvements in the treatment quality.

We examine the impact of dispensing on physician prescription decisions from different perspectives: Unlike previous work, the quasi-experimental setup created by the regime change allows us to infer counterfactuals for the actual observed prescription behavior of the self-dispensing physicians by exploiting the information available from a large pool of comparable non-dispensing physicians. Moreover, the panel structure of the data and the availability of detailed patient-pool characteristics enables us to account for time-varying observable factors as well as time-invariant unobserved heterogeneity between dispensing and non-dispensing physicians. Therefore, any effect of dispensing we find can be attributed to changes in prescription behavior as opposed to underlying differences in, e.g., adherence to professional ethics or practice style. In addition, we use detailed physician-, patient- and product-level data to examine four channels that potentially shape the prescription behavior of physicians as a reaction to the financial rewards inherent dispensing: We distinguish between a practice style, package size, cherry-picking and dosage channel and examine to what extent their behavioral implications coincide with the changes in prescription behavior we observe in the data.

Furthermore, we contribute to the small body of empirical literature that analyzes the influence of drug dispensing regimes on prescription behavior (e.g. Burkhard et al., 2019; Kaiser and Schmid, 2016; Trottmann et al., 2016; Rischatsch, 2014; Iizuka, 2012, 2007; Liu et al., 2009; Chou et al., 2003). Overall, this literature finds that the dispensing physicians are highly responsive to markup differentials between generic and brand-name drugs and that dispensing significantly affects drug expenditures. Although closely related, this paper differs in two key dimensions from prior work. First, the majority of studies do not attempt to estimate the causal effect of dispensing and instead explicitly report associations between dispensing and, e.g., the use of generics or pharmaceutical expenditures (e.g. Rischatsch, 2014; Rischatsch et al., 2013). Because the dispensing status of physicians is often not directly observed and has to be imputed, which may introduce measurement error, the corresponding findings may be biased (e.g. Trottmann et al., 2016). Second, the studies asking the causal question impose rather strong identifying

assumptions¹ and are not able to account for time-constant unobserved characteristics such as risk preferences and practice style of providers. In contrast, we observe the same pool of physicians both before and after the regime-change which allows to analyze their behavior when exposed to different incentive structures.

Using rich claims data from a large health insurer and a weighted difference-in-differences approach, we find that dispensing leads to significant increases in drug expenditures per patient. Specifically, the drug costs of dispensing physicians are up to 15% above the predicted level without dispensing. Moreover, our analysis shows that dispensing physicians prescribe more packages to their patients which is compatible with a package size channel through which doctors substitute larger with smaller packages to enhance markup revenues. For three major drugs, we document that patients of dispensing physicians are more likely to receive high markup brands implying a cherry-picking response of doctors. However, our analysis does not provide evidence that physicians systematically adjust their practice style by prescribing drugs to a larger share of their patient population to generate extra income. Also, our analysis does not indicate that doctors significantly adjust their dosage-decision as a response to financial incentives. In addition, the responses in prescription behavior we observe in the data are not compatible with physicians prescribing higher volumes of low-dose drugs to their patients to increase their revenues. Finally, our estimates lend evidence for effect heterogeneity across medical specialties: Self-dispensing general practitioners generate significantly higher drug expenditures by expanding prescription volumes. Specialties with a low share of dispensing physicians (e.g. surgeons), for whom drug revenues account for a comparably small share of their revenues, show no significant response to dispensing.

Overall, our analysis provides evidence that profit motives indeed influence the prescription decisions of physicians. At the same time, we find no evidence that financial considerations systematically work against patient interests as dispensing does not affect treatment (dosage) decisions. Nonetheless, our results show that dispensing induces rent-seeking behavior among physicians leading to wasteful resource use and avoidable costs for the health care system.

Besides the economic relevance of the problem, our findings are also relevant for policy makers. Drug expenditures amounted to about 15-20% of total health care spending across the OECD in 2017. Switzerland and the USA and have the highest drug expenditures per capita with more than 1000 dollars in 2017 (OECD, 2018). In light of this, the question arises whether it is a good idea to expose physicians to monetary incentives. This paper gives a clear answer with respect to drug prescribing and thus provides policy makers valuable insights for the design of reimbursement schemes in the future.

¹For example, Kaiser and Schmid (2016) exploit the regional variation in dispensing regimes between Swiss cantons imposing the assumption that conditional-on-observables (e.g. age of provider and patient characteristics) the dispensing status of physicians is “as good as randomly assigned”.

The remainder of the paper is organized as follows. In section 2, we briefly discuss the institutional background and outline the financial incentives inherent in drug dispensing. Section 3 elaborates on the potential behavioral responses to dispensing. Section 4 introduces the data sources used in the analysis. Section 5 presents the identification strategy to estimate the effects of dispensing on prescription behavior. In section 6, we discuss our main results and provide evidence on the different underlying behavioral channels. Section 7 discusses effect heterogeneity between medical specialties. Robustness checks are presented in section 8 and section 9 concludes the paper.

2 Institutional Background

Since 1996, the Swiss health insurance system is organized according to principles of regulated competition (the following description draws on Schmid et al., 2018). This implies inter alia that health insurers and providers compete on price and quality while regulation ensures risk solidarity and individual affordability. In that sense, the system is similar to the Dutch health care system and the US Marketplaces. Enrollment in basic health insurance is mandatory, but consumers can freely choose among approximately 60 private insurers (annual open enrollment). Besides the standard health plan with a deductible of CHF 300 and free (outpatient) provider choice, most insurers offer a variety of health plans in terms of voluntary deductibles and managed care features.² In any case, each health plan has to offer the same coverage in terms of outpatient and inpatient services, prescription drugs, physiotherapy, old-age care, and so on. In addition, health insurers are de facto obliged to contract with all licensed physicians running independent practices.

While health plans, drug approval and pricing, physician licensing and many other health market features are regulated on the federal level, the cantons have some leeway in the regulation of the provision of health care. In particular, cantons can determine whether physicians are allowed to dispense drugs and specify further regulations concerning drug dispensing.³ As a result, there are roughly three categories: prohibition of self-dispensation, self-dispensation in areas with few pharmacies, and unrestricted self-dispensation (for a cantonal overview and details, see Table B.2 in Burkhard et al., 2019). Note that some of these regulations date back to the early 19th century and all of them remained relatively stable over time. Even after the introduction of regulated competition, there have been hardly any changes in the cantonal legislations.⁴

²The selectable deductibles for adults (2019) are CHF 500, 1000, 1500, 2000, and 2500; from the consumer's perspective, managed care primarily implies some sort of gatekeeping.

³Besides physician dispensing, cantons can for instance determine whether pharmacists are allowed to vaccinate or not.

⁴Before 1996, there was no regulation on the federal level at all. Today, physician dispensing is regulated in Art. 37 KVG, which implies that the cantons (can) determine the conditions under which

The canton of Zurich is, however, an exception in two regards. First, the regulation changed in the middle of the last century. While the earliest regulation known to us allowed physician dispensing in the entire canton, it was prohibited in 1951 for physicians in the cities of Winterthur and Zurich to deliver drugs.⁵ Beginning in 1998, there were several political and also legal attempts to make physician dispensing possible again in the two largest cities, but none of them was successful. Nevertheless, the physicians started in 2006 a new attempt to change the regulation by initiating a popular vote. They won on November 30th, 2008, with 53.7% affirmative votes and physician dispensing should have been possible in Winterthur and Zurich by 2010. In response, the defeated pharmacists immediately seized various legal steps to prevent the planned implementation. However, the Federal Court rejected all complaints.⁶ With its final decision on April 20th, 2012, physician dispensing has been permitted on May 1st, 2012, throughout the canton of Zurich. Thus, there was only a very short time between the final decision and the implementation.

Turning to prices and financial incentives, it is important to note that prescription drug prices are administered in Switzerland. In particular, the Federal Office of Public Health is responsible to bargain the ex-factory price with producers. Given the ex-factory price, a bylaw determines the retail price (see Table 1). The markup, i.e., the difference between the retail and the ex-factory price, is increasing in the ex-factory price in a step-wise fashion. As a result, dispensing physicians can increase their revenues by increasing the number of packages dispensed or by choosing the optimal package size.⁷ Rischatsch (2014) provides some evidence that physicians dispense *ceteris paribus* smaller package sizes where the absolute markup per dose tends to be higher. It is important to note the markup should cover only the costs that arise in the distribution process and storage of the drugs. However, this is unlikely to be realized in the heterogeneous pharmaceutical market in Switzerland (Hunkeler, 2008). In other words, the markup is likely to exceed these costs for some drugs. In addition, dispensing physicians can have a much smaller range of drugs in stock compared to pharmacies. Overall, dispensing physicians can potentially increase their revenue by the selection of the stocked drugs (in terms of active

medical doctors are allowed to dispense drugs. In other words, the introduction of regulated competition did not alter the dispensing regulations.

⁵The regulations we refer to are Art. 14f of the Cantonal Health Act of October 2nd, 1854, and Art. 35 of the revised Health Act of July 8th, 1951, respectively. The latter was replaced by Art. 17 in the new Cantonal Health Act of November 4th, 1962.

