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# Rents for Pills: Financial Incentives and Physician Behavior

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## Abstract

We study the impact of financial incentives on the prescription behavior of physicians based on a natural experiment that resulted from a recent reform in two large Swiss cities. The reform opened up an additional income channel for physician by allowing them to earn a markup on drugs they prescribe to their patients. We find that the reform leads to an increase in drug costs by about +\$20 per patient translating to significantly higher physician earnings (+\$30). We show that the revenue increase can be decomposed into a substitution and rent-seeking component. Our analysis indicates that physicians engage in rent-seeking by substituting larger with smaller packages and by cherry-picking more profitable brands. Although patient health is not sacrificed, the rent-seeking behavior results in unnecessary costs for society.

*JEL Classification:* D01, C21, I11

*Keywords:* Financial incentives, rent-seeking, prescription behavior, health care costs

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# 1 Introduction

Health economics has a long history of analyzing physician induced demand and agency issues, both theoretically and empirically. A broad consensus exists in the field that fee-for-service reimbursement systems lead to overuse of medical services (see e.g. Gottschalk et al., 2020; Johnson, 2014; McGuire, 2011, 2000, for surveys of the literature). Physicians, the rationale goes, are able to provide care beyond clinically optimal levels and patient preferences because patients lack medical expertise. In an ideal world, physicians would act as “perfect agents” for their patients and simply assist them 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). In the real world, however, physicians need to balance private interests (e.g., income goals) and patient welfare (Ellis and McGuire, 1986). Reimbursement systems that financially reward the quantity of care might therefore distort treatment decisions as some physicians may be willing to trade-off patient benefits for a higher income. Whether physicians actually engage in such behavior ultimately remains an empirical question.

Previous work typically exploits changes in physician fees to analyze the doctors’ responses to financial incentives (see e.g. Clemens and Gottlieb, 2014; Jacobson et al., 2010; Gruber et al., 1999; Yip, 1998; Nguyen and Derrick, 1997). The more recent study by Clemens and Gottlieb (2014), for example, examines the consolidation of geographic regions through Medicare in the late 1990s and provides evidence for the presence of substitution effects. Physicians tend to shift quantities from areas that experience fee reductions to services with fee increases to compensate for income losses. Allowing physicians to earn money by selling drugs through their in-house pharmacy to patients - the setting we study in this paper - is equivalent to a fee increase providing an incentive to increase the supply of drugs. Our setting, however, differs from previous studies as physicians may profit from the fee increase even without changing treatment decisions. In case of pharmaceutical prescribing, physicians often face the choice among several product alternatives for a particular diagnosis that provide identical medical benefits to patients but may differ in the financial reward to the physician. To illustrate, the high-market share hypertension drug “Amlodipin” is sold by seven different drug companies. Although the active ingredient is identical between suppliers, the markup differs not only between the brand-name product and the generics but also between generics. Therefore, physicians may increase their income by prescribing more expensive “brands” without sacrificing patient health at all. Engaging in such behavior is a textbook example of rent-seeking behavior: physicians extract a bigger piece of the pie without increasing medical productivity.

In this paper we analyze whether physicians engage in such rent-seeking behavior by exploiting a recent reform in two large Swiss cities. The reform allowed physicians to sell drugs to their patients (through so-called “physician dispensing”) and opened up an additional

income channel to them: while only pharmacies earned a markup on drugs before the reform, these markups are now pocketed by the physicians themselves. So even in the absence of behavioral changes, physicians' earnings are increased by the substitution of markups from pharmacies to physicians. Besides pure substitution, the changes in the incentive structure might also trigger behavioral changes. First, physicians might choose to prescribe more drugs, potentially sacrificing patient benefits to some extent. This could be both at the extensive (more patients are medicated) or at the intensive margin (patients already treated with medication receive more drugs). On the other hand, they might prescribe more profitable brands without changing the treatment, which would impose additional costs on the patients and the health care system without generating improvements in the treatment quality.

Unlike previous work on drug dispensing (see below), we are able to exploit the variation created by a natural experiment that divides patients into a treatment (having a dispensing physician) and a control group (having a non-dispensing physician). Since dispensing physicians systematically differ in attributes like practice style, adherence to medical guidelines and costs per patient from their non-dispensing counterparts, we do not base identification on direct group comparisons. Instead, we make use of a special feature in our data: We observe the interaction between patients and physicians both before and after the reform and see the drugs that doctors prescribe to their patients. Specifically, the data offers information on the number of packages, the markups, the costs and the price category of drugs physicians prescribe to the same patients before and after the introduction of dispensing. This data structure has the advantage that we are able to directly address selection biases as we are able to condition on existing physician-patient relationships. For a selection of high market share hypertension and reflux drugs and an antibiotic, we further observe the substance class, the drug brand (e.g., generics or brand-name), the dosage, and the number of pills on each prescription. As a stylized example, suppose Patient A suffers from hypertension and is regularly prescribed the 4-month package (120 pills) of the generic drug "Amlodipin" in the years before the reform. After the reform, Patient A still receives the same active ingredient, but now in the form of two 2-month packages (60 pills) from "Norvasc", the brand-name drug. Given the current drug price regulation in Switzerland, such a switch is profitable for self-dispensing physicians. For this subset of drugs, we are able to precisely track such changes in physician prescription decisions.

To estimate the effects of dispensing, we apply a two-step procedure that combines balancing with difference-in-difference estimation. Specifically, we apply entropy balancing to derive sampling weights that balance the distributions of both pre-treatment outcomes and covariates between patients with and without dispensing physicians. The balancing step makes the common trends assumption more credible. Based on the re-weighted data, we then estimate difference-in-differences models that include physician-patient interaction

fixed effects and a rich set of patient characteristics (e.g. age, comorbidities, insurance choice, deductibles).

Our paper contributes 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 three dimensions from prior work. *First*, the majority of studies does not attempt to estimate the causal effect of dispensing and instead reports 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 the corresponding findings may be biased due to measurement error (e.g. Trottmann et al., 2016). *Second*, the studies asking the causal question impose rather strong identifying assumptions<sup>1</sup> and thus the results might be biased due to differences in unobservables. In contrast, as described we explicitly address such selection issues. *Third*, we extend the analysis by analyzing possible channels through which physicians adapt their prescription behavior in response to dispensing.

Our analysis yields four main results: *First*, we find that dispensing leads to a significant increase in drug costs of about CHF 20 (+4%) per patient and year. This finding implies a behavioral response of physicians as we would not observe an effect on total drug costs if physicians simply dispensed the drugs for which they previously wrote prescriptions to be filled at pharmacies. *Second*, we provide evidence that dispensing results in an increase in physician earnings by approximately CHF 30 per patient. We show that the increase in earnings is composed of a substitution and a rent-seeking component. The latter is the result of a behavioral response and we estimate it to be around one third of the revenue increase. *Third*, we explore possible channels through which the behavioral response we observe may operate. Our analysis is indicative that two channels drive our main findings: a) physicians substitute larger with smaller packages because the current price regulation of pharmaceuticals generates higher markups per pill for smaller package sizes. Our analysis is compatible with such a “package size channel” as significantly more packages are prescribed to patients of dispensing physicians while simultaneously we find no evidence for a dosage change among the same patients; b) physicians prescribe more profitable drugs to patients (the “cherry-picking channel”) as also documented by Iizuka (2012). *Fourth*, we provide evidence for considerable effect heterogeneity. We show that dispensing unilaterally affects the behavior of classic fee-for-service physicians while HMO physicians do not respond to

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<sup>1</sup>For 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”.

dispensing. Furthermore, our analysis suggests that dispensing physicians “target” less price sensitive patients with low deductibles as we solely find effects in this patient segment (i.e., no effect for higher deductible groups).

Overall, our analysis provides evidence that profit motives indeed influence the prescription decisions of physicians. However, we do not find evidence for physicians trading-off patient benefits for profits, a result regularly found in the previous agency literature. Instead, our results indicate that physicians act in the patients’ best medical interest - they do not unnecessarily expand medication or alter dosage decisions - but at the same time, at least some of them also do not shy away from “playing the system” and earn some extra dollars. Hence, even if physicians do not seem to be willing to trade in patient health for profit, they engage in rent-seeking behavior 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 amount to about 15-20% of total health care spending across the OECD in 2017. Switzerland and the US and have the highest drug expenditures per capita in the world with more than \$1,000 (OECD, 2018). In light of this, the question arises whether it is a smart idea to expose physicians to additional monetary incentives. This paper gives a clear answer to this question. Our analysis suggest that efficiency gains can simply be achieved by eliminating the counterproductive financial incentives introduced by dispensing. Whether these low-hanging fruits are “harvested”, however, lies in the hands of policy makers.

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, provide evidence on the different underlying behavioral channels, and analyze potential effect heterogeneity. Section 7 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.<sup>2</sup> 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.<sup>3</sup> As a result, there are roughly three categories: prohibition of self-dispensation, self-dispensation in areas with few pharmacies, and unrestricted self-dispensation (see 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.<sup>4</sup>

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.<sup>5</sup> 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 30<sup>th</sup>, 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.<sup>6</sup> With its final decision on April 20<sup>th</sup>, 2012, physician dispensing has been permitted on May 1<sup>st</sup>, 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

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<sup>2</sup>The 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.

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

<sup>4</sup>Before 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 medical doctors are allowed to dispense drugs. In other words, the introduction of regulated competition did not alter the dispensing regulations.

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

<sup>6</sup>The relevant Federal Court decisions are 2C\_53/2009, 1C\_468/2010, 1C\_472/2010, and 2C\_158/2012.

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. TABLE A1 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. Rischatsch (2014) provides 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 of 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 pharmaceutical ingredient), the package size of these drugs, and the number of packages they sell.

— TABLE 1 —

### 3 Channels

As a starting point, we sketch four channels through which physicians may alter their prescription behavior as a response to the financial rewards inherent in dispensing. These channels are: a) the *practice style* channel, b) the *package size* channel, c) the *dosing* channel and d) the *cherry-picking* channel.

The practice style channel refers to the possibility that dispensing physicians start to favor medication over other treatment alternatives (e.g. monitoring, therapy) with the result of medicating a larger fraction of their patient pool. This would increase markup revenues of the physician leading to higher average drug costs per patient. The package size channel may be attractive because, as demonstrated by Rischatsch (2014) and illustrated in TABLE A1, the drug price regulation in Switzerland incentivizes the prescription of smaller package sizes because the combined markup on two small packages (e.g. 10 pills) is larger than the markup on one larger package (e.g. 20 pills) with the same dose. Hence, dispensing physicians might



start to substitute larger with smaller packages to increase markup revenues which would lead to higher average number of packages per patient. Next, dispensing might also induce dose adjustments because the Swiss drug price regulation also provides monetary incentives for dose reductions. The prescription of larger amounts of low-dose drugs (e.g.  $20 \times 10\text{mg}$  pills) is more profitable than a lower number of high-dose pills (e.g.  $10 \times 20\text{mg}$ ) for a fixed daily dosage (also illustrated in TABLE A1). This adjustment would also lead to an increase in the number packages. Finally, 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 their markup. Dispensing thus might induce doctors to prescribe more lucrative brand name drugs to their patients instead of generics or, if they stick to generics, pick the highest markup generic in the choice set.

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. We put these channels to the empirical test and check which of them is compatible with the physician responses we observe in the data.

## 4 Data

We have access to the individual-level claims data of a large health insurer in Switzerland (CSS Insurance) for the years 2009-2014. The insurer has an annual enrollment of roughly 1.1 million individuals in compulsory health plans (Swiss population: 8.5 million).<sup>7</sup> Our data comprises all individuals who visited a physician at least once between 2009 and 2014. Moreover, the data allows us to identify the individual physicians that were visited by patients. The special feature of our data is that we observe all physician-patient interactions that took place in the years before as well as after the reform and for each of these interactions, we have precise information on all the medical services (e.g. therapies, vaccines, imaging services, tests) and drugs that were provided. Hence, the richness of our data enables us to follow patients over time who visit a doctor that potentially starts dispensing after 2012 and changes the prescription behavior thereafter. Moreover, for each individual, we have information on the year of birth, gender, language and Swiss nationality. In addition, the data includes detailed information on patient comorbidities through so-called pharmaceutical costs groups (PCGs), which are based on the drug consumption history of patients. These indicators provide information on major chronic conditions such as diabetes, hypertension, heart diseases, depression and so on.

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<sup>7</sup>CSS Insurance held a market share of more than 16% in the basic health insurance market in 2018.

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.<sup>8</sup> 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.

Also, the data contains detailed information on the individuals' health care expenditures (i.e., different cost categories including physician costs, lab costs, drug costs, etc.) and the starting month of treatment. 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.

Finally, we enrich the existing data set with two additional data 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-patient interaction panel data set by imposing the following set of restrictions: *First*, health care providers without a "Zahlstellenregister" 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 physician-patient relationships in the cities of Zurich and Winterthur, and patients need to have at least one doctor consultation per year in four years between 2009-2014.<sup>9</sup> *Fourth*, we exclude patients in the top 1% of the drug cost distribution, which has a very long upper tail. It is difficult to fit a linear model with average effects when these observations are included. Also it seems unlikely that these

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<sup>8</sup>CSS Insurance consists of four different risk-bearing carriers: CSS, INTRAS, Arcosana, and sanagate.

<sup>9</sup>I.e. in the six years of our observation window, patients need to see one of their potentially multiple physicians at least once per year in four of the six years. Hence, we observe between four to six annual physician-patient interactions in our estimation sample.

observations are relevant for our research question because typically the very high cost drugs are not dispensed.

Imposing these sample restrictions results in an annual panel data set covering 92,792 physician-patient interactions between 1,092 (unique) physicians and 14,486 (unique) patients. Note that this is a sample of patients who see their doctor(s) quite regularly, implying that we possibly lose the more healthy patients. However, given our setup this selection seems necessary to have a cleaner identification of the behavioral effects by holding the existing patient pool fixed. Also, the population we study may be the one in which prescription decisions are most important both for patients and physicians.

## 4.1 Descriptive Statistics

FIGURE 1 shows the evolution of the share of dispensed drugs (% of total drug costs) for the patients of dispensing and non-dispensing physicians. We see that the share of dispensed drugs is slightly below 15% among (future) dispensing physicians and about 9% for non-dispensing physicians in the years 2009-2011. The reason for a positive share of dispensed drugs before the reform is that physicians in Switzerland are allowed to dispense a limited number of drugs (e.g. vaccines, emergency pain medication) even prior to the regime-change. Besides the differences in levels, the graph shows that the share of dispensed drugs diverges after the reform. This development indicates that the physicians in the dispensing group actually actively start dispensing drugs to their patients reaching a share of 25% in 2014. At the same time, no change in the share of dispensed drugs is visible among the non-dispenser physicians. <sup>10</sup>

— FIGURE 1 —

TABLE 2 displays summary statistics at the physician-patient-interaction-level for the pre-reform year 2011 stratified by the future dispensing status of the physicians. The table shows distinct differences in provider and patient attributes already before the regime-change: The share of general practitioners (GPs) is significantly higher among the future self-dispensing physicians (46% vs. 34%), the dispensing doctors are predominantly male and have more than 2 years less work experience than their non-dispensing colleagues. In addition, the patients of dispensing physicians are slightly younger, more likely female, have less comorbidities and chronic conditions.<sup>11</sup> Moreover, they choose higher deductibles and are more likely to opt for health care plans with managed care features (15% vs. 10%).

— TABLE 2 —

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<sup>10</sup>Note that this share is computed using only observations with positive drug costs.

<sup>11</sup>The data contains indicators for 26 chronic illnesses based on the types of drugs patients consume (PCGs). For the sake of brevity, we do not show the corresponding summary statistics in the table.

Despite the more favorable risk pool of patients of dispensing physicians, the annual pre-reform drug costs are about 20% higher per patient than those of non-dispensing doctors. As a consequence, the total annual markup is also significantly higher among dispensing physicians. Of course, before the reform the markups were mostly earned by pharmacies, but this number gives an indication of earnings potentials even without behavioral change. In tandem with the higher drug costs, dispensing physicians prescribe more packages to patients, both overall (12 vs. 10 packages) and within the largest category, 4, which has a market share of roughly 50%. The number of therapy days is a commonly used measure for volume and is computed as the product of the prescribed number of units (e.g., pills) and the dose (e.g., in mg) divided by the drug-specific constant defined daily dose (DDD).<sup>12</sup> Unfortunately, the DDD is not available for all drugs which reduces the sample size for the analysis of this outcome.<sup>13</sup>

FIGURE 2 depicts the evolution of average drug costs, markups, number of packages and therapy days per patient. In line with TABLE 2, the graph shows that the outcomes of patients of dispensing physicians persistently exceed the ones of patients of non-dispensing doctors both before and after the regime-change. The level differences reflect systematic differences in medical-decision making and practice style between the two types of physicians. However, the graph also shows that the outcomes have fairly similar time trends prior to the reform even unconditional on patient and provider characteristics. There is a spike in drug spending in 2012, which is also present in the raw data, although less pronounced, so our sample selection appears to amplify this spike. The high drug spending in 2012 mostly comes from the 4th quarter, which is the quarter with the largest spending in our data, exceeding the second largest spending per quarter by more than 15%. Reassuringly for our analysis, this is the case both for the control and the treatment group, so it is not driven by the reform.

— FIGURE 2 —

## 5 Identification Strategy

The main goal of this paper is to identify the causal effect of self-dispensing on physician prescription behavior. The dispensing status of physicians is not randomly assigned, but is a choice based on individual physician characteristics, part of which are observed (e.g., specialization, patient pool), while others are not (e.g., practice style, profit motives). The fact that we observe significant differences across many observable dimensions between treated

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<sup>12</sup>The DDD refers to average maintenance dose per day for a drug used for its main indication in a "standard" patient.