⁶The relevant Federal Court decisions are 2C_53/2009, 1C_468/2010, 1C_472/2010, and 2C_158/2012.

⁷Table A4 provides a few examples for a given medical treatment of 30 daily doses. There are three important differences: The package size (number of pills per package), the dosage (milligrams per pill) and branded versus generic drug. Consider, for instance, Amlodipinum. As evident from the table, the markup for a *30-day treatment* is highest if the physician prescribes or dispenses the smallest package size with the lowest dosage of the brand (30 pills with 5 mg). The markup decreases when the physician switches to a generic drug, increases the dosage and/or increases the package size.

pharmaceutical ingredient), the package size of these drugs, and the number of packages they sell.

— TABLE 1 —

3 Channels

As a starting point, it is worthwhile to elaborate on the different potential behavioral reactions of physicians to the financial rewards inherent in dispensing. In the context of dispensing, four main channels may shape physician prescription behavior: a) the *practice style* channel, b) the *cherry-picking* channel, c) the *package size* channel and d) the *dosage* channel. In the practice style channel the dispensing physicians might react by starting to favor medication over other treatment alternatives (e.g. monitoring, therapy) with the result of medicating larger fractions of their patient pool. This would increase markup revenues of the physician leading to higher average drug costs per patient. The cherry-picking channel operates through substitution of low with high markup drugs: Once a patient is diagnosed and an active substance is chosen, physicians face the choice among several brand name and generic alternatives which differ in the financial reward they offer. Dispensing thus might induce doctors to prescribe lucrative brand name drugs to their patients instead of resorting to generics or alternatively pick the highest markup generic in the choice set. As a third possible reaction, physicians might alter the package size they prescribe to their patients: the package size channel may be attractive because, as demonstrated by Rischatsch (2014), the current drug price regulation in Switzerland incentivizes the prescription of smaller package sizes since the combined markup on two small packages (e.g. 10 pills) is larger than the markup on one larger package (e.g. 20 pills). Hence, dispensing physicians might systematically substitute larger with smaller packages to increase markup revenues which would be reflected in higher average number of packages per patient. Finally, dispensing might induce dosage adjustments: Besides the incentive to prescribe smaller packages, the Swiss drug price regulation also provides monetary incentives for dosage reductions since the prescription of larger amounts of low-dose drugs (e.g. $20 \times 10\text{mg}$ pills) is more profitable than lower number of high-dose pills (e.g. $10 \times 20\text{mg}$) for a fixed daily dosage.

Of course, physicians may follow more than one strategy. For example, the cherry-picking channel may be chosen for patients with chronic conditions, while the threshold for medication may be slightly lowered for patients with acute symptoms. In the empirical analysis further below, we provide evidence on all these channels by shifting the perspective on the effects of dispensing between physician-, patient- and product-level data.

4 Data

We have access to the records of CSS Insurance, a large Swiss health insurer, for the years 2009 to 2014 with an annual enrollment of roughly 1.1 million individuals in compulsory health plans.⁸ Our data comprises all individuals who visited a physician at least once between 2009 and 2014. For each individual, we have information on the year of birth, gender, language and Swiss nationality. In addition, the data comprises pharmaceutical costs groups (PCG), which are based on drug consumption and informative about certain chronic conditions such as diabetes, hypertension, heart diseases, and so on. Regarding health plans, we observe the premium, the insurance carrier within CSS Insurance, the chosen deductible level and plan type in terms of managed care, and possibly accident coverage.⁹ As virtually all employees have an accident coverage through their employer, the latter is a proxy for non-participation in the labor market. While the health plan choice is made on an annual basis, changes due to retirement, relocation, migration, etc. are possible during the course of the year. Our data covers these changes on a monthly basis.

The data contains detailed information on the individuals' health care expenditures (i.e. different cost categories including physician costs, lab costs, drug costs, etc.), the starting month of treatment and the treating health care provider. Moreover, the data offers information on the source of the costs, i.e., whether they were directly caused by the treating physician or indirectly by the service provision of others (e.g. through a specialist referral or drug prescription). In addition to the cost information, the data provides detailed information on prescription volumes including the number of packages and the prescription volumes of the different drug categories (see Table 1). For a selection of drugs for chronic conditions, we also observe the unique drug identifier, which allows us to compare prescribing and dispensing physicians in more detail.

We complement the existing data set with two additional sources: First, we collected physician characteristics from the so-called "Medizinalberuferegister" (MedReg) containing information on a series of physician characteristics: the dispensing status of providers, their age, specialization, gender and years of experience. Second, we gathered information on drug prices and markups from the specialty list provided by the Federal Office of Public health. The specialty list is also used to add defined daily doses per package for drugs used in the treatment of chronic conditions.

Sample Construction

For our main analysis, we construct a physician-year level panel data set imposing the following set of restrictions: First, health care providers without a "Zahlstellenregister"

⁸CSS Insurance held a market share of more than 16% in the basic health insurance market in 2018.

⁹CSS Insurance consists of four different risk-bearing carriers: CSS, INTRAS, Arcosana, and sanagate.

number, a unique provider identifier, and physicians lacking information on provider characteristics (e.g. dispensing status, age, specialization) are excluded from the data. Second, due to incomplete cost information by one of the carriers within CSS insurance for the period between 2009-2010, we completely exclude the corresponding observations from the sample. Third, we restrict our sample to physicians active in the cities of Zürich, Winterthur and Basel-Stadt¹⁰ who are observed throughout from 2009 to 2014 leading to a sample of 10,194 physician-year-observations stemming from 1'699 physicians. Fourth, physicians treating less than 10 CSS patients per year are excluded from the main analysis.¹¹ Imposing the described restrictions results in a balanced panel including 7,722 observations from 1,255 physicians spanning over the years 2009-2014.

4.1 Descriptive Evidence

Table 2 shows summary statistics for the pre-treatment year 2011 stratified by the future dispensing status of physicians active in the cities of Zürich/Winterthur and Basel-Stadt based on annual data. The table clearly indicates that dispensing and non-dispensing physicians differ systematically along several provider characteristics prior to the regime-change. The share of GPs is significantly higher among the future self-dispensing physicians (41% among dispensing and 24% among non-dispensing physicians), and they have on average more than 3 years less work experience than their non-dispensing colleagues. In addition, distinct differences in the patient base can be observed: the patients of the dispensing physicians suffer less from chronic conditions¹², and visit their doctor less often. Moreover, patients of dispensing physicians choose on average higher deductibles and are more likely to opt for health care plans with managed care features as illustrated by the comparably high share of patients choosing HMO plans (16% among SD and 11% among non-SD physicians). Taken together, this descriptive analysis suggests that SD physicians treat a more favorable risk pool of patients on average, thus one would expect that they have lower medical costs per patient than the non-SD physicians.

— TABLE 2 —

¹⁰Physicians active in Basel-Stadt (BS) are not allowed to dispense pharmaceuticals. BS is large city which is comparable in many dimensions to the cities of Zurich and Winterthur. We include them in the analysis in order increase the statistical power of the analysis. As we show in the robustness checks the estimated effect sizes are invariant to the in- or exclusion of physicians from Basel-Stadt.

¹¹To put the low cut-off of 10 patients in perspective, physicians treat patients covered by several insurance companies, not just CSS Insurance.

¹²The data contains indicators for 26 chronic illnesses based on the types of drugs patients consume (so-called pharmaceutical cost groups (PCG)). For the sake of brevity, we do not show the corresponding summary statistics in the table.

Despite the seemingly more favorable risk pool of patients, the pre-treatment drug costs triggered by the dispensing physicians are approximately 36% higher (about CHF 400) per patient than those of non-dispensing doctors. A similar picture can be drawn when comparing prescription volumes prior to the regime-change: while SD physicians prescribe on average roughly 22 packages of drugs to their patients, the prescription volumes of non-SD physician is approximately 16. In accordance with this observation, dispensing physicians also prescribe significantly larger amounts of the most profitable category 4 drugs to their patients.

Figure 1 shows the evolution of annual drug costs and prescription volumes per patient. Several points are noteworthy: First, the drug costs and volume measures of SD physicians persistently exceed the ones of non-SD physicians in all years before and after the regime-change. The level differences in prescription outcomes between the two groups is indicative that they systematically differ along key dimensions such as risk preferences and practice style. That is, SD physicians seem to be more likely to resort to medication when treating their patients than the non-SD doctors (see also “Medicated” in Table 2). Second, in the pre-treatment period the curves of the SD and the non-SD physicians appear to evolve in a similar manner over time providing visual evidence for the validity of our identification strategy outlined below.