<sup>13</sup>For example, DDDs are not available for vaccines or anesthetics. See, e.g., [link](#) here for more details regarding DDDs.

and untreated physicians already before the reform indicates that such differences in composition indeed matter (see previous section). To address these selection issues we employ the two-step approach described below.

## 5.1 Step 1: Entropy Balancing

We apply entropy balancing to adjust the pre-treatment covariate and outcome distribution of patients of non-dispensing physicians by re-weighting observations in the control group so that the corresponding distribution is more similar to the one in the treatment group. Pre-processing the data in this manner, at the minimum, “irons out” imbalances in observable characteristics between groups.

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. standard propensity score weighting). Specifically, entropy balancing assigns a scalar weight to each control unit<sup>14</sup> such that a pre-specified set of balancing constraints on the first, second or higher moments of the covariate distributions between treated and controls are satisfied. That is, the weights  $w_i$  are chosen using the following re-weighting scheme minimizing the entropy distance metric:

$$\min_{w_i} H(w) = \sum_{i|D=0} w_i \log\left(\frac{w_i}{q_i}\right) \quad (1)$$

subject to the balancing constraints:

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

$$\sum_{i|D=0} w_i = 1 \quad (3)$$

$$w_i \geq 0 \quad (4)$$

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  $r^{\text{th}}$  moment of covariate  $x_j$  in the treatment group (e.g. mean, variance, skewness). The entropy weights that solve the above problem can directly be used to estimate the average counterfactual outcome for the dispensing physicians:

$$E(\widehat{Y_0 | D_i = 1}) = \frac{\sum_{\{i \in D_i=0\}} Y_i w_i}{\sum_{\{i \in D_i=0\}} w_i} \quad (5)$$

We apply entropy balancing to balance pre-treatment outcome and covariate distributions in each pre-reform year 2009-2011 separately and subsequently average the weights over these

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<sup>14</sup>Observations in the treatment group receive a weight of one.

years. The sampling weights are chosen such that the first and second order moments in the control group matches the values of the same moments in the group of patients with dispensing physicians. Note that the vector  $x_{ij}$  includes pre-treatment outcomes (total health care, drug, physician and other costs, number of packages (+ category 3 and 4 packages separately) and number of therapy days) which may allow to control for (time-varying) unobservables not captured by the physician-patient interaction fixed effect we include in all the regression model. TABLE A2 and FIGURE A1 in the Appendix exemplify that entropy balancing leads to identical means and variances between patients of dispensing and non-dispensing physicians in terms of both patient characteristics as well as pre-treatment outcomes.

## 5.2 Step 2: Difference-in-Differences

Next, we estimate the causal effect<sup>15</sup> of dispensing on physician prescription behavior in the re-weighted data with two-way fixed effects models of the following form:<sup>16</sup>

$$Y_{it} = \alpha_i + \lambda_t + \rho_t(\text{treat}_i \times \text{year}_t) + x'_{it}\gamma + \varepsilon_{it} \quad (6)$$

where  $Y_{it}$  is the observed prescription outcome (e.g., drug costs, markups, number of packages) for the physician-patient-pair  $i$  in year  $t$ ;  $\alpha_i$  is the physician-patient pair fixed effect, and  $\lambda_t$  are the corresponding year fixed effects.<sup>17</sup>  $\text{treat}_i$  is the binary treatment indicator which equals one in all periods if the physician in pair  $i$  becomes a dispensing physician and zero else, and  $\text{year}_t$  is a dummy equal to one in year  $t$  and zero otherwise. Under a (conditional) parallel trends assumption based on never-treated units, the parameter vector  $\rho_\tau$  recovers the possibly time-varying effects of interest (Goodman-Bacon, 2021; Callaway and Sant’Anna, 2020). We specify the year 2011 as the base period, i.e., all causal effects are measured relative to this baseline. Moreover, we include time-varying patient characteristics (age categories, 26 comorbidity indicators and indicators for the insurance model and deductible) captured in the vector  $x_{it}$ , to control for further potentially confounding factors. As the inclusion of time-varying controls may be problematic we also estimate the model without covariates (see TABLE 3).

This DiD specification offers a series of advantages: First, the model in (6) allows for varying effects of dispensing over time. This could be a relevant feature because physicians might need some time to adapt their prescription behavior in response to the financial incentives inherent in dispensing so that, e.g., the prescription of more profitable drugs

<sup>15</sup>To be precise, we estimate the average treatment effect on the treated, *ATT*.

<sup>16</sup>As explained in section 4 we do not observe a staggered adoption of the dispensing status, so the problems with TWFE raised recently by, e.g., (Goodman-Bacon, 2021; Callaway and Sant’Anna, 2020) do not arise.

<sup>17</sup>While we have monthly data we estimate annual effects because the monthly data are very 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.

might increase in the years after the regime-change as physicians first need to “optimize” their in-house pharmacy. Second, the specification allows to empirically assess the common trends assumption by estimating pre-treatment effects which should be zero. We display the corresponding tests for the pre-treatment effects in all estimation tables.

## 6 Results

We start the analysis with the discussion of the effects of dispensing on drug costs and markups (both prescribed and dispensed) (subsection 6.1). In subsection 6.2, we examine how dispensing shapes prescription behavior by studying the different channels that may explain the overall results. Next, we use detailed product-level data on two drugs with large market shares to further explore the behavioral responses that are triggered by dispensing (subsection 6.3). In the final step, we explore the effect heterogeneity by type of insurance (standard vs. managed care) and different levels of deductibles (subsection 6.4).

### 6.1 Dispensing and Financial Outcomes

TABLE 3 summarizes the estimated effects of dispensing on the annual drug costs and total markup per patient in Swiss Francs.<sup>18</sup> The estimates are based on the weighted DiD model outlined in the previous section. All specifications include patient-physician pair and year fixed effects. The even numbered columns further condition on time-varying patient covariates (indicators for chronic illnesses, age categories, deductibles and insurance model). To assess the parallel trends assumption, the table additionally shows the  $p$ -values for the null of no pre-treatment effects for the specifications with a time-varying treatment effect (columns 1-4).

— TABLE 3 —

Our estimates show that dispensing leads to a significant increase in drug costs per patient. Specifically, we find that dispensing increases the annual drug costs by 20-30 CHF or 4-5% compared to the counterfactual spending without dispensing. In other words, our estimates indicate that patients who see the same physician before and after the regime change face higher medical bills after 2011 because their physician starts to dispense. The rise in costs cannot be attributed to a deterioration in patient health as the point estimates are basically unchanged by the inclusion of patient characteristics (column 2). Moreover, the estimated effects are similar in magnitude in all post-treatment years, and we cannot reject the null of a time-constant effect. In fact, when we impose the restriction of a constant treatment effect, we find an average annual cost increase of CHF 21 per patient (column 5).

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<sup>18</sup>The USD-CHF exchange rate averaged at about 1 CHF = 1.05 USD between 2012-2014.

Finally, based on the joint test for pre-treatment effects we cannot reject the null of parallel trends prior to the reform. FIGURE A2 in the Appendix plots the estimated effects for all time periods. It clearly shows that the failure to reject the hypothesis of no pre-treatment effects is not only due to low power, since the point estimates are almost zero. The same is true for the markups.

It may seem surprising that the largest effect is estimated for the year 2012, in which the reform was implemented only in May, so the time window to take advantage of dispensing was shorter than in 2013 and 2014. However, as discussed already in section 4.1 the large increase in drug costs in 2012 is mostly driven by very high costs in the fourth quarter of 2012, which is the main reason for the estimated effect size in this year. As a robustness check we also estimate the model excluding all observations from 2012 and the results are not affected by this restriction (see TABLE A3 in the Appendix). We also estimated the model using the estimator proposed by Callaway and Sant’Anna (2020), and the results were almost identical.

The effect size seems rather small at 21 CHF per patient and year, with an estimated counterfactual of about CHF 550. However, as shown in FIGURE 1, the share of dispensed drugs is at most 25% of total drug costs so that within the relevant set of drugs the increase is more pronounced (approximately 17%). The overall increase in drug costs also hides the fact that the increase in dispensed (drug) costs exceeds the reduction in prescribed costs after the reform. Put differently, if physicians simply started to dispense part of the drugs they previously prescribed via pharmacies (i.e., plain substitution), then the total drug costs would not be affected by dispensing. This is, however, not what we see in the data implying a behavioral response of doctors to dispensing. It may also seem surprising that the effect is constant, given the steady increase in the share of dispensed drugs. We will address this point in more detail in the discussion of the effects of dispensing on markups further below.

As a consequence of the cost increase, we also find a significant increase in markups. This finding is not surprising as there exists a mechanical relationship between drug costs and markups. The total markup (markup on dispensed and prescribed drugs) per patient is used as the dependent variable in columns 3, 4, and 6. Importantly, the results for this dependent variable are estimates of the extracted (physician) rents. As mentioned before, dispensing leads to a mechanical and a behavioral effect. The mechanical effect is the pure substitution of markups from pharmacies to physicians when physicians prescribe the same drugs as before. This can be estimated using the markup on prescribed drugs bought at pharmacies as dependent variable. On the other hand, using the markup on dispensed drugs as dependent variable yields an estimate of the combined mechanical and behavioral effect. By construction, the difference between these effects is the effect on the total markup, which allows us to estimate the behavioral component. The results are displayed in columns 3 and 4. Again, there is little variation over time, and the effects for the three years are not



statistically different. Imposing a constant effect yields an estimate of CHF 8.50 (column 6) which captures the extracted rent per patient and year.

To provide more detail about the mechanisms at work, FIGURE 3 shows the estimated effects of dispensing for two additional outcomes. The first outcome are the markups on prescribed drugs which are sold by pharmacies. The estimated effects, which are negative, measure how much earnings the pharmacies lose due to dispensing. The absolute value of these results can be interpreted as the amount of earnings that is substituted between pharmacies and physicians, i.e., the mechanical effect of dispensing absent behavioral change (black diamonds). The second outcome is the markup earned on dispensed drugs only. Here, the effects can be interpreted as the total effect of dispensing on physician earnings, both substitution and rent-seeking (gray squares). Hence the difference between the results for the two outcomes is an estimate of the rent-seeking component.

FIGURE 3 shows that both substitution and total physician earnings increase steadily over the treatment period. This finding is consistent with the descriptive result in FIGURE 1 showing an increase of the share of dispensed drugs after 2011. It also shows that our finding of a constant rent-seeking effect is consistent with the dynamics of the substitution and the overall physician earnings effect. It appears as if dispensing physicians do not want to or are not able to increase the extracted rents, at least in the 3 year window we analyze. It is also important to stress again that the rent-seeking effect is not equal to the effect of dispensing on physician earnings. The results in FIGURE 3 indicate that physician earnings increase by CHF 30 per patient in the year 2014. This may translate into a substantial earnings gain, depending on how many patients physicians treat. Swiss doctors treat about 900 patients on average per year, but given our sample selection the earnings gain does not apply to all patients of the physician.

— FIGURE 3 —

## 6.2 Dispensing Channels

As laid out in section 3, dispensing can modify physician prescription behavior through several mechanisms that may result in higher drug costs per patient. In the next two sections, we assess which channels are compatible with the responses we observe in the data. As a starting point, we examine 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. A lower threshold would imply that a larger fraction of patients is medicated resulting in higher average drug costs (and revenues) per patient. We empirically assess the practice style channel by estimating (constant effects) DiD specifications using a binary indicator for positive amounts of packages prescribed to patients as dependent variable. The corresponding estimates can be found in column 1 of TABLE 4. Overall, we find no evidence

for an impact of dispensing at the extensive margin. The estimated effect is close to zero and insignificant so that the practice style channel does not explain the increase in costs and markups we covered in the previous section.

Physicians might start to substitute larger with smaller packages to increase markup revenues as the current drug price regulation in Switzerland financially incentivizes such behavior (see section 2). To examine the relevance of this “package size” channel, columns 2 and 3 in TABLE 4 show the estimated effects of dispensing on the prescribed number of packages and therapy days (number of pills times dose relative to the standard daily dose). First, column 3 shows that the number of therapy days are not affected, indicating that treatment decisions (in terms of daily doses) do not change. Second, we find a significant increase in the number of packages prescribed to patients (column 2). Patients of dispensing physicians receive about 0.5 additional packages after the reform (+5%). One plausible explanation for this result is that physicians in fact substitute larger with smaller packages (i.e., the package size channel). Alternatively, physicians could also leave the number of therapy days unchanged by prescribing more pills (packages) of a lower dose to patients (i.e., the dosing channel). However, unlike the package size channel, this “approach” bears the risk of serious health issues for patients as tinkering with the dose more likely translates to medication errors. If patients, for example, are used to a given routine, say one pill in the morning ( $1 \times 1g$ ), it may be unsafe to change to two pills during the day ( $2 \times 500mg$ ), because this may lead to over- or under-use of the prescribed medication. Although we cannot completely rule out this channel, the next section provides evidence that physicians do not alter previous dosing decisions when treating patients with chronic illnesses (prescription of hypertension & reflux drugs) or acute conditions (prescription of antibiotics).

— TABLE 4 —

### 6.3 A Closer Look at Three High Market Share Drugs

In this section, we use product-level data to examine the role of the cherry-picking and the dosing channels. To study these channels, we follow a panel of patients between 2009-2014 who were prescribed the active ingredient “Amlodipin” used to treat hypertension<sup>19</sup>, “Omeprazol”<sup>20</sup>, a reflux drug or an antibiotic of the agent class “Ciprofloxacin”. The patients we follow did not switch their doctor during the observation window so that we again base our analysis on existing physician-patient relationships where the doctor potentially changed the dispensing status after the reform. We choose the three drugs as for all of them a series of bio-equivalent generic competitors are available in the market and they have a large market share in terms of sales/prescription volumes in the Swiss pharmaceutical market.

<sup>19</sup>Amlodipin is a calcium channel blocker used to treat angina and hypertension.

<sup>20</sup>Omeprazol is used to treat certain stomach and esophagus problems (such as acid reflux, ulcers).

Regarding the hypertension drug, physicians have the choice among 32 alternatives from seven suppliers (“brands”).<sup>21</sup> The drug comes in two package sizes (30 and 100 pills) and two doses (5 and 10mg). 87.5% of the alternatives (28 out of 32) in the choice set of doctors are generics.<sup>22</sup> The choice set for the active ingredient “Omeprazol” contains 108 alternatives from nine producers and the physicians have the choice among seven package sizes (7, 14, 28, 56, 98 and 100 pills) and three doses (10, 20 and 40mg).<sup>23</sup> Finally, doctors have the choice between 9 different pharmaceutical companies distributing the antibiotic. The drug can be prescribed in three package sizes (6, 10 and 20 tablets) and three doses (250, 500 and 750mg) resulting in a choice set of 56 alternatives.<sup>24</sup>

For all three drugs, we construct a separate data set that contains the most frequently prescribed dose and brand as well as the markup rank in the pre- (2010/2011) and the post-reform period (2013/2014). Hence, within each physician-patient bond we have precisely one pre- and one post-reform observation showing what was prescribed to the patient before and after the reform. In tandem to the main analysis, we have information on the dispensing status of physicians and the same set of patient characteristics. Regarding the hypertension drug, our estimation sample consists of 312 unique physician-patient relationships spanning over the years 2010-2014.<sup>25</sup>

The product-level analysis allows us to address a series of relevant questions. For example, are patients treated by a dispensing physician more likely to receive a different dose than they used to before the reform? Are they more likely to get another, potentially more pricey brand? To address these and related questions, we generate a series of switching indicators: *dose switch* is a binary indicator that captures changes in the dose (in mg) that equals one if a doctor changed the dose for an existing patient between 2010/2011 (pre-period) and 2013/2014 (post-period). To address the question whether physicians substitute low with high markup drugs (i.e., the cherry-picking channel), we construct the dummies *higher markup* which equals one if there was a switch to a higher markup alternative between the pre- and post-regime-change period and *generic switch* which equals one if the prescription changed from brand-name to generic. For these switching indicators (dose, markup and generic switch), we estimate linear probability models with a time-constant treatment effect while controlling for time-varying patient characteristics (age, gender, chronic condi-

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<sup>21</sup>The suppliers are Axapharm, Helvepharm, Mepha, Norvasc, Pfizer, Sandoz and Spirig. Mepha is the largest producer with a market share in prescriptions of approximately 46%; followed by Sandoz (25%) and Norvasc (17%, the brand-name alternative).

<sup>22</sup>The first generic was introduced in 2005, 15 years after the release of the brand-name drug.

<sup>23</sup>99 out of the 108 drug alternatives are generics and the first generic came on the market in 2004.

<sup>24</sup>The brand-name alternative “Ciproxin” was introduced in 1988 and the first generic entered the market in 2002.

<sup>25</sup>Regarding the reflux drug (antibiotic) we observe 53 (63) unique physician-patient pairs over the estimation window.

tions, deductibles & insurance choice). The corresponding parameter estimates alongside the baseline switching rates can be found in TABLE 5.

— TABLE 5 —

In line with the results from TABLE 4, we do not find that dispensing leads to a significant change in the dosing-decision of physicians. For all three drugs, there is no effect of dispensing on the probability of a dose switch after the reform (column 1). This finding is evidence against the dosing channel and suggests that the dosing-decisions of physicians are not guided by financial consideration but merely on medical grounds. This finding, albeit based on only three pharmaceuticals, is the basis for our conjecture in the previous section that physicians are not willing to risk medication errors. Also, and in contrast to recent work (Trottmann et al., 2016), our estimates indicate that dispensing does not affect generic substitution (last column). While generics already have a high market share of more than 90% for the hypertension drug and 84% for the antibiotic, the same is to a lesser extent true for the reflux drug (approximately 60%). Besides the potential for generic substitution, we do not observe any switches from the brand-name to the generic alternative for the reflux drug so that the corresponding parameter could not be estimated.