— FIGURE 1 —

5 Identification Strategy

The main goal of this paper is to identify the causal effect of self-dispensing on physician prescription behavior. Such an analysis is complicated by the fact that the dispensing status is not randomly assigned, but a choice based on observed (e.g. patient pool, markups on pharmaceuticals) and unobserved factors (e.g. practice style, professional ethics). Indeed, as shown in the descriptive analysis, the dispensing and the non-dispensing physicians differ in many dimensions already before the reform indicating self-selection into dispensing. We address these selection issues by exploiting the within physician variation in our panel data as we observe physicians and their corresponding prescription behavior both before and after the regime-change. To maximize treatment and control group comparability, we follow the approach proposed in the literature by combining balancing and difference-in-differences estimation (e.g. Ho et al., 2007; Abadie, 2005): in a first step, treated and controls are balanced based on observable pre-treatment (including outcomes) characteristics. The balancing step is followed by estimating the DID model using the corresponding balancing weights, controlling for a broad set of physician and patient-pool characteristics as well as time-invariant unobserved heterogeneity between SD and non-

SD physicians. We first discuss the specification of the DID model, followed by a brief description of the balancing step.

5.1 Specification of the DID model

We estimate the causal effects of dispensing on physician prescription behavior using a weighted fixed effects model with time-varying treatment effects of the following form:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{\tau=t}^T \rho_{\tau} D_i I[\tau = t] + X'_{it} \gamma + \varepsilon_{it} \quad \text{for } t = 2009 - 2014 \quad (1)$$

where Y_{it} is the observed prescription outcome (e.g. drug expenditures, number of packages prescribed) of physician i in year t ; α_i is a time-constant unobserved physician-specific fixed effect capturing factors such as a physicians risk preferences or profit orientation, and λ_t are time fixed effects.¹³ D_i is the binary treatment indicator which equals one for physicians in the treatment group (i.e. the SD physicians) and zero for the control units (i.e. non-SD physicians). The vector ρ_{τ} captures the treatment effects of interest. A positive sign on ρ_{τ} would indicate that the financial incentives inherent in dispensing indeed distort the prescription decisions of physicians inducing them to increase revenues and expand drug quantities. We specify the year 2011 as the base period, i.e., all treatment effects are measured relative to this baseline. This allows to test whether pre-treatment effects are jointly zero. Failing to reject this hypothesis lends credibility to the common trend assumption. The weights are estimated using the procedure outlined below.

Moreover, we include time-varying patient-pool (e.g. age, gender, co-morbidities, deductible choice) captured in the vector X_{it} , removing potentially (trend) confounding factors. In our application it is more reasonable to assume that physician prescription outcomes would have developed identically over time in the absence of dispensing conditional on dispensing and non-dispensing physicians sharing for example a comparable risk pool of patients. The model is estimated using the weights described in the next section.

5.2 Entropy Balancing

As shown by Hainmueller (2012), entropy balancing balances covariate distributions between the treatment and control group more effectively than conventional common support methods (e.g. propensity score balancing). Specifically, entropy balancing assigns a scalar weight to each control unit¹⁴ such that a pre-specified set of balancing constraints on the first, second or higher moments of the covariate distributions between treated and

¹³While we have monthly data we estimate annual effects because the monthly data are noisy. Part of that noise is due to seasonality in drug prescription, and another part is due to accounting cycles, leading to bunching at the end of quarters and particularly at the end of the year.

¹⁴Observations in the treatment group receive a weight of one.

controls are satisfied. That is, the weights w_i are chosen using the following reweighting scheme minimizing the entropy distance metric:

$$\min_{w_i} H(w) = \sum_{i|D=0} w_i \log\left(\frac{w_i}{q_i}\right) \quad (2)$$

subject to the balancing constraints:

$$\sum_{i|D=0} w_i x_{ij} = m_r \quad \text{with } r \in 1, 2, \dots, R \quad (3)$$

$$\sum_{i|D=0} w_i = 1 \quad (4)$$

$$w_i \geq 0 \quad (5)$$

where $q_i = \frac{1}{n_0}$ with n_0 control units; x_{ij} is the value of covariate j for individual i to be balanced between treated and control and m_r is the r^{th} moment of covariate x_j in the treatment group.

We apply entropy balancing to balance covariates one year prior to the regime-change. Additional to the variables in the vector X_{it} , we also use pre-treatment outcomes, which may allow to control for (time-varying) unobservables not captured by the fixed effects. Table A1 in the Appendix shows that entropy balancing leads to almost perfectly identical means between SD and non-SD physicians in terms of both patient and provider characteristics as well as lagged outcomes (total costs and drug expenditures).

6 Results

We examine the impact of self-dispensing on physician prescription behavior from different perspectives: First, we provide empirical evidence on the practice style channel by quantifying the impact of dispensing at the extensive margin using patient-level data (subsection 6.1). Next, we present the estimates of the impact of dispensing on drug costs and number of prescribed packages per patient (subsection 6.2). Then, we explore the cherry-picking and the package size channel using detailed product-level data on three major drugs (subsection 6.3). In the last part of the analysis, we explore effect heterogeneity by the specialization of the health care providers (see section 7).

6.1 Effects of Dispensing at the Extensive Margin

In the first step of the analysis, we analyze the practice style channel, i.e., the question whether dispensing changes the threshold for the patient who is at the margin of being prescribed medication. **To this end, we shift to the patient perspective (WE NEED**

TO EXPLAIN WHY - IT LOOKS REALLY WEIRD BECAUSE IT WAS NOT MENTIONED BEFORE) @Mike: In general, I agree as the shift between perspectives might be a bit confusing for the reader. However, don't you think the shift to the patient level becomes clear here in the next two sentences? At the same time, I would not mind if you want to add more meat here. and construct a patient-level panel data set that allows us to examine the question whether dispensing has changed the patients' propensity to leave the doctor's office with pharmaceuticals. In other words, the patient perspective offers the possibility to explore the effects of dispensing at the extensive margin. We restrict the analysis to patients who are at the minimum observed two years before and after the regime change. Also, we confine our analysis to patients for which we have access to information about their provider (i.e. dispensing status and other physician characteristics) leaving us with an estimation sample of 471,767 observations from 21,761 patients. Using a patient fixed effects specification, we estimate the impact of being exposed to a dispensing physician.¹⁵ The corresponding parameter estimates can be found in Table 3.

Overall, the table shows that patients are not systematically more likely to be medicated after the reform as the estimated effect sizes are small for all outcomes. Specifically, although our estimates show that the likelihood of leaving the doctor's office with a positive amount of pharmaceuticals (first column) is significantly affected, the corresponding effects are not economically meaningful as indicated by an effect size close to zero across all years after the regime change in 2012.¹⁶ Similarly, our estimates provide no evidence that patients are more likely to leave the doctor's office with category 3 and category 4 drugs. These findings imply that the financial incentives inherent in dispensing do not induce physicians to prescribe drugs to a higher share of patients thereby effectively closing down the practice style channel as the mechanism shaping physician prescription behavior.

— TABLE 3 —

6.2 Effects of Dispensing on Physician Prescription Behavior

In the next step of the analysis, we use physician-level data to examine the impact of dispensing on various aspects of physician prescription behavior. This shift in perspective allows us to examine the cost implications of dispensing as well as changes in prescription patterns as described in the package size and dosage channel. Table 4 summarizes

¹⁵The analysis is restricted to patients being fully exposed to either a dispensing or non-dispensing physician after the regime-change. Note that less than 3% of patients visit multiple doctors with differing dispensing status during a month.

¹⁶Note that the baseline probability of leaving with a positive amount of drugs is slightly above 70%.

the estimated annual self-dispensing effects per patient on drug expenditures, number of packages prescribed, as well as the impact on the number of the most profitable category 3 and 4 packages based on the balancing and DID specification outlined in section 5.

As evident from the table, dispensing significantly increases the drug costs per patient indicating that physicians systematically adjust their prescription behavior as a response to the introduction of the financial rewards. In particular, our estimates suggest that self-dispensing increased drug costs significantly between 9% in 2012 and 15% in 2014. In other words, the average patient of a dispensing physician would have had up to 15% lower drug expenditures per year in the absence of dispensing. Given that the counterfactual annual drug expenditures would have amounted to approximately CHF 1,130 per patient in the absence of dispensing after the regime-change, the estimated effects imply additional drug costs between approximately CHF 100-170 per patient and year.¹⁷

Important to note here is that the estimated effects cannot be attributed to differences in patient characteristics or time-constant unobservables (e.g. practice style) as we explicitly condition on these factors. Moreover, at the bottom of table 4, we report the p -values for the null of no pre-treatment effects. Across all specifications, the corresponding tests do not reject the null, giving credibility to the common trend assumption and thus reinforcing our identification strategy.

— TABLE 4 —

Besides the cost effects, the table shows effects on the number of prescribed packages. Our baseline estimates show that dispensing increases the number of packages, but the estimated overall quantity responses have large standard errors. However, we find that the dispensing physicians significantly increase the number of packages in the most profitable category 4. These results do not indicate that the dispensing physicians prescribe more drugs, but is indicative for a substitution from larger to smaller packages. We elaborate on this point further below.

To further illustrate the estimated effects, Figure 2 shows the predicted prescription outcomes of dispensing physicians (blue lines) alongside the estimated counterfactual paths (red lines).¹⁸ The top left graph provides information on the post regime-change dynamics. In particular, the figure shows a negative trend in counterfactual drug costs after 2012. At the same time, the negative dynamics in the predicted drug costs are less

¹⁷Drug expenditures averaged at a level of CHF 1,430 among the dispensing physicians one year prior to the regime-change. In the control group, drug expenditures decreased by roughly -21% in the years after the regime-change. Applying the corresponding time effect to the average in the treatment group generates the counterfactual average drug expenditures of roughly CHF 1,130 for the dispensing physicians after the regime-change.