However, the estimates show that dispensing induces physicians to prescribe higher markup drugs to patients with chronic conditions. In particular, patients with high blood pressure or reflux are significantly more likely to leave the doctors office with a more pricey brand after the reform (column 2).<sup>26</sup> In contrast, we do not find any evidence for an effect on the prescription behavior of the antibiotic implying no response to dispensing when medicating patients with acute conditions.

In summary, the product-level analysis suggests that at least part of the reason why patients face higher drug costs after the reform is that their physicians start prescribing higher markup drugs to them. Such behavior is supportive of the cherry-picking channel and constitutes a classical example of rent-seeking behavior: physicians extract a larger share of the pie without increasing medical productivity.

## 6.4 Effect Heterogeneity

In this section we address potential effect heterogeneity. We are interested in two dimensions that may be related to one another, because they are both defined by the health insurance plan of the patients. First, we examine differences in the response to dispensing by insurance model. Patients who are enrolled in the standard model have open access to both primary

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<sup>26</sup>The lion's share of brand switches goes from Helvepharm, the lowest markup brand in the choice set for both drugs, to Sandoz in case of the hypertension drug and to Omeprax/Streuli in case of the reflux drug.

care providers and specialists. Physicians in these models are reimbursed based on fee-for-service and their income directly depends on the amount of medical services they provide to patients. In contrast, patients enrolled in managed care plans (PPO, HMO & Telmed) do not have open access to health care providers. Instead, a “gatekeeper”, usually a GP, is the first point of contact when in need of care. Although physicians are also compensated by fee-for-service, two cost containment mechanisms are typically part of managed care arrangements (see Glied, 2000, for a comprehensive overview): *First*, insurance companies can choose who to contract with so that high cost physicians might be systematically excluded from managed care plans (selective contracting). *Second*, HMO physicians typically are employees and receive a fixed salary but performance based bonuses can be earned. These bonuses usually come in two forms (Beck, 2013): capitation-based bonus payments (so-called efficiency bonuses) that are rewarded if the total costs of the HMO patient pool is lower than the one of (comparable) patients in the standard model and quality bonuses which are rewarded if certain pre-defined quality standards are met (e.g., if they prescribe a certain percentage of generics to patients). In light of these differences, it is conceivable to see differential responses to dispensing between standard and managed care patients.

Columns 1-4 in TABLE 6 show the constant effect estimates based on the same model as in 6.1, stratified by standard and managed care patients. The results clearly show that our results in sections 6.1 and 6.2 are completely driven by physicians treating patients enrolled in the standard model. The estimated effect sizes in this group are larger than above (CHF 35 and .65 packages, respectively). Within physicians treating managed care patients on the other hand we find small and insignificant effects of dispensing on costs and packages. Cost savings and lower utilization of managed care patients have been repeatedly documented in the literature (e.g. Kauer, 2017; Gaynor et al., 2004; Cutler et al., 2000). While part of the lower costs can be explained by patient selection, these studies highlight the relevance of incentives and provider selection. In the same spirit, our results imply that HMO physicians do not engage in rent-seeking as a response to dispensing. Although we can only speculate about the underlying causes, a plausible explanation could be that HMO physicians differ in dimensions like professional ethics and profit motives from their colleagues and/or that supply-side incentives indeed hold undesirable behavior in check.

Second, we differentiate between patients by their deductible. Patients enrolled in the minimum deductible (CHF 300) plan likely hit the deductible during the year and thus face considerably lower out-of-pocket costs thereafter (10% co-insurance with a CHF 700 stop-loss). The probability of hitting the deductible is substantially lower for patients enrolled in higher deductible plans. In our data roughly 70% of patients in the minimum deductible plan hit the deductible (by the end of the year), whereas this fraction is only half as large in the higher deductible plans. Iizuka (2012, 2007) provides evidence that dispensing physicians in Japan take the trade-off between physician profits (markups) and patient out-of-pocket costs into account when deciding on generic substitution. Put differently, physicians are to some

degree willing to forego profits if that reduces the financial burden of patients. Studying the potential effect heterogeneity by deductibles allows us to indirectly test whether physicians in Switzerland also take this trade-off into account.

Columns 5-8 in TABLE 6 indeed show that dispensing exclusively affects the drug costs and number of prescriptions of minimum deductible patients. The effects we find are both somewhat larger than the effects in TABLE 3. Patients with higher deductibles and thus higher out-of-pocket costs are not affected by dispensing. One interpretation of this result could be that physicians in fact internalize patient costs and thus are more hesitant in prescribing unnecessary packages or expensive brands to patients who likely pay out-of-pocket. Another explanation, however, could be that the minimum deductible patients are a selection of less healthy patients who generally have a high demand for medical services and drugs and typically are less price sensitive. Hence, physicians could target their rent-seeking behavior to such patients as they expect more “compliance” than among other more cost conscious groups.

— TABLE 6 —

## 7 Conclusion

This paper has analyzed the question of how physicians react to the possibility of selling pharmaceuticals in their practices and earning a markup on these sales. Exploiting a natural experiment in Switzerland we find that treatment decisions per se are not affected by the possibility of dispensing. Physicians prescribe pharmaceuticals to the same pool of patients as before, and the treatment volume of those receiving drugs is not altered. This is an important result. Overall, physicians’ revenues through earned markups are increased by CHF 30 per patient and year, which is an increase by about 17% compared to the time period when self-dispensing was only possible for a limited number of drugs (e.g. vaccines, emergency pain medication). About 66% of this earnings increase is simply due the fact that prescriptions previously filled at pharmacies are now directly dispensed by the physicians, so it reflects a mechanical substitution, which has no impact on total drug spending. The remainder of the earnings increase is due to rent-seeking behavior, which operates through prescribing more (smaller) packages or more expensive brands of the same drug, without altering the dosage. This translates into an increase in annual drug spending by roughly 3.5% (21 CHF per patient) due to the reform change.

While the estimated effects are not large, they still reflect an inefficiency that should be addressed by a more clever design of the dispensing regime. For example, the markups on dispensed drugs may be capped at the markup of the least-cost option for a given pharmaceutical. Patients in Switzerland already face a higher co-payment for branded drugs if

generics exist, so to balance the scale eliminating the markup incentive on the supply side should be a worthwhile goal to pursue. A more radical alternative would be to abolish self-dispensing altogether to avoid the unnecessary cost increase and iron-out the inefficiencies it creates in the health care sector. However, since dispensing was supported in a popular vote, it appears to reflect public preferences. Therefore, making the system as efficient as possible seems to be the appropriate way to respect these preferences.

There is potentially important heterogeneity in the response to self-dispensing. We find that the increase in drug spending is concentrated among physicians treating patients with standard insurance plans (free choice of providers) and physicians treating patients with the lowest levels of cost-sharing. There is a large overlap between these groups, so it is hard to interpret these findings separately. In both cases we find effects in a sub-population where patients are less healthy, so the results may be driven by larger opportunities to extract rents. On the other hand, these patients may demand more treatment because they selected into more comprehensive health insurance plans. With the data at hand, however, we cannot disentangle to which extent supply and demand side factors drive the observed heterogeneity. This is an interesting issue for future research. Another important question for future research is the role of pharmaceutical companies. Their sale representatives have a strong incentive to target self-dispensing physicians with the goal of persuading them to stock their practice pharmacies with the drugs of their employer.

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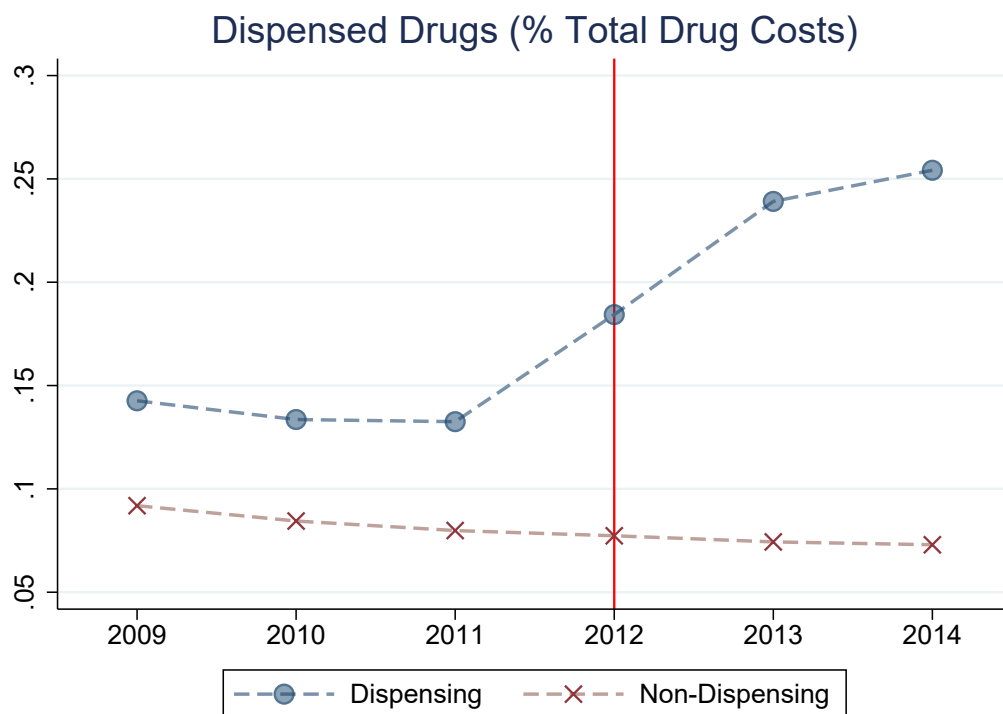
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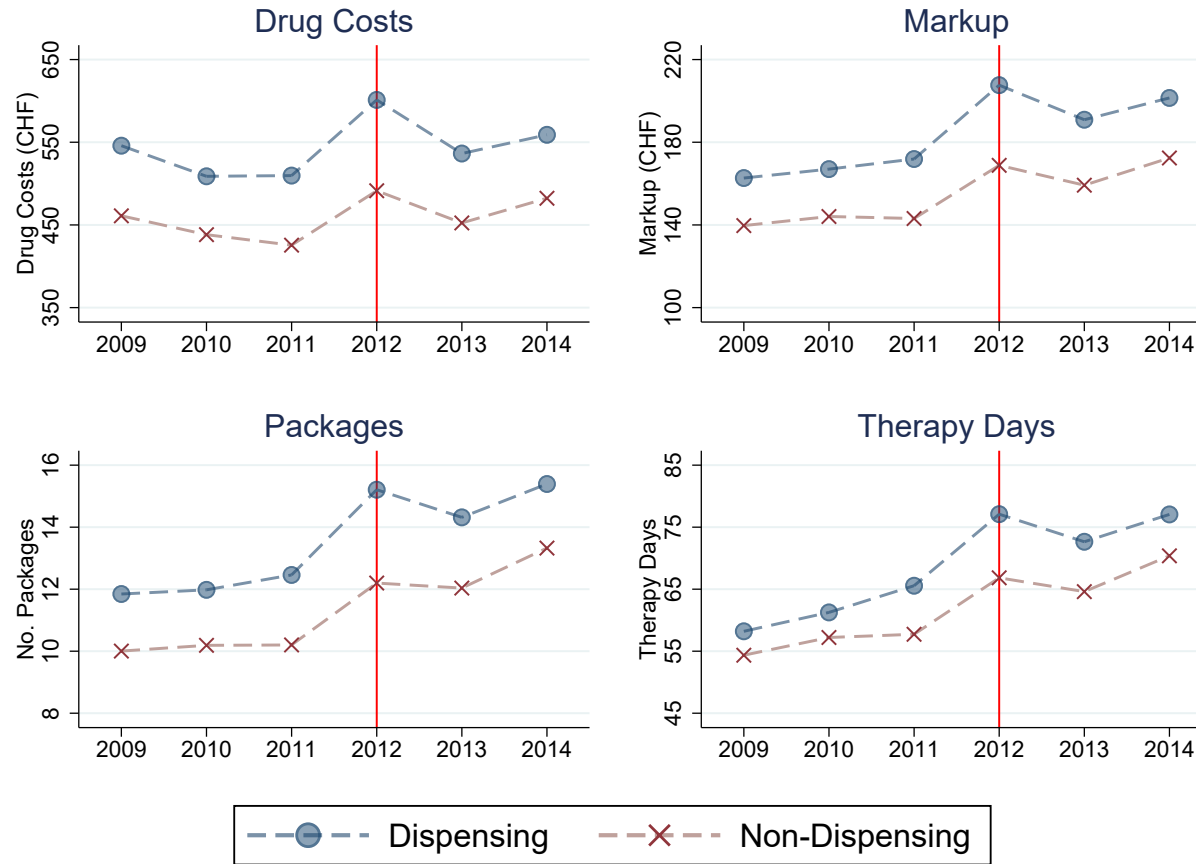
## FIGURES

FIGURE 1: SHARE DISPENSED DRUGS



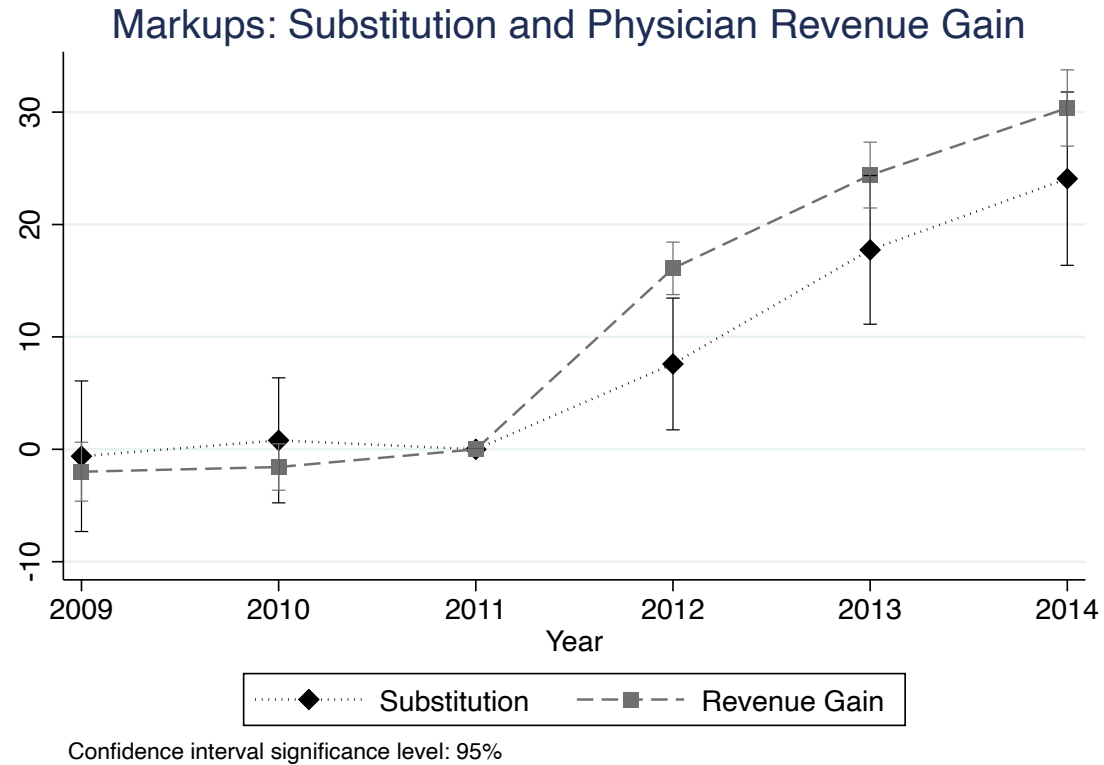
*Notes:* The graph shows the average share of dispensed (% of total drug costs) for dispensing and non-dispensing physicians over the years before and after the reform in 2012. Note that the share of dispensed drugs is non-zero in the years prior to the reform as physicians can directly prescribe a limited set of drugs (mostly vaccines) to patients already before the reform.

FIGURE 2: OUTCOMES BY DISPENSING STATUS



Notes: The graph shows the annual average drug expenditures and markup per patient in Swiss Francs (CHF), the number of prescribed packages and therapy days for patients with a self-dispensing (blue line) and non-dispensing physician (red line) before and after the regime-change in 2012 based on the raw data.

FIGURE 3: PHYSICIAN REVENUES AND RENTS



*Notes:* The graph shows estimated effects of dispensing on *a*) the markups on drugs that are sold by pharmacies (i.e., not dispensed by physicians; black diamonds) and *b*) the markup earned on dispensed drugs (gray squares). The difference between the effects on the two outcomes is an estimate of the extracted rent by dispensing physicians.

## 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-REFORM SUMMARY STATISTICS

	<i>Dispensing</i>		<i>Non-Dispensing</i>	
	Mean	Std	Mean	Std
<i>Provider Information</i>				
General Practitioner (%)	0.46	-	0.34	-
Male (%)	0.72	-	0.65	-
Years of Experience	16.10	7.36	18.44	8.35
<i>Patient Structure</i>				
Doctor Visits	3.66	2.65	3.64	2.69
Male (%)	0.26	-	0.35	-
German Speaking (%)	0.98	-	0.98	-
Age	56.93	17.56	59.15	17.52
<i>Plan Choice</i>				
Deductible (CHF)	585	556	543	520
Monthly Premium (CHF)	332	69	341	65
Standard Model (%)	0.68	-	0.73	-
PPO (%)	0.17	-	0.16	-
Telmed (%)	0.00	-	0.00	-
HMO (%)	0.15	-	0.10	-
<i>Cost Categories</i>				
Drug Costs (CHF)	510	782	426	677
Markup (CHF)	172	257	143	224
<i>Volumes</i>				
Packages	12	20	10	17
Cat.4 Packages	5	9	5	8
Therapy Days (DDD)	66	180	58	169
Patient-Physician Interactions	8,613		8,092	
Patients	7,747		7,164	
Physicians	399		678	

*Notes:* The table shows the summary statistics for the estimation sample of patients with and without a (future) dispensing physician for the pre-treatment year 2011. The estimation sample contains 16,705 unique patient-physician interactions in 2011. Patient-physician interactions occur when a patient sees one of the 1,077 physicians we observe in the data. Patients consulting multiple physicians in a given year are treated as separate (unique) interactions.