¹⁸The predictions are based on the estimates shown in Table 4.

pronounced leading to a divergence of the two lines. In terms of interpretation, this result implies that the opportunity to dispense did not lead to an overall growth in drug costs. Instead, the reductions in drug costs per patient would have been substantially larger in the absence of dispensing. Assuming that these doctors did not withhold necessary and beneficial medication from their patients prior to the regime-change, these results indicate unnecessary additional health care costs to society thus wasteful resource use.

— FIGURE 2 —

So far, the empirical evidence suggests that physicians expand the number of packages to generate extra income. However, the question on potential changes in treatment decisions can not be answered based on these results. To do so, we make use of additional information available in our data: for a subset of drugs, we observe the prescribed usage of the drugs measured in terms of the defined daily dose (DDD), i.e., the average maintenance dose per day for a drug used for its main indication. Unfortunately, the DDD is not available for all drugs which reduces the sample size for the analysis.¹⁹ This normalized usage is the product of the prescribed number of units (e.g. pills) and the dosage (e.g. in mg) divided by the drug-specific constant DDD.

In the next step of the analysis, we thus re-estimate the balanced DID estimates in the DDD subset and the corresponding results can be found in table 5. Overall, the estimated effects coincide with the main findings from above as we find that dispensing leads to higher drug costs per patient and an expansion of the prescribed number of packages. The effect sizes are also comparable, although they imply slightly stronger responses and a significant increase in overall package quantities of up to 3.6 additional packages per patient and year. More notable however, our estimates in the DDD subset provide evidence that the financial rewards from dispensing do not significantly alter the prescribed usage measured in daily dosages. This is an important finding as it indicates that physicians do not systematically change previous treatment decisions in order to increase their net income.

There are three possibilities for observing a constant normalized usage: a) both the prescribed number of units and the dosage remain the same; b) the number of prescribed units increases while the dosage decreases; and c) the number of prescribed units decreases while the dosage increases. Despite the described potential to optimize revenues via the dosage channel, it seems rather unlikely that physicians systematically change the dosage of their chronic patients. If patients are used to a given routine, say one pill in the morning, it may be unsafe to change this to half a pill or two pills during the day, because

¹⁹For example, DDDs are not available for vaccines or anesthetics. See, e.g., www.who.int/medicines/regulation/medicines-safety/toolkit_ddd/en/ for more details regarding DDDs.

this may lead to over- or under-use of the prescribed medication which might translate into severe health issues. This leaves the first possibility with constant prescribed number of units and dosage. Combined with the finding of an increased number of packages, our estimates imply that physicians tend to switch to smaller packages, e.g., by prescribing and dispensing two 10-pill packages instead of one 20-pill package with identical dosage per pill providing indirect evidence for the package size channel. The institutional design makes this financially attractive, as described in section 2.

Overall, our physician-level estimates suggest that financial considerations indeed influence the prescription behavior of doctors but the pursuit of profit motives does not alter the treatment decisions (in terms of normalized usage) in a systematic way. Nonetheless, our results imply that dispensing induces rent-seeking behavior among physicians via the package size channel resulting in a misalignment of the overarching goals of the health care system and the one of physicians.

— TABLE 5 —

6.3 Effects of Dispensing on the Prescription of Three Drug Categories

In this part of the analysis, we use product-level data to shift the perspective to the prescription of specific drugs which enables us to examine further channels that might shape physician prescription decisions. In particular, we are interested in the role of the cherry-picking and the package size channel but the product view also allows us to learn more about the dosage channel. To study these channels, we follow a panel of patients between 2009-2014 who do not change their doctor of trust and observe the drugs they were prescribed in that time frame. We focus on three major drugs: the active ingredient “Amlodipin” used to treat hypertension²⁰, “Omeprazol”²¹ a reflux drug and an antibiotic of the agent class “Ciprofloxacin”. For all these drugs a series of bio-equivalent generic competitors are available in the market and they all have a large market share in terms of sales/prescription volume in the Swiss pharmaceutical market.

As for the hypertension drug, physicians have the choice among 28 alternatives from seven providers (“brands”)²² in the drug class under consideration. The drug comes in

²⁰Amlodipin is a calcium channel blocker used to treat angina and hypertension.

²¹Omeprazol is used to treat certain stomach and esophagus problems (such as acid reflux, ulcers).

²²The suppliers are Axapharm, Helvepharm, Mepha, Norvasc, Pfizer, Sandoz and Spirig. Mepha is the largest provider with a market share in prescriptions of approximately 46%; followed by Sandoz (25%) and Norvasc (17%, the brand-name alternative).

two package sizes (30 and 100 pills) and two dosages (5 and 10mg). 87.5% of the alternatives (28 out of 32) in the choice set of doctors are generics.²³ The final estimation sample consists of 18,212 monthly physician-patient interactions. The choice set for the active ingredient "Omeprazol" contains 108 alternatives from nine providers and the physicians have the choice among seven package sizes (7, 14, 28, 56, 98 and 100 pills) and three dosages (10, 20 and 40mg).²⁴ The estimation sample for the reflux drug entails 5,365 physician-patient interactions between 2009-2014. Finally, doctors have the choice between 9 different providers offering the antibiotic. The drug can be prescribed in three package sizes (6, 10 and 20 tablets) and three dosages (250, 500 and 750mg) resulting in a choice set of 56 alternatives.²⁵ The analysis of the impact of dispensing on the prescription of the antibiotic is based on 10'793 physician-patient interactions.

The product-level analysis allows us to address a series of relevant questions. For example, are patients "exposed" to a dispensing physician more likely to leave the doctor's office with a smaller package or different dosage than they used to before the reform when their doctor was not yet allowed to dispense? Are they more likely to go home with another, potentially more pricey brand? To address these and related questions, we study the impact of dispensing on the following set of outcomes: First, we use the dosage in mg per package and the package size measured by the number of pills per package as two continuous outcomes to paint a more complete picture about the dosage and package size channel. Second, we generate a series of binary switching indicators to study the cherry picking channel, i.e., whether physicians substitute low with high markup drugs as a response to dispensing. We define the switching indicators as changes in the prescription behavior of doctor j treating patient i between 2010/2011 (pre-period) and 2013/2014 (post-period). Note however that since we are holding constant the physician-patient relationship and study potential changes between the pre- and post-reform period, the resulting sample sizes drastically reduce relative to the initial data. Yet, this setup ensures that the estimated effects can be more cleanly attributed to dispensing. The set of switching indicators includes: *brand switch* which equals one if another brand was prescribed to the patient post-reform; *generic switch* which equals one if the prescription changed from brand-name to generic; and *higher markup* which equals one if there was a switch to a higher markup alternative in the choice set holding constant package size and dosage between the pre- and post-regime-change period.

We estimate fixed effects specifications for the continuous outcomes (dosage, package size) exploiting the within-patient variation and linear probability models for the switching indicators (brand, generic and markup switch) to quantify the influence of be-

²³The first generic was introduced in 2005, fifteen years after the release of the brand-name drug.

²⁴99 out of the 108 drug alternatives are generics and the first generic came on the market in 2004.

²⁵The brand-name alternative "Ciproxin" was introduced in 1988 and the first generic entered the market in 2002.

ing exposed to a dispensing physician while controlling for the same set of time-varying patient characteristics (e.g. age, gender, chronic conditions, insurance choice) as in the main analysis above. The corresponding parameter estimates alongside the baseline rates can be found in Table 6.

— TABLE 6 —

In line with the DDD finding above (see table 5), our analysis provides no evidence that patients whose doctor starts to dispense are systematically more likely to receive higher/lower dosages than patients with a non-dispensing physician providing evidence against the dosage channel. Reassuringly, this finding suggests that the dosage-decisions of physicians are not guided by financial consideration but merely on medical grounds based on patient needs. Moreover, we find that dispensing does not influence the choice of the package size, i.e., doctors do not seem to optimize markup revenues via the package size channel by systematically prescribing smaller packages in larger quantities to patients with chronic conditions.²⁶ Also and in contrast to more recent work (Trottmann et al., 2016), our estimates indicate that dispensing is not associated with generic substitution as the prescription of generics seems to be unaffected by the financial rewards in dispensing.

However, as evident from the table, patients of dispensing physicians are significantly more likely to receive an active ingredient from a different brand in the post-period and one that more likely grants a higher markup to the dispensing physician providing evidence in support of the cherry-picking channel. Hence, when prescribing drugs to patients with chronic conditions, physicians tend to travel the “safest” road to improve their income: by substituting low with high markup drugs instead of risking health consequences that might arise when prescribing lower dosages or smaller packages to patients. In accordance with the main results, the product-level analysis thus indicates that physicians, after they have decided on the dosage and package size, respond to the financial incentives introduced by dispensing by opting for drugs that are more profitable thereby engaging in rent-seeking.