TABLE 3: THE EFFECTS OF DISPENSING:  
MAIN RESULTS

Dispensing Effects						
Outcome	Drug Costs		Markup		Drug Costs	Markup
	(1)	(2)	(3)	(4)	(5)	(6)
Treat×2012	26.796*** (9.090)	28.272*** (9.072)	8.737*** (3.044)	9.300*** (3.039)		
Treat×2013	18.798* (10.568)	18.696* (10.439)	7.447** (3.478)	7.547** (3.447)		
Treat×2014	20.641* (11.610)	21.639* (11.471)	7.846* (4.015)	8.392** (3.976)		
Treat×After					20.986** (8.195)	8.497*** (2.698)
Patient Characteristics	No	Yes	No	Yes	Yes	Yes
$p$ -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.63	0.59	0.92	0.85	-	-
Patient-Physician Interactions	18,232	18,232	18,232	18,232	18,232	18,232
Physicians	1,092	1,092	1,092	1,092	1,092	1,092
Patients	14,486	14,486	14,486	14,486	14,486	14,486
Observations	92,792	92,792	92,792	92,792	92,792	92,792

*Notes:* The table shows the estimated parameters of DiD specifications that allow for a time-varying treatment effect (columns 1-4) or impose a constant effect (columns 5-6) (for details see 5.2). Entropy balancing is applied to balance the covariate distributions (patient characteristics and lagged outcomes) between patients of dispensing and non-dispensing physicians (see TABLE A2 for details). Drug costs and markups per patient are measured in Swiss Francs (CHF). "Treat" is a binary treatment indicator that is one for dispensing physicians and zero else in all periods. The coefficient on the interaction terms "Treat×Year" captures the potentially time-varying effect of dispensing after the reform. The coefficient on the interaction with the post-treatment dummy ("After") shows the estimates of the time-constant effects. All specifications include patient-physician interaction and time fixed effects. The even numbered columns and columns 2 and 4 additionally include time-varying patient characteristics (chronic illness indicators, age categories, deductibles and insurance model). Standard errors clustered at the patient-physician level in parentheses: \*  $p < 0.1$  , \*\*  $p < 0.05$  , \*\*\*  $p < 0.01$ .



TABLE 4: THE EFFECTS OF DISPENSING:  
CHANNELS

<b>Dispensing Effects: Channels</b>			
<b>Outcome</b>	<b>P(Packages&gt;0)</b>	<b>Packages</b>	<b>Therapy Days</b>
	(1)	(2)	(3)
Treat×After	0.002 (0.005)	0.465** (0.223)	1.906 (2.862)
Patient-Physician Interactions	18,232	18,232	17,112
Physicians	1,083	1,083	1,083
Patients	13,861	13,861	13,861
Observations	92,792	92,792	69,440

*Notes:* The table shows the DiD estimates of the (constant) treatment effect of dispensing on the number of packages prescribed to patients at the extensive and intensive margin as well as the therapy days. The dependent variable in column 1 is a binary indicator for a positive amount of packages (extensive margin). The specifications in column 2 shows the number of packages (intensive margin). The last column shows the effect on the number of therapy days prescribed to patients. Therapy days are computed as the number of standardized dosages prescribed to patients in days (DDD). "Treat" is a binary treatment indicator that is constantly one for patients of dispensing physicians and zero for patients of non-dispensers. "After" is a dummy that equals one from 2012 onward. The lower number of observations in column 3 results from the absence of DDDs and thus therapy days for certain prescription drugs. All specifications include patient-physician and year fixed effects and the same set of patient attributes as our main specification (see TABLE 3). Standard errors clustered at the patient-physician level in parentheses: \*  $p < 0.1$  , \*\*  $p < 0.05$  , \*\*\*  $p < 0.01$ .

TABLE 5: CHANGES IN THE PRESCRIPTION OF  
THREE HIGH MARKET SHARE DRUGS

<b>Hypertension</b>	<b>Dose Switch</b>	<b>Higher Markup</b>	<b>Generic Switch</b>
	(1)	(2)	(3)
Dispensing Physician	0.029 (0.030)	0.045** (0.021)	0.015 (0.020)
Baseline	7.69%	4.17%	3.21%
Observations	312	312	312
<b>Reflux Drug</b>			
Dispensing Physician	0.084 (0.098)	0.190** (0.078)	0.000 (.)
Baseline	9.43%	11.32%	0.00%
Observations	53	53	53
<b>Antibiotic</b>			
Dispensing Physician	-0.112 (0.073)	-0.038 (0.128)	-0.090 (0.096)
Baseline	12.70%	23.81%	9.52%
Observations	63	63	63

*Notes:* The table shows linear probability model estimates of the effect of dispensing on the prescription of three high market share drugs: Amlodipin, a hypertension drug and Omeprazol, a reflux drug. "Dispensing Physician" is a binary indicator that equals one for patients of dispensing physicians and zero otherwise. The set of dependent variables includes: *Dose Switch* (=1 if the dose was altered between the pre- (2010-2011) and post-period (2013-2014)); *Higher Markup* (=1 if a drug with a higher markup was prescribed after the reform) and *Generic Switch* (=1 if prescription changed from brand-name to generic between the pre- and post-period). Standard errors clustered at the patient-physician level in parentheses: \*  $p < 0.1$  , \*\*  $p < 0.05$  , \*\*\*  $p < 0.01$ .

TABLE 6: EFFECT HETEROGENEITY

Subgroup	Standard		Managed Care		Min. Deductible		Other Deductible	
	Drug Costs	Packages	Drug Costs	Packages	Drug Costs	Packages	Drug Costs	Packages
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dispensing Physician	35.305*** (10.400)	0.652** (0.281)	-5.398 (14.227)	0.064 (0.399)	25.916** (11.071)	0.642** (0.295)	7.012 (12.135)	-0.020 (0.341)
Patient-Physician Interactions	13,924	13,924	5,400	5,400	11,694	11,694	7,096	7,096
Observations	65,273	65,273	24,852	24,852	58,456	58,456	32,725	32,725

*Notes:* The table shows the estimated treatment effects within different subgroups: patients enrolled in the standard model or a managed care model (PPO, HMO or Telmed) and patients choosing the minimum deductible (CHF 300) or a higher deductible (CHF 500, 1,000, 1,500, 2,000 or 2,500). All specifications include patient-physician and year fixed effects, time-varying patient characteristics and subgroup-specific entropy weights are applied. In contrast to the main analysis, we impose a constant treatment effect. “Dispensing physicians” is one for patients of dispensing physicians from 2012 onward and constantly zero for patients of non-dispensers. Standard errors clustered at the patient-physician level level in parentheses: \*  $p < 0.1$  , \*\*  $p < 0.05$  , \*\*\*  $p < 0.01$ .

## APPENDIX

TABLE A1: 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
Omeprazolom	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

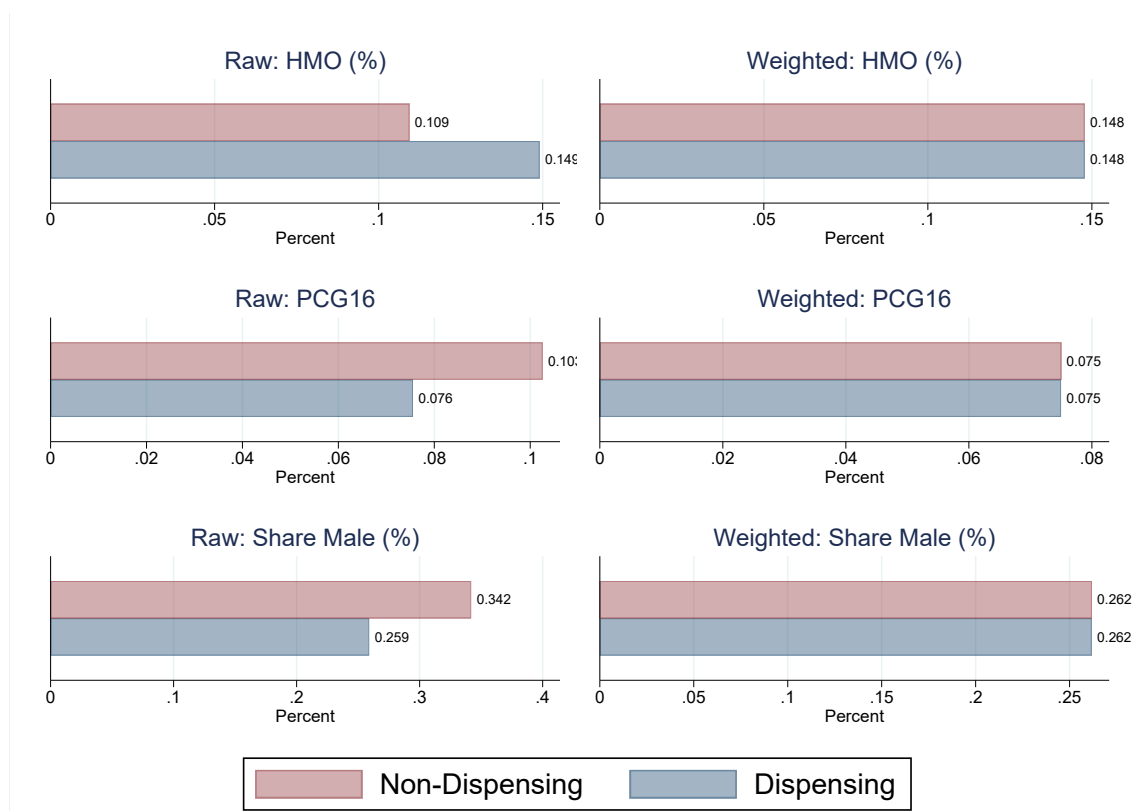
*Notes:* The table presents costs and markups in Swiss francs (CHF) for a 30-day treatment in terms of defined daily doses (i.e., 30 DDD); for generics, we report averages over all available products. The net costs reflect the number of packages times the ex-factory price; the markup is given by the 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 1<sup>st</sup> 2012.