7 Heterogeneity by Specialization

In the final part of the analysis, we further explore the effects of dispensing on physician behavior by focusing on the question whether physicians show differences in their response to dispensing based on their specialization. A preliminary analysis indicates that risk-

²⁶Note however, that the prescription of small package sizes is rare (less than 3% of prescriptions) in the treatment of hypertension, which may explain the inconsistency of the result for this particular drug with the general result discussed at the end of the previous section.

adjusted²⁷ drug expenditures are significantly higher among general practitioners (henceforth GPs) than specialists (e.g. dermatologists, psychiatrists). Moreover, pharmaceutical costs account for a significantly higher proportion of total costs suggesting that they are a more important source of revenue for GPs than other specializations.²⁸ However, the share of dispensing physicians varies greatly between specialties as illustrated in Table 7, which shows the share of SD physicians active in Zürich and Winterthur by specialization for the year 2012: As evident from the table, the top 3 dispensing shares can be found among rheumatologists (65%), gynecologists (54.8%) and gastroenterologists (52.4%). Moreover, about half of the the primary care providers prescribe and sell drugs directly to their patients.

To empirically address potential effect heterogeneity by specialization, we re-estimate the balanced DID specifications within the sub-samples of GPs and specialists with low and high SD-shares separately.²⁹ We classify surgeons, psychiatrists, cardiologists and ophthalmologists into the group of medical specialties with low SD-shares as they show a significantly lower likelihood to dispense than GPs.³⁰ All other medical disciplines with a similar propensity to dispense as the GPs are also grouped together (“High SD specialists”). The result of this subgroup analysis can be found in Table 8.

— TABLE 8 —

Overall, we find empirical support for the key takeaways from the main analysis. The subgroup analysis shows that physicians of different medical specialties indeed show a significant response to dispensing. In particular, primary care providers and specialists with a high SD-share tend to react most strongly to dispensing: drug expenditures are significantly increased by 12% (GPs) and 17% (High SD Specialists) in 2012 and up to 30% in 2014. In contrast, the analysis provides no evidence for an increase in drug costs among specialists with a low SD-share. Typically, medication is of less importance for these specialties (e.g. surgery) and drug expenditures account for a comparably small fraction of the health care costs they cause.³¹ In addition, the increase in drug costs goes hand in hand with the package effect as both GPs and high SD-share specialties tend to increase the number of prescribed packages as a response to dispensing. Our estimates

²⁷Risk-adjustment involves controls for chronic disease (PCGs), age structure and insurance setting (deductible, health insurance model) of patients. Results are available upon request.

²⁸Drug expenditures amount to 47% of total costs for GPs and 28% for specialists.

²⁹Note that we estimate the entropy balancing weights separately within each group of physicians.

³⁰Estimates based on a linear probability model using the SD status of a physician as the outcome variable while controlling for patient- and physician characteristics, show a significantly lower dispensing probability for those groups of specialists (reference group: GPs).

³¹On average, the share of drug costs in percentage of total health care costs amounts to 24% among low SD-share specialties; 32% among high SD-share physicians and 47% among primary care providers.

indicate that primary care providers show the strongest package response which again could be rationalized by the financial importance of medication for them.

8 Robustness Checks

In this section, we provide several robustness checks based on alternative control group definitions and sample construction schemes. First, concerns about the validity of the chosen control group are addressed by demonstrating robustness of our findings to an alternative definition of the control group by exclusively focusing on physicians active in the cities of Zürich/Winterthur. Second, we check robustness of our estimates to restrictions placed on the minimum number of patients per physician imposed in the main analysis.

8.1 Alternative Control Group

There may be concerns about the validity of the donor pool of control units in the main analysis, where the control group consisted of physicians active in the cities of Zurich/Winterthur and Basel-Stadt. While the chosen identification strategy should ensure that the treated and control units are comparable along both observable patient- and provider characteristics and time-invariant unobservables, it may be argued that physicians active in Basel-Stadt differ from their colleagues in Zurich/Winterthur in unobserved dimensions not captured by our specification. We address this concern by excluding physicians from Basel-Stadt from the control group. The corresponding estimates can be found in Table A2 in the Appendix. Sample size is reduced by more than 25% compared to the main analysis leading to slightly larger standard errors of the estimated treatment effects. The estimated dispensing effects are comparable to the main results, so the composition of the control group does affect our main conclusions.

8.2 Minimum Number of Patients

As described in the data section, the sample used in the main analysis is restricted to physicians with a minimum of 10 patients per year. To demonstrate that our results are not driven by the corresponding restriction, we drop the restriction and re-estimate the model for all outcomes increasing the sample size by roughly 25%.³² Table A3 in the Appendix shows that the estimated effects of dispensing are not sensitive to the patient number restriction.

³²The number of physicians in the estimation sample is increased from 1,255 to 1,584.

9 Conclusion

This paper empirically examines the "perfect agent" hypothesis by analyzing the impact of financial incentives on the medical decisions of physicians. The granularity in the physician, patient- and product-level claims data we use in the analysis, allows us to paint a detailed picture about the question whether physicians adjust their prescription decisions as a response to financial rewards and the channels that drive the observed changes in drug prescribing. In contrast to previous work (e.g. Kaiser and Schmid, 2016; Rischatsch, 2014; Iizuka, 2012, 2007, Liu et al., 2009), our analysis is based on a quasi-experimental setup that enables us to bring forward causal evidence and we furthermore study an aspect that has received surprisingly little attention: the role of rent-seeking behavior among physicians.

Our results provide evidence against the "perfect agent" hypothesis as we find that monetary incentives systematically influences the prescription decisions of physicians. In particular, we show that dispensing leads to significantly higher drug costs per patient as physicians tend to adapt their behavior through two channels: *a*) they prescribe higher numbers of packages to their patients coinciding with a package size channel and *b*) within an active substance, drugs with higher markups are more likely prescribed to patients indicating a cherry-picking response. Reassuringly, we find that physicians neither adjust their dosage-decision nor do they medicate larger fractions of their patient pool. Yet, we find that physicians systematically engage in rent-seeking behavior resulting in avoidable costs for the health care system and inefficient resource use.

A recent report by the OECD identifies major inefficiencies in current medical practice and claims that up to one-fifth of world's health spending is wasteful (OECD, 2017). Experts argue that sizeable numbers of patients receive inappropriate or ineffective care that make little to no difference to their health including – for instance – the excessive use of imaging services in case of lower back pain or unnecessary surgical interventions such as knee arthroscopy for osteoarthritis (Hurley, 2014). From a societal perspective, physicians should tailor care to the needs of the individual and choose the type and quantity of medical services that maximize patient benefit at the lowest possible cost (Johnson, 2014). Although our analysis shows that physicians seem to base their dosage decision entirely on patient needs, physicians seem to exploit dispensing to generate extra income. This behavior contributes to the proclaimed inefficiencies in the health care sector as the same "treatment quality" could have been achieved at lower costs. In other words, we observe a classic case of rent-seeking.

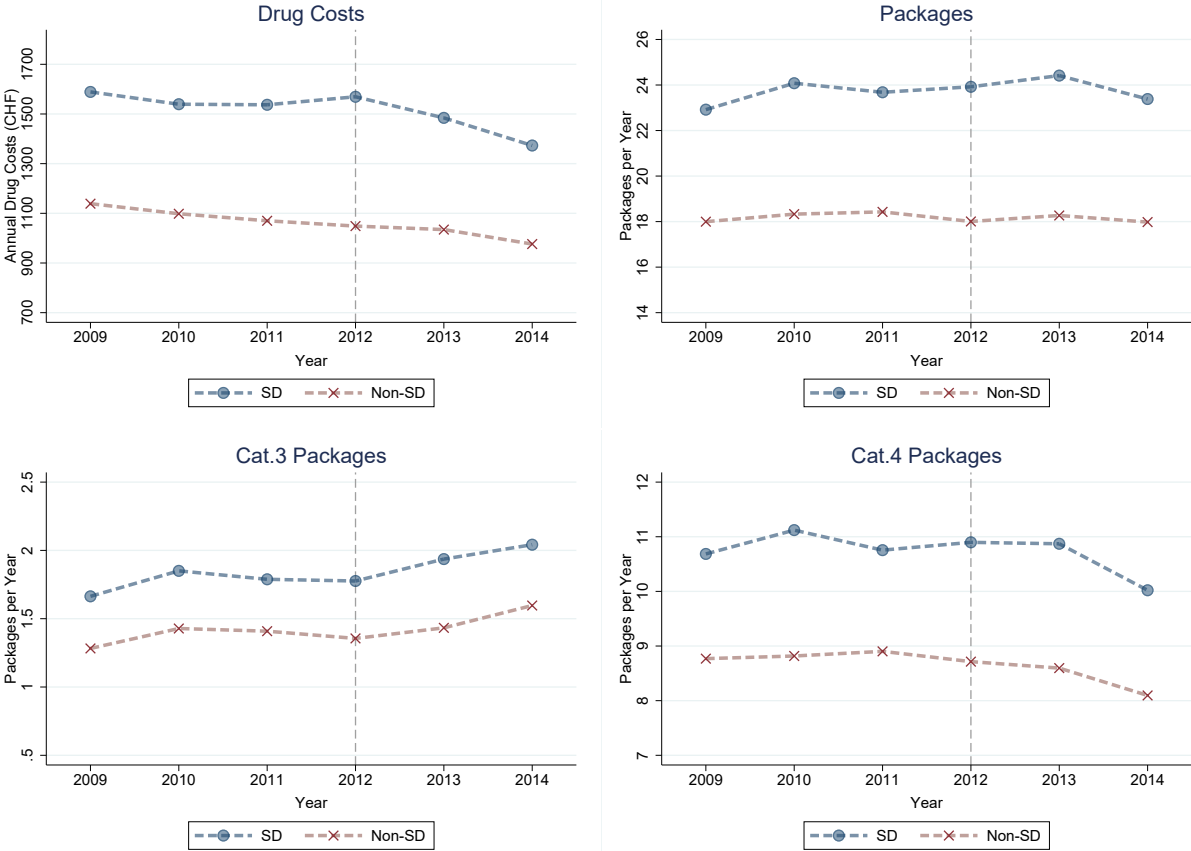
10 References

- ABADIE, A. (2005): “Semiparametric difference-in-differences estimators,” *The Review of Economic Studies*, 72, 1–19.
- BURKHARD, D., C. SCHMID, AND K. WÜTHRICH (2019): “Financial incentives and physician prescription behavior: Evidence from dispensing regulations,” *Health Economics*, 28.
- CHOU, Y., W. C. YIP, C.-H. LEE, N. HUANG, Y.-P. SUN, AND H.-J. CHANG (2003): “Impact of Separation Drug Prescribing and Dispensing on Provider Behaviour: Taiwan’s Experience,” *Health Policy and Planning*, 18, 316–329.
- ELLIS, R. P. AND T. G. MCGUIRE (1986): “Provider behavior under prospective reimbursement: Cost sharing and supply,” *Journal of Health Economics*, 5, 129–151.
- HAINMUELLER, J. (2012): “Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies,” *Political Analysis*, 20, 25–46.
- HO, D. E., K. IMAI, G. KING, AND E. A. STUART (2007): “Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference,” *Political analysis*, 15, 199–236.
- HUNKELER, J. (2008): “SL-Logistikmarge: Probleme und Reformansätze im SD-Markt,” Tech. rep., Eidgenössisches Volkswirtschaftsdepartement, Preisüberwachung, Bern.
- HURLEY, R. (2014): “Can doctors reduce harmful medical overuse worldwide?” *British Medical Journal*, 349, g4289.
- IIZUKA, T. (2007): “Experts’ Agency Problems: Evidence from the Prescription Drug Market in Japan,” *RAND Journal of Economics*, 38, 844–862.
- (2012): “Physician Agency and Adoption of Generic Pharmaceuticals,” *The American Economic Review*, 102, 2826–2858.
- JOHNSON, E. M. (2014): “Physician-Induced Demand,” *Volume 3 of Encyclopedia of Health Economics*.
- KAISER, B. AND C. SCHMID (2016): “Does physician dispensing increase drug expenditures? Empirical evidence from Switzerland,” *Health economics*, 25, 71–90.
- LIU, Y.-M., Y.-H. K. YANG, AND C.-R. HSIEH (2009): “Financial incentives and physicians’ prescription decisions on the choice between brand-name and generic drugs: Evidence from Taiwan,” *Journal of Health Economics*, 28, 341–349.

- McGUIRE, T. G. (2000): “Physician Agency,” *Handbook of Health Economics*, 1, 461–536.
- (2011): “Physician agency and payment for primary medical care,” in *The Oxford handbook of health economics*.
- OECD (2017): “Tackling Wasteful Spending on Health,” Available at <https://doi.org/10.1787/9789264266414-en>.
- (2018): “Health spending,” *doi: 10.1787/8643de7e-en* (Accessed on February 2020).
- PAULY, M. (1980): “Doctors and Their Workshops: Economic Models of Physician Behavior,” University of Chicago Press, 119–122.
- RISCHATSCH, M. (2014): “Lead me not into temptation: drug price regulation and dispensing physicians in Switzerland,” *The European Journal of Health Economics*, 15, 697–708.
- RISCHATSCH, M., M. TROTTMANN, AND P. ZWEIFEL (2013): “Generic substitution, financial interests, and imperfect agency,” *International Journal of Health Care Finance and Economics*, 13, 115–138.
- SCHMID, C. P., K. BECK, AND L. KAUER (2018): “Health Plan Payment in Switzerland,” in *Risk Adjustment, Risk Sharing and Premium Regulation in Health Insurance Markets: Theory and Practice*, ed. by T. G. McGuire and R. C. van Kleerf, Academic Press (Elsevier), chap. 16, 453–489.
- TROTTMANN, M., M. FRUEH, H. TELSER, AND O. REICH (2016): “Physician drug dispensing in Switzerland: association on health care expenditures and utilization,” *BMC health services research*, 16, 238.

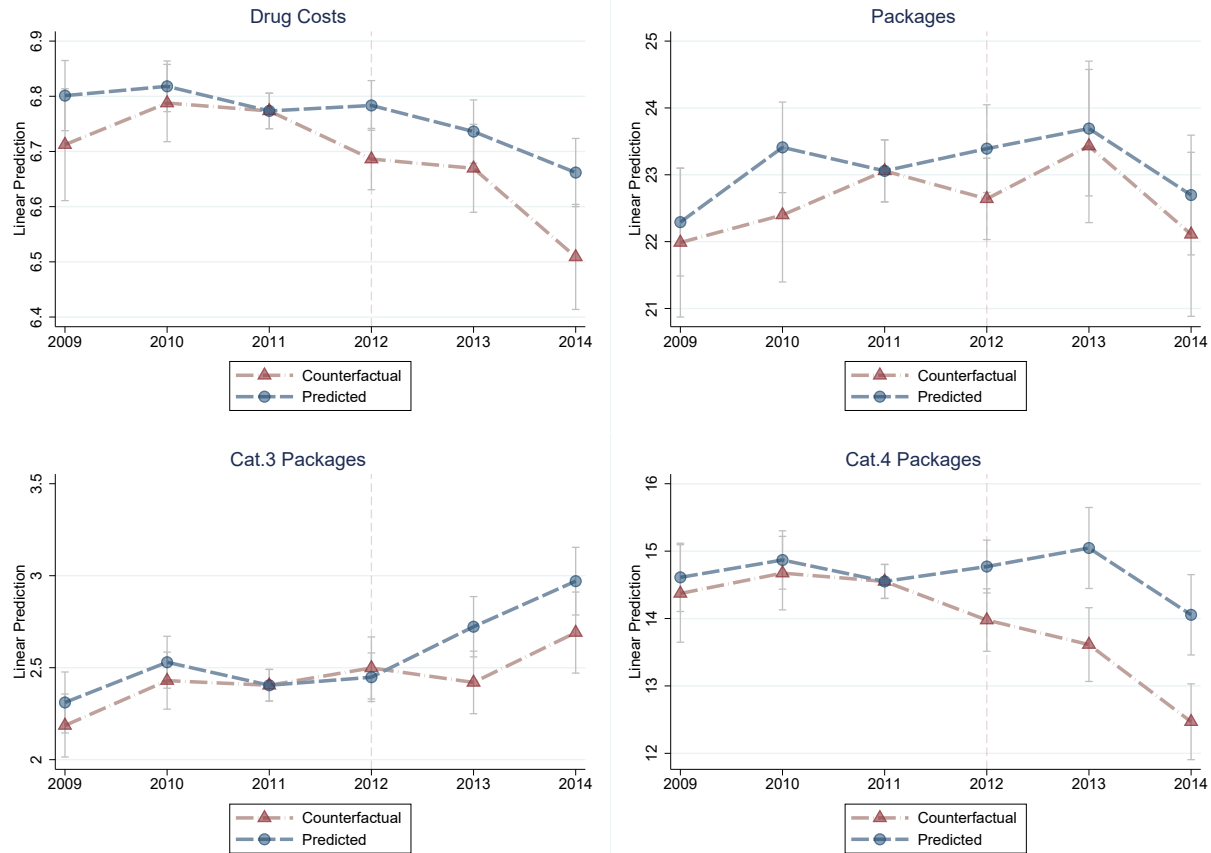
Figures

Figure 1: Development of Prescription Behavior:
Dispensing vs. Non-Dispensing Physicians



Notes: The graph shows the development of annual average drug expenditures and prescription volumes per patient for self-dispensing (SD) and non-SD physicians before and after the regime-change in 2012.

Figure 2: Counterfactual Plots



Notes: The graph shows the predicted development of the drug costs (in logs) and prescription volumes (blue lines) alongside the counterfactual trajectories (red lines). The estimates of the predictions and counterfactuals are based on the balanced DID estimates from table 4.

Tables

Table 1: Pharmaceutical Price Setting

Category	Ex-factory price (CHF)	Additional fee (%)	Additional fee (CHF)	Retail price (CHF)
1	0.05-4.99	12%	4.00	4.06-9.59
2	5.00-10.99	12%	8.00	13.60-20.31
3	11.00-14.99	12%	12.00	24.32-28.79
4	15.00-879.99	12%	16.00	32.80-1001.59
5	880.00-2569.99	7%	60.00	1001.60-2809.89
6	>2570.00	0%	240.00	>2810.00

Notes: The table shows how prices are determined for different drug categories (1-6).

Table 2: Pre-Treatment Summary Statistics

	<i>Dispensing Docs</i>		<i>Non-Dispensing Docs</i>	
	Mean	STD	Mean	STD
<i>Provider Information</i>				
General Practitioner (%)	0.41	-	0.24	-
Men (%)	0.68	0.47	0.66	0.47
Years of Experience	13.88	7.84	17.34	9.13
<i>Patient Structure</i>				
Doctor Visits	9.91	8.49	11.71	11.42
Men (%)	0.33	0.21	0.35	0.27
German Speaking (%)	0.97	0.07	0.97	0.10
Patient Age	51.63	15.94	51.33	15.96
Medicated (% of patients)	0.70	0.20	0.63	0.25
<i>Plan Choice</i>				
Deductible	524.61	231.29	523.85	260.47
Annual Premium	3470.96	864.86	3615.42	940.80
Standard Model (% of patients)	0.67	0.22	0.72	0.23
PPO (% of patients)	0.17	0.15	0.18	0.18
Telmed (% of patients)	0.00	0.00	0.00	0.00
HMO (% of patients)	0.16	0.20	0.11	0.18
<i>Cost Categories</i>				
Total Costs	3558.00	3303.95	3630.34	3252.01
Drug Costs	1433.46	2715.38	1016.16	2096.27
Physician Costs	1624.47	1384.86	2251.51	2392.60
Markup	364.56	357.93	269.78	301.59
<i>Volumes</i>				
Packages	22.05	13.82	16.27	15.28
Cat. 3 Packages	1.66	1.47	1.22	1.67
Cat. 4 Packages	9.95	7.47	7.87	8.20
Number of Observations	465		1,901	

Notes: The table shows summary statistics for the pre-treatment year 2011 stratified by the future dispensing status of physicians active in Zürich/Winterthur and Basel-Stadt. Cost and volume indicators are reported by patient and year. Costs categories, premiums and deductibles are measured in Swiss Francs.

Table 3: The Effects of Dispensing at the Extensive Margin

Dispensing Effects: Extensive Margin			
Outcome	P(Packages>0)	P(Cat.3 Packages>0)	P(Cat.4 Packages>0)
Dispensing Physician ₂₀₁₂	0.00 (0.00)	-0.01 (0.01)	-0.01* (0.01)
Dispensing Physician ₂₀₁₃	0.00** (0.00)	-0.00 (0.01)	0.00 (0.01)
Dispensing Physician ₂₀₁₄	0.00* (0.00)	0.00 (0.01)	0.01 (0.01)
Number of Patients	8,753	8,753	8,753
Number of Observations	172,284	172,284	172,284

Notes: The table shows the fixed effects estimates of the impact of being exposed to a dispensing physician ($Dispensing_t = 1$ if visiting a dispensing physician in year t) on the likelihood of leaving the doctors office with a positive quantity of drugs using patient-level data for the cities of Zurich and Winterthur. All specifications include patient and year fixed effects as well as time-varying patient (age, deductible, insurance model and indicators for chronic conditions) and physician characteristics (years of experience, GP). Standard errors clustered at the patient level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 4: The Effects of Dispensing:
Balanced DID Estimates

Dispensing Effects				
Outcome	Drug Costs	Packages	Cat.3 Packages	Cat.4 Packages
ρ_{2012}	0.09** (0.04)	0.74 (0.49)	-0.09 (0.10)	0.58** (0.26)
ρ_{2013}	0.07 (0.06)	0.16 (0.90)	0.04 (0.11)	0.52 (0.37)
ρ_{2014}	0.15** (0.07)	0.59 (0.92)	0.01 (0.13)	0.63* (0.37)
p -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.56	0.31	0.49	0.52
Number of Observations	7,496	7,496	7,496	7,496
Number of Physicians	1,255	1,255	1,255	1,255

Notes: The table shows the balanced DID estimates of the impact of dispensing on annual drug expenditures (in logs), number of packages and number of category 3 and 4 packages per patient based on a fully balanced panel of physicians observed between 2009-2014. Entropy balancing was used in the first step to balance covariate distributions between dispensing and non-dispensing physicians one year prior to the policy change. The corresponding weights are subsequently used in the DID estimation. All regressions include physician fixed effects, year fixed effects, and patient pool characteristics. Standard errors clustered at the provider level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 5: The Effects of Dispensing for Drugs with observed normalized prescribed usage (in terms of DDD)

Outcome	Drug Costs	Packages	Cat.3 Packages	Cat.4 Packages	Norm. Daily Usage
ρ_{2012}	0.04 (0.04)	1.05 (0.93)	-0.25* (0.14)	0.67 (0.57)	-20.33 (24.51)
ρ_{2013}	0.09 (0.07)	2.69* (1.43)	0.18 (0.18)	1.83** (0.92)	1.54 (21.23)
ρ_{2014}	0.22** (0.09)	3.63** (1.38)	0.27 (0.21)	2.07** (0.83)	4.72 (34.37)
Number of Observations	5,592	5,592	5,592	5,592	5,592
Number of Physicians	932	932	932	932	932

Notes: The table shows the balanced DID estimates of the impact of dispensing based on a subsample of drugs with information on the defined daily dose (DDD). The normalized prescribed usage is defined as (number of units \times dosage of unit)/DDD. All regressions include physician fixed effects, year fixed effects, and patient pool characteristics. Standard errors clustered at the provider level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 6: Changes in Prescription Behavior for Three Major Drugs

Hypertension	Dosage	Package Size	Brand Switch	Generic Switch	Higher Markup
Dispensing Physician	0.00 (0.06)	0.68* (0.40)	0.03* (0.02)	-0.01 (0.01)	0.02** (0.00)
Baseline	6.72	98.04	17.91%	4.15%	2.16%
Observations	18,041	18,041	3,277	3,244	3,003
Reflux					
Dispensing Physician	0.23 (0.36)	1.81 (1.98)	0.06** (0.02)	-0.00 (0.00)	0.08** (0.02)
Baseline	24.82	64.49	1.83%	0.15%	1.77%
Observations	5,292	5,292	655	655	509
Antibiotic					
Dispensing Physician	5.85 (9.30)	-0.56 (0.55)	0.11* (0.06)	-0.02 (0.03)	0.15** (0.06)
Baseline	449.71	13.92	35.27%	6.28%	14.09%
Observations	10,689	10,689	478	446	285

Notes: The table shows the estimated effects of being exposed to a dispensing physician for the prescription of a major hypertension drug (Amlodipin), a reflux drug (Omeprazol) and an antibiotic (Ciprofloxacin) using patient-level claims data for the years 2009-2014. We use the following set of dependent variables: dosage is a continuous measure of the dosage in mg per package that was prescribed to patient i ; package size is a continuous measure of the number of pills per package; brand switch (=1 if another brand was prescribed between 2010-2011 (pre-period) and 2013-2014 (post-period)); generic switch (=1 if prescription changed from brand-name to generic between the pre- and post-period) and markup improvement (=1 if a drug with a higher markup was prescribed holding constant dosage and package size after the regime-change). We estimate (patient) fixed effects specifications for the continuous outcomes (dosage, package size) using patient-level clustered standard errors and linear probability models using heteroscedasticity-robust standard errors for the switching indicators (brand, generic and markup switch) using data for the post-period only as the indicators capture changes relative to the pre-period: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 7: Dispensing Status by Specialization

Specialization	Self-Dispensing		
	No	Yes	Total
General Practitioners	176	176	352
	50.0%	50.0%	100.0%
Cardiology	21	7	28
	75.0%	25.0%	100.0%
Gynecology	38	46	84
	45.2%	54.8%	100.0%
Non-invasive: Dermatology und Venerology	17	7	24
	70.8%	29.2%	100.0%
Non-invasive: Gastroenterology	10	11	21
	47.6%	52.4%	100.0%
Non-invasive: Rheumatology	7	13	20
	35.0%	65.0%	100.0%
Non-invasive: Other	37	23	60
	61.7%	38.3%	100.0%
Paediatrics	28	18	46
	60.9%	39.1%	100.0%
Psychiatry	95	13	108
	88.0%	12.0%	100.0%
Surgery	53	17	70
	75.7%	24.3%	100.0%
Ophthalmology	39	11	50
	78.0%	22.0%	100.0%
Other	32	21	53
	60.4%	39.6%	100.0%

Notes: The table shows the share of dispensing physicians per specialization active in the cities of Zurich and Winterthur for the year 2012.

Table 8: Dispensing Effects by Specialization

SD effects												
Outcome Variable Specialization	ln(Drug Costs)			Packages			Cat.3 Packages			Cat.4 Packages		
	GPs	High SD Specialists	Low SD Specialists	GPs	High SD Specialists	Low SD Specialists	GPs	High SD Specialists	Low SD Specialists	GPs	High SD Specialists	Low SD Specialists
ρ_{2012}	0.12** (0.05)	0.17* (0.09)	-0.00 (0.14)	0.73 (1.33)	-0.53 (0.98)	0.19 (1.68)	-0.12 (0.21)	-0.15 (0.20)	0.23 (0.34)	0.37 (0.76)	0.33 (0.71)	1.38* (0.81)
ρ_{2013}	0.12 (0.08)	0.21 (0.14)	-0.12 (0.14)	3.87** (1.78)	0.19 (1.35)	-0.81 (1.81)	0.04 (0.21)	0.10 (0.30)	1.17** (0.35)	1.03 (0.86)	0.34 (0.93)	0.56 (0.93)
ρ_{2014}	0.28** (0.09)	0.30** (0.12)	0.25 (0.16)	5.57** (1.88)	2.46** (1.16)	-0.45 (2.18)	-0.05 (0.25)	0.49 (0.33)	0.85* (0.44)	2.88** (0.85)	1.07 (0.77)	0.22 (1.05)
p -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.55	0.72	0.61	0.85	0.57	0.66	0.06	0.07	0.37	0.75	0.70	0.91
Number of Observations	2,536	1,166	1,912	2,536	1,166	1,912	2,536	1,166	1,912	2,536	1,166	1,912
Number of Physicians	433	197	356	433	197	356	433	197	356	433	197	356

Notes: The table shows the balanced DID estimates of the impact of dispensing separately among GPs and specializations with low or high SD-shares. Specializations with low SD-shares comprise of surgeons, psychiatrists, cardiologists and ophthalmologists. Other specializations with a comparably high SD share as the GPs are grouped together (High SD specialists). Entropy balancing was used in the first step to balance covariate distributions in 2011 for each group of physicians separately. The corresponding weights were then used in the second step in the DID estimation. All regressions include physician fixed effects, year fixed effects, and patient pool characteristics. Standard errors clustered at the provider level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Appendix

Table A1: Entropy Balancing

	Before Balancing				After Balancing			
	SD Physicians		Non-SD Physicians		SD Physicians		Non-SD Physicians	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
<i>Lagged Outcomes</i>								
Total Costs	3600.50	10655559.08	3594.87	5695067.04	3600.50	10655559.08	3606.89	8264963.34
Drug Costs	1518.84	7208883.28	1112.67	1415136.83	1518.84	7208883.28	1522.97	5319735.25
Cond. Drug Costs	2127.13	13492694.73	1628.99	2642957.58	2127.13	13492694.73	2136.41	8185890.28
<i>Provider Characteristics</i>								
General Practitioner (GP)	0.44	0.25	0.32	0.22	0.44	0.25	0.44	0.25
Share of Men (%)	0.70	0.21	0.70	0.21	0.70	0.21	0.70	0.21
Years of Experience	14.71	51.36	17.85	64.07	14.71	51.36	14.71	49.12
<i>Patient Characteristics</i>								
Share of Men (%)	0.32	0.03	0.35	0.04	0.32	0.03	0.32	0.03
Share German Speaking (%)	0.98	0.00	0.97	0.00	0.98	0.00	0.98	0.00
Age of Patients	52.63	240.22	53.76	251.69	52.63	240.22	52.63	324.39
PCG1	0.08	0.01	0.08	0.01	0.08	0.01	0.08	0.01
PCG2	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00
PCG3	0.08	0.01	0.07	0.01	0.08	0.01	0.08	0.01
PCG4	0.05	0.01	0.05	0.01	0.05	0.01	0.05	0.01
PCG5	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG6	0.20	0.02	0.19	0.02	0.20	0.02	0.20	0.02
PCG7	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG8	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PCG10	0.05	0.01	0.04	0.01	0.05	0.01	0.05	0.01
PCG11	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG12	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00
PCG13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PCG14	0.04	0.00	0.05	0.01	0.04	0.00	0.04	0.00
PCG15	0.09	0.01	0.10	0.01	0.09	0.01	0.09	0.01
PCG16	0.06	0.00	0.07	0.01	0.06	0.00	0.06	0.01
PCG17	0.07	0.01	0.07	0.01	0.07	0.01	0.07	0.01
PCG18	0.05	0.00	0.04	0.00	0.05	0.00	0.05	0.01
PCG19	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00
PCG20	0.15	0.02	0.19	0.03	0.15	0.02	0.15	0.02
PCG21	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00
PCG22	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG23	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
PCG24	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG25	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
PCG26	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00
<i>Plan Choice</i>								
Deductible (CHF)	519.41	34565.27	538.19	40467.24	519.41	34565.27	519.41	46636.42
Premium (CHF)	313.29	4490.00	334.24	5582.86	313.29	4490.00	313.29	7101.89
Standard Model (%)	0.67	0.04	0.72	0.03	0.67	0.04	0.67	0.04
PPO (%)	0.17	0.01	0.18	0.01	0.17	0.01	0.17	0.01
HMO (%)	0.16	0.04	0.10	0.02	0.16	0.04	0.16	0.04

Notes: The table shows the balancing of pre-treatment patient and provider characteristics before and after applying entropy balancing for the year 2011. The sample contains physicians active in Zurich/Winterthur and Basel-Stadt.

Table A2: The Effects of Dispensing:
Alternative Control Group

Dispensing Effects				
Outcome	Drug Costs	Packages	Cat.3 Packages	Cat.4 Packages
ρ_{2012}	0.09** (0.05)	0.98 (0.63)	-0.10 (0.10)	0.68* (0.38)
ρ_{2013}	0.07 (0.06)	0.42 (1.01)	0.11 (0.11)	0.58 (0.47)
ρ_{2014}	0.18** (0.07)	1.27 (0.97)	0.14 (0.13)	0.72* (0.40)
p -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.60	0.82	0.57	0.92
Number of Observations	5,555	5,555	5,555	5,555
Number of Physicians	931	931	931	931

Notes: In comparison to the main results in Table 4, the table shows the balancing and DID estimates when exclusively using physicians practicing in Zurich and Winterthur. Specifically, the control group no longer contains physicians active in Basel-Stadt as in the main analysis. All regressions include physician fixed effects, year fixed effects, and patient pool characteristics. Standard errors clustered at the provider level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A3: The Effects of Dispensing:
Relaxation of Restriction on Number of Patients

Dispensing Effects				
Outcome	Drug Costs	Packages	Cat.3 Packages	Cat.4 Packages
ρ_{2012}	0.08 (0.05)	0.94 (0.68)	0.06 (0.12)	0.72** (0.36)
ρ_{2013}	0.09 (0.07)	0.85 (0.85)	0.14 (0.12)	0.75* (0.42)
ρ_{2014}	0.14** (0.07)	0.95 (0.84)	0.09 (0.14)	0.83** (0.41)
p -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.60	0.82	0.59	0.78
Number of Observations	9,348	9,348	9,348	9,348
Number of Physicians	1,584	1,584	1,584	1,584

Notes: In comparison to the main findings in Table 4, no sample restriction on the annual minimum number of patients is imposed when estimating the balanced DID specifications. Standard errors clustered at the provider level in parentheses: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A4: Price and Markup for 30-day Treatment

		Brand		Generic(s)	
		Net. costs	Markup	Net. costs	Markup
Amlodipinum	30 (5mg)	12.46	14.14	10.69	9.77
	100 (5mg)	11.62	6.64	8.31	6.14
	30 (10mg)	10.53	9.75	7.41	7.65
	100 (10mg)	10.20	3.97	8.01	3.64
Ciprofloxacinum	6 (250mg)	183.22	190.78	163.60	187.40
	10 (250mg)	171.19	172.61	145.44	168.84
	20 (250mg)	146.56	119.84	118.86	115.86
	10 (500mg)	140.27	118.93	108.28	114.26
	20 (500mg)	134.13	69.12	110.82	65.64
	20 (750mg)	119.47	50.53	107.11	48.65
Omeprazolium	14 (10mg)	40.66	41.20	46.84	53.66
	28 (10mg)	35.88	40.41	42.34	39.19
	56 (10mg)	35.60	22.85	41.86	23.75
	98 (10mg)			34.77	15.18
	100 (10mg)	36.47	15.22	28.10	13.99
	7 (20mg)			35.84	40.39
	14 (20mg)	33.10	40.08	28.42	30.51
	28 (20mg)	31.80	22.25	29.14	21.86
	56 (20mg)	31.22	13.40	29.72	13.18
	98 (20mg)			26.74	8.98
	100 (20mg)	31.25	9.55	26.32	8.81
	7 (40mg)			23.28	23.19
	28 (40mg)	28.78	13.06	21.44	11.95
	56 (40mg)			19.03	7.21

Notes: The table presents costs and markups in Swiss francs for a 30-day treatment in terms of defined daily doses (i.e. 30 DDD); for generics, we report averages over all available products. The net. costs reflect the number of packages times the ex-factory price; the markup is given by the difference between the retail price and the ex-factory price, which is then also multiplied by the number of packages needed for 30 DDD. Price information is as of May 1st 2012.