TABLE A2: ENTROPY BALANCING

	Before Weighting				After Weighting			
	Dispensing		Non-Dispensing		Dispensing		Non-Dispensing	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
<i>Pre-Treatment Outcomes</i>								
Total Costs	1,048	1,689,204	1,145	2,295,546	1,048	1,689,204	1,048	1,691,540
Drug Costs	510	611,435	426	458,534	510	611,435	510	611,451
Markup	172	65,835	143	50,274	172	65,835	172	65,837
Total Packages	12.5	401	10.2	283	12.5	401	12.5	401
Cat.4 Packages	5.36	86.5	4.55	70	5.36	86.5	5.36	86.5
Cat.3 Packages	.776	6.12	.711	6.43	.776	6.12	.776	6.12
Therapy Days	65.6	32,311	57.7	28,718	65.6	32,311	65.6	32,313
<i>Patient Characteristics</i>								
PCG1	0.064	0.060	0.062	0.058	0.064	0.060	0.064	0.060
PCG2	0.010	0.010	0.014	0.014	0.010	0.010	0.010	0.010
PCG3	0.080	0.073	0.078	0.072	0.080	0.073	0.080	0.073
PCG4	0.035	0.034	0.043	0.041	0.035	0.034	0.035	0.034
PCG5	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
PCG6	0.164	0.137	0.170	0.141	0.164	0.137	0.164	0.137
PCG7	0.008	0.007	0.016	0.016	0.008	0.007	0.008	0.008
PCG8	0.006	0.006	0.008	0.008	0.006	0.006	0.006	0.006
PCG9	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
PCG10	0.042	0.040	0.031	0.030	0.042	0.040	0.042	0.040
PCG11	0.011	0.011	0.015	0.015	0.011	0.011	0.011	0.011
PCG12	0.003	0.003	0.004	0.004	0.003	0.003	0.003	0.003
PCG13	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
PCG14	0.035	0.034	0.054	0.051	0.035	0.034	0.035	0.034
PCG15	0.096	0.087	0.115	0.102	0.096	0.087	0.096	0.087
PCG16	0.075	0.069	0.100	0.090	0.075	0.069	0.075	0.069
PCG17	0.072	0.067	0.078	0.072	0.072	0.067	0.072	0.067
PCG18	0.057	0.054	0.049	0.047	0.057	0.054	0.057	0.054
PCG19	0.015	0.015	0.013	0.013	0.015	0.015	0.015	0.015
PCG20	0.129	0.112	0.158	0.133	0.129	0.112	0.129	0.112
PCG21	0.008	0.008	0.013	0.013	0.008	0.008	0.008	0.008
PCG22	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
PCG23	0.001	0.001	0.002	0.002	0.001	0.001	0.001	0.001
PCG24	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
PCG25	0.007	0.007	0.009	0.009	0.007	0.007	0.007	0.007
PCG26	0.007	0.006	0.010	0.010	0.007	0.006	0.007	0.006
Family Doctor	0.170	0.141	0.164	0.137	0.170	0.141	0.170	0.141
Standard	0.684	0.216	0.734	0.195	0.684	0.216	0.684	0.216
HMO	0.148	0.126	0.104	0.093	0.148	0.126	0.148	0.126
Age	56.930	308.341	59.151	307.051	56.930	308.341	56.930	308.348
Male	0.262	0.193	0.346	0.226	0.262	0.193	0.262	0.193
Deductible (CHF)=300	0.622	0.235	0.655	0.226	0.622	0.235	0.622	0.235
Deductible (CHF)=500	0.204	0.163	0.204	0.162	0.204	0.163	0.204	0.163
Deductible (CHF)=1000	0.018	0.018	0.015	0.015	0.018	0.018	0.018	0.018
Deductible (CHF)=1500	0.104	0.093	0.082	0.075	0.104	0.093	0.104	0.093
Deductible (CHF)=2500	0.039	0.037	0.034	0.033	0.039	0.037	0.039	0.037

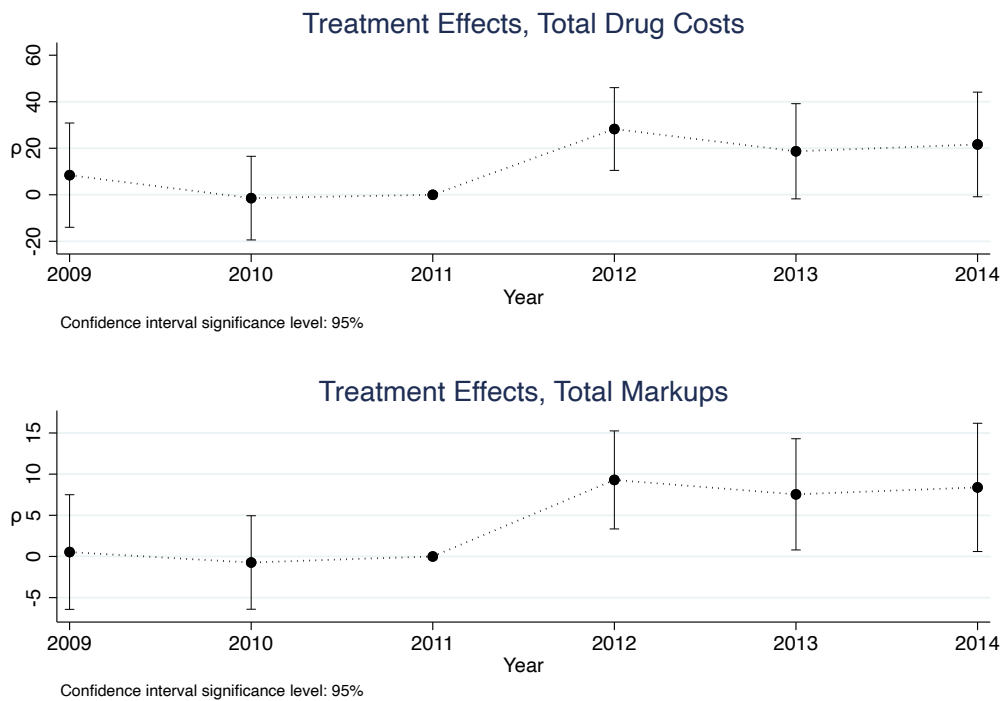
*Notes:* The table exemplifies the balancing of pre-treatment patient characteristics and outcomes before and after applying entropy balancing exemplified for the year 2011. The estimates in our main analysis are based on the average weights over the years 2009-2011.

FIGURE A1: RAW VERSUS WEIGHTED DATA



Notes: The graph shows the raw (left column) and weighted (right column) data for a selection of categorical physician and patient characteristics that showed large imbalances before balancing.

FIGURE A2: MAIN EFFECTS



Notes: This figure shows the estimated treatment effects,  $\hat{\rho}$ , for the specifications also displayed in TABLE 3 (columns 2 and 4).

TABLE A3: ROBUSTNESS:  
2012 EXCLUSION

Outcome	Drug Costs	Markup
	(1)	(2)
Treat × 2013	18.777* (10.481)	7.627** (3.459)
Treat × 2014	22.837** (11.564)	8.725** (4.007)
$p$ -value $H_0 : \rho_{2009} = \rho_{2010} = 0$	0.67	0.91
Patient-Physician Interactions	18,232	18,232
Physicians	1,092	1,092
Patients	14,486	14,486
Observations	76,221	76,221

*Notes:* The table shows the effects of dispensing under the exclusion of data from the year 2012. The specification is identical to the even numbered specifications in TABLE 3. Standard errors clustered at the patient-physician level in parentheses: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .