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Preface

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Bern, March 2024 *Linn Hjalmarsson*

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Introduction

Many developed countries currently face increasing health care costs, with Switzerland being no exception. Part of this development can be explained by inefficiencies. Therefore, the main objective of this thesis is to elaborate on the causes of such inefficiencies and find possible solutions. This thesis consists of three separate chapters in empirical health economics. For all of these chapters, I use very detailed claims-level data obtained from one of the largest health insurers in Switzerland.

In the first chapter of this thesis, I analyse together with Boris Kaiser and Tamara Bischof how practice handovers induced by general practitioner (GP) retirements affect patients' health care utilization and the associated costs. We conclude that, given access to care is provided, changes in the main GP are not necessarily bad, and thus policy makers should preserve patients' access to primary care in the case of GP exits.

In the second chapter, I analyse together with Christian Schmid and Nicolas Schreiner how a targeted mailing campaign of a large Swiss health insurer, informing their clients about cheaper generic alternatives of brand-name drugs, impacts generic substitution. We conclude that simple but concise information about generic alternatives can significantly increase the probability of generic substitution. In particular, we observe a nearly fourfold increase in the probability to purchase generics following the information letter. This paper thus highlights the potential of a simple and comparably cheap instrument in reducing health care costs.

Finally, in the last chapter, I analyse together with Michael Gerfin whether patients with chronic conditions who appear forward-looking and rational in their deductible choice, are also forward-looking with respect to their prescription drug demand. Our results show that patients heavily react to spot prices, which is not what we would expect from rational patients. We conclude that in health insurance, alternatives to deductibles should be considered for treatments such as medications used to treat chronic conditions.

As mentioned before, the first chapter deals with practice handovers in primary care. GPs are at the heart of primary care and thus constitute a foundational element of the health care system. Compared to other entry points in the healthcare system, GPs offer low-threshold and low-cost treatment for acute and chronic health problems. However, GPs not only act as

providers of primary care, they also issue referrals and coordinate care across various providers. This gives them a more complete picture of the entire patient journey. Over time, GPs thus accumulate valuable knowledge about the health status of their patients and can provide or suggest appropriate treatments. Through these repeated patient-provider interactions, patients also build trust with their primary care physicians. The resulting, often long-standing doctor-patient relationship, the so-called interpersonal continuity of care, is considered a key factor for efficient health care provision.

However, at some point GPs exit the labour market due to retirement. Such GP exits have several consequences. First, the interpersonal continuity of care is disrupted. Second, patient access to primary care may be limited if the retiring GP cannot find a suitable successor. Third, the new physician's practice style may differ from that of her predecessor. To make policy recommendations, it is necessary to understand exactly how and to what extent each of these mechanisms affects primary care provision itself.

The existing literature has so far focused on the overall healthcare impacts after the loss of a GP. A majority of these studies find a shift from primary care to often more expensive secondary care, resulting in increased overall expenditures. However, it mostly remains uncertain which of the aforementioned transmission channels is responsible for the observed cost increases.

In order to identify and quantify the transmission channels individually, we focus on GP handovers. A handover means that the retiring GP directly hands over her physician office including the patient pool to a successor. Hence, access, journey to the GP office, and often also the non-medical staff and infrastructure remain the same for patients, only the GP changes. This is an ideal setting to study the effects of interpersonal discontinuity and the physician's practice style.

The effects of the discontinuity tend to be short-term, as the physician-patient relationship is re-established with the new physician after a couple of patient visits. The effects of a different practice style exhibited by the succeeding physician, on the other hand, continue perpetually. We apply a differences-in-differences type of method where we compare the evolution between patients affected by a practice handover and a group of similar patients who do not experience a practice handover within the time period under consideration. Assuming that the outcomes in the two groups would have evolved in the same way over time if none of the individuals had been affected by a practice handover, this approach allows us to estimate the causal effects of handovers. As we observe outcomes up to five years after the practice handover, we are able to distinguish between short-run and long-run effects.

Our results show that a practice handover leads to an increase in the total number of physician visits and health care costs in the short term. These observations can be explained mainly by the new GP's initial reassessment of patients' health status. In the long term, we observe a persistent increase in specialist care utilization, outpatient costs, laboratory analysis

costs, and costs per physician visit. The latter can be explained by a change in the practice style of the new GP. Since succeeding physicians are substantially younger on average and more often women, it is not very surprising that practice styles differ.

Medical education, training, and guidelines evolve over time. Previous studies have shown that practice styles vary, sometimes widely, especially with respect to age and gender of doctors. For example, female physicians are more likely to perform laboratory analyses, refer patients to a specialist, and to spend more time in consultations with their patients. All of these previous insights are thus consistent with our findings regarding the evolution of health care use and the associated costs after practice handovers.

In contrast to previous studies, where the focus lies on practice closures without regulated succession, we do not find a decline in primary health care utilization. On the contrary, our findings provide evidence for a potential increase in the quality of primary care. For instance, we observe significant increases in the prevalence of common chronic diseases that can be identified by prescription drug use. There are mainly two reasons for these findings. First, the new GP may diagnose previously unnoticed or undetected chronic diseases. Second, the increased prevalence may reflect the GP's preferences regarding prescription drug use. The second reason can be explained by differences in practice styles. Overall, our results show that given access to primary care is provided, a change of GP leads to a slight increase in costs but may also have a positive effect on the quality of care. Thus, the organized replacement of retiring GPs with their younger, more often female successors may improve patient health in the long run.

In light of the upcoming wave of retirements among GPs, policymakers should ensure that access to primary care is guaranteed at all times. While practice closures without coordinated succession, especially in rural areas, have negative effects on health care, we do not observe the same adverse consequences in the case of practice handovers. A change in GP, as long as the succession is organized, can even be beneficial to patient health. These findings underscore the need to strive for continuous access to primary care to maintain a cost-effective healthcare system. For example, patients of retiring GPs without coordinated succession can be assisted in their search for a suitable new GP. Alternatively, other medical professionals could temporarily provide certain health services, as is done in the US with practical nurses.

As stated at the beginning, the second chapter analyses how patient information can improve generic substitution. Generic substitution offers one of the most straightforward ways to reduce health care costs, without harming the quality of care. Generic drugs provide the same active pharmaceutical ingredient as the brand-name version of the drug. While the therapeutic effect remains the same, generic alternatives cost up to 90% less, highlighting substantial savings potential. As a consequence, many policies aim at fostering generic substitution. Typ-

ically, these policies consist of financial incentives targeting patients and/or providers, such as physicians and pharmacists. Nevertheless, patients often still purchase the expensive brand-name drug. A potential reason for this is that patients are simply not aware of the existence of cheaper generic alternatives.

In this study, we analyse whether specific information about generic alternatives directly targeted to patients increases generic substitution. More specifically, we analyse the impact of a mailing campaign conducted by a large Swiss health insurer. Patients who previously purchased certain brand-name drugs received a letter informing them about generics. The letter listed the names of all existing generic alternatives for a specific brand-name drug, including the savings potential in relative terms. This generics mailing campaign aimed at directly reducing health care costs and was not designed as a randomized-controlled trial.

However, we exploit exogenous variation in treatment timing to estimate the causal effect of patient information on generic substitution. Employing a slightly adapted version of an event study with staggered treatment adoption, we find that the generics letter substantially increased generic substitution by 30 percentage points following the information letter. In relation to a baseline probability of around 10%, this corresponds to a fourfold increase in the share of generics.

Further heterogeneity analyses show that this effect persists at a relatively high level, independent of whether patients benefit financially from switching. By switching to cheaper generic alternatives, these patients reduce overall health care expenditures, without personally benefiting. Thus, strengthening patient sovereignty by providing essential information seems to have a much broader impact than financial incentives alone.

Overall, our findings clearly show that providing patients with simple but concise information can significantly increase generic substitution. Thus, offering a rather cheap but powerful tool for policy makers aiming at reducing total health care costs.

Last, the third chapter investigates whether deductibles induce irrational patient behavior. Many modern health insurance contracts include a combination of deductibles, co-insurance rates and stop-loss. The main goal of this combination is to trade-off risk-protection and maintaining incentives. However, the combination of these features results in nonlinear price schedules. In other words, current health care consumption dynamically impacts future prices. This creates a complex environment with multiple prices which patients need to consider when making health care consumption decisions. Policy makers, while designing such contracts, generally assume that patients are rational and forward-looking implying that they understand the entire complexity of the contract.

In this chapter, we exploit the fact that for patients with chronic conditions (who surpass the deductible with near certainty), the deductible reset at the turn of the year induces a strong

and salient increase in the short-term price (spot price) while the long-term price (expected end-of-year price) remains largely unchanged. In particular, we focus on purchases of prescription drugs used to treat frequent chronic conditions. In contrast to other health care treatments, prescription drugs have the distinct feature that time of purchase and time of consumption generally do not overlap. Furthermore, patients with chronic conditions have very predictable future prescription drug needs. Thus, patients can easily time prescription drug purchases.

If patients are completely forward-looking, they should anticipate that their expected end-of-year price does not change due to the deductible reset. As a consequence, we should observe a smooth purchasing pattern at the turn of the year. In contrast, if patients react to the short-term increase in the spot price, we can expect to observe an increase in the volume of prescription drug purchases in December as compared to January. Employing a regression discontinuity design, we find that the volume of prescription drugs purchased, measured in defined daily dosages (DDDs), is substantially higher at the end of December compared to the beginning of January. Specifically, the difference in DDDs purchased between December and January corresponds to around 50% of the annual daily average amount of DDDs purchased.

By further decomposing the overall effect into a potential holiday effect and price effect, we find that around one third of the overall effect can be explained solely by the price incentive. Overall, we find compelling evidence that there is a strong increase in the volume of drugs purchased in the last weeks of the year, a behavior which we term Christmas shopping. The observed excess volume is compensated by a below-average volume in the first few weeks of the following year. Due to the fact that the expected end-of-year price hardly changes as opposed to the spot price, which significantly increases due to the deductible reset, we conclude that patients heavily react to spot prices.

From a welfare point of view, Christmas shopping behavior in the prescription drug market has no direct adverse consequences. Individuals simply shift out-of-pocket payments from one health care good (prescription drugs) to another (physician visit). Nevertheless, there may be possible negative consequences, such as drug shortages following the increasing demand in December.

Our paper contributes to the literature showing that deductibles in health insurance can induce irrational and even dangerous behavior. These findings suggest that alternatives to deductibles should be considered when designing health insurance contracts, especially for treatments such as medications used for chronic condition. A possible solution would be to exempt such treatments from the deductible and employ constant cost-sharing instead. In addition, patients should be informed appropriately such that they understand the complexity of the health insurance contract in order to make better decisions.

Chapter 1

The Impact of Phyisican Exits in Primary Care: A Study of Practice Handovers

Abstract

Recent studies on physician exits suggest that general practitioners (GPs) have an important impact on health care utilization and costs, but the transmission channels – interpersonal discontinuities of care, practice style differences and deterioration in access – are usually not clear. Our objective is to estimate the short-run and long-run impacts of switches in GPs on patients' health care utilization and costs, while all other factors of the health care setting remain the same. To do this, we collect data on handovers of primary care practices in Switzerland, occurring between 2007 and 2015. We link this data to rich insurance claims to construct a panel dataset of roughly 240,000 patients. Employing a difference-in-difference type framework, we find transitory increases in overall visits and costs, which are likely caused by the entering GP's initial re-assessment of patients' health care needs. Additionally, we find long-term increases in specialist health care utilization and ambulatory costs. The latter finding can be explained by changes in practice styles between the exiting GP and her successor, who is typically much younger and more likely to be female. In contrast to the literature on practice closures, we do not find evidence on reduced overall utilization rates. An important lesson for health policy is thus to preserve patients' access to care in the case of GP exits.

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1.1 Introduction

Primary care is a cornerstone of the healthcare system, as it is often the first source of care. General practitioners (GPs) not only act as providers of primary care, they also issue referrals and coordinate care across various providers, which helps to curb care fragmentation (Agha et al., 2019; Cebul et al., 2008; Frandsen et al., 2015). Moreover, through continuous doctor-patient relationships, GPs accumulate valuable knowledge on patients' health status and health behaviors over time (Scott, 2000). Therefore, interpersonal continuity of care is often considered to be a key factor in primary care, although the bulk of the evidence only provides descriptive associations (Freeman et al., 2003; Haggerty et al., 2003; Saultz and Lochner, 2005; Cheng et al., 2010; Van Walraven et al., 2010; Wolinsky et al., 2010; Hansen et al., 2013; Leleu and Minvielle, 2013; Nyweide et al., 2013). At the same time, research has also shown that GP practice styles vary considerably, which may strongly influence patients' health care utilization and the associated costs (Kwok, 2019; Fadlon and Van Parys, 2020).

Although the importance of primary care with regard to coordination, utilization rates and patient outcomes is widely acknowledged, isolating the causal impact of primary care is a challenging task. An emerging strand of literature seeks to provide causal evidence by studying the effects of physician exits, which occur due to retirement or relocation. The idea is that physician exits induce an exogenous change in primary care provision that is typically independent of patient behavior (Bischof and Kaiser, 2021; Sabety et al., 2021; Piwnica-Worms et al., 2021; Staiger, 2022; Zhang, 2022; Simonsen et al., 2021b). Besides these empirical considerations, physician exits are an important and timely issue from the perspective of health policy and planning. In many OECD countries, the physician workforce has been ageing considerably, implying that the number of physician retirements will increase in the forthcoming years (OECD, 2021). At the same time, population ageing raises the demand for primary care services, which will further exacerbate the potential shortages of trained GPs.

On the patient level, physician exits have different implications in the short and long run. First, physician exits disrupt an often long-standing patient-provider relationship. This allows researchers to study the short-run effects of an interpersonal discontinuity of care. Second, once patients rematch to a new GP, they are exposed to a new practice style that persists in the long run. A very recent strand of the literature exploits the exogeneity of physician exits to estimate the causal impact of discontinuities of care on various measures of patient utilization and outcomes. Several studies report a shift from primary to specialist care and increases in costs, especially in settings where patients may have a hard time finding a new GP (e.g., when the exiting GP closes his solo practice) (Bischof and Kaiser, 2021; Sabety et al., 2021; Piwnica-Worms et al., 2021; Staiger, 2022; Zhang, 2022). In contrast, one study finds only minor effects on primary care utilization (Simonsen et al., 2021b). A possible reason for

the disparate result is that the latter analyses a setting where seamless access to a new GP is maintained, thus highlighting the importance of having continuous access to care. Several studies additionally suggest that a change in GP may ameliorate the quality of care, such as the detection of previously unnoticed chronic conditions (Simonsen et al., 2021b; Zhang, 2022).

While these studies all provide credible causal estimates of physician exits, it remains often unclear which transmission channels are at play. For example, when studying practice closures, the effects on utilization can arise from the interpersonal discontinuity, practice style differences and/or a deterioration in local access to care (Bischof and Kaiser, 2021). Moreover, most of the previous work does not explicitly differentiate between short-run and long-run effects. However, this distinction is crucial when assessing the relative importance of each channel: Short-run effects are driven by the disruption in the doctor-patient relationship and practice styles, whereas persistent effects are likely to be due to differences in practice styles and access-related issues (the latter only applies to closures). Another limitation of the existing literature is that studies for the United States mostly focus on a specific subgroup of the population (patients enrolled in Medicare or Medicaid), thereby limiting the generalizability of the results (Sabety et al., 2021; Piwnica-Worms et al., 2021; Staiger, 2022; Zhang, 2022).

The objective of this study is to examine both the short-run and long-run effects of an exogenous switch in GPs on patients' health care utilization and the associated costs. To do this, we focus on practice handovers, a situation in which a retiring GP sells his practice to a successor. First, this setting allows us to study how patients are affected in the short run when they transfer to a new provider. Second, we analyse whether and how physician practice styles affect patients' utilization, costs and outcomes by estimating long-run effects. The setting of practice handovers is appealing because apart from the change in physicians, all other factors such as access to primary care, travel distance, non-physician staff, health insurance contracts etc. remain unchanged. Therefore, studying handovers allows us to isolate the role of the GP in absence of changes in access that occur when practices are closed down. Understanding the consequences of GP exits is important from the perspective of health policy and planning across many countries. The findings of this study should therefore prove relevant for those health care systems beyond Switzerland which face similar challenges with respect to an ageing physician workforce and demographic changes.

1.2 Institutional Setting

In Switzerland, 90% of residents report to have a regular source of primary care, which is usually a private GP practice (Merçay, 2016). Swiss GPs are typically self-employed, and work in solo or shared practices (Senn et al., 2016). The patient is responsible to enroll with a GP and to transfer to a new GP if required. Depending on the mandatory health insurance plan,

patients either enjoy direct access to all licensed physicians including specialists (standard plan) or they must visit their regular GP first (managed care plan; preferred provider (PPO), health maintenance organization (HMO), and telemedicine). The costs for primary care are covered by mandatory health insurance, although patients bear some of the costs through deductibles and co-payments. We refer to previous work for a thorough overview of the institutional setting (Bischof and Kaiser, 2021).

1.3 Sources of Data

We use detailed data from mandatory health insurance claims provided by a large Swiss health insurer. The data covers the period 2005 to 2018 and includes only individuals who were continuously insured for a period of at least six years. For each individual, we observe basic demographics, the region of residence and health plan characteristics. Claim records include information on the provider, the number of visits, costs, and information on individual services. The data are aggregated to a matched patient-provider-year panel dataset containing annual health care utilization and costs. Information on the occurrence of handovers of GP practices in Switzerland was gathered in a primary data collection, building on previous work (Bischof and Kaiser, 2021). We first analysed existing provider-level register data to match exiting GPs with entering GPs. In a second step, we conducted extensive field research, to identify practice handovers among other possible events (see Appendix 1.A for more information). In total, we identified 652 exiting GPs who handed over their practice to a successor between 2007 and 2015 ("treated" GPs). Most exits are due to retirements given the age structure of the treated GPs (see Figure 1.C.4 in Appendix 1.C.3). We assign 3,236 GP practices to the control group, which consists of those practices that were active during the entire observation period. This ensures that the control group does not contain any GPs who interrupted or stopped their activity.

1.4 Study Design

1.4.1 Treatment and Control Group

Patients are included in the main sample if they live in Switzerland, are at least 18 years old at the beginning of the observation period and still alive at the end of the observation period, i.e., if they are observed for the entire period 2005 - 2018. For the construction of treatment and control group we closely follow the procedure in previous work (Bischof and Kaiser, 2021). We define the "treated" group as those patients who experience a change in their regular GP caused by a practice handover. Since patients' regular GP must be determined empirically, we match patients to GPs based on the observed distribution of doctor visits. First, we consider

all patients who visited any exiting GP at least once in the two years preceding the event. Second, we assign patients to the treatment group only if the majority (i.e., at least 50%) of their primary care visits were made to the exiting GP. The control group should consist of patients who do not experience any exit of their regular GP, but who are otherwise similar. For this reason, we first assign a hypothetical event year to each control GP ("pseudo handover"). To do this, we generate random draws from the distribution of event years (i.e., years when the handovers took place) in the treatment group. Second, we assign patients to the control group based on the same sampling procedure used for the treated group. This ensures that the data are well balanced in terms of calendar year. Our main sample consists of 241,429 patients, whereof 43,767 experience a practice handover (treated group) and 197,662 do not (control group).

1.4.2 Empirical Strategy

Our setting consists of a difference-in-differences (DiD) framework in which we compare health care utilization between the treated and the control group before and after a practice handover takes place. Since the initial year of treatment varies across individuals, our framework is referred to as a staggered adoption design. For this design, the recent econometric literature shows that standard fixed-effects models pooling all treatment cohorts do not recover meaningful estimates of causal effects (Roth et al., 2023; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Borusyak et al., 2021). Simply speaking, the main reason is that early-treated cohorts contaminate the counterfactual time trend of the later-treated cohorts. To avoid this problem, we apply a type of the "stacked" DiD estimator (Cengiz et al., 2019; Deshpande and Li, 2019; Baker et al., 2022). First, we estimate a fixed-effects model separately for each cohort, where a cohort contains all treated patients with the same initial year of treatment and all control patients with the same initial year of pseudo treatment, i.e., $g \in \{2007, ..., 2015\}$. The cohort-specific regression equation is as follows:

$$Y_{it} = \mu_i + \theta_t^g + \tau_t^g (D_i \times e_t) + u_{it} \tag{1.4.1}$$

where Y_{it} is the dependent variable of interest for patient i in the time period relative to the first year of treatment t (i.e., $t = 0$ corresponds to calendar year g), μ_i are patient fixed-effects, θ_t^g are cohort-specific time fixed-effects, $D_i \times e_t$ are interaction terms between a treatment group dummy $D_i \in \{0, 1\}$ and a range of event time dummies $e_t \in \{0, 1\}$ and u_{it} is an error term. Thus, the parameter τ_t^g is the average treatment effect on the treated (ATT) for cohort g and event time t. The central identifying assumption in the DiD design is that trends in the dependent variable between the treated and control group would have been parallel in the absence of the treatment. To increase the credibility of this assumption and to ensure

balance between groups, we enhance the fixed-effects regression with balancing weights (Cefalu et al., 2020). If treatment effects are, for instance, heterogeneous across age groups or regions, balancing weights help to avoid bias by rendering the two groups comparable in terms of these characteristics. We estimate these weights separately for each cohort using the entropy balancing method suggested by Hainmueller (2012) (see Appendix 1.A.3). For each event time t, we aggregate the estimated ATTs across cohorts as follows: $\tau_t = \sum_g \frac{n_{g1}}{n_1} \tau_t^g$, where n_{g1} is the number of treated patients in cohort g and n_1 is the number of treated patients across all cohorts. This aggregation procedure is very similar to the procedure suggested by Callaway and Sant'Anna (2021).

1.5 Variables

The claims data allows us to construct a range of dependent variables on the patient-year level. First, we use the number of ambulatory visits made to GP practices, specialists and outpatient departments of hospitals as well as the total number of specialist and ambulatory providers visited. For health-related outcomes, we generate an indicator for having any hospitalization and the number of days spent in inpatient care. We also consider several measures of health care costs: overall costs, ambulatory costs, costs per visit, prescription drug costs and laboratory costs. Furthermore, we focus on a variety of services that are often considered to be potentially of low value in primary care: spine imaging, lipid measurements for elderly patients, MRI of the knee, prostate specific antigen (PSA) tests, and vitamin D tests (Schweizerische Gesellschaft für Allgemeine Innere Medizin (SGAIM), 2023; Will et al., 2018; Armitage et al., 2019; Bunt et al., 2018; US Preventive Services Task Force, 2018; LeFevre, 2015). Finally, we look at four frequent chronic conditions: reflux disease, high cholesterol and hypertension, depression and anxiety, and type 2 diabetes. Since data on diagnoses is absent, chronic conditions are proxied by pharmaceutical cost groups (PCGs).

For the estimation of balancing weights, we include a rich set of covariates: age, gender, nationality, language of correspondence, region of residence (NUTS-2 level), local physician density, deductible level (high, medium, low), health plan (standard plan, preferred provider, HMO, telemedicine), accident coverage, indicators for 24 pharmaceutical cost groups (PCGs) and a measure of continuity of care with the regular GP in the pre-treatment period. Moreover, we include lagged dependent variables taken from several pre-treatment periods. To keep the specification concise, we use two-year averages for up to four years prior to the event. A detailed description of all variables can be found in Appendix 1.A.

1.6 Results

1.6.1 Descriptive Statistics

Descriptive statistics for the treated and control groups of patients from the year prior to the (pseudo-) handover are shown in Table 1.1. The statistics for the control group are weighted using the balancing weights. Utilization patterns show that more than half of all ambulatory visits are made to GPs. About 12% of patients are hospitalized at least once. Total annual costs in mandatory health insurance are roughly CHF 4,000 per patient, of which almost half are generated in an ambulatory setting. Demographics suggest that our sample of patients is on average somewhat older, more likely to be female and more likely to be German-speaking compared to the overall adult population of Switzerland (Bischof and Kaiser, 2021). Comparing the means across the two groups, we note that the balancing weights ensure that average characteristics are nearly identical. This is also reflected in the standardized difference, which is indeed very small for all of the covariates (rightmost column). The standardized difference is an adequate measure to assess the degree of imbalances in the covariates across treatment groups because it does not depend on the sample size (Imbens and Wooldridge, 2009). For the sake of brevity, Table 1.1 only contains a small selection of the available PCGs, the full list is found in Table 1.C.1 in Appendix 1.C. For completeness, descriptive statistics without using balancing weights can be found in Table 1.C.2 in Appendix 1.C.

Figure 1.1 displays average characteristics of patients' main GP over time and across groups. If patients visit several GPs in a given year, the main GP is the one to whom most visits are attributed. The figure illustrates that the transition from a retiring to a new GP in the treated group is associated with a sharp and persistent change in physician demographics. The average physician age decreases from roughly 64 years in $t = -1$ to 49 years in $t = 1$. In contrast, the main GP's average age gradually and smoothly increases over time in the control group. As younger GPs are more likely to be female, it is not surprising that we observe a sharp increase in the share of female physicians following the handover (Cohidon et al., 2015). Around 25% of the main GPs in the post-treatment period are women, compared to only 5% of the exiting GPs before the handover. Taken together, Figure 1.1 demonstrates that the transfer to a new regular GP is accompanied with a substantial change in average physician demographics and thus, in turn, with changes in physician practice styles that are associated with these demographics.

1.6.2 Difference-in-Differences Estimates

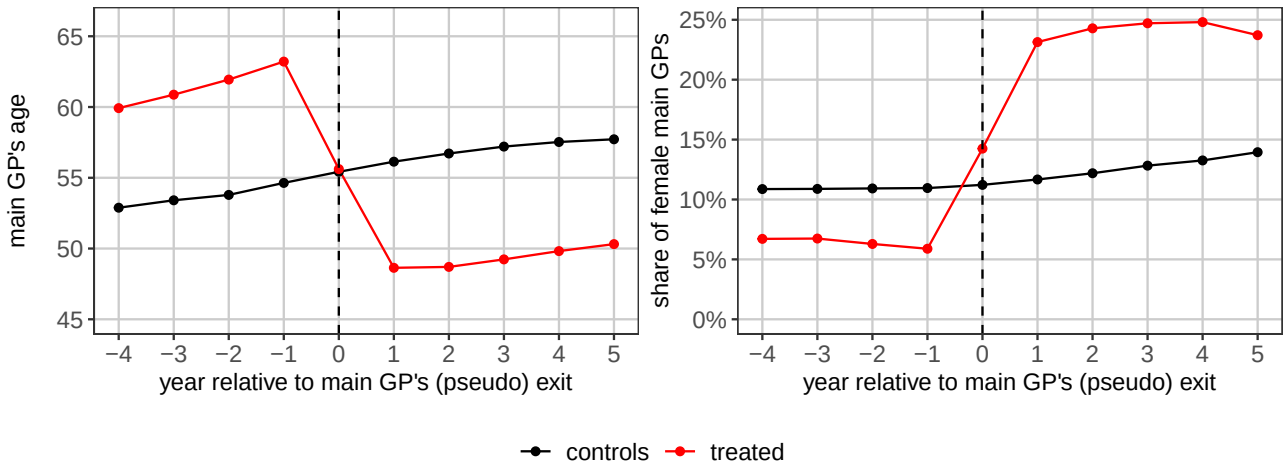
Conceptually, we might expect two different effects from a switch in the regular GP on patients' utilization and costs. First, in the short run, the disruption in the continuity of care may trigger a change in health care utilization due to the initial re-assessment of a patient's health care

Table 1.1: Descriptive Statistics, Pre-Treatment Period

	Treated		Controls		
	Mean	SD	Mean	SD	Std. Diff.
Ambulatory utilization					
Total visits	9.36	9.64	9.35	10.1	-0.001
GP visits	5.21	5.74	5.22	6.15	0.002
Specialist visits	2.69	4.76	2.68	4.98	-0.003
Hospital outpatient visits	1.46	3.48	1.45	3.48	-0.004
Number of providers	1.30	2.32	1.29	2.34	-0.003
Number of specialist providers	1.12	1.32	1.12	1.33	-0.002
Usual provider continuity index	0.93	0.12	0.93	0.12	0.002
Inpatient utilization					
Hospitalization	12.2%		12.1%		-0.004
Number of inpatient days	1.82	9.45	1.85	9.95	0.003
Costs (in CHF)					
Total costs	3,962	7,651	3,948	7,660	-0.002
Ambulatory costs	1,817	2,684	1,808	2,669	-0.003
Costs per visit	127	153	127	143	-0.006
Prescription drug costs	1,061	4,087	1,054	3,857	-0.002
Laboratory costs	103	204	100	205	-0.011
Demographics					
Age	56.4	14.8	56.4	15.0	-0.004
Female	54.3%		54.3%		0.001
Swiss nationality	84.1%		84.1%		0.000
German language	79.0%		78.9%		-0.001
Health plan					
Medium deductible	22.4%		22.5%		0.003
High deductible	19.3%		19.1%		-0.004
Preferred provider plan	29.8%		29.4%		-0.010
HMO plan	4.2%		4.0%		-0.007
Telemedicine plan	0.9%		0.9%		0.000
Regional information					
Lake Geneva	11.9%		11.9%		0.001
Central Switzerland	28.4%		28.2%		-0.004
Espace Mitteland	19.1%		19.4%		0.008
Northwestern Switzerland	11.8%		11.6%		-0.008
Eastern Switzerland	14.6%		14.6%		-0.001
Ticino	1.8%		1.8%		0.001
Local physician density	0.76	0.33	0.76	1.15	0.000
PCGs (selection)					
Reflux diseases	13.7%		13.6%		-0.003
Type 2 diabetes	5.9%		5.9%		0.000
high cholesterol and hypertension	10.6%		10.6%		-0.002
Depression and anxiety	9.7%		9.7%		0.001
Number of GP practices	652		3,236		
Number of patients	43,767		197,662		
Number of observations	603,806		2,718,039		

Notes: The numbers are measured in annual terms based on the calendar year prior to the (pseudo-) handover. The control group is weighted using entropy balancing weights. The standardized difference is the difference in sample means divided by the square root of the average of the two sample variances. Abbreviations: GP, general practitioner, HMO, health maintenance organization, PCG, pharmaceutical cost group, SD, standard deviation, Std. Diff., standardized difference.

Figure 1.1: GP characteristics over time



Notes: This figure shows weighted averages of main GP characteristics by treatment group over time. Weights are estimated by entropy balancing. The main GP is assigned to patients annually based on observed GP visits. If a patient has no GP visits in a given year, the last known value is carried forward. Patients with missing information on main GP characteristics are excluded (treated=11%, controls=12%).

needs. In doing so, the new GP may initiate additional diagnostic measures, for example, by referring patients to specialists or hospitals or by conducting blood tests. Indeed, two recent studies find that the new physician might diagnose conditions that had gone unnoticed by his predecessor (Simonsen et al., 2021b; Zhang, 2022). Second, the handover from a retiring to a new GP potentially entails a change in practice styles. This may also affect utilization and costs.

In the longer run, the effects of the interpersonal discontinuity of care are expected to vanish, once the new GP has learned about his patients' health status and health behaviors. In contrast, the effects of practice styles are arguably persistent over time. In addition, new health care needs detected at the initial re-assessment may require more health care services in the long run, for example in the case of chronic conditions.

Table 1.2: Effects on Utilization, Hospitalization, Costs and Prevalence Chronic Condition

	short-run (t = 1)			long-run (t = 5)		
	ATT	SE	Baseline	ATT	SE	Baseline
A. Utilization						
Total visits	2.6%**	(0.009)	9.78	-0.7%	(0.010)	10.28
GP visits	0.5%	(0.013)	5.01	-3.7%*	(0.017)	4.94
Specialist visits	5.4%**	(0.012)	3.08	3.7%**	(0.014)	3.35
Hospital outpatient visits	4.1%**	(0.016)	1.68	1.6%	(0.019)	1.93
Number of providers	7.2%**	(0.013)	1.48	2.2%	(0.015)	1.61
Number of specialist providers	6.3%**	(0.008)	1.27	5.4%**	(0.010)	1.39
B. Hospitalization						
Hospitalization	1.8%	(0.020)	0.13	0.0%	(0.020)	0.14
Number of inpatient days	0.2%	(0.035)	1.95	1.6%	(0.038)	2.33
C. Costs						
Total costs	3.3%**	(0.011)	4,629	2.1%	(0.012)	5,693
Ambulatory costs	6.2%**	(0.011)	2,142	3.0%*	(0.012)	2,461
Costs per visit	2.7%**	(0.009)	138.1	3.2%**	(0.011)	151.6
Prescription drug costs	2.7%	(0.014)	1,207	2.8%	(0.019)	1,423
Laboratory costs	18.5%**	(0.029)	234.6	8.1%**	(0.025)	250.3
D. Costs potentially low-value care						
Spine imaging costs[a]	6.8%	(0.057)	22.99	11.7%*	(0.058)	25.41
Lipid measurement costs[b]	36.8%**	(0.077)	4.27	26.3%**	(0.084)	3.78
Knee MRI costs[a]	-8.7%	(0.093)	5.19	11.5%	(0.102)	5.62
PSA test costs	12.5%**	(0.048)	2.63	7.2%	(0.049)	2.74
Vitamin D test costs	33.3%**	(0.083)	12.81	12.5%*	(0.057)	15.37
E. Prevalence of chronic conditions (PCGs)						
Reflux disease	4.1%**	(0.010)	0.17	2.9%*	(0.014)	0.21
High cholesterol and hypertension	10.0%**	(0.014)	0.13	10.3%**	(0.020)	0.15
Depression and anxiety	-2.4%*	(0.011)	0.10	-4.6%**	(0.017)	0.11
Type 2 diabetes	4.7%**	(0.012)	0.07	3.6%*	(0.016)	0.09

Notes: This table shows weighted short-run and long-run estimates of causal effects of practice handovers on outcomes in relative terms, that is, the aggregated coefficients of the interaction between the treatment group and time period t = 1 and t = 5. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. Estimates of panel D. and laboratory costs are based on cohorts 2012-2015, due to limited data availability for earlier cohorts. Long-run estimates for these outcomes correspond to those in time period t = 3. $^{*}p < 0.05$, $^{**}p < 0.01$. Abbreviations: ATT, average treatment effect on the treated, GP, general pracitioner, MRI, magnetic resonance imaging, PCG, pharmaceutical cost group, PSA, prostate specific antigen, SE, standard error. [a] treatment due to illness, [b] patient age $\geq$ 75.

To investigate the importance of these channels, we report short-run effects calculated in the first year after the handover ($t = 1$) as well as long-run effects calculated in the fifth year after the handover ($t = 5$). Since practice style effects are relevant in the short run and long run, a reasonable approximation of the short-run effect of disruption is to consider the difference between the short-run effect and the long-run effect. We explain this in more detail in Appendix 1.B.

Table 1.2 reports the estimated causal effects, the treatment effect on the treated (ATT), of practice handovers on a wide range of dependent variables. Since the dependent variables are measured on different scales, we focus on the relative effect which is computed by dividing the absolute effect by the average counterfactual mean in the treated group. To assess the validity of the estimation strategy, Figure 1.2 shows that there are no discernible pre-trends in the estimated effects for a selected number of utilization and cost measures. Similar plots for all other outcomes reported in Table 1.2 are depicted in Figures 1.C.1 - 1.C.3 in Appendix 1.C.1.

A series of robustness checks in Appendix 1.C.4 shows that long-run effect estimates are not sensitive to different choices of the relative time period t, or to binning the endpoints (Schmidheiny and Siegloch, 2023). We additionally show unweighted results (Table 1.C.3) and results including patients that eventually die (Table 1.C.4).

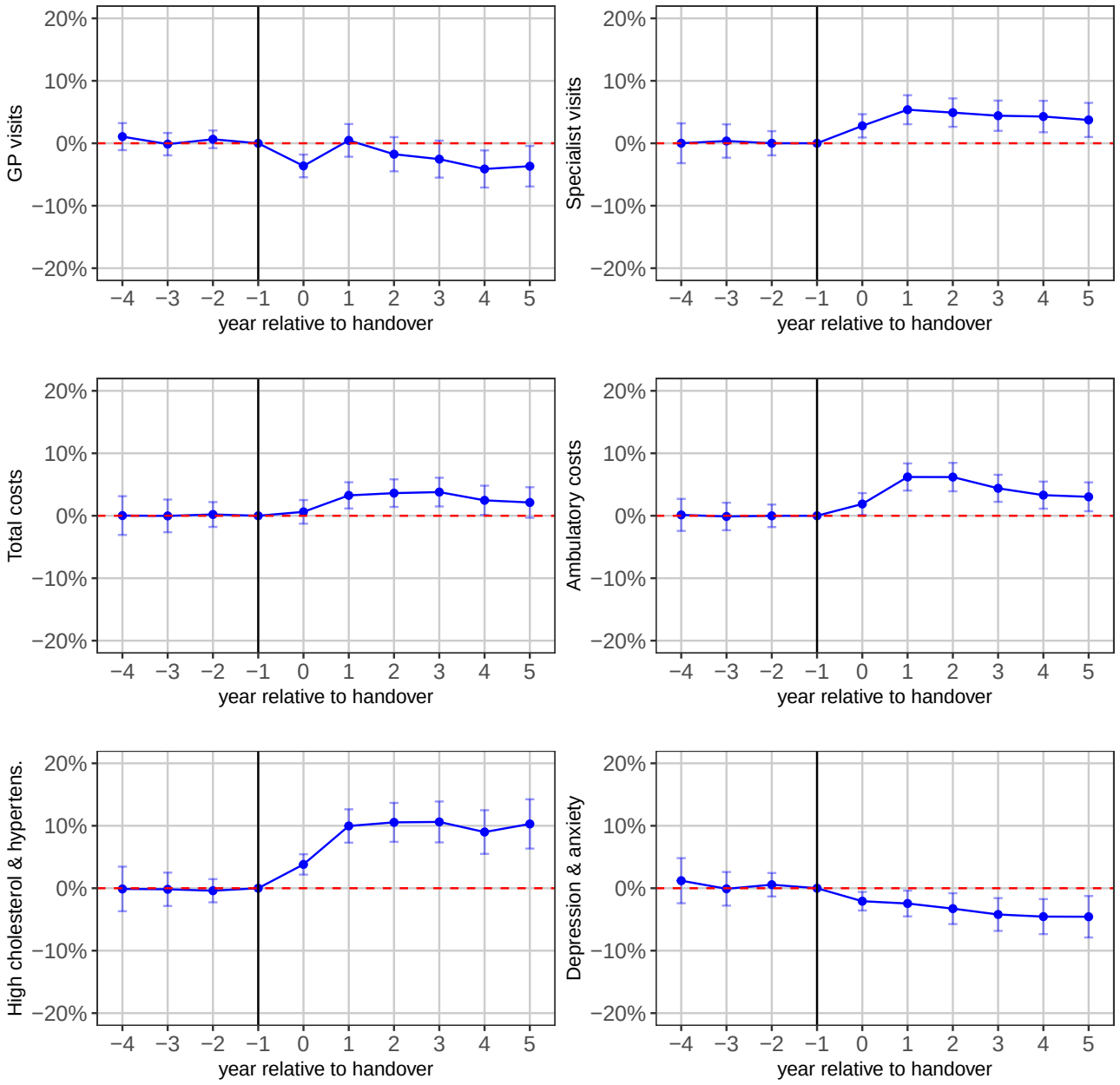
Utilization and Costs

Panel A in Table 1.2 shows the average effects of a practice handover on patients' utilization patterns. In the short run, a practice handover leads to a transitory increase in total visits of 2.6%, essentially no change in GP visits, and significantly more specialist and hospital outpatient visits. Furthermore, we observe a short-term increase in the number of providers which is partly driven by the switch to a new GP and a rise in the number of specialist providers. Considering the long-run effects, we see that the effect on total visits, hospital outpatient visits and the number of providers is only transitory, as the effects are smaller and insignificant in the long run. A different pattern emerges when comparing GP visits to specialist visits. While the number of GP visits significantly decreases in the long run (-3.7%), the positive effects on specialist visits and the number of specialist providers amount to 3.7% and 5.4%, respectively. These findings indicate that there is a persistent shift from primary to specialist care following the handover.

We do not find any evidence for adverse health effects as measured by the hospitalization rate and the number of days spent in hospitals. The estimated impacts are small in magnitude and statistically insignificant (see Panel B of Table 1.2).

Panel C of Table 1.2 presents the causal short-run and long-run effects on various cost categories. In the short run, we observe an increase in overall costs of 3.3%, mainly driven by

Figure 1.2: Relative effects on selected outcomes



Notes: Dots correspond to the average relative effect at a given relative time period, measured in years. Vertical lines represent 95%-Confidence intervals of the relative effect. These plots are the result of estimating the dynamic model. The effect for the year just before the handover ($t = -1$) is set equal to zero.

higher ambulatory costs. The reason for this is twofold: First, there is an increase in doctor visits, and second, visits become more expensive on average (2.7%). Possible reasons for the persistently higher costs per visit are that consultation time increases and/or more expensive treatments are administered. The latter may be associated with specialist visits, which generally entail more costly health care services. We also note that the largest effect (in relative terms) concerns laboratory costs, amounting to 18.5% in the short run.

The transitory short-run effects on the number of visits and total costs suggest that entering GPs initially use more resources because they conduct a re-assessment of their patients' medical needs, for example, by having longer consultations or running more diagnostic tests such as blood tests. After five years, some effects still persist, however. In particular, we observe a shift from primary to secondary care, more expensive visits and higher laboratory costs. Most likely, these long-run effects are associated with differences in physician practice styles between exiting and entering GPs. In light of Figure 1.1, this explanation is plausible because entering GPs, on average, are less experienced, younger and are more often female compared to their retiring counterparts.

Potentially Low-Value Care

Given the evidence discussed above, an obvious follow-up question is whether the rise in costs and utilization is in fact beneficial for patients' health or whether it merely represents an increase in resource use. We tackle this question by focusing on a selected number of specific services that are often considered to be potentially of low value in a primary care setting (Schweizerische Gesellschaft für Allgemeine Innere Medizin (SGAIM), 2023). These include spine imaging (excluding accidents), lipid measurements with elderly patients, MRI of the knee (excluding accidents), PSA tests and vitamin D tests (Will et al., 2018; Armitage et al., 2019; Bunt et al., 2018; US Preventive Services Task Force, 2018; LeFevre, 2015). The corresponding results are depicted in Panel D of Table 1.2. We find large and significant increases in costs for lipid measurements (36.8%), PSA tests (12.5%) and vitamin D tests (33.3%) in the short run. The effects tend to partially fade out in the long run. Overall, our results provide some suggestive evidence for an increased use of potentially low-value care, but absent data on health outcomes, it is difficult to draw strong conclusions.

Chronic Conditions and Prescription Drug Use (PCGs)

In a next step, we analyse whether practice handovers affect the prevalence of four common chronic conditions as proxied by PCGs. The results are shown in Panel E of Table 1.2. The most pronounced and persistent effect can be observed for high cholesterol and hypertension, where

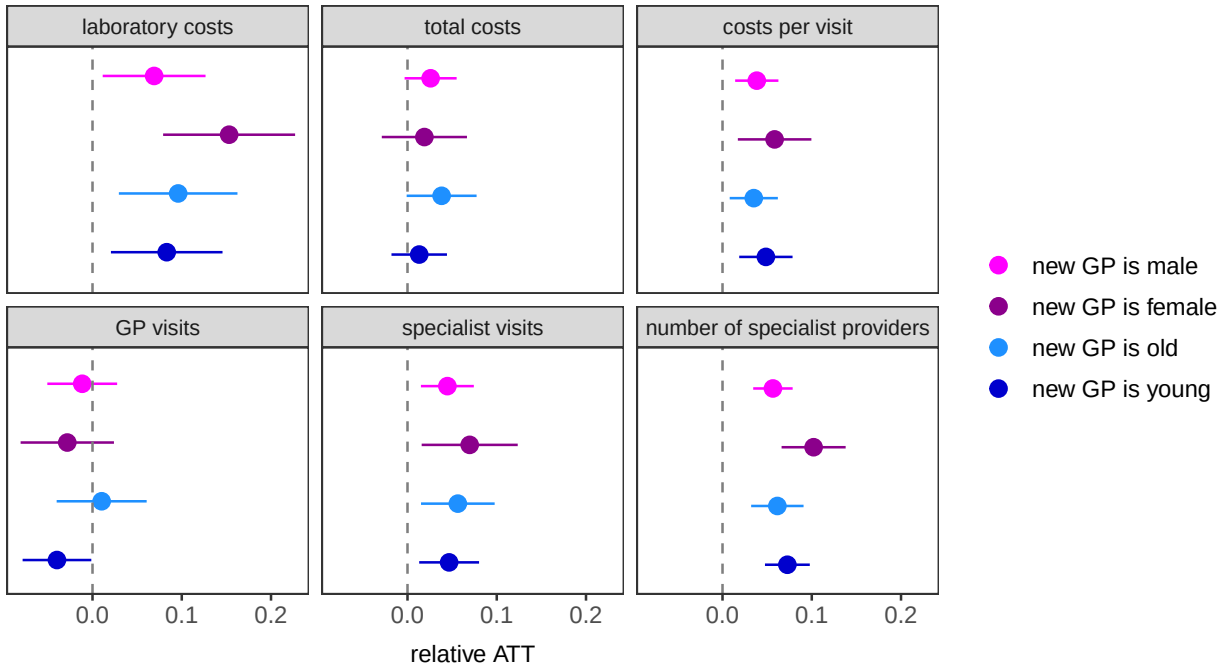
the prevalence persistently increases by around 10%. The prevalence of the PCGs for reflux disease and type 2 diabetes also increase, albeit to a lesser extent. In contrast, the prevalence of the PCG for depression and anxiety significantly decreases both in the short and long run. As the prevalence of chronic conditions is measured by prescription drug use, we consider two potential explanations. First, as new GPs re-assess patients' health status after taking over the cases, they may diagnose chronic conditions that had previously gone unnoticed, and consequently, start administering new pharmaceutical treatments. This effect can persist over time because they are long-run treatments. Second, the findings may also reflect differences in practice styles with regard to prescription drug use. The new GPs may be more or less inclined to prescribe certain drugs compared to their predecessors. For example, entering GPs may be more hesitant to prescribe antidepressants or tranquilizers, and in contrast, may prefer alternative treatments (such as psychotherapist counseling in this case). These changes are most likely associated with a re-assessment of patients' health status and, in addition, may be linked to physicians' preferences towards drug-related treatments.

1.6.3 Heterogeneity analysis

In a next step, we investigate whether the estimated effects are heterogeneous across different GP characteristics. Since practice styles are generally associated with physician demographics, studying heterogeneous effects are informative with respect to practice style variation. Indeed, previous studies report that practice styles differ considerably with respect to physician age and gender (Currie et al., 2016; Hedden et al., 2014; Kaiser, 2017). It is therefore interesting to examine whether the effects depend on age and gender of the entering GP. To categorize by physician age, we split the treated group at the median age of the entering GP (46 years) in $t = 1$. To categorize by physician gender, we simply split the treated group according to their main GP's gender in $t = 1$.

Figure 1.3, shows the results for selected utilization measures across different GP characteristics. Consistent with previous studies, switching to a female GP leads to higher laboratory costs compared to a male GP, which suggests that female doctors run more diagnostic tests such as blood tests (Kaiser, 2017; Hedden et al., 2014). Female doctors have somewhat longer (but fewer) consultations, as indicated by higher costs per visit. They also refer patients more frequently to specialists compared to their male colleagues. Overall, there is some evidence for gender-specific practice styles among GPs that is in line with other existing studies (Kaiser, 2017; Hedden et al., 2014). Comparing entering GPs by age, the estimates indicate that younger GPs have fewer consultations with their patients than older GPs, which may explain the smaller effect on total health care costs. For the other utilization measures considered, the effect heterogeneity across GPs' age seems less pronounced. It is worth noting that handovers

Figure 1.3: Long-term effects by physician demographics



Notes: This figure shows estimates of long-term causal effects of practice handovers on utilization and costs. We report the relative average treatment effect on the treated (ATT) because dependent variables are measured on different scales. The dots represent the point estimates and the horizontal lines depict the corresponding 95% confidence interval.

lead to significantly more specialist visits and a larger number of specialist providers visited in all subgroups. Overall, these results are consistent with findings from previous studies which report variation in practice styles due to differences in physician demographics (Choudhry et al., 2005; Hedden et al., 2014; Kaiser, 2017).

1.7 Discussion

Our results show that a practice handover leads to a transitory rise in the total number of visits and total health care costs. Comparing short-run and long-run effects provides some information as to whether the interpersonal discontinuity of care affects outcomes. We note that the effects on total number of visits, hospital outpatient visits, number of providers, total health care costs, ambulatory costs and laboratory costs are substantially larger in the short-run than in the long-run. This suggests that there exists some transitory effect of practice handovers on these outcomes. A plausible explanation is that new GPs initially have a higher resource use because they re-assess patients' health status when taking over the cases. In contrast to the literature on interpersonal continuity of care (Cheng et al., 2010; Hansen et al., 2013; Nyweide

et al., 2013), we do not find any evidence that discontinuities of care lead to adverse health effects, to the extent that this can be measured by hospitalizations and the number of days spent in inpatient care. Since our empirical design allows for causal conclusions under plausible assumptions, disruptions in the doctor-patient relationship may not be as important for patient health as this literature suggests given that access to care is preserved.

Certain effects also persist in the long run. For example, we document a significant and persistent increase in specialist health care utilization, ambulatory costs, laboratory costs and costs per visit. One plausible explanation is related to physician practice styles, which have a persistent impact on the delivery of health care (Song et al., 2010; Gowrisankaran et al., 2022). This notion is supported by the fact that patients affected by a handover experience a substantial change in average physician demographics, i.e., the entering GP is more likely to be female and on average much younger than their predecessor. Recent studies indeed report that female GPs tend to have fewer but longer visits, solve more problems in one consultation and are more likely to refer patients to specialists Hedden et al., 2014. Female GPs are also found to perform more laboratory tests, but prescribe fewer drugs compared to their male counterparts Kaiser, 2017. This implies more expensive GP visits as well as more specialist visits, which is consistent with our results. Another explanation for higher utilization and costs in the long run is that newly detected chronic conditions have a persistent impact on patients' utilization and costs.

Besides utilization and costs, we also document that a practice handover leads to changes in the prevalence of certain chronic conditions measured by PCGs. In the case of reflux disease, type 2 diabetes, high cholesterol and hypertension, the increase could be a consequence of a re-assessment of patients' health status. Entering GPs administer drug treatments for chronic conditions that were untreated or undetected by their predecessors. Indeed, these results are consistent with findings for practice closures in Denmark and GP exits in the US (Simonsen et al., 2021b; Zhang, 2022). Another explanation is that entering GPs may have different practice styles with respect to diagnostic intensity (Song et al., 2010; Gowrisankaran et al., 2022), and/or prescription drug use. In the case of depression and anxiety, entering GPs may de-prescribe certain medication and place more emphasis on psychotherapist counseling instead. This presumption is supported by a recent study reporting a positive association between years of practical experience and over-prescription of antidepressants (Hengartner et al., 2021).

A limitation of our study is that the claims data does not contain any information on diagnoses, e.g. ICD-10 codes. While PCGs are informative on the prevalence of certain chronic conditions, they also reflect physicians' prescribing behavior to some extent. Data on diagnoses could shed some light on the question as to whether the increase in health care utilization is due to newly detected chronic conditions, which warrants more health care and higher costs, or due to inefficiencies in the delivery of health care. Another limitation is that claims data

contain only limited and indirect information on patient health. Our results suggest that changing GP does not lead to more hospitalizations, but patient health could also be affected in different ways that we fail to capture with our data. As a last limitation, we are unable to identify the uncontaminated effect of practice styles and the discontinuity of care, even though we distinguish between short- and long-run effects. While short-run effects are a combination of the initial disruption effect and practice styles, long-run effects are likely a combination of practice styles and the long-run consequences of the initial re-assessment.

1.8 Conclusion

Our findings provide important insights with regard to previous work that focuses on closures of GP practices. Practice closures simultaneously affect access to care, continuity of care and physician practice styles such that it is hard to assess the relative importance of each of these channels. A recent study finds that practice closures lead to a decrease in overall doctor visits and a sharp drop in GP visits, which are particularly pronounced in areas with low physician density (Bischof and Kaiser, 2021). In contrast, in the present study, access to care remains unchanged and we do not observe any significant negative effects on overall health care utilization. We therefore conclude that deteriorating access to a primary care provider is the main explanation of the drop in utilization observed after practice closures. Moreover, previous studies show that practice closures lead to shifts towards more specialist care and hospital outpatient care (Bischof and Kaiser, 2021; Sabety et al., 2021). We also find these types of substitution effects in the case of practice handovers where access to care does not change. This suggests that physician practice styles at least partially explain the observed shifts towards specialists and hospitals in the case of closures.

From a policy perspective, our findings carry certain lessons in the face of the increasing number of retiring GPs in the forthcoming years. First, while practice closures have adverse effects on health care utilization, especially in peripheral areas, practice handovers do not affect overall utilization rates. In other words, smooth transitions from an exiting GP to a new GP help to ensure continuous access to primary care, which is crucial from the patient perspective. One problem is that patients lack easily accessible information as to which practices take on new patients. Registering with a new practice can therefore be time consuming. One policy recommendation could be to actively assist patients in transferring to a new GP when their previous GP retires. At the very least, patients should be provided with lists of available GPs in their resident area who take on new patients. Second, our findings suggest that transitioning to a new GP induces more services and costs, potentially due to an initial re-assessment of the patient's health status. One policy tool aimed at reducing re-assessment costs is the introduction of individual electronic patient records (EPRs), which contain all relevant medical information

across providers. Switzerland introduced an EPR system in 2021, but its dissemination has been limited so far. More widespread use of EPRs could foster digitization of medical records in ambulatory practices and thereby contribute to lower re-assessment costs. Third, the change in practice style raises the question whether policies should respond to the shift from GP to specialist care. However, it is not clear from our results to what extent a higher referral rate to specialists affects the quality of care.

1.A Appendix I: Additional Information on Methods

1.A.1 Data Sources

The insurance claims data is provided by CSS Insurance. CSS and its subsidiaries have about 1.4 million people enrolled in mandatory health insurance plans (in 2020) and thus constitute the largest mandatory health insurer in Switzerland. For each claim record, we observe the provider accounting number (so-called ZSR number), the provider category (practice, hospital, pharmacy etc.), the provider sub-category (GP, specialist, etc.) the start date and end date of the treatment spell, the cause of treatment (illness or accident), the number of visits and the incurred costs grouped into several categories. Data on individual services, such as diagnostic tests or imaging, is only available from 2010 and thus only for a subset of the claims data.

Reliable data on practice handovers is not available in any existing data source. We therefore followed a similar approach as in our previous work Bischof and Kaiser (2021), where we collected data on primary care practice closures. In a first step, we drew on the so-called Datenpool provided by SASIS AG, which is a data service provider of the Swiss health insurers. The Datenpool contains provider-level data on aggregated mandatory health insurance costs and utilization that are gathered from all Swiss insurers on a monthly basis. In a first step, we use monthly time series of consultation volumes for each provider to identify events that could potentially represent practice handovers. We exploit the fact that providers are identified by a unique accounting number and that this number is not transferable across physicians. We use the data to identify instances where the consultation volume drops to zero (or close to zero) for one provider and rises sharply for another (new) provider around the same time. We use address details to connect exiting and entering providers, since practice handovers typically mean that the practice address remains the same.

Since the address data may not be completely reliable and since the exact location of a practice may change in the course of relocations, we investigated unclear circumstances on a case-by-case basis by conducting short telephone interviews with existing GP practices and by searching the internet (e.g. local newspaper articles). We only included cases in the treated group where a handover from an exiting GP to an entering GP could be clearly confirmed. Consequently, we excluded cases where (i) the practice was temporarily closed, (ii) the exiting GP kept working part-time in the same practice, or (iii) circumstances remained unclear. In the case of shared group practices, we only included cases where an entering GP actually replaced an exiting GP.

1.A.2 Definition of Variables

Table 1.A.1 contains information on the construction and definition of variables used in this paper. Unless otherwise stated, all variables are constructed from the mandatory health insurance claims data and are defined on the patient-year level. All costs are measured in nominal (current) Swiss francs (CHF) and include both the costs borne by the insurer and costs borne by patients due to deductibles and co-payments.

Table 1.A.1: Variable Definitions

variable name	definition / construction
GP	GPs are physicians who hold a title in "General Internal Medicine" or "General Medical Practitioner". Mixed practices with several specialties are characterised as GP practices if at least 80% of their physician service costs fall into so-called basic primary care services (German: Grundleistungen) according to the Swiss fee-for-service structure (TARMED).
Regular GP	The identification of the regular GP in the pre-treatment period is based on the distribution of a patient's visits in the two years prior to the (pseudo-) handover. Patients are matched to a regular GP if the share of visits is at least 50% of all GP visits in that period. In other words, patients without a sufficiently strong relationship to any GP are excluded from the analysis. In the post-treatment period, we identify the regular GP based on the distribution of a patient's visits in each year after the (pseudo-) handover.
Treatment group indicator	Patients are assigned to the treated group if their regular GP retires/exits and hands over the practice to a successor during the observations period. Patients are assigned to the control group if their regular GP does not display any change in activity during the observation period.
Total visits	Total number of ambulatory visits to any physician (all practices and hospitals).
GP visits	Number of visits to any GP practice.
Specialist visits	Number of visits to any specialist practice.

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Table 1.A.1 – continued from previous page

variable name	definition / construction
Hospital outpatient visits	Number of visits to any outpatient department of a hospital, including emergency departments.
Number of providers	The number of providers visited for ambulatory care.
Number of specialist providers	The number of specialist providers visited for ambulatory care.
Hospitalization	Binary indicator for obtaining any acute inpatient care.
Number of inpatient days	The total number of days spent in acute inpatient care.
Total costs	Total gross health care costs charged to mandatory health insurance, including out-of-pocket payments due to deductibles and co-payments.
Ambulatory costs	Total health care costs generated in ambulatory settings (physician services, laboratory tests, physiotherapy, midwives, preventive care etc.), excluding prescription drug costs.
Costs per visit	Costs for ambulatory care divided by the number of visits.
Prescription drug costs	Costs for prescription drugs that are covered by mandatory health insurance.
Laboratory costs	Costs for laboratory analyses covered by mandatory health insurance.
Spine imaging costs	Costs for spine imaging (X-ray, MRI, CT) due to illness (i.e., excluding traumatic injuries).
Lipid measurement costs	Costs for several lipid measurements (LDL-Cholesterol, HDL-, HDL-2-, and HDL-3-Cholesterol) for patients older than 75.
Knee MRI costs	Costs for MRIs of the knee due to illness (i.e., excluding traumatic injuries).
PSA test costs	Costs for PSA blood tests.
Vitamin D test costs	Costs for vitamin D blood tests.
Usual provider continuity index	The ratio of the number of visits to the regular GP relative to the number of visits to any GPs.

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Table 1.A.1 – continued from previous page

variable name	definition / construction
Age	Patient's age in years.
Female	Indicator for female patients.
Swiss nationality	Indicator for patients who hold the Swiss citizenship.
German language	Indicator for patients whose language of correspondance with the insurer is German. This is roughly an indicator for patients living in the German-speaking part of Switzerland.
Low deductible	*(Reference category)* The deductible level is CHF 300 or CHF 500.
Medium deductible	The chosen deductible level is CHF 1,000 or 1,500.
High deductible	The chosen deductible level is CHF 2,000 or CHF 2,500.
Accident coverage	The patient's health plan includes accident coverage. This is an approximate indicator for non-employment or self-employment since employees are covered through their employer and not through their mandatory health insurer.
Standard plan	*(Reference category)* The standard plan entails no managed care element. Patients have free choice of physician.
Preferred provider plan	The chosen health plan specifies a preferred provider, tyically a GP. The patient has to visit this provider first when seeking care, except for emergencies. The patient requires a referral to obtain secondary care.
HMO plan	The chosen health plan specifies that the patient must seek care within an HMO network of providers. Care outside the network is possible only through referrals.
Telemedicine plan	The chosen health plan specifies that the patient must first call a telemedicine service before visiting any physician.
Regions	The regions correspond to the seven NUTS-2 regions of Switzerland: Zurich (reference category), Lake Geneva, Central Switzerland, Espace Mittelland, Northwestern Switzerland, Eastern Switzerland and Ticino.

Continued on next page

Table 1.A.1 – continued from previous page

variable name	definition / construction
Local physician density	The local physician density is defined on the zip-code level and measures the ratio between the utilization of physician services (as a proxy for physician supply) relative to the needs-adjusted population size. The measure covers a radius of 8 kilometers and is inverse-distance weighted, i.e., close physicians/populations are given more weight in the calculation. Needs-adjustment is proportional to the utilization levels of different age groups on the national level.
PCGs	24 binary indicators for pharmaceutical cost groups (PCGs). Patients fall into a PCG if their annual defined daily dose (DDD) pertaining to a specific set of drugs exceeds a pre-defined threshold. The PCGs are largely based on the definition that the Federal Office of Public Health issued in December 2016. The PCGs are used as risk-adjusting variables in the Swiss risk equalization scheme between health insurers.

Abbreviations: CT, computed tomography, GP, general practitioner, HDL, high-density lipoprotein, HMO, health maintenance organization, LDL, low-density lipoprotein, MRI, magnetic resonance imaging, PCG, pharmaceutical cost group, PSA, prostate specific antigen.

1.A.3 Econometric Approach

The recent econometrics literature points out that traditional event-study regressions with two-way fixed effects do not recover meaningful causal parameters when treatment adoption is staggered and when there are heterogeneous treatment effects (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Borusyak et al., 2021; Roth et al., 2023). This literature proposes various estimation strategies to avoid these problems. The common principle of these new estimation strategies is to estimate effects separately for each treatment cohort to avoid contamination bias induced by later-treated cohorts. We follow this idea and use a variant of the so-called stacked difference-in-difference (DiD) estimator (Cengiz et al., 2019; Deshpande and Li, 2019; Baker et al., 2022). The stacked DiD involves a separate regression for each cohort and an aggregation of the cohort-specific regression coefficients. Alternatively, one can also run a single regression with the stacked data where all regressors are interacted with cohort indicators.

Our main reason for choosing this estimator is that it allows for a separately tailored control

group for each treated cohort (Baker et al., 2022). As explained in Section 2.3 of the main text, we need to assign patients to their main GP based on observed doctor visits in the pre-treatment period. In other words, the sampling of treated patients conditions on observing a positive number of doctor visits in the pre-treatment period. Since this is a non-random sample from the population, it is important to apply the same sampling procedure when selecting the control group, which involves assigning pseudo treatment events. This results in a separate control group for each treated cohort. The stacked DiD naturally handles estimation in this setting.

One methodological question is whether a control GP is used for one or for several treated cohorts. In fact, we assign a hypothetical pseudo handover to each control GP only once. In other words, a control unit is not used multiple times across treated cohorts. There are three reasons for this. First, aggregation of cohort-specific ATTs and their standard errors is much easier because they are based on independent (non-overlapping) samples. If control units were used multiple times, a joint clustered covariance matrix of all cohort-specific treatment effects would be necessary to conduct statistical inference. Second, the control group is much larger than the treated group such that the potential efficiency gain of re-using control units is perhaps small in our context.

Compared to our stacked DiD approach, other DiD estimators rely on a *common* control group, which contains all units who never (or not yet) experience a treatment (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Borusyak et al., 2021). Due to our specific sampling design, having a common control group does not seem appropriate. By design, a treated cohort and a common control group would exhibit different pre-treatment outcome levels because there may be individuals in the control group with no doctor visits in the pre-treatment period. In contrast, treated patients visited their GP, by definition, at least once in the pre-treatment period. It seems likely that the common trends assumption of the DiD design would not be valid in this case.

Entropy Balancing

Balancing weights (or inverse-probability weights) ensure that the means of the covariates are the same across the treated and control group. While balancing weights are often encountered in cross-sectional studies, it is straightforward to enhance DiD estimators with balancing weights (Cefalu et al., 2020). In general, the main motivation for using balancing weights in a DiD design is to strengthen the credibility of the common trends assumption. For example, it is conceivable that individuals with different characteristics respond differently to a treatment. If treated and control patients are on average very different in terms of their characteristics (demographics, regions, insurance plans, health status etc.), this potential treatment effect heterogeneity could bias the estimated counterfactual trend and therefore bias the estimated

treatment effects.

In our context, for instance, we observe that older patients are slightly more likely to be treated and that patients living in the German-speaking part of Switzerland are also more likely to be treated. We therefore employ entropy balancing weights in order to achieve perfect balance between the treatment and control group with respect to these characteristics.

In the following, we illustrate the entropy balancing method formally. Let X_i be the vector of covariates and w_i the balancing weight for individual i. The entropy balancing method (Hainmueller, 2012) consists of the following constrained minimization problem:

$$\begin{aligned}
\mathbf{w} = \arg\min \sum_{i:D_i=0} w_i \ln(w_i) \text{ s.t.} \\
\sum_{i:D_i=0} w_i X_i = \frac{1}{n_1} \sum_{i:D_i=1} X_i \\
\sum_{i:D_i=0} w_i = 1 \\
w_i \geq 0 \text{ for all } i
\end{aligned}$$

The objective function ensures that the weights have minimal variability given the constraints. The first constraint is the balancing of covariate means, while the second and third constraint ensure that weights are all positive and sum to one. The entropy balancing weight for patient i is finally defined as $w_i^{eb} = D_i + (1 - D_i)w_i$, i.e., the weight for treated patients is set to unity.

1.B Appendix II: Contrasting the Effects

In the following, we contrast the short-run and long-run effect estimates to identify a proxy for the initial re-assessment effect. Short-run effects are driven by the rematch to a new GP which may induce an initial re-assessment of a patient's health care needs. Because the scope of the re-assessment depends on physician practice styles, for example preferences for blood tests, or referrals, short-run effects are also driven by practice styles. Considering long-run effects, practice styles play a major role. Furthermore, the consequences of the initial re-assessment may still persist in the long run. Consequently, if we subtract the long-run estimate from the short-run estimate, we obtain a lower bound of the re-assessment effect, under the assumption that practice styles are constant over time. Especially, if we can reject the Null-hypothesis of equality of the short- and long-run effects, we can identify the re-assessment effect. To conduct this t-Test, we only use those cohorts that are observed both in the short run ($t = 1$) and long run ($t = 5$), i.e., cohorts 2007 - 2013.

Table 1.B.1 shows the short-run and long-run ATTs in absolute terms. The rightmost corner additionally provides the p-value for the test of the Null-hypothesis that both ATTs are equal. We find statistically significant differences on the 5%-significance level for total visits, GP visits, laboratory costs and vitamin D test costs. This finding indicates that the initial re-assessment leads to temporary increased total visits, and essentially no change in GP visits, whereas patients affected by a handover experience significantly fewer GP visits in the long-run. Considering laboratory costs and vitamin D test costs, these findings are consistent with the presumption that the initial re-assessment is conducted by employing significantly more diagnostic measures. For all other outcomes, we are unable to reject the Null-hypothesis of equality between short- and long-run effects, indicating that the rematch to a new physician initially leads to a level-shift which remains constant over time. The latter finding suggests that the largest part of the observed effects both in the short run and long run is mainly driven by practice styles.

Table 1.B.1: Difference in Short- and Long-run Effects

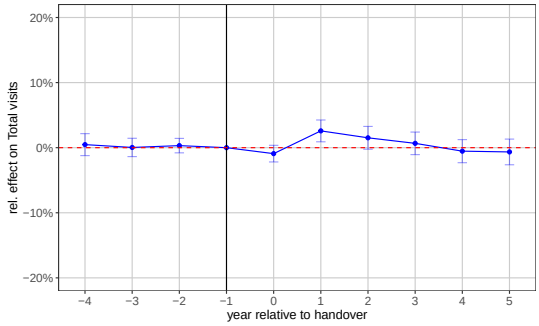
	short-run (t = 1)		long-run (t = 5)		
	ATT	SE	ATT	SE	diff. p-value
A. Utilization					
Total visits	0.18	(0.092)	-0.07	(0.104)	0.021
GP visits	-0.02	(0.078)	-0.19*	(0.085)	0.032
Specialist visits	0.14**	(0.039)	0.12**	(0.045)	0.684
Hospital outpatient visits	0.06*	(0.027)	0.03	(0.037)	0.562
Number of providers	0.07**	(0.020)	0.03	(0.024)	0.164
Number of specialist providers	0.07**	(0.011)	0.07**	(0.013)	0.719
B. Hospitalization					
Hospitalization	0.002	(0.003)	0.000	(0.003)	0.681
Number of inpatient days	-0.02	(0.078)	0.04	(0.088)	0.663
C. Costs					
Total costs	124.1*	(50.27)	118.5	(69.57)	0.953
Ambulatory costs	110.6**	(23.64)	72.4*	(28.17)	0.303
Costs per visit	3.6*	(1.41)	4.7**	(1.55)	0.583
Prescription drug costs	29.7	(16.33)	39.4	(26.87)	0.787
Laboratory costs	36.7**	(5.74)	18.7**	(5.75)	0.002
D. Costs potentially low-value care					
Spine imaging costs[a]	1.46	(1.218)	2.65*	(1.321)	0.483
Lipid measurement costs[b]	1.15**	(0.241)	0.79**	(0.252)	0.166
Knee MRI costs[a]	-0.49	(0.527)	0.58	(0.516)	0.123
PSA test costs	0.29**	(0.111)	0.18	(0.125)	0.253
Vitamin D test costs	3.20**	(0.796)	1.71*	(0.772)	0.041
E. Prevalence of chronic conditions (PCGs)					
Reflux disease	0.007**	(0.002)	0.006*	(0.003)	0.764
High cholesterol and hypertension	0.011**	(0.002)	0.014**	(0.003)	0.417
Depression and anxiety	-0.003*	(0.001)	-0.005**	(0.002)	0.349
Type 2 diabetes	0.003**	(0.001)	0.003*	(0.001)	0.966

Notes: This table shows weighted short-run and long-run estimates of causal effects of practice handovers on outcomes in absolute terms, that is, the aggregated coefficients of the interaction between the treatment group and time period t = 1 and t = 5. The rightmost column depicts the pvalue for the Nullhypothesis that the short- and long-run effects are equal. The model includes patient fixed effects and time effects. Data is measured in annual terms. at the physician level. Estimates of panel D. and laboratory costs are based on cohorts 2012-2015, due to limited data availability for earlier cohorts. Long-run estimates for these outcomes correspond to those in time period t = 3. For all other outcomes cohorts 2007 - 2013 are used, as we don't observe t = 5 for later treated cohorts. $^*p < 0.05$, $^{**}p < 0.01$. Abbreviations: ATT, average treatment effect on the treated, diff., difference, GP, general pracitioner, MRI, magnetic resonance imaging, PCG, pharmaceutical cost group, PSA, prostate specific antigen, SE, standard error. [a] treatment due to illness, [b] patient age $\geq$ 75.

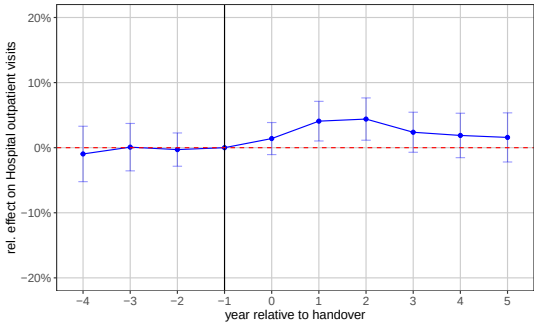
1.C Appendix III: Additional Results

1.C.1 Event Time Plots

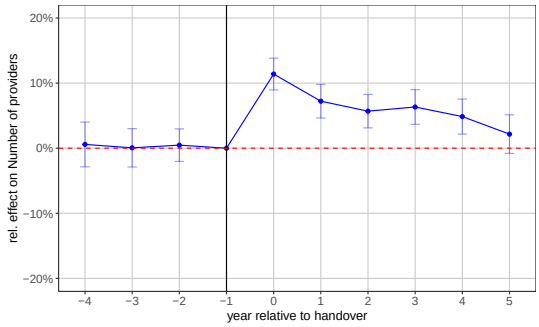
Figure 1.C.1: Event Time Plots of Additional Results I



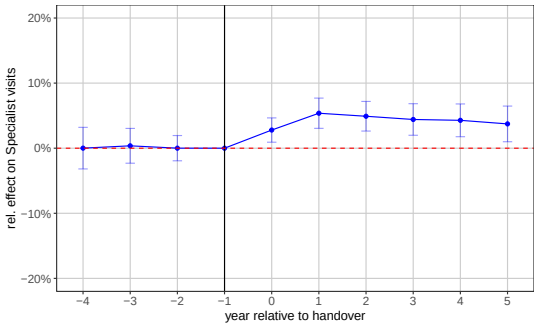
(a) Total visits



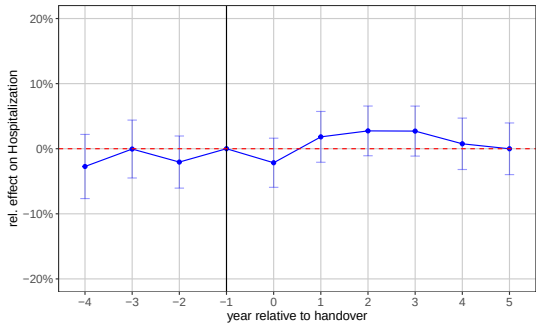
(b) Hospital outpatient visits



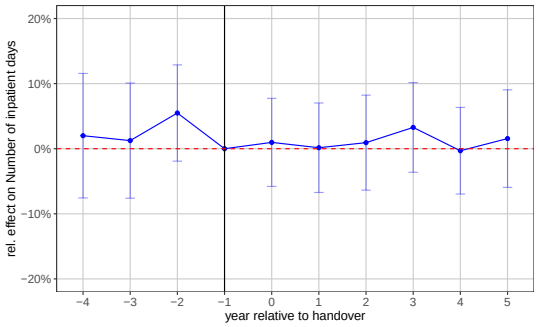
(c) Number of providers



(d) Number of specialist providers



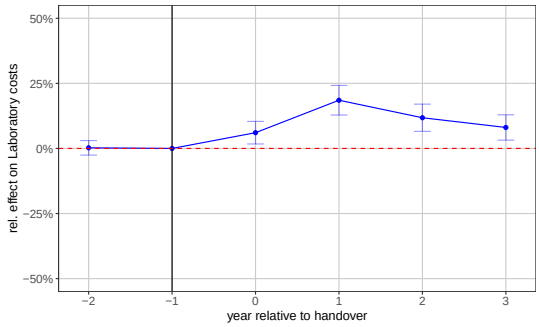
(e) Hospitalization



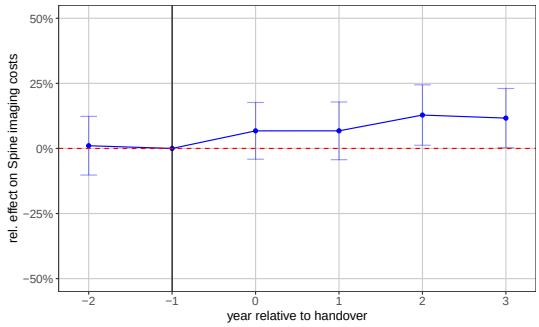
(f) Number of inpatient days

Notes: Dots correspond to the average relative effect at a given relative time period, measured in years. Vertical lines represent 95%-Confidence intervals of the relative effect. These plots are the result of estimating the dynamic model in Equation (1.4.1). The effect for the year just before the handover ($t = -1$) is set equal to zero.

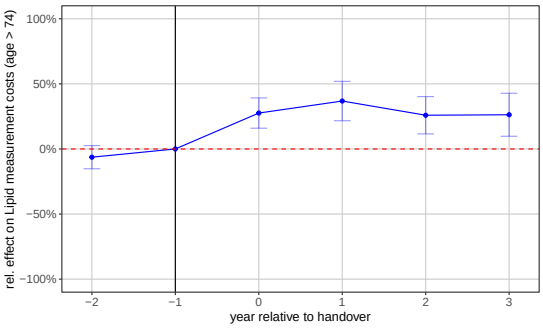
Figure 1.C.2: Event Time Plots of Additional Results II



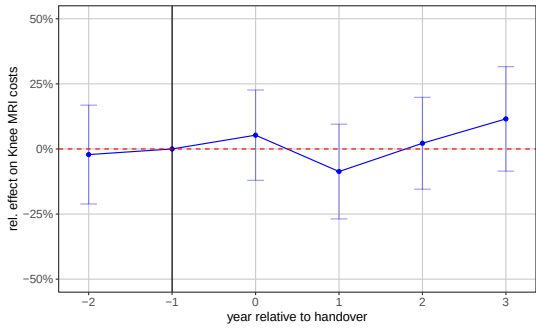
(a) Laboratory costs



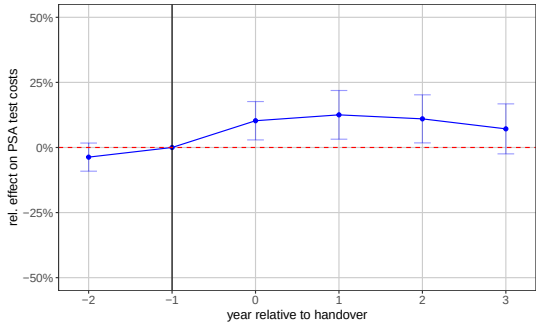
(b) Spine imaging costs



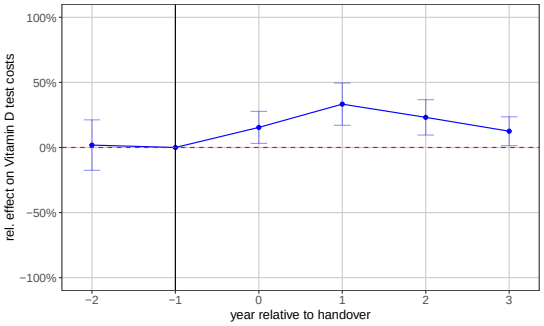
(c) Lipid measurement costs



(d) Knee MRI costs



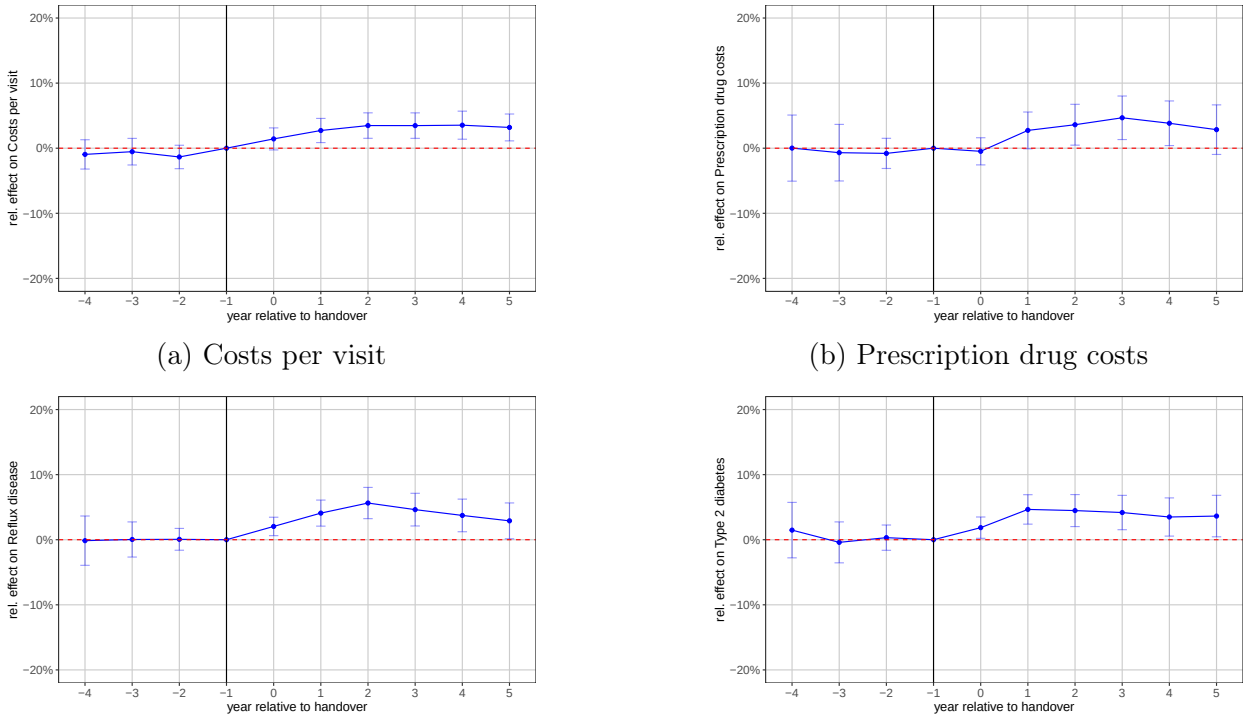
(e) PSA test costs



(f) Vitamin D test costs

Notes: Dots correspond to the average relative effect at a given relative time period, measured in years. Vertical lines represent 95%-Confidence intervals of the relative effect. These plots are the result of estimating the dynamic model in Equation (1.4.1). The effect for the year just before the handover ($t = -1$) is set equal to zero.

Figure 1.C.3: Event Time Plots of Additional Results III



(a) Costs per visit

(b) Prescription drug costs

(c) Reflux disease

(d) Type 2 diabetes

Notes: Dots correspond to the average relative effect at a given relative time period, measured in years. Vertical lines represent 95%-Confidence intervals of the relative effect. These plots are the result of estimating the dynamic model in Equation (1.4.1). The effect for the year just before the handover ($t = -1$) is set equal to zero.

1.C.2 Descriptives

Table 1.C.1: Descriptive Statistics, Full List of PCGs

	Treated	Controls	
	Mean	Mean	Std. Diff.
Asthma, respiratory diseases	4.5%	4.4%	-0.001
Epilepsy	1.0%	1.0%	0.000
Rheumatic disorders	6.9%	6.9%	0.000
Heart conditions	3.0%	3.0%	0.000
Crohn's disease and ulcerative colitis	0.7%	0.7%	-0.001
Reflux diseases	13.7%	13.6%	-0.003
Type 1 diabetes (mellitus)	0.7%	0.7%	-0.001
Parkinson's disease	0.6%	0.6%	-0.001
Transplants	0.1%	0.1%	-0.001
Malignant tumors	2.1%	2.0%	-0.001
HIV, AIDS	0.2%	0.2%	0.001
Kidney diseases	0.2%	0.2%	0.000
high cholesterol and hypertension	10.6%	10.6%	-0.002
Glaucoma	4.5%	4.4%	-0.005
Thyroid gland	4.5%	4.5%	-0.001
Osteoporosis	2.4%	2.4%	-0.001
Migraine	1.1%	1.1%	0.000
Depression and anxiety	9.7%	9.7%	0.001
Chronic psychoses	0.9%	0.9%	0.001
Addictions (alcohol and heroin)	0.4%	0.4%	0.000
Alzheimer's	0.1%	0.1%	0.000
Neuropathic pain	0.7%	0.7%	0.000
COPD	0.6%	0.6%	-0.001
ADHD	0.2%	0.2%	0.000

Notes: The numbers are based on the calendar year prior to the (pseudo-) handover. The controls group is weighted using entropy balancing weights. The standardized difference is the difference in sample means divided by the square root of the average of the two sample variances.

Table 1.C.2: Unweighted Descriptive Statistics, Pre-Treatment Period

	Treated		Controls		
	Mean	SD	Mean	SD	Std. Diff.
Ambulatory utilization					
Total visits	9.36	9.64	9.36	10.2	-0.001
GP visits	5.21	5.74	5.01	5.89	-0.034
Specialist visits	2.69	4.76	2.83	5.30	0.028
Hospital outpatient visits	1.46	3.48	1.52	3.64	0.015
Number of providers	1.30	2.32	1.35	2.39	0.021
Number of specialist providers	1.12	1.32	1.17	1.37	0.035
Usual provider continuity index	0.93	0.12	0.94	0.11	0.145
Inpatient utilization					
Hospitalization	12.2%		11.9%		-0.012
Number of inpatient days	1.82	9.45	1.86	10.2	0.004
Costs (in CHF)					
Total costs	3,962	7,651	4,037	7,967	0.010
Ambulatory costs	1,817	2,684	1,884	3,016	0.023
Costs per visit	127	153	132	174	0.026
Prescription drug costs	1,061	4,087	1,062	3,633	0.000
Laboratory costs	103	204	103	215	0.000
Demographics					
Age	56.4	14.8	55.1	15.2	-0.091
Female	54.3%		57.3%		0.062
Swiss nationality	84.1%		83.4%		-0.019
German language	79.0%		70.3%		-0.201
Health plan					
Medium deductible	22.4%		23.8%		0.034
High deductible	19.3%		20.2%		0.022
Preferred provider plan	29.8%		26.3%		-0.078
HMO plan	4.2%		5.2%		0.049
Telemedicine plan	0.9%		1.0%		0.013
Regional information					
Lake Geneva	11.9%		16.7%		0.136
Central Switzerland	28.4%		16.4%		-0.291
Espace Mitteland	19.1%		20.7%		0.042
Northwestern Switzerland	11.8%		15.3%		0.101
Eastern Switzerland	14.6%		14.0%		-0.018
Ticino	1.8%		4.9%		0.171
Local physician density	0.76	0.33	0.76	1.45	0.005
PCGs					
Asthma, respiratory diseases	4.5%		4.4%		-0.002
Epilepsy	1.0%		1.2%		0.018
Rheumatic disorders	6.9%		6.6%		-0.013
Heart conditions	3.0%		2.9%		-0.005
Crohn's disease and ulcerative colitis	0.7%		0.7%		-0.007
Reflux diseases	13.7%		13.8%		0.004
Type 1 diabetes (mellitus)	0.7%		0.6%		-0.006
Parkinson's disease	0.6%		0.6%		-0.002
Transplants	0.1%		0.1%		0.003
Malignant tumors	2.1%		2.1%		0.000
Type 2 diabetes	5.9%		5.7%		-0.009
HIV, AIDS	0.2%		0.2%		-0.004
Kidney diseases	0.2%		0.2%		-0.006
high cholesterol and hypertension	10.6%		9.5%		-0.037
Glaucoma	4.5%		4.2%		-0.017
Thyroid gland	4.5%		4.7%		0.010
Osteoporosis	2.4%		2.5%		0.002
Migraine	1.1%		1.3%		0.014
Depression and anxiety	9.7%		10.6%		0.033
Chronic psychoses	0.9%		0.9%		-0.002

Continued on next page

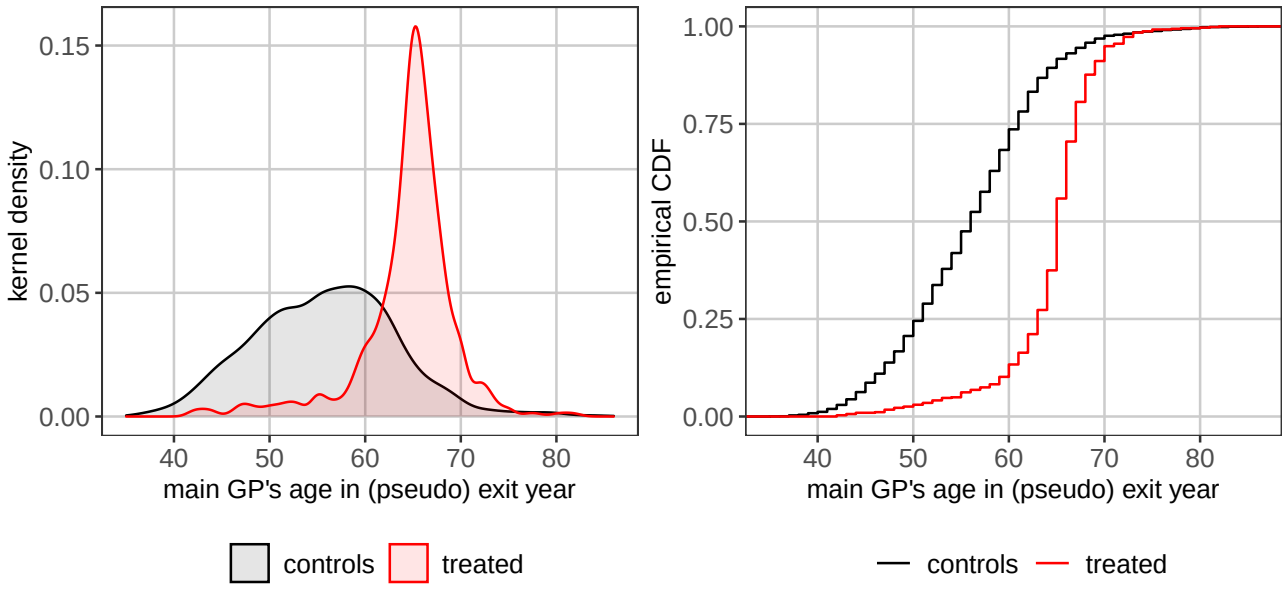
Table 1.C.2 – continued from previous page

	Treated		Controls		
	Mean	SD	Mean	SD	Std. Diff.
Addictions (alcohol and heroin)	0.4%		0.4%		0.005
Alzheimer's	0.1%		0.1%		0.005
Neuropathic pain	0.7%		0.7%		0.008
COPD	0.6%		0.6%		-0.001
ADHD	0.2%		0.2%		0.001
Number of GP practices	652		3,236		
Number of patients	43,767		197,662		
Number of observations	603,806		2,718,039		

Notes: The numbers are based on the calendar year prior to the (pseudo-) handover. The standardized difference is the difference in sample means divided by the the square root of the average of the two sample variances.

1.C.3 Physician Demographics

Figure 1.C.4: Age distribution of main GPs



Notes: This figure shows the age distribution of main GPs by treatment group, measured in the (pseudo) exit year. The peak in the density of treated GPs at 65 corresponds to the official retirement age for men in Switzerland. 90% of GPs in the treated group are at least 60 years old when they exit.

1.C.4 Robustness

Table 1.C.3: Unweighted Effects on Utilization, Hospitalization, Costs and Prevalence Chronic Condition

	short-run (t = 1)			long-run (t = 5)		
	ATT	SE	Baseline	ATT	SE	Baseline
A. Utilization						
Total visits	2.6%**	(0.008)	9.78	-1.0%	(0.010)	10.28
GP visits	0.2%	(0.013)	5.01	-3.9%*	(0.016)	4.94
Specialist visits	5.4%**	(0.012)	3.08	2.6%	(0.013)	3.35
Hospital outpatient visits	4.8%**	(0.015)	1.68	2.2%	(0.019)	1.93
Number of providers	7.9%**	(0.013)	1.48	2.7%	(0.015)	1.61
Number of specialist providers	6.1%**	(0.008)	1.27	4.7%**	(0.010)	1.39
B. Hospitalization						
Hospitalization	2.6%	(0.019)	0.13	0.2%	(0.019)	0.14
Number of inpatient days	1.8%	(0.034)	1.95	1.5%	(0.036)	2.33
C. Costs						
Total costs	4.7%**	(0.010)	4,629	3.5%**	(0.012)	5,693
Ambulatory costs	7.5%**	(0.011)	2,142	3.8%**	(0.012)	2,461
Costs per visit	4.2%**	(0.010)	138.1	5.2%**	(0.011)	151.6
Prescription drug costs	3.0%*	(0.014)	1,207	3.4%	(0.019)	1,423
Laboratory costs	19.5%**	(0.029)	234.6	9.3%**	(0.025)	250.3
D. Costs potential low value care						
Spine imaging costs[a]	5.2%	(0.054)	22.99	9.2%	(0.056)	25.41
Lipid measurement costs[b]	36.6%**	(0.076)	4.27	23.9%**	(0.081)	3.78
Knee MRI costs[a]	-8.2%	(0.089)	5.19	10.4%	(0.098)	5.62
PSA test costs	9.8%*	(0.046)	2.63	4.9%	(0.047)	2.74
Vitamin D test costs	33.0%**	(0.082)	12.81	12.3%*	(0.056)	15.37
E. Prevalence of chronic conditions (PCGs)						
Reflux disease	5.2%**	(0.010)	0.17	5.6%**	(0.014)	0.21
High cholesterol and hypertension	9.6%**	(0.013)	0.13	11.2%**	(0.020)	0.15
Depression and anxiety	-1.5%	(0.010)	0.10	-2.1%	(0.017)	0.11
Type 2 diabetes	5.1%**	(0.011)	0.07	5.0%**	(0.016)	0.09

Notes: This table shows unweighted short-run and long-run estimates of causal effects of practice handovers on outcomes in relative terms, that is, the aggregated coefficients of the interaction between the treatment group and time period t = 1 and t = 5. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. Estimates of panel D. and laboratory costs are based on cohorts 2012-2015, due to limited data availability for earlier cohorts. Long-run estimates for these outcomes correspond to those in time period t = 3. *$p < 0.05$, **$p < 0.01$. Abbreviations: GP, general pracitioner, MRI, magnetic resonance imaging, PSA, prostate specific antigen. [a] treatment due to illness, [b] patient age $\geq$ 75.

Table 1.C.4: Effects on Utilization, Hospitalization, Costs and Prevalence Chronic Condition (including patients that eventually die)

	short-run (t = 1)			long-run (t = 5)		
	ATT	SE	Baseline	ATT	SE	Baseline
A. Utilization						
Total visits	2.5%**	(0.008)	10.55	-1.0%	(0.010)	10.69
GP visits	0.2%	(0.012)	5.59	-4.3%**	(0.016)	5.26
Specialist visits	6.1%**	(0.012)	3.10	3.8%**	(0.014)	3.31
Hospital outpatient visits	3.7%**	(0.014)	1.86	1.8%	(0.018)	2.06
Number of providers	7.4%**	(0.012)	1.50	2.9%*	(0.015)	1.62
Number of specialist providers	6.9%**	(0.008)	1.25	5.6%**	(0.010)	1.37
B. Hospitalization						
Hospitalization	2.5%	(0.016)	0.16	0.9%	(0.018)	0.16
Number of inpatient days	4.3%	(0.028)	3.06	4.6%	(0.037)	3.11
C. Costs						
Total costs	2.3%*	(0.009)	6,098	2.2%	(0.013)	6,795
Ambulatory costs	6.3%**	(0.011)	2,368	2.8%*	(0.012)	2,592
Costs per visit	3.1%**	(0.010)	141.3	3.0%**	(0.010)	153.4
Prescription drug costs	1.5%	(0.013)	1,434	2.1%	(0.019)	1,569
Laboratory costs	17.7%**	(0.029)	242.1	8.0%**	(0.025)	254.4
D. Costs potentially low-value care						
Spine imaging costs[a]	7.9%	(0.055)	22.58	13.4%*	(0.059)	25.02
Lipid measurement costs[b]	37.8%**	(0.086)	3.75	25.2%**	(0.080)	3.53
Knee MRI costs[a]	-12.0%	(0.089)	4.79	7.6%	(0.099)	5.33
PSA test costs	9.5%*	(0.048)	2.63	4.8%	(0.046)	2.73
Vitamin D test costs	36.1%**	(0.084)	12.82	14.8%*	(0.058)	15.27
E. Prevalence of chronic conditions (PCGs)						
Reflux disease	4.3%**	(0.009)	0.19	3.1%*	(0.014)	0.22
High cholesterol and hypertension	8.7%**	(0.012)	0.14	9.1%**	(0.019)	0.15
Depression and anxiety	-2.0%*	(0.009)	0.12	-4.7%**	(0.016)	0.12
Type 2 diabetes	5.3%**	(0.010)	0.08	4.4%**	(0.016)	0.09

Notes: This table shows weighted short-run and long-run estimates of causal effects of practice handovers on outcomes in relative terms, that is, the aggregated coefficients of the interaction between the treatment group and time period t = 1 and t = 5. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. Estimates of panel D. and laboratory costs are based on cohorts 2012-2015, due to limited data availability for earlier cohorts. Long-run estimates for these outcomes correspond to those in time period t = 3. $^{*}p < 0.05$, $^{**}p < 0.01$. Abbreviations: ATT, average treatment effect on the treated, GP, general pracitioner, MRI, magnetic resonance imaging, PCG, pharmaceutical cost group, PSA, prostate specific antigen, SE, standard error. [a] treatment due to illness, [b] patient age ≥ 75.

Table 1.C.5: Long-run Effects on Utilization, Hospitalization, Costs and Prevalence Chronic Condition

	(t = 4)			(t = 5)			(t = 6)		
	ATT	SE	Baseline	ATT	SE	Baseline	ATT	SE	Baseline
A. Utilization									
Total visits	-0.5%	(0.009)	10.23	-0.7%	(0.010)	10.28	-1.2%	(0.011)	10.46
GP visits	-4.1%**	(0.015)	4.87	-3.7%*	(0.017)	4.94	-5.4%**	(0.018)	4.91
Specialist visits	4.3%**	(0.013)	3.35	3.7%**	(0.014)	3.35	4.4%**	(0.015)	3.45
Hospital outpatient visits	1.9%	(0.017)	1.93	1.6%	(0.019)	1.93	1.0%	(0.022)	1.99
Number of providers	4.9%**	(0.014)	1.62	2.2%	(0.015)	1.61	1.9%	(0.016)	1.65
Number of specialist providers	5.6%**	(0.009)	1.38	5.4%**	(0.010)	1.39	4.4%**	(0.011)	1.41
B. Hospitalization									
Hospitalization	0.8%	(0.020)	0.14	0.0%	(0.020)	0.14	0.6%	(0.022)	0.14
Number of inpatient days	-0.3%	(0.034)	2.31	1.6%	(0.038)	2.33	0.4%	(0.042)	2.40
C. Costs									
Total costs	2.5%*	(0.012)	5,612	2.1%	(0.012)	5,693	1.1%	(0.014)	5,920
Ambulatory costs	3.3%**	(0.011)	2,436	3.0%*	(0.012)	2,461	2.7%*	(0.013)	2,559
Costs per visit	3.5%**	(0.011)	149.9	3.2%**	(0.011)	151.6	5.8%*	(0.024)	157.7
Prescription drug costs	3.8%*	(0.017)	1,416	2.8%	(0.019)	1,423	4.1%*	(0.021)	1,466
D. Prevalence of chronic conditions (PCGs)									
Reflux disease	3.7%**	(0.013)	0.20	2.9%*	(0.014)	0.21	3.4%*	(0.015)	0.21
High cholesterol and hypertension	9.0%**	(0.018)	0.14	10.3%**	(0.020)	0.15	11.7%**	(0.022)	0.15
Depression and anxiety	-4.5%**	(0.014)	0.11	-4.6%**	(0.017)	0.11	-5.0%**	(0.019)	0.11
Type 2 diabetes	3.5%*	(0.015)	0.08	3.6%*	(0.016)	0.09	4.9%**	(0.019)	0.09

Notes: This table shows weighted different unbinned long-run estimates as robustness-checks of causal effects of practice handovers on outcomes in relative terms, that is, the aggregated coefficients of the interaction between the treatment group and time period t = 4, t = 5 and t = 6. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. *$p < 0.05$, **$p < 0.01$. Abbreviations: ATT, average treatment effect on the treated, GP, general pracitioner, PCG, pharmaceutical cost group, SE, standard error.

Table 1.C.6: Long-run Binned Effects on Utilization, Hospitalization, Costs and Prevalence Chronic Condition

	(t = 4)			(t = 5)			(t = 6)		
	ATT	SE	Baseline	ATT	SE	Baseline	ATT	SE	Baseline
A. Utilization									
Total visits	-0.7%	(0.009)	10.63	-1.0%	(0.010)	10.69	-1.2%	(0.011)	10.81
GP visits	-3.3%*	(0.015)	4.93	-3.6%*	(0.017)	4.99	-4.2%*	(0.018)	4.99
Specialist visits	3.4%**	(0.011)	3.44	3.3%**	(0.013)	3.44	3.3%*	(0.015)	3.49
Hospital outpatient visits	1.4%	(0.016)	2.08	1.1%	(0.018)	2.09	0.6%	(0.020)	2.12
Number of providers	3.8%**	(0.013)	1.69	2.3%	(0.014)	1.68	1.7%	(0.015)	1.69
Number of specialist providers	5.0%**	(0.009)	1.42	4.6%**	(0.010)	1.42	3.8%**	(0.011)	1.43
B. Hospitalization									
Hospitalization	0.4%	(0.016)	0.15	0.6%	(0.017)	0.15	0.6%	(0.019)	0.15
Number of inpatient days	0.4%	(0.028)	2.55	1.1%	(0.031)	2.58	0.3%	(0.034)	2.64
C. Costs									
Total costs	2.1%*	(0.010)	6,304	1.8%	(0.011)	6,389	1.3%	(0.013)	6,556
Ambulatory costs	2.6%**	(0.010)	2,627	2.3%*	(0.011)	2,647	1.8%	(0.012)	2,697
Costs per visit	2.8%**	(0.009)	156.0	3.1%**	(0.010)	156.9	3.1%**	(0.012)	158.1
Prescription drug costs	3.7%*	(0.016)	1,566	3.6%*	(0.018)	1,580	4.8%*	(0.020)	1,618
D. Prevalence of chronic conditions (PCGs)									
Reflux disease	3.4%**	(0.012)	0.22	3.1%*	(0.013)	0.22	3.1%*	(0.015)	0.22
High cholesterol and hypertension	8.5%**	(0.017)	0.15	9.0%**	(0.019)	0.15	10.4%**	(0.021)	0.16
Depression and anxiety	-4.4%**	(0.014)	0.11	-4.0%*	(0.016)	0.11	-4.0%*	(0.018)	0.12
Type 2 diabetes	3.7%**	(0.014)	0.09	4.1%**	(0.016)	0.09	4.8%**	(0.018)	0.09

Notes: This table shows weighted different binned long-run estimates as robustness-checks of causal effects of practice handovers on outcomes in relative terms, that is, the aggregated coefficients of the interaction between the treatment group and binned time periods $t \geq 4$, $t \geq 5$ and $t \geq 6$. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. $^{*}p < 0.05$, $^{**}p < 0.01$. Abbreviations: ATT, average treatment effect on the treated, GP, general pracitioner, PCG, pharmaceutical cost group, SE, standard error.

1.C.5 Heterogeneity Results

Table 1.C.7: Long-run Effects By Physician's Age

	new GP is old				new GP is young			
	ATT (abs.)	SE	ATT (in %)	Baseline	ATT (abs.)	SE	ATT (in %)	Baseline
A. utilization								
total visits	0.33	(0.178)	3.0%	11.21	-0.08	(0.135)	-0.7%	10.93
GP visits	0.06	(0.142)	1.0%	5.58	-0.22*	(0.108)	-4.0%*	5.27
specialist visits	0.19**	(0.070)	5.6%**	3.50	0.16**	(0.059)	4.7%**	3.58
hospital outpatient visits	0.08	(0.059)	3.8%	2.04	0.05	(0.045)	2.3%	2.04
number of providers	0.08*	(0.039)	4.8%*	1.70	0.10**	(0.032)	5.7%**	1.81
number of specialist providers	0.08**	(0.020)	6.1%**	1.41	0.10**	(0.018)	7.3%**	1.52
B. hospitalization								
hospitalization	0.000	(0.004)	0.1%	0.14	0.000	(0.004)	-0.1%	0.15
number of inpatient days	0.024	(0.142)	1.0%	2.45	-0.037	(0.135)	-1.5%	2.52
C. costs								
total costs	221.9	(116.08)	3.8%	6,028	80.3	(97.12)	1.3%	6,204
ambulatory costs	110.1*	(44.13)	4.4%*	2,595	116.3**	(40.47)	4.6%**	2,665
costs per visit	5.2*	(2.03)	3.5%*	152.8	7.3**	(2.29)	4.9%**	157.4
prescription drug costs	75.2	(51.04)	5.3%	1,491	49.3	(35.47)	3.2%	1,602
laboratory costs	22.7**	(8.02)	9.6%**	259.3	20.8**	(7.96)	8.3%**	270.5
D. prevalence of chronic conditions (PCGs)								
reflux disease	0.01**	(0.004)	5.7%**	0.22	0.01*	(0.004)	4.9%*	0.23
high cholesterol and hypertension	0.02**	(0.004)	14.6%**	0.16	0.02**	(0.004)	12.2%**	0.17
depression and anxiety	0.00	(0.003)	-3.2%	0.12	0.00	(0.003)	-3.3%	0.12
type 2 diabetes	0.01*	(0.002)	6.4%*	0.09	0.01**	(0.002)	6.1%**	0.10
Patients (control)				156,494				156,494
Patients (treated)				12,658				14,534

Notes: This table shows weighted long-run estimates of causal effects of practice handovers on outcomes in percentage and absolute terms, that is, the aggregated coefficients of the interaction between the treatment group and post-treatment period t = 5. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. *$p < 0.05$, **$p < 0.01$.

Table 1.C.8: Long-run Effects By Physician's Gender

	new GP is male				new GP is female			
	ATT (abs.)	SE	ATT (in %)	Baseline	ATT (abs.)	SE	ATT (in %)	Baseline
A. utilization								
total visits	0.10	(0.132)	0.9%	11.02	0.14	(0.198)	1.2%	11.24
GP visits	-0.06	(0.110)	-1.2%	5.44	-0.16	(0.147)	-2.8%	5.35
specialist visits	0.15**	(0.050)	4.5%**	3.48	0.25*	(0.097)	7.0%*	3.78
hospital outpatient visits	0.05	(0.044)	2.3%	2.04	0.07	(0.073)	3.5%	2.04
number of providers	0.07*	(0.030)	4.2%*	1.72	0.14**	(0.045)	8.2%**	1.89
number of specialist providers	0.08**	(0.015)	5.6%**	1.43	0.15**	(0.026)	10.2%**	1.59
B. hospitalization								
hospitalization	0.000	(0.004)	0.3%	0.15	0.000	(0.006)	-0.3%	0.15
number of inpatient days	0.046	(0.109)	1.8%	2.51	-0.116	(0.206)	-4.6%	2.44
C. costs								
total costs	153.9	(88.40)	2.6%	6,099	115.6	(148.89)	1.9%	6,232
ambulatory costs	102.8**	(36.02)	4.1%**	2,612	135.0*	(55.95)	5.2%*	2,711
costs per visit	5.7**	(1.83)	3.8%**	153.8	8.8**	(3.18)	5.8%**	160.2
prescription drug costs	46.1	(36.31)	3.1%	1,537	96.9	(55.74)	6.4%	1,609
laboratory costs	16.6*	(7.08)	6.9%*	257.6	38.2**	(9.42)	15.3%**	287.8
D. prevalence of chronic conditions (PCGs)								
reflux disease	0.01**	(0.004)	6.4%**	0.23	0.00	(0.004)	1.7%	0.22
high cholesterol and hypertension	0.02**	(0.004)	12.1%**	0.16	0.03**	(0.005)	16.5%**	0.18
depression and anxiety	0.00	(0.003)	-3.7%	0.12	0.00	(0.004)	-1.7%	0.12
type 2 diabetes	0.01**	(0.002)	6.3%**	0.10	0.01*	(0.002)	5.7%*	0.10
Patients (control)				156,494				156,494
Patients (treated)				20,778				6,497

Notes: This table shows weighted long-run estimates of causal effects of practice handovers on outcomes in percentage and absolute terms, that is, the aggregated coefficients of the interaction between the treatment group and post-treatment period t = 5. The model includes patient fixed effects and time effects. Data is measured in annual terms. Standard errors are clustered at the physician level. *$p < 0.05$, **$p < 0.01$.

Chapter 2

A Prescription for Knowledge: Patient Information and Generic Substitution

Abstract

Markets require perfectly informed participants to function effectively. In this paper we study how providing patients with targeted information influences their purchasing decisions between the brand and generic versions of prescription drugs. If patients remain unaware of having this choice, any cost savings offered by cheaper generic alternatives cannot be realized. We exploit the dissemination of informational letters by a large Swiss health insurer to patients purchasing brand-name drugs as a novel natural experiment to estimate the causal impact of patient information in health care decisions. Using detailed individual-level data of 540,000 drug purchases by 60,000 patients, we find that the provision of information regarding generic alternatives leads to a nearly fourfold increase in the likelihood of generic substitution. Furthermore, the effect does not substantially depend on whether patients face a co-payment for their drug purchase and thus financially profit from switching. Our results highlight the limits of health care policies that rely solely on financial incentives, particularly if patients lack sufficient information in their decision-making.

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2.1 Introduction

One of the fundamental requisites for functioning markets lies in both buyers and sellers having sufficient information in their decision-making. Despite the unique nature of the health care market, characterized by uncertainty and asymmetric information (Arrow, 1963), and the actual low consumer knowledge levels in the health sector (see, e.g., Handel and Schwartzstein, 2018), many health care systems are nonetheless structured akin to typical consumer markets. Given the large degree of information asymmetry between medical providers and patients, health policies that primarily rely on financial incentives may fail to fully achieve their objectives.

Much of the economic literature on informational frictions in the health domain focuses on insurance plan choices (see, e.g., Baicker et al., 2015; Drake et al., 2022; Handel and Kolstad, 2015; Heiss et al., 2021). These findings highlight an apparent disconnect between optimal decision-making and observed consumer behavior. Not only does inattention and lack of knowledge often come at a substantial financial detriment to consumers, markets as a whole become less efficient as an allocation mechanism. Yet, seemingly minor information interventions can have significant efficacy in redirecting consumer choices. Goldin et al. (2020), for example, find that a simple letter, providing information on a tax penalty for lacking health insurance coverage and on how to acquire coverage, increased enrollment substantially.

While inefficiencies in health insurance markets have been well-documented, less attention has been paid to the consequences of informational frictions in the market for health care itself. The inherent complexity of medical treatments, patients rarely bearing the full costs of their decisions and government regulations lead to additional barriers, that make acquiring relevant information even more challenging for consumers in this domain. Despite many health policies attempting to steer patient decisions to limit overall expenditures, these informational aspects are often neglected. In this paper, we study to what extent providing targeted information directly to patients influences their decision-making. We do so for the relatively straightforward choice between expensive brand-name drugs and their therapeutically equivalent, low-cost generic counterparts. Given its potential to reduce health care expenditures, many health policy makers have implemented various schemes to encourage generic substitution (see Socha-Dietrich et al., 2017, for an overview). Since the final decision usually rests with the end consumer, patient-directed measures primarily leverage financial incentives beyond the already existing price differences. Yet, for any market mechanisms to apply, consumers must first be aware that a choice between multiple products exists at all.

Bronnenberg et al. (2015) show that healthcare professionals, who have generally deeper product knowledge, exhibit higher levels of generic adoption than the general public. We study empirically to what extent providing information to patients purchasing brand-name drugs on available generic alternatives, some of whom presumably have previously lacked knowledge,

increases the substitution probability. Thus, our focus is on estimating to what extent the lack of basic patient information drives decision-making and how yielding generic substitution is to being provided this information. To do so, we analyse the effect of informational letters a Swiss health insurer sent to patients who had recently purchased a brand-name drug. These letters included a list of currently available generic alternatives for the respective brand-name drug and the savings from switching to the cheapest option. While the campaign was not implemented as a randomized controlled experiment, we exploit quasi-randomized timing of the information treatment within the drug purchase history of the respective patient. Converting this setting to an event study design with staggered treatment adoption, we compare the not-yet-treated with the already treated patients at each purchase "number" (using the method proposed by Callaway and Sant'Anna, 2021) to estimate the causal effect of basic patient information on generic substitution probability. We use a detailed individual-level data set from insurance claims, containing approximately 540,000 drug purchases of roughly 60,000 patients that received the informational letter.

We find that the informational letter increases the probability of a generic drug by nearly 30 percentage points. In comparison to a baseline probability of 10.2%,[1] this corresponds to almost a fourfold increase in the substitution probability among previous brand-buyers. Our findings highlight how even quite limited but specific information provided by a non-medical third party can have a major impact on patient decisions and improvement on their alignment with preferences. A back-of-the-envelope calculation shows that patient information constitutes a highly cost-effective measure to reducing health care expenditures. Overall, costs per letter amounted to less than one Swiss franc, while leading to additional annual savings of over 36 Swiss francs per dispatched letter.

Our findings contribute to the rising strand of literature showing the significance of consumer information in the context of health care decisions. Whereas our paper focuses on choices between therapeutically equivalent products and thus on the cost consequences, most decisions by (potential) patients also directly affect their health outcomes. Compared to other goods markets, the restrictions on consumer-directed information provision are often more stringent for health care products and services. For example, many countries ban direct-to-consumer-advertising (DTCA) for pharmaceutical drugs. Such additional informational frictions may impose welfare losses, however, as Shapiro (2022) finds that television advertisements in the US markedly decrease absenteeism at work due to previously untreated individuals learning about the existence of appropriate drugs. Sinkinson and Starc (2019) similarly show the cost-effectiveness of DTCA in attracting new patients to a category of highly effective drugs, namely statins, even to the non-advertised generic versions therein. Still, large-scale advertising cam-

[1] This share is non-zero due to everyone who bought a brand version within the respective drug group being included in the mailing campaign, even if this was only a one-time "accidental" purchase or the patient having switched to a generic version on their own prior to the dispatch of the informational letter.

paigns by pharmaceutical firms are resource-intensive and directly organized by the seller of the product. In the context of generic drugs, Carrera and Villas-Boas (2023) provide an example of a simple, inexpensive and patient-directed information treatment by a (non-medical) third party. The authors show that product-specific information labels displaying the share of generics, increases the probability of patients switching to generics. In contrast, the authors find the effect of labels highlighting price differences to be dependent on framing and that information regarding the general safety of generics does not change purchase choices. Even in the absence of legal barriers for third parties, physicians remain the predominant source of information for (potential) patients. If the primary source of information and medical provider constitute the same individual, agency problems can arise (Clemens and Gottlieb, 2014).[2]

The rest of this paper is structured as follows. In Section 2.2, we describe the setting of our study, pharmaceutical drugs in Switzerland and the generics information campaign. Next, Section 2.3 explains our empirical strategy using a staggered treatment event study design, while Section 2.4 details the health insurance claims data we employ. Section 2.5 presents our main results and subgroup heterogeneity analyses, before Section 2.6 offers concluding remarks.

2.2 Setting

2.2.1 Generic Substitution

Following the expiration of patent protection for a brand-name drug, other manufacturers are permitted to produce generic versions of the same active ingredient that offer equivalent therapeutic effects. Since the expensive drug development and trial process does not have to be repeated for generics, prices can be set close to marginal costs of production. The resulting price differences, up to 90% lower than their branded counterparts, underscore the significant cost-saving potential for overall health care expenditures inherent in generic substitution. Policymakers worldwide have consequently elaborated a variety of strategies to encourage the shift from branded to generic drugs. Given the pivotal role of medical providers in determining drug selection, these policies mainly target physicians and pharmacists. These approaches predominantly involve both non-financial mandates and added flexibility, such as prescribing only the active substance, rather than a specific brand, and empowering pharmacists to substitute generics (Socha-Dietrich et al., 2017). In contrast, patient-centred policies have mostly focused on augmenting the financial burden for those choosing brand-name drugs. Apart from broad public awareness campaigns, there have been only few initiatives aimed directly at motivating patients to choose generics. This gap in policy initiatives could be attributed to the limited em-

[2] Johnson and Rehavi (2016) show that better informed patients (in their case physicians themselves) can act as protection from financial incentives of providers negatively influencing treatment decisions.

pirical evidence on factors influencing patients' choice between generic and brand-name drugs, particularly beyond financial incentives.

A growing strand of the literature underscores the significance of patient inertia and a propensity to adhere to physicians' drug choices, especially when patients lack access to alternative sources of information that are both readily available and comprehensible. Granlund and Sundström (2018) illustrate how patients' conflicting desires to follow their doctor's prescription while also selecting the least expensive option can lead to welfare losses in instances where physicians do not recommend generics. Janssen and Granlund (2023) use a similar empirical approach as we do and discover that a patient's initial decision not to refuse a generic substitution significantly influences their probability of opting for generics in subsequent purchases. Song and Barthold (2018) exploit exogenous changes across various US states' laws regarding generic substitution and find that unless patient consent is not required, allowing pharmacists to substitute has limited impact due to the strong preferences of patients to stick with their doctor's initial brand prescription. This heavy reliance of patients on their physicians, presumed to act in the patients' best interests, can be problematic. In particular when physicians' financial incentives are misaligned. Liu et al. (2009) present evidence that financial incentives significantly influence the probability of generic substitution among physicians who both prescribe and dispense drugs. Addressing this over-reliance may not require complex interventions, as the findings of Ito et al. (2020) suggest that minor external nudges can effectively counter patient inertia regarding generic substitution. Nonetheless, patients are also susceptible to financial incentives. Dafny et al. (2017) demonstrate that the probability of patients opting for generics diminishes considerably when pharmaceutical companies offer copay coupons for brand-name drugs.

2.2.2 Health Insurance and Prescription Drugs in Switzerland

Similar to the Netherlands and Germany, compulsory health insurance in Switzerland is based on principles of regulated competition (the following description draws on Schmid et al., 2018). While regulation guarantees risk solidarity, individual affordability, and access to care, competition among insurers and health care providers should promote quality and efficiency. Consumers can freely choose from over 50 private health insurers during the annual open enrollment period (there is no public option). In the standard health plan, consumers have unrestricted choice of health care providers, an individual deductible of 300 Swiss francs and generally a co-insurance rate of 10% up to the stop-loss amount of 700 Swiss francs, which both reset yearly. However, consumers can opt for preferred provider, health maintenance organisation, or telemedicine health plans and choose higher deductibles ranging from 500 to 2,500 Swiss francs. Both choices lead to a lower premium, albeit subject to strong regulations to preserve

risk solidarity. Notably, every health plan has to offer identical coverage for services, including prescription drugs. While supplementary health insurance plans exist, these exclusively offer additional services and as such do not impact prescription drugs.

Compulsory health plans have to cover (prescription) drugs that are listed in the so-called specialties list, which is compiled and published monthly by the Federal Office of Public Health (FOPH). In order to be listed, a drug first has to be approved by the national drug approval agency named Swissmedic. Subsequently, its producer has to bargain with the FOPH on the ex-factory price, which then applies uniformly to all medical providers and health insurance plans. While launch prices of new brand-name drugs are determined by reference pricing using comparison countries and similar, already listed drugs, launch prices of generics are based on the price and market volume of the corresponding brand-name drug (see Gerfin et al., 2024, for further details). Consequently, generic drugs are generally less expensive than brand-name drugs, though there is considerable variation in ex-factory prices per unit among substitutable drugs. Retail prices vary even more markedly as the (regulated) distribution margins increase step-wise in the ex-factory price.

Health plans reimburse the retail price for drugs either directly dispensed by a physician or prescribed by a physician and then dispensed at a pharmacy.[3] While physicians only earn the distribution margins on dispensed drugs, pharmacists additionally receive consultation fees to compensate them for their services. Both dispensing physicians and pharmacists have an incentive to sell more expensive, typically brand-name, drugs due to higher margins (Müller et al., 2023). However, there are several measures on the supply and the demand side to encourage generic use. First, pharmacists have the right to substitute a prescribed brand-name drug with generic versions unless the prescribing physician explicitly indicated otherwise. In addition, physicians and pharmacists have to inform patients about the availability of generic drugs listed on the specialties list.[4] Pharmacists also receive a one-time payment for substituting a patient's brand-name prescription for the first time, providing a modest financial incentive. Second, for substitutable drugs exceeding a certain price threshold, patients incur a co-insurance rate of 20% instead of 10% (see Gerfin et al., 2024, for details), intended to motivate drug manufacturers to reduce prices and patients to select less expensive options. While this policy successfully lowered drug prices, its impact on generic drug utilization has been minimal, similar to other implemented measures.

[3]Some Swiss cantons (partly) allow physicians to dispense drugs, that is, physicians are allowed to sell drugs in the office (for further details, see Kaiser and Schmid, 2016; Trottmann et al., 2016; Burkhard et al., 2019).

[4]Although the law does not further detail what this information needs to entail or possible sanctions for violating the requirement.

2.2.3 Generics Mailing Campaign

In 2010, a few years after the introduction of the increased 20% co-insurance rate on sufficiently more expensive branded drugs, Switzerland's largest health insurer initiated a mailing campaign designed to encourage generic substitution among its patients. Rather than conducting a universal campaign to raise general awareness about generic drugs for all insurees, this initiative was specifically directed only at patients who had recently purchased a brand-name drug. To conform to Switzerland's prohibition against promotion of specific prescription drugs, the campaign was framed as primarily informing patients about the existence of the increased 20% co-insurance rate.[5]

Initially, the campaign started with dispatches concerning three different drug substitution categories, expanding to 20 categories in the following years.[6] Not all drugs subject to a 20% co-insurance were incorporated in the mailing. Inclusion criteria required that the drugs must be for long-term treatments of chronic conditions and exhibit sufficiently large price differentials between the brand-name and generic versions. Furthermore, to guarantee reliable accessibility of established substitutes, the dispatch of letters was conditioned upon the presence of a minimum of three generic alternatives in the corresponding drug category.

Content — Each informational letter started with a uniform introduction explaining that generics are less costly alternatives that contain the same active ingredient as their brand-name counterparts. Subsequently, a tailored section informed the recipient about the existence of generic alternatives for their specific branded medication, followed by an alphabetically ordered list of currently available generic versions. Finally, the letter indicated the potential cost savings of switching to the least expensive alternative and advising patients to consult with their healthcare provider or pharmacist to determine the most appropriate generic medication for their treatment. The letters were dispatched in German, French and Italian, corresponding to the patient's preferred contact language. An English translation of a sample letter is exhibited in Figure 2.A.6 in the Appendix.

Mailing procedure — The process governing the dispatch of generic drug letters was automated and constituted a component of the broader marketing communication system employed by the health insurer. The initiation of this process was contingent upon either a patient or a drug provider submitting a claim for a brand-name drug listed in the substitution groups included in the campaign. Health insurers typically receive such claims with some delay subsequent to the actual purchase. This delay arises either from drug providers consolidating individual patient claims into a single monthly bill or from patients who, having directly paid for the

[5]The FOPH nevertheless banned informational letters targeted to relevant patients in 2022, deeming them to be in violation with data protection laws.

[6]Table 2.A.1 in the Appendix provides a list of included drug categories alongside the respective number of letters sent and inclusion dates.

drug at the point of sale, defer submitting their bill until a later point in time. Consequently, the time lapse between purchase and claim submission introduces a largely randomized initial element of timing variation into the mailing process. Upon receipt of a claim for a branded drug on the specified list, the system initiates a verification process to check whether the individual satisfied additional eligibility criteria. Children, adults older than 85 years, and patients receiving home care services are excluded from the generics campaign. Once a patient is deemed eligible, a lead is generated. Thereby enrolling the respective patients into the campaign and starting the standard marketing communication procedure. A mandatory waiting period of a minimum of three weeks follows the claim's receipt. Subsequent to this interval, the system becomes primed for the potential dispatch of a letter. However, to prevent overwhelming patients with excessive simultaneous communications, the system imposes a cap on the volume of correspondence issued within a given time frame.[7] Each communication category, is assigned an internal priority ranking.[8] This ranking dictates the sequence of dispatch in instances where multiple communications are queued simultaneously. Letters already in the queue can also be pushed back further by later incoming leads. This prioritization check is conducted every 14 days (on Saturdays) and thus represents the shortest additional delay arising from communication blocking. Additionally, each communication item is also assigned a specific interval, often exceeding the two-week minimum and usually lasting well over a month, during which it precludes the dispatch of other communications. If no higher-priority item is identified during the check, the generics letter is dispatched via regular mail on the following Monday, typically requiring an additional two to three days for delivery to the patient. Figure 2.1 provides a simplified overview of this process.

Ultimately, these delays, which are reasonably exogenous to the decision-making process between branded and generic drugs, create considerable variation in the duration between the initial purchase, which triggers the mailing process, and the eventual dispatch of the letter across patients.

2.3 Empirical Strategy

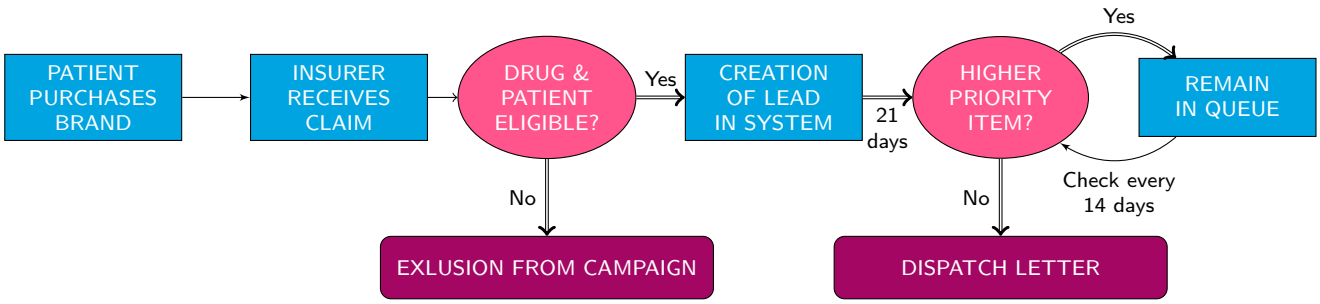
2.3.1 Event Study

Neither the content nor the process of the mailing was designed within an experimental framework aimed at investigating the causal effect of the informational letter. In scenarios involving

[7] This system applies solely to marketing communications. Correspondence related to billing (for both insurance premiums or medical claims) or the annual insurance quote issued at close to year-end does not affect the timing of the letter's dispatch in the marketing system.

[8] If clients have brand purchases in different medication categories, they receive a separate letter for each drug group. However, there is an additional three month minimum interval imposed before the next generics letter can be sent after the previous one.

Figure 2.1: Generics Mailing Procedure Steps



Note: This figure illustrate the different steps within the automated process of the generics mailing campaign. The time between the purchase of the drug and the receipt of the claim by the health insurer can vary depending on the billing system and the provider.

repeated decisions, such as purchases for chronic medication, there is an increasing probability of individuals becoming better informed over time. Information could emerge from patients inquiring about more cost-effective generic alternatives or from healthcare providers disclosing these options during successive prescriptions. Under these circumstances, generic substitution becomes more likely with each purchase, irrespective of the patient receiving an informational letter. Notably, the campaign system did not verify whether the patient had already transitioned to a generic option since creation of the lead before dispatching the letter. Additionally, some activations of the mailing process may have originated from patients who typically opt for generics but made an exceptional brand-name purchase. A possible reason would be temporary unavailability of generic versions on a particular day.

A naïve approach of simply considering the letters responsible for all switches to generic alternatives would overestimate the causal impact of targeted patient information. Instead, we exploit the quasi-random, exogenous delays in the mailing process (detailed in Section 2.2.3). At each subsequent purchase within a drug group, a proportion of patients will already have received the informational letter, while others have not yet. Our novel approach thus mimics a natural experiment, where there is a quasi-random division into groups: those who have not yet received the treatment and those who have. Should self-informed decision-making become increasingly probable with each purchase, our control group's evolution should accurately reflect changes in substitution probability due to factors other than the informational letter. Leveraging the exogenous variation in treatment timing within purchase histories thus enables us to estimate the causal effect of providing information to patients on their propensity to choose generic drugs. Our approach ultimately parallels a standard event study design with staggered treatment adoption, with the unique aspect of substituting standard time measures, such as years, with the sequence of drug purchases within a substitution group.

A client may receive multiple generics letters for different drugs. Nevertheless, our analysis

concentrates on the drug group corresponding to the patient's initial informational letter. Receipt of a subsequent letter for another drug group implies a brand-name purchase within that second group. Thus, the population receiving multiple letters likely exhibits a general reluctance to switch to generics (or the initial treatment only works within the specifically targeted drug group). This leads to heterogeneous control groups, with some individuals having already experienced a "partial treatment" prior to the actual treatment in the second drug group. Conversely, patients who switch to generics in both the initially targeted and subsequent drug groups will not receive additional letters, thus excluding purchases in other drug groups from our analysis. By focusing exclusively on the first drug group for which a patient received a letter, we ensure a homogeneous population experiencing a known uniform treatment. The sole remaining variation being the timing of treatment within each individual's purchase history. Consequently, we observe a single sequential drug purchase history for each individual who has ever received an informational letter.

2.3.2 Method

Our empirical setting corresponds to a slightly adapted version of an event study with staggered treatment adoption. Instead of considering the outcome at different points in time, we compare outcomes at different purchase numbers. As described in the previous section, our unit of observation is the patient-drug purchase. In line with the recent advancements in the econometrics literature (Borusyak et al., 2022; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Roth et al., 2023; Sun and Abraham, 2021) we omit the conventional two-way fixed effects (TWFE) model for estimating the causal effect of the informational letter on generic drug purchases. Instead, we employ the estimator suggested by Callaway and Sant'Anna (2021).

We now elaborate on our setting in more detail. For each patient i, we observe all purchases $c \in \{1, 2, ..., 10\}$.[9] We classify patients into different treatment cohorts $g \in \{3, 4, ..., 10\}$, with g denoting the first purchase following the letter's dispatch. As all patients in our sample eventually receive the treatment, there is no never treated group that could serve as a control group. Therefore, we rely on the not-yet-treated patients as controls. Callaway and Sant'Anna (2021) suggest three different estimands to identify causal effects (outcome regression, inverse probability weighting, doubly-robust). Given the lack of necessity to condition on covariates (pre-treatment outcomes are adequately similar across cohorts, as we will later show), we opt for the outcome regression (OR) approach.

The main estimation consists of a two-step procedure. First, a series of cohort-purchase number average treatment effects on the treated (ATTs) are nonparametrically identified using

[9]This applies for the majority of patients. However, as illustrated in Section 2.4, we allow the panel to be unbalanced if a patient has less than 10 total purchases within the relevant drug category.

OR, defined as

$$\text{ATT}(g,c) = E[Y_c - Y_{g-1}|G_g = 1] - E[Y_c - Y_{g-1}|D_c = 0], \tag{2.3.1}$$

where $D_c = 0$ for all $g > c$, i.e. all cohorts that are not yet treated at purchase c. Subsequently, these cohort specific estimates are then aggregated to obtain event study type estimates,

$$\theta_{es}(e) = \sum_{g \in G} \frac{n_{g,e}}{n_e} \text{ATT}(g, g+e), \tag{2.3.2}$$

with e representing the relative purchase ($e = c - g$), $n_{g,e}$ indicating the number of patients in treatment cohort g observed at relative purchase e, and n_e the total number of units observed at e. This aggregation yields an estimate for each relative purchase number under consideration $e \in \{-3, ..., 1\}$.[10]

2.4 Data

2.4.1 Data Sources

Our study principally utilizes individual-level data provided by the health insurer responsible for the generic drug information campaign. The core dataset is a comprehensive panel of all medication purchases by clients who received a generics information letter.[11] Each transaction record includes a unique identifier for each specific drug, the type of dispenser, cost allocation between patient and insurer, and the exact date of purchase. This allows us to create an ordered purchase sequence within each drug substitution group for each patient.[12] If there are multiple packages of the same drug group purchased on the same date, they are considered one purchase.

As our interest lies in decisions between brand and generic drugs, we start the enumeration of purchases only when at least one alternative to the brand-name drug becomes available.[13] Additionally, we exclude "purchases" made in hospitals as part of outpatient treatment, as patients usually are precluded from making their own choices.[14] Thus, each numbered instance in the respective patient's purchase history should represent observed outcomes where individuals exercised direct agency in the decision.

[10] Given that we only observe two pre-tretment purchases for the cohort first treated at the third purchase $g = 3$, this cohort is not included in $e = -3$.

[11] Due to bundled payment for inpatient treatment, drug consumption is not separately itemized and thus not included in our claims data. Given the absence of patient choice in drug selection during such stays, this does not pose a problem for our study of generic substitution.

[12] We define a drug substitution group by the active ingredients of the brand version of the drug.

[13] Data concerning available alternatives (and prices) on the level of each drug group is derived from a modified version of the publicly available "specialities list" the FOPH publishes once per month.

[14] Hospital outpatient treatments with direct drug dispension mostly occur due to emergencies.

Data regarding the informational letters mainly contains information on the targeted drug group and the dispatch date.[15] We first assess whether a purchase took place before or after the dispatch of the letter, thereby creating a binary pre- or post-treatment period indicator. Following standard event study methodology, we then re-enumerate purchases in relation to the dispatch of the informational letter. Zero denotes the first purchase made by the patient subsequent to receiving the treatment, i.e., the informational letter.

2.4.2 Data Preparation

From 2010 to 2018, approximately 200,000 informational letters were sent as part of the generics campaign.[16] As explained in Section 2.3.1, we focus solely on the first drug group for which a patient received the informational letter. Combined with the initial exclusion criteria on purchases (and the removal of clients with erroneous or incomplete data), and the necessary exclusion of patients who did not make any further purchases of the relevant drug post-treatment, our sample reduces to roughly 100,000 letters, i.e., individual patients.

We observe that about 20% of the patients received the informational letter between their first and second purchases. While the control group (the not-yet-treated) should largely reflect any general trend towards generic substitution following the initial purchase, their inclusion could nonetheless lead to an overestimation of the letters' impact. Therefore, we adopt a conservative approach and focus only on individuals who received the treatment after their second purchase at the earliest. The proportion of not-yet-treated individuals declines with each successive purchase. Relying on these patients as the control group implies increasing disparity between the already treated and control group as the purchase count rises. Therefore, we set a threshold of only including patients who received treatment by their 10th purchase, thereby removing an additional approximately 10,000 individuals from our dataset.[17] Lastly, we restrict our sample to include only patients with at least one purchase within both the 180 days preceding and following the dispatch of the letter. Again, this criterion is intended to ensure that any observed changes in purchasing behavior are attributable to the informational treatment rather than other external factors. Our final sample comprises 61,456 patients and thus purchase histories within the treated drug group. We limit our analysis to the first 10 purchases, although do not require that patients fully complete this number of purchases. Instead, we require that patients are observed continuously up until the first treated purchase

[15] While we cannot determine the exact transaction that triggered inclusion in the campaign, particularly in cases involving repeated brand purchases, this detail is not crucial for our identification strategy.

[16] Although the campaign (temporarily) concluded in early 2020, we limit our analysis to letters sent until the end of 2018. This ensures a complete year of observation for all patients prior to the onset of the Covid-19 pandemic, which could have influenced purchase decisions due to factors such as drug shortages and hoarding behavior.

[17] These decisions have minimal effect on our results, however.

(see Figure 2.A.1 in the Appendix). This results in a slightly unbalanced panel, totaling 538,797 observations. On average, we observe 8.8 purchases per individual.

2.4.3 Summary Statistics

Table 3.1 provides summary statistics for our sample at purchases across different stages of treatment: before receiving the informational letter, at the first purchase after the letter and the subsequent purchases afterwards. On average, the interval between drug purchases within the same category is approximately 106 days both in the pre-treatment period and at the first purchase post-letter, equating to slightly over three months. This aligns with expectations, given that a drug package typically contains a total dosage lasting for a three-month period. Contrarily, the intervals extend to about four months in the remaining period following the letter.

Table 2.1: Summary Statistics

	Before Letter		First After Letter		Remaining After	
	Mean	SD	Mean	SD	Mean	SD
nth Purchase of drug	2.93	1.87	4.88	1.95	7.39	1.85
Days since previous purchase of drug	106	150	106	49.0	119	142
Average drug price (in CHF)	67.3	34.1	63.9	27.4	63.9	26.2
Potential savings by switch to generic (in CHF)	44.3	31.3	46.5	30.0	45.2	27.9
Potential savings by switch to generic (rel.)	0.42	0.15	0.45	0.13	0.44	0.13
Available alternatives for drug	5.53	2.29	6.68	2.10	7.01	2.15
Any copayment by patient	83.1%		80.9%		83.6%	
Physician dispensed drug	29.9%		31.0%		31.3%	
Patient living in Latin language canton	44.7%		44.5%		44.2%	
Female patient	52.8%		51.8%		51.3%	
Patient age (at purchase)	64.3	13.9	64.9	13.9	66.0	13.3
Lowest deductible model	68.0%		68.1%		68.5%	
Total health care exp. in year of purchase	10,569	16,157	10,509	16,012	9,409	14,425
Observations (drug purchases)	238,627		61,456		238,714	
Unique individuals with drug purchases	61,456		61,456		54,953	

Note: "Before Letter" summarizes the outcomes of interest at all purchases that occurred before the patient received the letter. "First After Letter" corresponds to the average outcomes at the time of the first purchase after the letter. "Remaining After" summarizes the outcomes of interest at all purchases that occurred after the first treated purchase (i.e., $e > 0$). All cost-related outcomes are measured in CHF. In the period "Remaining After" we observe around 11% individuals less, as we do not condition our sample to be observed for all purchases after the first treated purchase. This indicates that we have an unbalanced panel which however hardly impacts our results as robustness-checks show.

The drug categories targeted in the generics campaign are relatively high-priced, with average costs of 67 Swiss francs pre-treatment, 64 Swiss francs just after the letter and in the subsequent period (measured by the list prices in the category at the time of purchase, not the average price paid by patients). Hence, these negligibly lower prices post-treatment do not indicate any changes in drug choices arising from general changes to the price environment coinciding with the timing of the letter. Substantial cost-saving opportunities persist through-

out the entire observation period. Switching from the most expensive brand name drug to the cheapest generic alternative within a substitution group can yield average savings between 44 and 46.5 Swiss francs across the periods. In relative terms, this corresponds to savings in the range of 42% - 45% relative to the highest-priced drug. We thus observe modestly higher savings opportunities post-treatment, however we deem it unlikely that these changes are of sufficient magnitude to explain any large shifts towards generics even in a hypothetical absence of the informational letter.

The number of available generic alternatives within each substitution group increase as purchase counts rise, from just under six pre-treatment to around seven options post-treatment. As more time passes since patent expiration, more generic producers enter the market. However, we would argue that already during purchases prior to the letter, the choice set of patients was rather large and the emergence of an additional option on average post-treatment is unlikely responsible for large portions of patients switching to generics. Over 80% of patients incur at least some out-of-pocket drug costs at the respective purchase, with this share remaining roughly constant over the different periods. This indicates the presence of financial incentives to substitute generics for patients both before and after receiving the informational letter. Any changes to patient choices post-treatment should thus not arise from altered incentives. About 30% of drug purchases occurred at a physician's office, with the majority (69%) coming from pharmacies, again without any substantial shifts between pre- and post-treatment.

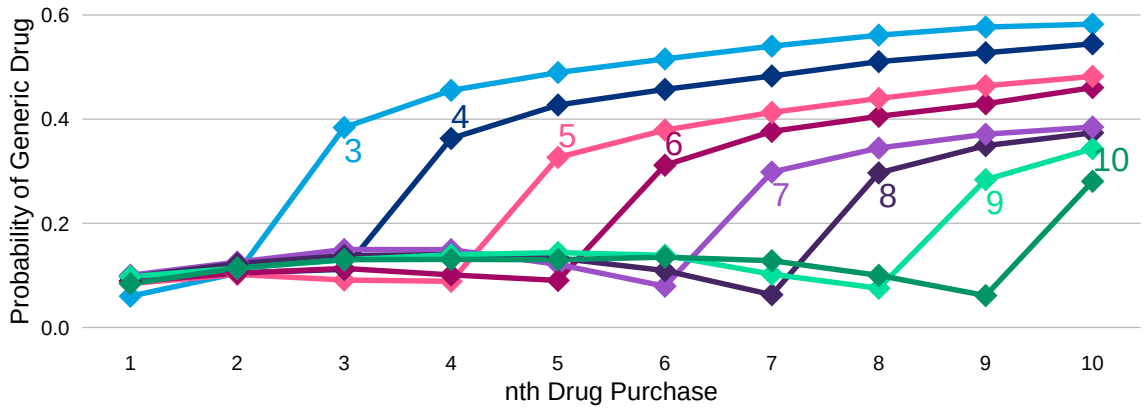
Considering patient demographics, around 44% of patients live in a majority Latin-language canton, encompassing the French-speaking regions of Switzerland or the Italian-speaking canton of Ticino. With approximately 50%, there are slightly more female than male patients in the sample. Given that many drugs involved in the generics campaign are used to treat chronic conditions prevalent among older individuals, the average patient age is notably high with 64 in the pre-treatment period, increasing to 65 at the first post-letter purchase, and 66 subsequently. Around 68% of patients opt for the lowest deductible level (300 Swiss francs), which is consistent with their total health care expenditures that average at around 10,500 Swiss francs in the pre-treatment period and the year of the first purchase after the letter. Health care expenditures are marginally lower in years of later purchases, averaging about 100 Swiss francs less. In total, our sample consists of 61,456 individual patients for which we observe 238,627 distinct pharmaceutical purchases pre-treatment, with each individual also observed by requirement at their first post-treatment purchase. Around 11% of initial patients are no longer observed in the remaining periods, where we still observe additional 238,714 pharmaceutical purchases from 54,953 patients.

2.5 Results

2.5.1 Descriptive Evidence

We first present the probability of a generic drug purchase at the n-th purchase for all treatment cohorts ($g \in \{3, 4, ..., 10\}$) in Figure 2.2. The different cohorts are represented by colored lines, with the corresponding treatment cohort numbers. While none of the groups received treatment before the third purchase, we note a baseline probability of 10.2% for generic drug selection during the pre-treatment period across all cohorts. This indicates that a subset of individuals had already opted for generic alternatives even before receiving the treatment. For some cohorts this share increases incrementally up to at most around 15%, especially among cohorts treated at later stages. This suggests that a relatively minor fraction of patients may self-learn about generic substitution, but it is more probable that the majority of pre-treatment generics purchases are due to patients who had "unintentional" one-time brand buys which caused inclusion in the generics campaign. The observed decline in the generic drug share immediately preceding treatment also supports this hypothesis. With the trigger purchase often being the one immediately before the letter's dispatch, the temporary increase in brand-name selections likely arises from patients who regularly chose generics in previous purchases. Given the similar trends across all cohorts, this pattern should not adversely impact our subsequent analysis using a staggered treatment event study design.

Figure 2.2: Share of Generic Drugs at Each nth Drug Purchase Across Treatment Cohorts



Note: Diamonds represent raw means for the seven treatment cohorts at each of the ten purchases within the same drug substitution group we include a patient for. Figure 2.A.1 in Appendix A shows the number of observations in each of the cohort-nth purchase combinations shown here.

Examining the initial purchase following the dispatch of the informational letter, we observe a significant shift in the average generic share, increasing by approximately 25 percentage points. Before the treatment, roughly one in eight purchases involved a generic drug; this proportion increases to one in three post-treatment. Cohorts treated later exhibit a marginally

lower response to the informational treatment, with the initial increase being closer to 20 percentage points. A diminished impact on more experienced patients is plausible, as some individuals might have independently become aware of generic options but consciously do not switch. Beyond the first post-treatment purchase, the probability of choosing a generic drug continues to rise with each additional purchase, with the most notable increase occurring at the second treated purchase. However, from the third post-treatment purchase onward, the rate of increase stabilizes and becomes mostly linear. This pattern suggests that the influence of the informational letter diminishes after this point, with subsequent marginal increases likely due to patients obtaining information from other sources. This observation reinforces our decision to exclude purchases beyond the second post-treatment in our event study, as attributing further rises in the generics share to the informational treatment becomes increasingly speculative. The significant increase in the generics share at the second treated purchase is likely a direct effect of the letter. Considering the delivery time of standard mail and the time required for recipients to read the letter, it is evident that for many, their second post-dispatch purchase effectively constitutes their first informed decision. A closer analysis reveals that the generics share in the first post-treatment purchase remains at baseline levels for at least up to five days after the letter's dispatch. Therefore, for a subset of patients, their second purchase post-dispatch in reality represents their first decision-making opportunity with the newly acquired information.

2.5.2 Event Study Estimates

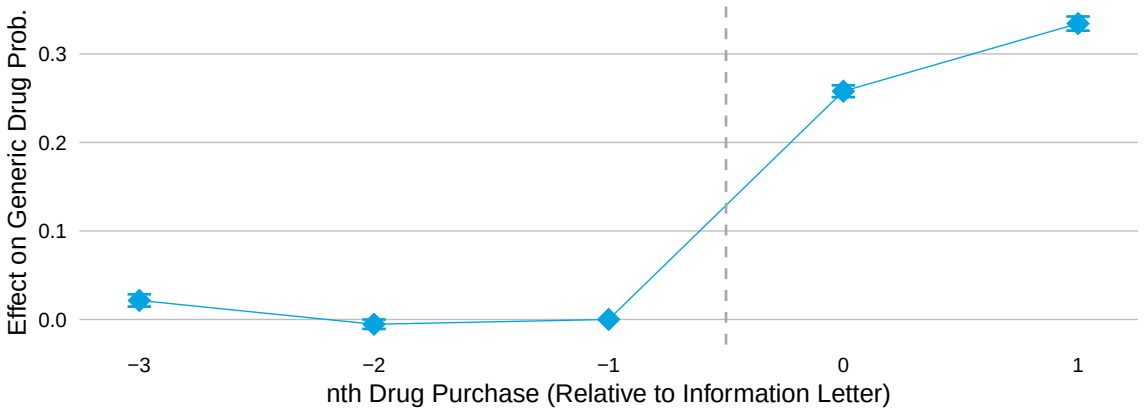
We now proceed with our main results from the event study design, which are presented in Figure 2.3. Echoing the descriptive evidence in the previous subsection, we obtain an ATT for patient information of a 25.8 percentage points increase in the probability of switching from brand-name to generic drugs in the first treated purchase.[18] Owing to the substantial effect magnitude and the large sample size, we can decisively reject the null hypothesis at any conventional significance level.[19] Relative to the pre-treatment baseline probability of 10.2% for selecting a generic drug, the impact of the informational letter is substantial, amounting to 3.5 times its original size immediately after treatment.

As with the descriptive findings, we assert that attributing further changes in generic substitution at the second post-treatment purchase to the letter is justifiable, even in our generally conservative approach. The ATT estimate at this juncture corresponds to 33.4 percentage points, together with the previous purchase resulting in an overall ATT of 29.6 percentage points. This demonstrates that already a simple, yet specific and targeted informational letter, primarily listing available alternatives, can quadruple the rate of substitution. The evident

[18] Table 2.A.2 in the Appendix shows the full pairwise difference-in-differences coefficients.

[19] In fact, the 99% confidence intervals using standard errors clustered on the patient level, as depicted in Figure 2.3, are virtually imperceptible.

Figure 2.3: Event Study Estimates for Effect of Information on Generic Substitution



Note: The aggregated difference-in-differences coefficient (average treatment effect on the treated (ATT) of information on generic substitution) is 0.296. The baseline probability of purchasing a generic drug in the three purchases prior to the treatment information letter was 10.2%. Horizontal lines surrounding the coefficients (shown as diamonds) represent the 99% confidence interval of the estimate, with standard errors clustered at the patient level.

lack of adequate patient information and attentional barriers are significant impediments for brand-drug purchasers transitioning to more affordable generic alternatives. Despite health insurers (at least in Switzerland) often being ranked low in trust among healthcare system actors in patient surveys, the minimal level of patient awareness renders even such sources influential in persuading approximately one third of brand buyers to switch to generics upon realizing their consumer choices. Given that the letters originated from an automated system and were sent via regular mail, at a total cost of less than one Swiss franc each, they represent a highly cost-effective intervention. A back-of-the-envelope calculation suggests that each letter yielded additional annual savings of approximately 36 francs for the targeted drug alone, underscoring the efficiency of targeted patient information as a policy strategy to influence patient behavior.

To conclude our main analyses we perform two additional estimations. As discussed in Section 2.4.2, we do not require patients to have at least 10 claims for inclusion in our sample, resulting in a slightly unbalanced panel analysis thus far. To evaluate the potential impact of this, we rerun our analysis using only the data from the 44,374 individuals with a complete set of 10 purchases, thus excluding about 15,000 patients). Figure 2.A.2 in the Appendix compares the estimates from our primary sample with those from the balanced dataset. The latter's estimates align closely with the former, indicating no discernible bias from the lack of a fully balanced panel. If anything, the balanced estimates are marginally higher. Lastly, instead of aggregating the ATT over purchases relative to the informational letter, we analyse it across the seven treatment cohorts. Figure 2.A.3 in the Appendix depicts these cohort-specific heterogeneity estimates. Intriguingly, the informational treatment exhibits nearly a uniform effect across cohorts, irrespective of the number of prior purchases. This suggests that

patients influenced by the letter likely lacked any prior knowledge of generic alternatives for their medication, as well as the means to acquire such information.

2.5.3 Subgroup Differences

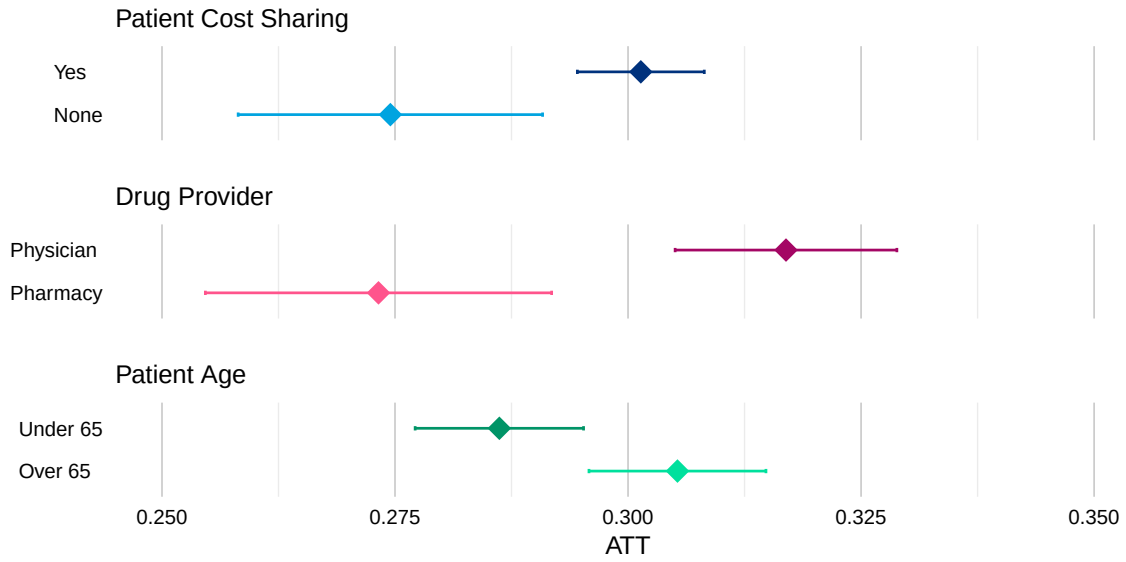
In our concluding series of analyses, we separate patients into subgroups to investigate potential differences in the influence of the informational letters on their drug selection. Unless noted otherwise, these heterogeneity analyses segregate all purchases at the patient level into distinct groups based on the classification determined by the patient's status at the time of their first post-treatment purchase. Subsequently, we apply the same estimation procedure as in our main analyses to each subgroup separately. The independence of the two samples enables simply checking whether the two resulting confidence intervals overlap to determine if we can reject the null hypothesis of no effect disparities between groups.

Given that many policies to encourage generic substitution heavily rely on price mechanisms, our initial analysis assesses whether the letter has a greater impact on patients who stand to gain financially from switching to a less expensive generic alternative. The letter's quasi-random timing should also assure that categorizing groups based on whether the annual stop-loss limit was reached by the time of the first post-treatment purchase does not introduce biased selections. The first panel in Figure 2.4 presents the two overall ATTs for these two groups. Predictably, patients with financial incentives for switching to generics are more likely to do so post-treatment compared to those for whom both the brand and generics are (spot) priced identically at zero. We estimate an ATT of 30.1 percentage points for the former group and in the latter an ATT of 27.5 percentage points, with the difference being statistically significant at the 1% level. The marginal effect attributed to financial incentives, when compared to the role of information alone, is therefore less than 10%.[20] We can only speculate on the reasons why roughly a third of patients who have no financial incentive to switch to a generic do so. One explanation could be the emphasis in the letter that generics help to reduce overall health care expenditures, appealing to patients' sense of contributing to the greater good. Others might choose generics as the same good for a lower price as a matter of principle, once informed about their options. Both underscore the promise of independently provided patient information for future health care policy-making. Figure 2.A.4 in the Appendix also suggests the potential of combining financial incentives with direct and easily understandable patient information. If

[20] In a subsidiary analysis, we further subdivide the group having to pay for the drug at least partially: those still below deductible and those above deductible but below stop-loss (i.e., patients pay 20% of the brand, 10% of the generic price). Among patients retaining the entire price differential between brand and generic, the effect is slightly larger. The ATT in the co-insurance group falls between the no cost-share group and the full cost-sharing group, indicating that financial incentives do influence consumer choices in the health care market and can thus inform policy. However, the marginal changes in patient behavior are limited compared to the influence of information.

the letter indicated higher relative savings for the drug group in question, patients were more likely to switch to a generic alternative.

Figure 2.4: Effect of Information on Generic Substitution by Subgroups



Notes: Patients are divided into the respective subgroup depending on their observed outcome relevant for the building of the group at the first purchase after the letter. Considering the place of dispensation, only patients that always lived in a canton allowing physician-dispensing, were considered in the analysis.

Furthermore, we examine the differential impact of the informational treatment across drug dispensation locations and patient age groups. For the analysis concerning physician dispensation, we restrict the sample to patients in German-speaking cantons permitting this practice.[21] In this instance, subgroup classification is based on whether a physician directly dispensed a drug to the patient at any point. This approach mitigates the potential bias wherein the intention to switch to generics as a consequence of the letter might influence the choice of dispensation location. As shown in the second panel of Figure 2.4, patients who received drugs from self-dispensing physicians demonstrated a markedly stronger response to the informational treatment. While the underlying reasons are uncertain, one possibility is that physician dispensing leads to a sole medical professional as the only source of information for patients. A self-dispensing physician neglecting the legal obligation to inform about generics, then precludes patients from learning about alternatives. Visiting a pharmacy provides an additional opportunity for patients to discover substitution options. Some patients may also feel more comfortable asking pharmacists than physicians about generics if prescribed the brand version. Importantly, the significant difference arising from the place of dispensation underscores that institutional frameworks may have a more profound impact on health care costs than mar-

[21] All French- and Italian-speaking cantons plus two German-speaking cantons only allow pharmacies to dispense drugs.

ket mechanisms alone. As for patient age, the last panel in Figure 2.4 suggests rather small differences. This finding indicates that in a complex and barrier-intensive sector like health care, where patients often do not perceive themselves as active consumers, the ability to seek additional information sources (such as the internet) might be limited.

2.6 Conclusion

Our findings demonstrate that the dissemination of clear and concise information can substantially influence patients' decisions. In the context of our analysis, an informational letter sent by a Swiss health insurer lead to a nearly fourfold increase in the probability for choosing the cost-effective generic drug among patients who previously purchased the brand-name version of the drug. While the efficiency of the mailing campaign seems impressive – per dispatched letter it generated savings of 36 Swiss francs per year – it is important to note that it is paper-based and its wording is primarily intended to meet legal requirements. In other words, it has not been optimized to maximize savings. Using today's technology it would be simple to make it even less expensive, more sophisticated and to scale it up.

Furthermore, we find that financial incentives towards generic substitution provide only a marginal effect compared to the impact of information itself. Almost one third of patients switch their choice even if they reap no monetary benefits from doing so. This could indicate that patients would like to make a contribution towards lower healthcare costs even if they have no direct monetary benefit from their (changed) decisions. Overall, the marked impact of a simple letter from a source with relatively low levels of trust among patients, also highlights the apparent unmet demand among many individuals for more readily available information for their healthcare decisions.

In sharp contrast to our findings, policymakers in the health domain often establish additional barriers to information gathering. As a consequence, medical professionals are often the sole available source for patients seeking information. This may result in time-consuming and costly one-on-one consultations. In the present case, the FOPH prohibited the insurer's generic mailings because the law does not allow the insurers to inform their clients about cheaper healthcare alternatives. They justify this decision by stating that this would be the task of physicians and pharmacists. Regarding generics, there is even a legal mandate for physicians and pharmacists to inform their patients about the possibility of generic substitution. In view of this regulation, the efficacy of the insurer's generic mailing is rather surprising. As dispensing brand-name drugs results in higher revenues to drug providers, however, we further highlight the pitfalls of policies restricting information provision to medical providers only.

2.A Appendix I

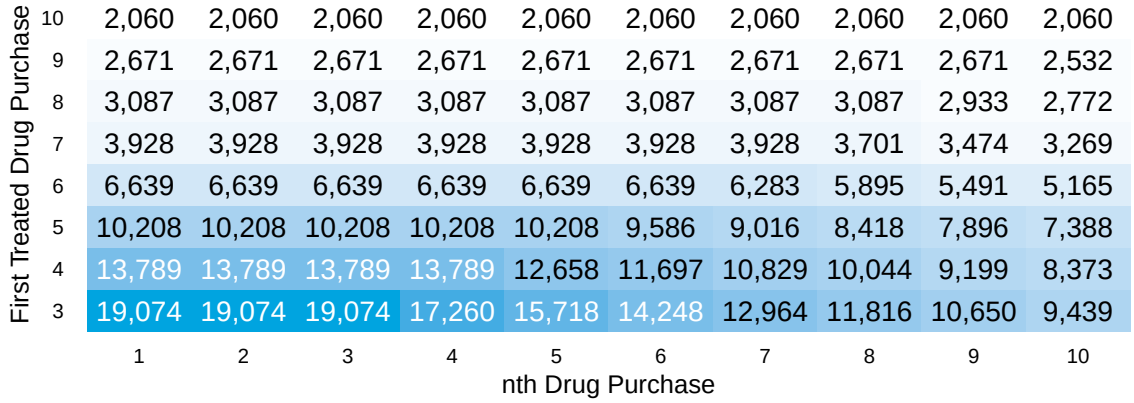
2.A.1 Additional Descriptives

Table 2.A.1: Drug Groups Included in Generics Mailing Campaign

Drug group	Letters sent	First letter
Atorvastatin	4,751	2012
Candesartan	6,187	2013
Celecoxib	673	2015
Clopidogrel	6,320	2010
Duloxetin	1,214	2017
Esomeprazol	3,560	2015
Ezetimib	558	2018
Lansoprazol	1,217	2011
Gliclazid	2,364	2015
Ibandronic acid	367	2015
Irbesartan	4,717	2013
Losartan	2,066	2011
Metoprolol	4,441	2011
Pantoprazol	8,255	2010
Pramipexol	1,272	2011
Pregabalin	1,088	2017
Rosuvastatin	4,234	2017
Valsartan	3,423	2012
Venlafaxin	3,623	2010
Zolmitriptan	1,126	2013

Notes: Drug group denotes the substances for which the mailing was ever active. Letters sent corresponds to the total number of letters sent for the respective drug group. Finally, first letter denotes the first year in which the mailing campaign was active for the respective drug group.

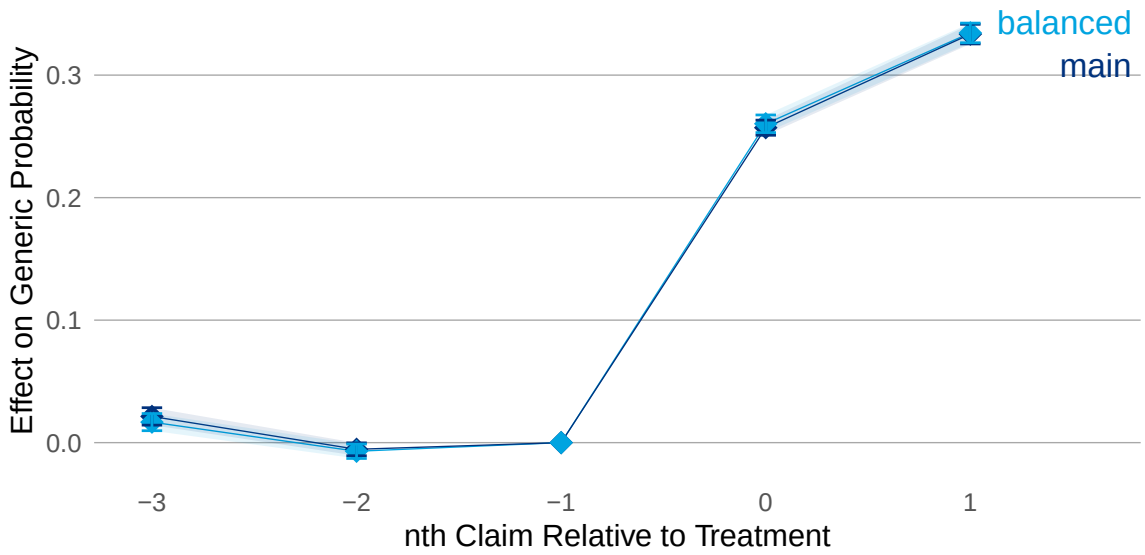
Figure 2.A.1: Distribution of Observations by nth Drug Purchases and First Treated Drug Purchase Groups



Notes: This figure shows the total number of observations by first treated drug purchase g at purchase c. The sample is balanced within the pre-treatment period ($c \leq g$) but not necessarily in the post-treatment period. This occurs due to the sample restrictions as illustrated in Section 2.4.2.

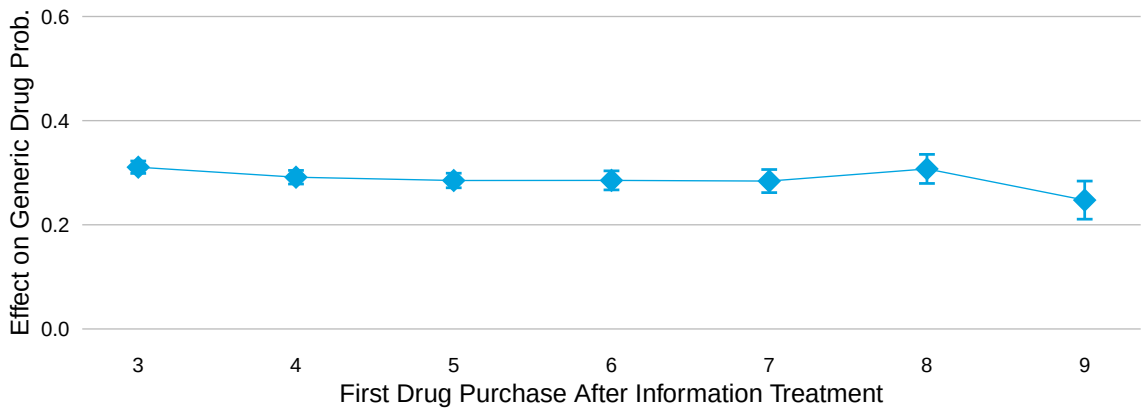
2.A.2 Additional Results

Figure 2.A.2: Main Estimates vs. Estimates Based on Balanced Panel



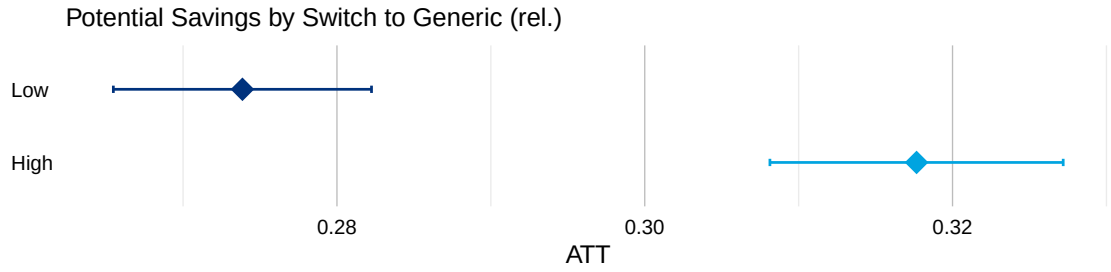
Notes: As a robustness-check this figure directly compares the event-study estimates of our main specification in Figure 2.3 and when using a balanced panel. We see that the estimates are very similar independent of balanced or unbalanced panel.

Figure 2.A.3: Effect of Information on Generic Substitution Across Cohorts



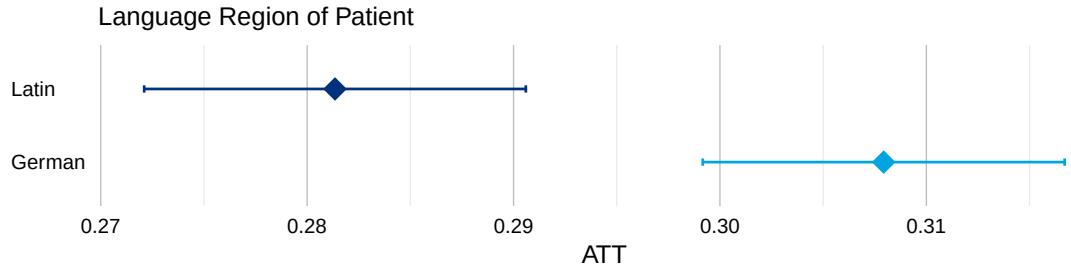
Notes: This figure compares the aggregated ATTs of all cohorts g. For the aggregation all ATTs up to $e = 1$ are considered where available. Because the latest treated cohort ($g = 9$) is only observed until $e = 0$, for this cohort the aggregation is based on fewer post-treatment periods (only one instead of two). The different cohorts are depicted on the x-axis.

Figure 2.A.4: Effect Across Savings Potential



Notes: This figure shows the aggregated ATT by savings potential. Specifically, savings are determined by comparing the difference between the costs of the most expensive drug and the cheapest alternative drug within the same substitution group, relative to the price of the most expensive drug. Patients are divided into subgroups depending on whether the potential relative savings are above (High) or below (Low) the median potential savings of all substitution groups.

Figure 2.A.5: Effect Across Language Regions



Notes: This figure shows the aggregated ATTs by language region of the patients. Patients living in the French- or Italian-speaking part of Switzerland belong to the "Latin" group. Patients that switch between language regions within the observation period are omitted from the estimation.

Table 2.A.2: Full Main Difference-in-Differences Results

Term	Estimate	Standard Error
ATT(3,1)	-0.026	0.003
ATT(3,2)	0.000	
ATT(3,3)	0.273	0.004
ATT(3,4)	0.348	0.004
ATT(3,5)	0.383	0.005
ATT(3,6)	0.421	0.005
ATT(3,7)	0.460	0.006
ATT(3,8)	0.485	0.006
ATT(3,9)	0.525	0.010
ATT(4,1)	0.004	0.004
ATT(4,2)	-0.001	0.003
ATT(4,3)	0.000	
ATT(4,4)	0.254	0.004
ATT(4,5)	0.329	0.005
ATT(4,6)	0.374	0.005
ATT(4,7)	0.411	0.006
ATT(4,8)	0.443	0.007
ATT(4,9)	0.485	0.009
ATT(5,1)	0.029	0.004
ATT(5,2)	0.026	0.004
ATT(5,3)	-0.000	0.004
ATT(5,4)	0.000	
ATT(5,5)	0.249	0.005
ATT(5,6)	0.322	0.005
ATT(5,7)	0.368	0.006
ATT(5,8)	0.401	0.007
ATT(5,9)	0.445	0.010
ATT(6,1)	0.032	0.005
ATT(6,2)	0.025	0.005
ATT(6,3)	0.015	0.005
ATT(6,4)	0.000	0.005
ATT(6,5)	0.000	
ATT(6,6)	0.242	0.006
ATT(6,7)	0.329	0.007
ATT(6,8)	0.367	0.008
ATT(6,9)	0.408	0.010
ATT(7,1)	0.053	0.008
ATT(7,2)	0.055	0.007
ATT(7,3)	0.063	0.008
ATT(7,4)	0.059	0.007
ATT(7,5)	0.032	0.006
ATT(7,6)	0.000	
ATT(7,7)	0.252	0.008
ATT(7,8)	0.316	0.009
ATT(7,9)	0.366	0.012
ATT(8,1)	0.056	0.008
ATT(8,2)	0.059	0.008
ATT(8,3)	0.059	0.008
ATT(8,4)	0.055	0.008
ATT(8,5)	0.046	0.007
ATT(8,6)	0.023	0.007
ATT(8,7)	0.000	
ATT(8,8)	0.261	0.009
ATT(8,9)	0.353	0.011
ATT(9,1)	0.038	0.010
ATT(9,2)	0.024	0.010
ATT(9,3)	0.025	0.011
ATT(9,4)	0.034	0.010
ATT(9,5)	0.038	0.010
ATT(9,6)	0.028	0.010
ATT(9,7)	-0.001	0.010
ATT(9,8)	0.000	
ATT(9,9)	0.247	0.011

Notes: This table shows the ATT(g, c) estimates and the corresponding standard errors for each cohort g at each purchase c. If $c < g - 1$, the estimates correspond to a test for pre-treatment trends. ATT(g, $g-1$) corresponds to the reference purchase, i.e., the last untreated purchase.

2.A.3 Example of Letter in Generics Mailing Campaign

Figure 2.A.6: Informational Letter for the Brand Drug *Crestor* (Rosuvastatin)

CSS
Communications
Tribschenstrasse 21
Mailbox 2568
6002 Lucerne

Telephone 0844 277 XXX
Telefax 058 277 XX XX
xxx@css.ch

css.ch

CH-6002
Lucerne

4XX-37-2XX / DCK
POST CH AG

Mr.
John Doe
Example Street 1
9999 Example Town

Lucerne, xx.xx.20xx

Generic drugs - Same effect, lower costs!

Dear Mr. Doe

Is there a less expensive alternative to my medications? Generic drugs could be an answer to this question.

Generic drugs are imitation products with the same active ingredient and dosage that are just as effective as the brand version of the drug and meet the same standards. The Swiss Agency for Therapeutic Products, Swissmedic, monitors this.

In the meanwhile, imitation products for the brand drug Crestor have come to market in Switzerland. The following generic versions are available:

Crestastatin, Rosuvastatin Axapharm, Rosuvastatin Mepha, Rosuvastatin NOBEL, Rosuvastatin Sandoz, Rosuvastatin Spirig HC, Rosuvastatin Viatris, Rosuvastatin Xiromed, Rosuvastatin Zentiva, Rosuvastax

Some of these alternatives are up to 61% less expensive. At your next drug purchase ask your physician or pharmacist about the appropriate generic for your branded drug --- or whether you should ahere to the brand. As attractive as generic drugs are, there are also limits in their usage.

If have you have any questions about this letter, we are happy to take time for you.

Kind regards,
CSS

First Name Last Name

Head of Communications Medical Claims
Member of Management

First Name Last Name

Domain Expert Communications Medical Claims

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Chapter 3

Christmas Shopping in the Prescription Drug Market

Abstract

Health insurance contracts typically include a combination of various cost-sharing features. These are designed to balance the trade-off between risk protection and maintaining incentives, but they also generate nonlinear price schedules and dynamic incentives. In this study, we analyse whether individuals react rationally to these incentives. To do so, we utilize extensive individual-level claims data obtained from a large Swiss health insurer linked to detailed pharmaceutical information. We focus on patients with chronic conditions. They experience a very salient increase of the spot price caused by the deductible reset at the start of a year, but their expected end-of-year price, the price they should react to, is unaffected by the deductible reset. Employing a regression discontinuity design, our analysis reveals that the difference between the amount of DDDs purchased in December compared to January corresponds to around 50% of the yearly average DDDs purchased. This is at least partially caused by individuals who purchase in December to avoid the high spot price early in the following year. In other words, a fraction of consumers is highly responsive to spot prices, indicating a limited understanding of the complexity of their health insurance contract. This is further evidence for apparent irrational behavior induced by deductibles.

Acknowledgment: Joint work together with Michael Gerfin. We would like to thank participants at the dggö conference in Hannover, the Brown Bag Economics seminar at the University of Bern, the PhD Workshop of the Swiss Health Economics Association in Bern, the applied Micro seminar at the University of Gothenburg, and the research seminar in health sciences at the University of Lucerne, for valuable comments. In addition, we would like to thank CSS health insurance for providing the data.

3.1 Introduction

The fundamental goal of health insurance is to protect patients from the financial consequences of unexpected health shocks. However, there is a trade-off between risk protection and maintaining incentives (Cutler and Zeckhauser, 2000). A well studied possible side-effect of health insurance is moral hazard, which means that individuals consume more health care because insurance lowers the marginal price for patients (see Einav and Finkelstein, 2018, for an overview). Therefore, many modern health insurance contracts include a combination of various cost-sharing features. One of the most common instruments aiming at containing health care costs are deductibles. Deductibles correspond to a fixed monetary amount up to which an individual has to bear 100% of health care costs. After surpassing the deductible, typically a co-insurance rate between 0% and 100% applies. Finally, if a predefined amount of out-of-pocket expenditures is reached, all additional health care is fully covered by the insurance. This is often referred to as a catastrophic cost limit, maximum dollar expenditure or stop-loss. Combining deductibles, co-insurance rates and stop-loss results in nonlinear price schedules. Put differently, current spending dynamically impacts future prices. This creates a complex environment with multiple prices which patients need to consider when making health care consumption decisions.

Theoretically, it has been shown that in the presence of deductibles, rational individuals should base their decisions on the expected end-of-year price throughout the year. As a consequence, they should ignore the spot price, the marginal price for the next unit of health care (Keeler et al., 1977). Whether consumers actually respond to the expected end-of-year price or rather to the spot price has been empirically analysed in several papers. Aron-Dine et al. (2015) find evidence for at least partial forward-looking, while the results in Brot-Goldberg et al. (2017) indicate that agents react only to the spot price, i.e. they are spot price biased. Both papers analyse only within year consumption decisions. Extending the analysis to multiple years, where health care consumption may be shifted intertemporally, reveals that consumers indeed shift the timing of their health care purchases to periods with lower prices (Cabral, 2017; Einav et al., 2015; Lin and Sacks, 2019). The incentive for this intertemporal shift is typically created by the reset of the deductible at the end of the year.[1]

In a broader context our paper contributes to the literature analysing whether patients react to dynamic incentives in health insurance (see e.g., Gerfin et al., 2015; Johansson et al., 2023; Klein et al., 2022; Lin and Sacks, 2019; Simonsen et al., 2021a). These studies conclude that individuals respond to dynamic incentives induced by nonlinear health insurance coverage. Specifically, in anticipation of higher future prices, individuals tend to strategically time health care consumption to minimize out-of-pocket spending. Using data from the well-known RAND

[1] Or the so-called donut hole in Medicare Part D, see Einav et al. (2015).

health insurance experiment, Lin and Sacks (2019) find that patients react more strongly to temporary price decreases than permanently low prices. These results are in line with findings for Switzerland where the authors report that patients in high deductible plans who unexpectedly surpass it, increasingly consume health care just before the deductible reset (Gerfin et al., 2015). In contrast, they do not find any effect for individuals in the lowest deductible group for overall health care except for prescription drugs. A possible explanation for this exception is the distinct feature of prescription drugs that time of purchase and time of consumption generally do not overlap. This makes prescription drugs especially prone to strategic timing. Specifically, when it comes to drugs used to treat chronic conditions (henceforth referred to as chronic drugs), where individuals have predictable future needs. Hence, this setting is somewhat comparable to consumer inventory shopping (Hendel and Nevo, 2006). If patients are spot price biased, the period before the deductible reset is comparable to a period with sales.

In this paper we analyse whether the prescription drug demand of chronically ill individuals reacts to the strong and salient increase in the spot price induced by the deductible reset at the beginning of the year. Employing a regression discontinuity design, we estimate the causal impact of the deductible reset on prescription drug demand in terms of defined daily dosages (DDDs). If patients are forward-looking and only consider the expected end-of-year price, we should not observe any change in purchasing behavior at the turn of the year. Our results show, however, that the difference between the amount of DDDs purchased in December compared to January corresponds to around 50% of the yearly average DDDs purchased. By further decomposing the overall effect into a holiday and price effect, we find that around one third of the overall effect can be explained purely by the price effect. Thus, patients seem to be spot price biased.

The paper is organized as follows; Section 3.2 illustrates the institutional setting in Switzerland, Section 3.3 explains the data and sample selection, Section 3.4 provides some theoretical considerations of optimal patient behavior in the present setting, Section 3.5 outlines the empirical strategy, 3.6 presents the results, and Section 3.7 concludes.

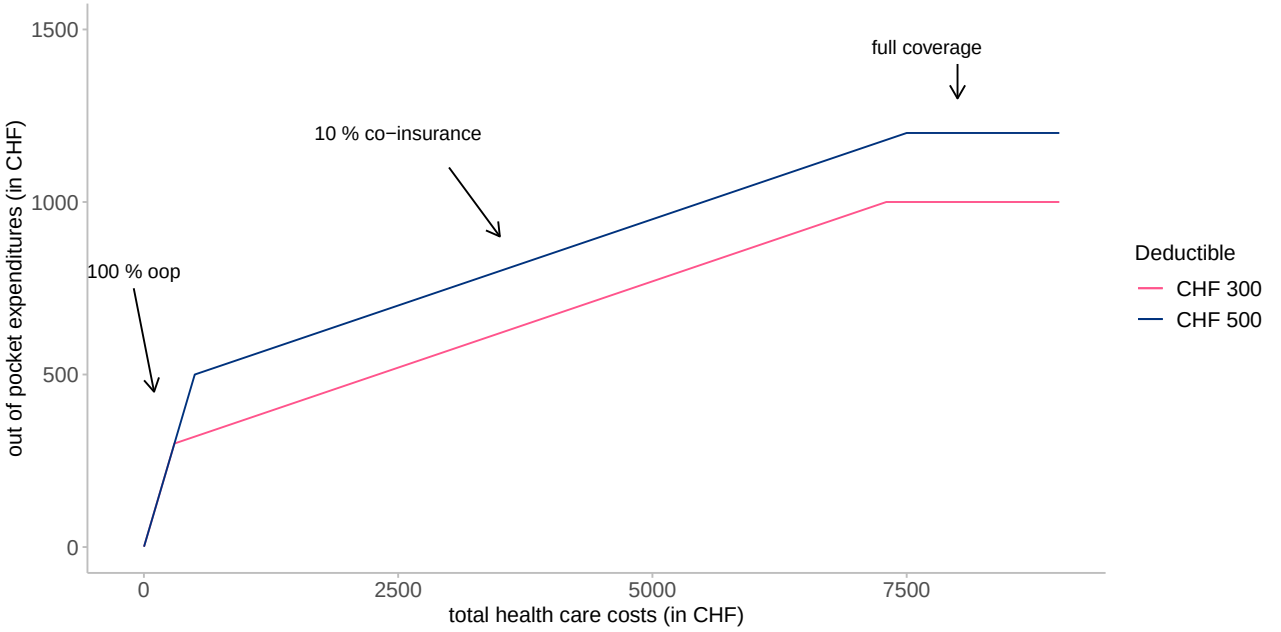
3.2 Institutional Setting

3.2.1 Health Insurance

Basic health insurance in Switzerland is mandatory for all Swiss citizens, including cross-border workers. Individuals can freely choose among over 50 health insurers. Health insurers are obliged to accept all patients for mandatory health insurance, independent of their underlying health status and background characteristics. Basic health insurance covers a broad range of services, which are determined centrally by the government. Hence, service coverage is

identical at all Swiss health insurers.[2] Considering pharmaceuticals, basic health insurance covers a positive list of pharmaceuticals which is published on a monthly basis by the Swiss federal office of public health (FOPH).

Figure 3.1: Nonlinear price schedule



Notes: The figure compares the nonlinear price schedule of a CHF 300 and CHF 500 deductible level. The first kink corresponds to the deductible level, before which patients face 100% out-of-pocket expenditures. Afterwards a co-insurance rate of 10% applies until the stop-loss is reached. Finally, patients enter the full coverage arm, where there is no more patient cost-sharing.

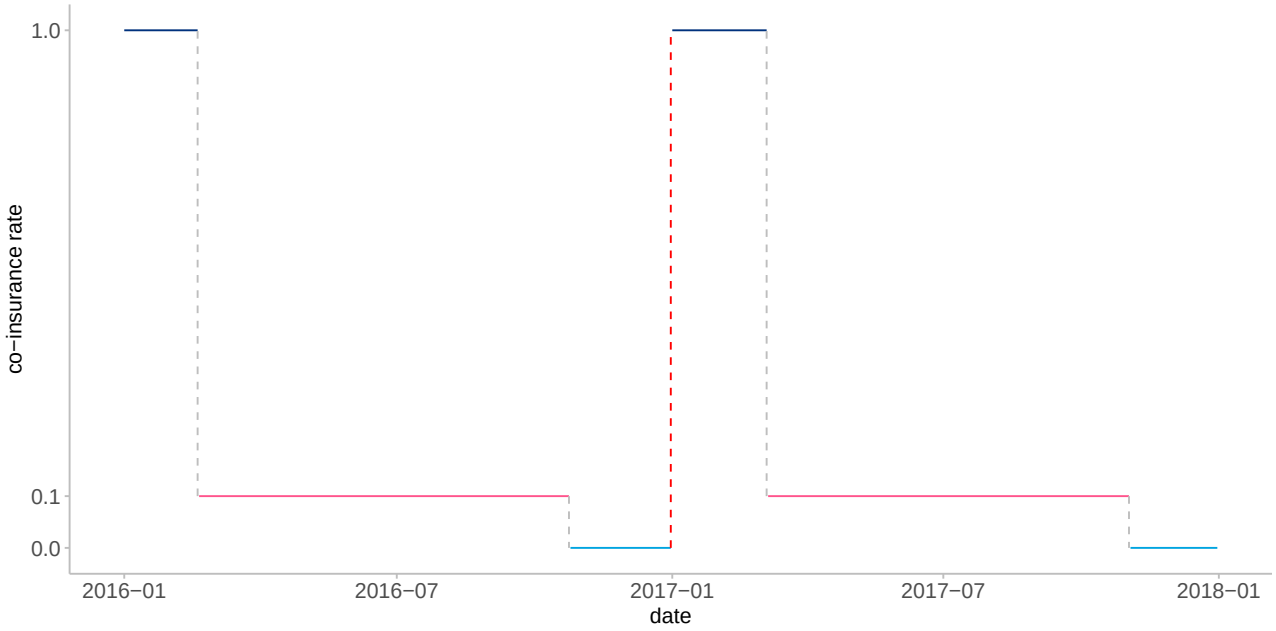
Contracts in mandatory health insurance consist of three main features: deductible, co-insurance, and stop-loss. The combination of these features results in a nonlinear price schedule as illustrated for the lowest two deductible levels (CHF 300, CHF 500) in Figure 3.1. Individuals can choose between several deductible levels.[3] At the beginning of each (coverage) year, the initial amount up until the deductible is reached, has to be payed out-of-pocket by the patients. This corrresponds to a 100% co-insurance rate, once the deductible is reached, patients have to pay a 10% co-insurance rate for each additional CHF of health care costs, until a maximum of CHF 700 in out-of-pocket expenditures is reached which corresponds to CHF 7,000 of total expenditures. After the total out-of-pocket expenditures exceed the deductible amount plus the additional CHF 700 of co-insurance payments, the stop-loss is reached. Subsequently, all health care costs are fully covered by health insurance, meaning that patients face a marginal price of zero. The deductible resets at the beginning of each calendar year on January 1st.

[2]This holds only with respect to mandatory health insurance. Supplementary insurance is optional and coverage may vary among insurers and plans.

[3]For adults these are CHF 300, CHF 500, CHF 1,000, CHF 1,500, CHF 2,000, CHF 2,500

Thus, patients who surpassed their deductible level in the previous year and therefore faced a marginal price close to zero, experience a sudden sharp increase in the marginal price of health care. This increase is represented by the dashed red line in Figure 3.2 which illustrates an exemplary evolvement of the co-insurance rate within and across years for an individual in the lowest deductible group. Price decreases within a year depend on year-to-date health care spending and therefore the timing of the price decreases vary from individual to individual as well as from year to year. In contrast, the price increase induced by the deductible reset at the turn of the year is equal for all patients that surpassed the deductible in the previous year.[4] This increase is at the core of this study, where we analyse what happens to prescription drug purchases just before and after the exogenous price increase at the turn of the year. The evolution of the empirical spot price is depicted in Figure 3.3.

Figure 3.2: Exemplary co-insurance path



Notes: This figure shows an exemplary evolution of the co-insurance rate within and across years for a patient who chooses the lowest deductible level. At the beginning of each year, a co-insurance rate of 100% applies. This is represented by the first short horizontal line. As soon as the deductible is reached, the co-insurance drops down to 10% up until the stop-loss is reached, where the co-insurance rate drops to zero. The vertical red dashed line represents the discrete increase in the co-insurance rate from zero to 100% induced by the deductible reset.

[4]If an individuals surpassed the deductible the co-insurance rate increases from 10% to 100%, if also the stop-loss was surpassed the co-insurance rate increases from 0% to 100%. For simplicity reasons, we do not distinguish between patients that only surpassed the deductible or those that also surpassed the stop-loss.

3.2.2 Prescription Drugs

In Switzerland, there exist two distinct dispensing schemes. In most of the German-speaking part, physicians are allowed to directly dispense pharmaceuticals to their patients. In the rest of the country patients can only obtain their prescribed pharmaceuticals at a pharmacy.[5] The general process in the case of no self-dispensing is the following: The physician issues a prescription which can be either a one-time prescription or a so called long-term prescription. One-time prescriptions are common for pharmaceuticals used to treat acute conditions such as antibiotics, whereas long-term prescriptions often apply to pharmaceuticals used to treat chronic conditions. A long-term prescription lasts for at most one year within which the patient can directly receive the prescribed drug from the pharmacist without having to visit the physician again. The maximum amount of the substance that the patient can obtain within that year corresponds to the prescribed dosage in terms of defined daily dosages (DDDs). To our knowledge, there are no other laws regulating the maximum amount of a specific substance that a patient can obtain at a single purchase or within a specific time period from a pharmacist or physician. Hence, the potential scope for stockpiling behavior is somewhat unclear.

3.3 Data

3.3.1 Data Sources

We use rich claims-level data in combination with detailed information on pharmaceuticals. The claims-level data is obtained from CSS health insurance, which is one of the largest health insurers in Switzerland with approximately 1.3 Mio insured individuals in 2016 ($\sim$ 16% of Swiss population). Our data covers the years 2015 - 2017 and contains around 7 Mio. pharmaceutical claims. In addition, the data contains basic patient demographics such as age and gender, contract information, daily data on all sorts of claims including the type of health care and the corresponding costs as well as provider information. We augment this claims data with detailed pharmaceutical data extracted from the official list of drugs that are covered by mandatory health insurance, published on a monthly basis by the FOPH. This data contains detailed information such as specific name of the product, active pharmaceutical ingredients, ATC codes, package size, ex-factory price, publication price, etc. on all (prescription) drugs that are covered by mandatory health insurance in a given month in Switzerland. We merge these two types of data by using a unique identifier for each pharmaceutical. Furthermore, we augment our data with information on the indication of the respective drugs, such that we can classify them into specific pharmaceutical groups. Due to the relevance in terms of frequency and costs,

[5] Self-dispensing is allowed in the following cantons: AI, AR, BL, GL, LU, NW, OW, SG, SH, SO, SZ, TG, ZG, ZH and some parts of GR and BE.

we focus on the following pharmaceutical groups used to treat the respective chronic condition; antidepressants (depression), antidiabetics (diabetes type II), antihypertensives (hypertension), insulins (diabetes type I), antihyperlipidemics (hyperlipidemia). Additionally, we consider the acute drug group antibiotics as a contrast to chronic drugs. An overview of all the substances under consideration together with the corresponding ATC codes and the respective condition can be found in Table 3.A.2 in the Appendix. Finally, information about DDDs is obtained from the official ATC/DDD Index provided by the world health organisation.

3.3.2 Sample Selection

The focus of our analysis lies on the change of the year 2016 - 2017. In a first step, we select all adult individuals that are enrolled at CSS for the entire observation period (2015 - 2017), where year 2015 is used for further sample selection purposes as described in the following. As we are interested in analysing how individuals react to (out-of-pocket) price increases in prescription drugs induced by the deductible reset at the beginning of each calendar year, our sample of interest are individuals that both experience the deductible reset and require frequent prescription drug intake. Hence, we focus on patients that suffer from at least one of the aforementioned chronic conditions and therefore require treatment with the respective substances.

As there is no diagnosis data available, we can not directly identify patients that suffer from these conditions. Thus, we proceed in the following two-step identification process. In a first step, we use pharmaceutical cost groups (PCGs) for the conditions of interest to identify patients suffering from depression, diabetes type I, diabetes type II, hyperlipidemia, and hypertension.[6] As a robustness check, we examine in a second step with the data at hand, whether the respective patients purchased at least 180 DDDs of the substances matched to the condition in the period of 2015-2016. We select patients that are assigned to the respective PCG and have effectively claimed at least 180 DDDs for substances related to that condition. Furthermore, we restrict the sample to patients in the lowest deductible levels (CHF 300, CHF 500) as patients with chronic conditions mostly choose these deductible levels.[7]

Finally, we restrict the sample to patients that surpass their deductible in 2016 before November 1st. We do this in order to make sure that patients are confronted with nonlinear prices. In particular, that they experience the sharp and salient price increase in the spot price induced by the deductible reset. We exclude patients that surpass their deductible late in the year. This is done to avoid misinterpreting changing consumption patterns due to unexpected

[6] PCGs are used by Swiss health insurers to identify chronically ill individuals for risk-adjustment purposes by considering previous prescription drug purchases.

[7] We do not consider individuals that choose higher deductible levels in the analysis as the sample size of patients suffering from chronic conditions within this group is too small to conduct meaningful statistical analyses.

late health shocks as price reactions. Our final sample consists of 73,522 individuals. We do not restrict the sample to patients that exclusively suffer from one of the considered conditions, as around 74% suffer from at least two (see Table 3.A.1 in the Appendix).

3.3.3 Summary Statistics

Table 3.1 depicts summary statistics for the years 2016 and 2017. Differences across years are minor. Considering costs, total health care costs as well as pharmaceutical costs are around CHF 100 higher in year 2017. However, this difference is negligible considering the size of the respective standard deviation. On average, patients purchase around five DDDs of antibiotics in both years. For the other substances, averages are calculated conditioning on patients that suffer from the respective condition. For example, individuals that suffer from depression, purchase an annual average around 400 DDDs of antidepressants in both years. Somewhat higher is the average annual amount of DDDs purchased for antihyperlipidemics and insulins, where it corresponds to around 440 in both years. By far the largest amount of DDDs is purchased for antidiabetics and antihypertensives with approximately 550 DDDs. Thus, patients suffering from hyperlipidemia and / or hypertension purchase more DDDs than what one would expect, considering that a year consists of 365 days. This could be an indication for either overuse including potential waste of the medications or patients may require higher dosages than what is suggested by the WHO for an average patient.[8]

On average, patients surpass their deductible level before the end of February and face an average spot price of 0.22 throughout the year. On the last day of a year, namely on December 31st, the average spot price corresponds to 0.07. Hence, around 30% of the individuals surpass the stop-loss level and therefore have no more cost-sharing, whereas the other 70% still have to pay 10% of the actual health care costs out-of-pocket. In contrast, one day later on January 1st of 2017, the average spot price jumps up to 0.99 indicating that the majority of patients faces 100% cost-sharing.[9] The difference of the spot price on December 31st 2016 and January 1st 2017 and the comparison between the average spot price on December 31st in both years are key to our research question. Assuming that patients are perfectly forward-looking, they should only consider the expected end-of-year price which can be approximated by the spot price on December 31st, patients should therefore not change purchasing behavior as there is no change across years. In contrast, if patients react to the spot price which increases from

[8]Many medications within antihyperlipidemics and antihypertensives are so-called "combination drugs", that consist of a fixed-dose combination of several substances for which it is hard to assign the respective suggested DDD as noted by the WHO. As a consequence, the WHO just recommends one pill per day and thus suggested and actually needed amount of daily dosage may vary.

[9]The spot price on January 1st is not equal to one, as there are some patients that already seek care which is more expensive than the deductible level and therefore already enter the 10% co-insurance arm of the health care contract.

0.07 to 0.99 within one day, purchasing behavior is very likely to change across the turn of the year. We elaborate on this in more detail in Section 3.4.

Table 3.1: Summary Statistics 2016 - 2017

	Year 2016		Year 2017	
	mean	sd	mean	sd
costs (in CHF)				
total health care	7,506	9,698	7,679	10,152
pharmaceuticals	2,377	4,883	2,472	5,134
DDDs purchased				
antibiotics	5.41	17.4	5.36	17.4
antidepressants[a]	409	286	395	296
antidiabetics[a]	542	377	551	377
antihyperlipidemics[a]	440	293	430	298
antihypertensives[a]	561	401	555	402
insulins[a]	446	313	444	322
spot price				
days to crossing deductible	52.5	51.1	52.6	52.8
average spot price	0.22	0.14	0.22	0.15
spot price December 31st	0.07	0.05	0.07	0.07
spot price January 1st	0.99	0.06	0.99	0.06

Notes: The numbers are measured in annual terms. Measures of DDDs correspond to the total amount of substance purchased divided by the suggested DDDs by the WHO. a: average DDDs are calculated using only those individuals that actually suffer from the respective condition. Abbreviations: DDDs, defined daily dosages.

Table 3.2 provides separate insights for the chronic conditions under consideration. Overall, we see that patients are on average rather old with around 64 years. Patients suffering from depression, the youngest patient group, are on average 58 years old. Somewhat older are patients suffering from diabetes type I with an average age of 61 years. Patients suffering from diabetes type II, hyperlipidemia and hypertension are the oldest with average ages ranging between 66 and 69 years. Around half of the sample are women, however, there are some differences between conditions. Whereas the share of women is 67.7% for depression patients, it is in the range between 40% and 50% for the other conditions. This observation can be explained by the fact that women are twice as likely to suffer from depression compared to men (Van de Velde et al., 2010). Most patients, around 80%, choose a deductible level of CHF 300, i.e., the lowest deductible level. This means that the other 20% choose a deductible of CHF

500 as we only consider patients in the lowest two deductible groups.

Total annual health care costs are very similar for patients suffering from diabetes type II, hyperlipidemia and hypertension with around CHF 7,500. We observe slightly higher health care costs for patients suffering from depression (CHF 8,654). By far the highest health care costs are observed for patients with diabetes type I, where average annual health care costs correspond to CHF 10,525. Part of this difference is most likely due to insulin which is a relatively expensive drug. A similar pattern emerges, when considering average annual pharmaceutical costs. Whereas average annual pharmaceutical costs are in the range of CHF 2,400 - CHF 2,800 for all conditions except diabetes type I, costs amount to almost CHF 4,000 on average for that group. Average annual costs for antibiotics are negligible ranging from CHF 18 to CHF 33. However, similar as before, we observe the highest average costs for patients with diabetes type I. This is not driven by them consuming more antibiotics, as can be seen from the average amount of antibiotics consumed in terms of DDDs. As some types of antibiotics may interact with the metabolism, it is possible that patients depending on insulin require specific, more expensive antibiotics.

Considering average annual pharmaceutical costs per condition, we observe variations depending on the condition. As in total costs, condition specific pharmaceutical costs are highest on average for patients suffering from diabetes type I with CHF 1,051. As a comparison, pharmaceuticals for hyperlipidemia and hypertension correspond to around a third of these costs. Pharmaceuticals used to treat depression are somewhat more expensive on average with CHF 408. The second most expensive drugs with an average of CHF 666 are medications used to treat diabetes type II.

Patients suffering from diabetes type I, surpass their deductible on average 31 days into the new year, meaning they already surpass it before February. As a consequence, the average annual spot price corresponds to 0.16 which is lower compared to the other conditions where it lies between 0.2 - 0.22. On January 1st all individuals suffering from diabetes type II, hyperlipidemia or hypertension are still under the deductible. In contrast, 1% of the patients suffering from depression and 2% of those suffering from diabetes type I are already in the 10% co-insurance arm. This indicates that these patients received expensive health care treatments on the first day of the new year. Based on the sample average spot price on the last day of 2016, we observe that between 30% and 50% of patients surpassed the stop-loss by the end of the year. Similar as before, the share is largest for patients suffering from diabetes type I, followed by depression patients and finally those patients suffering from diabetes type II, hyperlipidemia and hypertension.

Table 3.2: Descriptive Statistics by Chronic Condition in 2016

	depression	diabetes type I	diabetes type II	hyperlipidemia	hypertension	combined
age	57.6	60.5	66.3	68.7	68.4	64.3
	(14.4)	(14.9)	(10.6)	(9.95)	(10.3)	(13.4)
female	67.6%	40.8%	42.5%	43.6%	46.3%	51.4%
deductible CHF 300	81.9%	84.9%	79.4%	77.8%	78.4%	79.4%
costs total health care	8,654	10,525	7,540	7,432	7,434	7,506
	(10,462)	(12,690)	(8,643)	(9,614)	(9,447)	(9,698)
costs pharmaceuticals	2,614	3,928	2,790	2,397	2,416	2,377
	(5,459)	(6,524)	(4,066)	(4,550)	(4,391)	(4,883)
costs antibiotics	21.4	32.8	18.1	18.6	19.6	20.0
	(105)	(427)	(50.3)	(132)	(158)	(160)
pharm. costs condition[a]	408	1,051	666	349	316	848
	(326)	(757)	(737)	(257)	(220)	(761)
DDDs antibiotics	6.21	6.05	5.29	5.12	5.31	5.41
	(17.8)	(23.6)	(16.4)	(16.1)	(17.0)	(17.4)
days to crossing deductible	45.8	31.0	47.7	53.5	53.0	52.5
	(49.3)	(29.9)	(45.0)	(50.1)	(50.0)	(51.1)
average spot price	0.20	0.16	0.21	0.22	0.22	0.22
	(0.13)	(0.09)	(0.12)	(0.13)	(0.13)	(0.14)
spot price January 1st	0.99	0.98	1.00	1.00	1.00	0.99
	(0.08)	(0.10)	(0.05)	(0.06)	(0.06)	(0.06)
spot price December 31st	0.06	0.05	0.07	0.07	0.07	0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
N	25,968	5,873	19,803	44,559	51,465	73,522

Notes: The numbers are measured in annual terms. All costs are measured in CHF. Measures of DDDs correspond to the total amount of substance purchased divided by the suggested DDDs by the WHO. a = pharmaceutical costs condition, correspond to the annual average costs spent on pharmaceuticals for the respective condition. Standard deviations in parentheses. Abbreviations: DDDs, defined daily dosages, pharm., pharmaceutical.

3.4 Theoretical Considerations

Keeler et al. (1977) show that in the presence of deductibles and uncertain health shocks, forward-looking rational individuals should base their decisions on the marginal effective price at the time of the decision. This price is a function of accumulated demand prior to the decision and of the time remaining in the year. Ellis (1986) shows that the marginal effective price is very close to the expected end-of-year price. However, these results apply to within-year decisions, not to multiple period cases with a deductible reset between periods. Therefore we provide some theoretical considerations of the optimal behavior of a rational forward-looking patient in our setting. Until November of every year, patients can freely choose among several deductible levels as illustrated in Section 3.2. The choice of deductible depends on an individual's expected health care needs. Lower deductible levels come at a cost of higher premium payments. Thus, it is only rational to choose a low deductible level if the patient expects high health care costs in the following year. This is the case for patients with chronic conditions, which is the population we analyse.[10]

Consider the two-year case, each with T periods, so $t = T$ corresponds to the last period of the first year, $t = T + 1$ is the first period in the second year, and $t = 2T$ corresponds to the last period of the second year. For our analysis, only three prices are relevant: $p^e_T = p^s_T$ (the expected end-of-year price in T, which is equal to the spot price in T), p^e_{T+1} (the expected end-of-year price in $T+1$, which refers to the end of the second year), and p^s_{T+1} (the spot price in the first period after the deductible reset). The two spot prices are observable to both agents and researchers, while p^e_{T+1} can be approximated by the realized end-of-year price at $2T$, the end of the second year.

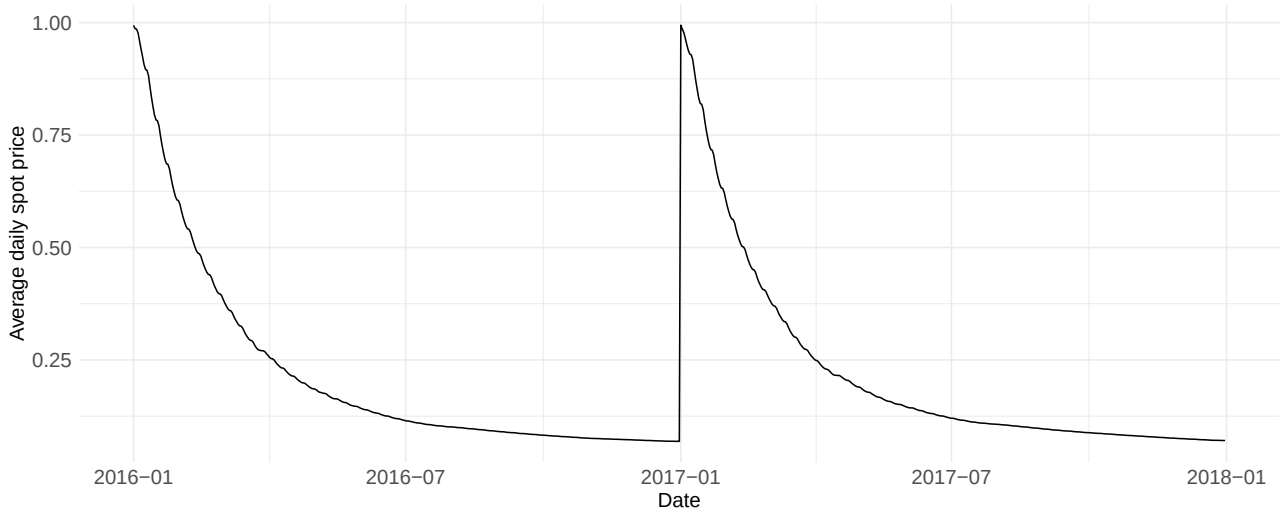
In our setting, p^e_{T+1} is expected to be low, because we look at patients with chronic conditions and low deductibles. This is confirmed in Fig 3.3, which clearly shows that $p^e_{T+1} \approx p^e_T \ (= p^s_T)$. Therefore, rational forward-looking agents should not react to the deductible reset in our setting because the reset only affects the spot price in $T+1$, not the expected end-of-year price.[11] Hence, if patients react to the increase in the spot price, they are pseudo-forward-looking. They think they take advantage of the system by purchasing at the low price p^s_T instead of purchasing at the high p^s_{T+1}. However, by doing so, they miss a crucial point of the health insurance plan. By purchasing an additional package of prescription drugs before the deductible reset instead of after, it takes the out-of-pocket price of that package longer to reach the deductible

[10] The deductible choice also depends on an individual's risk preferences, i.e., highly risk-averse individuals will choose a low deductible in any case. In our setting as all individuals eventually exceed the deductible level by far as illustrated in Section 3.3.3, we can assume that only a small part chooses the lowest deductible level due to high risk-aversion.

[11] Of course, this is not a general result. E.G., Gerfin et al. (2015) look at more healthy individuals with high deductibles, who had a health shock in the first year, but did not expect high spending in the next year (they still opted for the high deductible), so for them $p^e_T < p^e_{T+1}$.

in the subsequent year. Put differently, another health care good, for example a doctor visit, in January will be payed out-of-pocket instead of the prescription drug package. Hence, there occurs a shift in out-of-pocket payments from one health care good to another, without changing overall health care expenditures of that patient. A rational and forward-looking individual should be aware of this.

Figure 3.3: Empirical spot price 2016 - 2017



Notes: This figure shows the empirical evolution of the spot price over the years 2016 - 2017. The average daily spot price corresponds to the daily sample averages of individual spot prices. Individual daily spot prices are calculated as illustrated in the Appendix 3.A.2.

A possible barrier to forward-looking behavior are liquidity constraints (Ericson and Sydnor, 2018; Simonsen et al., 2021a). If patients are liquidity constrained, they may overreact to spot prices because they are unable to purchase the health care good out-of-pocket when under the deductible, even though the expected end-of-year price is close to zero. In our setting, liquidity constraints should play no major role. First, the majority of the patients we consider have to pay only CHF 300 out-of-pocket, which corresponds approximately to the costs of two physician visits. Second, most of the prescription drug purchases occur within the so-called "Tiers Payant" billing scheme. In this scheme, patients receive the prescribed medication at a pharmacy or physician's office without having to instantly pay for it. The bill goes directly from provider to health insurance, which subsequently sends an invoice for the cost-sharing amount to the patient. The lag between purchase and actual payment can be as long as three months. Furthermore, given that the patient instantly receives the medication, she can still choose not to pay the invoice.[12] Hence, even without having any cash available, patients obtain prescription drugs in any case, conditional on having a valid prescription.

[12]Not paying the bill has the usual consequences of getting a dunning.

3.5 Empirical Strategy

We exploit the exogeneity of the sharp increase in the spot price induced by the deductible reset at the beginning of each calendar year, to estimate the causal effect of this price increase on prescription drug purchases. We choose DDDs as a measure of quantity as DDDs are more robust compared to expenditures in CHF and enhance comparability across conditions.[13]

Our setting is well suited to employ a sharp regression discontinuity design (RDD), where the deductible reset is the exogenous treatment. In contrast to a standard RDD, we use time measured in days as the running variable, as was previously done in Gerfin et al. (2015). A critical requirement of an RDD setting is a continuous running variable. Therefore we construct a daily panel data set, where we observe each patient at each point in time (day) allowing us to calculate daily sample averages.[14] Because we observe the same individuals on both sides of the cut-off, we can estimate an average treatment effect for the entire sample, which is generally not possible in standard RDDs. However, our identification is only valid if the underlying health of the patients does not change systematically at the turn of the year, which is very credible.

For the estimation of the treatment effect τ, we closely follow the procedure suggested by Cattaneo et al. (2019). The parameter of interest, i.e., the treatment effect, is defined as follows

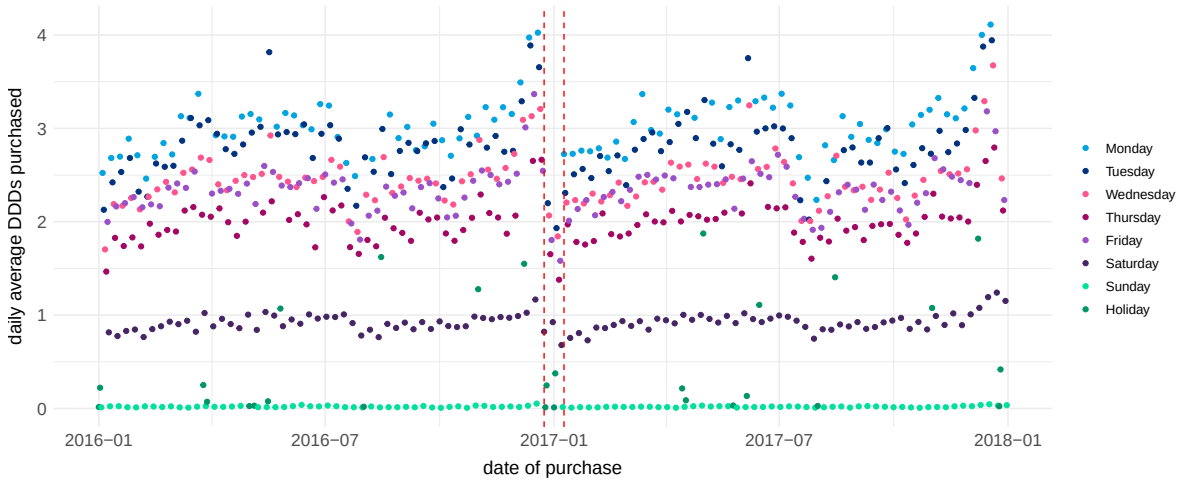
$$\tau = \mathbb{E}[Y(1) - Y(0)|t = c], \tag{3.5.1}$$

where the cut-off (in our case the turn of the year) is denoted by c, $Y(0)$ corresponds to the daily average DDDs purchased before the turn of the year $t < c$ (untreated state) and $Y(1)$ corresponds to the respective daily average DDDs just after the turn of the year $t \geq c$ (treated state). We employ a local linear estimator due to its favorable properties (Cattaneo et al., 2019). Additionally, we choose a triangular kernel in combination with a MSE-optimal bandwidth choice as this results in a point estimate with optimal properties (Cattaneo et al., 2019). As we are working with daily data, there are possibly underlying differences in the outcome depending on the specific day of the week. For example, purchases can be expected to be lower on weekends, where access to physicians and pharmacies is restricted, especially on Sundays. Figure 3.4 visualizes these differences. Purchases are generally highest on Mondays and basically zero on Sundays and holidays. To account for this, we additionally include day of the week fixed-effects α and entirely exclude Sundays and holidays from the estimation. Results without excluding Sundays and holidays and without using day of the week fixed-effects are

[13] Expenditures can be problematic if new expensive drugs enter the market, as they would increase average costs without an impact on quantity consumed. Nevertheless, we provide the main results in CHF in Table 3.A.3 the Appendix for the interested reader.

[14] Days are of course not continuous, they are discrete. However, as long as we have enough observations at each point of the running variable (every day) and enough days around the cut-off, the RDD estimation is still valid (Cattaneo et al., 2019).

Figure 3.4: Average daily DDDs purchased



Notes: This figure plots the daily average amount of chronic drugs purchased in terms of DDDs from January 1st in 2016 to December 31st in 2017. The different colors indicate the different days of the week. The area between both vertical dashed lines marks the donut-hole of the RDD estimation, i.e., we exclude these observations from the estimation.

shown in Tables 3.A.4 and 3.A.5 in the Appendix.

The local linear point estimates at both sides of the cutoff are obtained by solving the following minimization problem:

$$\begin{aligned} &\underset{(\mu_-,\mu_{-,1},\alpha_-)}{\arg\min} \sum_{t=1}^{T} 1\{t<c\}K(\frac{t-c}{h})(Y_t-\mu_- -(t-c)\mu_{-,1}-\alpha_-)^2 \\ &\underset{(\mu_+,\mu_{+,1},\alpha_+)}{\arg\min} \sum_{t=T+1}^{2T} 1\{t\geq c\}K(\frac{t-c}{h})(Y_t-\mu_+ -(t-c)\mu_{+,1}-\alpha_+)^2 \end{aligned} \tag{3.5.2}$$

The estimate of the treatment effect is the difference between both point estimates,

$$\hat{\tau} = \hat{\mu}_- - \hat{\mu}_+ \tag{3.5.3}$$

A key choice in an RDD is the bandwidth h, which defines the range of the running variable considered. Therefore we search for the MSE-optimal bandwidth in a data-driven way (see Cattaneo et al., 2019, for a detailed illustration). This approach results in a MSE-optimal bandwidth of 40 for point estimation and a bandwidth of 69 for bias-correction. We employ these two separate bandwidths in order to construct bias-corrected robust standard errors for inference.

As the very last and first days of a year are mostly holidays (Christmas, new year), during which access to health care providers including pharmacies is limited, we decide to exclude

all days after the last Friday before Christmas and the first days of the year before the first Monday after new year's day. The excluded days correspond to the dots between the dashed red lines in Figure 3.4. Hence, we conduct a donut-hole RDD, which was initially introduced by Barreca et al. (2011) for the estimation of birthweight on infant mortality and applied to a similar setting as the present in Gerfin et al. (2015).

3.6 Results

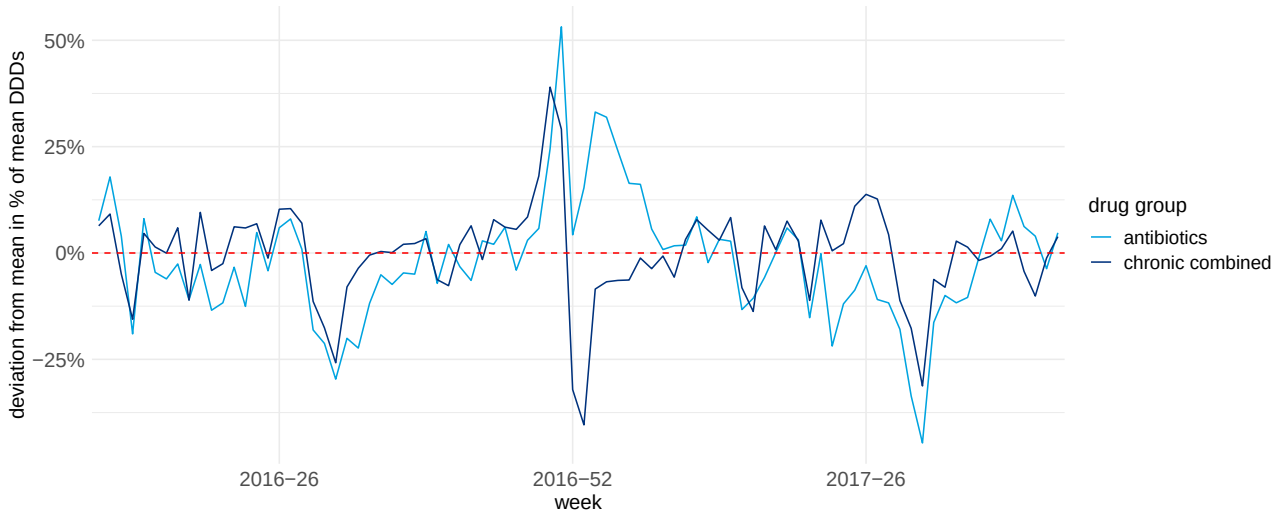
3.6.1 Descriptive Evidence

Figure 3.5 directly compares the evolution of chronic drugs under consideration to the evolution of antibiotics. From the beginning of March 2016 to December 2016 we observe a very similar pattern for antibiotics and chronic drugs. The drop starting after week 26 affects both groups of drugs equally and can be explained by summer holidays. There is a major peak in December for both of the drug groups which amounts up to 50% more compared to the annual average purchasing level measured in DDDs. In the first weeks of 2017 we observe the key difference. While this increase is just off-set by a large drop below average purchasing level for chronic drugs, antibiotics remain on a comparably high level. This shows that there is a general increase in December most likely due to the "influenza-season", which still persists in January. However, due to the drop in January for chronic drugs, the pattern of these drugs in December can not be explained by the "influenza-season". The main difference between antibiotics and chronic drugs is that the need for antibiotics is hardly predictable as they are required to treat acute illnesses, whereas the need for chronic drugs is easily predictable making them prone to strategic timing of the purchase. Figure 3.5 provides suggestive evidence that patients actually choose to purchase drugs in December where their out-of-pocket costs for the drugs are close to zero rather than in January when they would have to pay the full price. In the following, we are elaborating the extent of this behavior in a causal framework.

3.6.2 Main Results

Figure 3.6 (a) plots the RDD estimates in terms of DDDs for all considered pharmaceutical groups separately, and for the chronic drugs combined. An important insight is delivered by comparing the estimates of chronic drugs to the one for antibiotics. Whereas the effect is essentially zero for antibiotics, we observe negative and statistically significant effects for all chronic drugs under consideration. Effect sizes range from around -0.6 DDDs for antidepressants up to -1.1 DDDs for antidiabetics and antihypertensives. As these estimates are based on daily averages, an estimate of -1 DDDs indicates that at the beginning of January one DDD less is purchased on average per day compared to at the end of December. Put differently, in

Figure 3.5: Comparison of antibiotics and chronic drugs



Notes: This figure plots the evolution of the weekly %-deviation from the average weekly amount of DDDs purchased for antibiotics and the chronic drugs under consideration from March 2016 to October 2017. The group chronic combined includes antidepressants, antidiabetics, antihyperlipidemics, antihypertensives and insulins. The mean corresponds to the annual mean of the average weekly amount of DDDs purchased. An overview of the evolution of all drug groups separately can be found in Figure 3.A.2 in the Appendix.

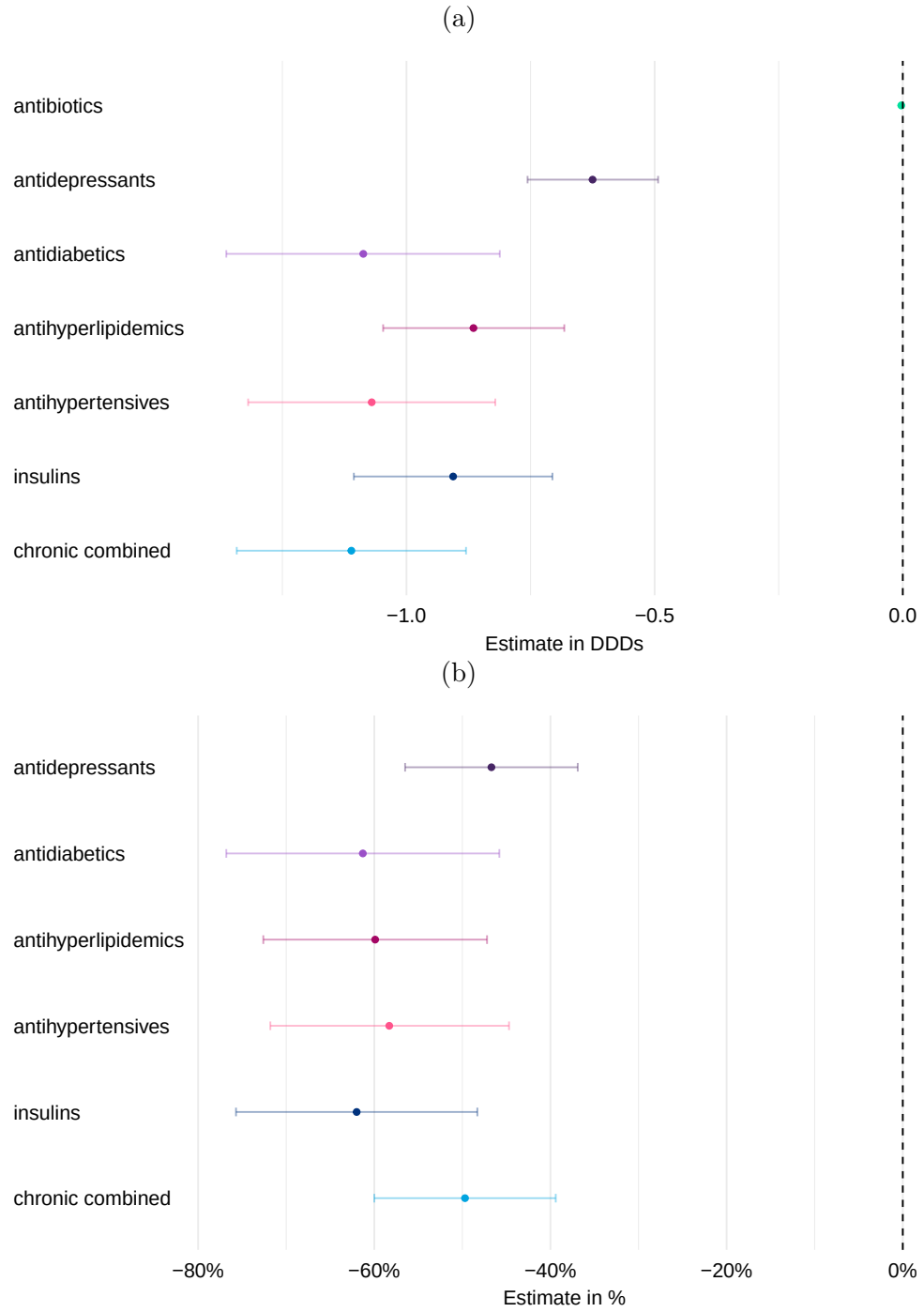
the entire month of December, patients purchase on average an additional month's dosage of pharmaceuticals compared to January.

However, to obtain an order of magnitude of increased quantities purchased towards the end of the year, we need to relate the absolute effect sizes to a meaningful baseline purchasing level per pharmaceutical group. Therefore, we provide estimation results relative to the average daily amount of DDDs purchased in 2016 in Figure 3.6 (b). Antibiotics are now omitted because there is no meaningful baseline level of antibiotic consumption as this is an acute drug. Relative to baseline purchasing levels, the decrease at the turn of the year corresponds to around 60% for all substance groups except for antidepressants, where the decrease equals approximately 48%. Similarly, for all substances combined the effect corresponds to roughly 50%.

These findings provide suggestive evidence that patients with chronic conditions tend to strategically time prescription drug purchases to December, where they face a comparably low marginal price instead of January, where the out-of-pocket expenditures for the same pharmaceutical is substantially higher. However, it is possible that there are other mechanisms apart from the price driving the observed effect. For example, patients may be worried that they are unable to have access to a pharmacy or physician during Christmas holidays, thus deciding to purchase their medication just before that time. We denote this the holiday effect. To obtain a better understanding of the relative importance of the price effect vs. holiday effect, we conduct the same estimation with a cut-off in mid-July where there is a holiday effect but no price effect.

Table 3.3 directly compares our main estimates, denoted by Christmas, to the summer estimates. For all substance groups, the average amount of DDDs purchased to the left of the cutoff is larger before Christmas than in summer. However, compared to the baseline purchasing level, both summer and Christmas estimates are relatively high. The column "estimate" directly compares the RDD estimates and shows that estimates are substantially larger for Christmas compared to summer. The rightmost column in Table 3.3 shows the absolute difference between both estimates relative to the baseline amount of DDDs purchased, serving as a proxy for the share of the total effect that is driven by the price effect. Overall, the share amounts to roughly 24% for all chronic drugs considered with some variation depending on the specific pharmaceutical group. For antidepressants, the price effect is by far the smallest with around 16%, considering the other substances, the share amounts to 32% for antihyperlipidemics and 33% for antihypertensives. Interestingly, the share is largest for antidiabetics and insulins which are both comparably expensive pharmaceutical groups. Moreover, patients suffering from diabetes type I are dependent on the intake of insulin for their entire life making their future prescription drug needs especially predictable. However, these results are an upper bound for the price effect due to the fact that the summer holidays are distributed much more smoothly across the summer compared to the well-defined Christmas holidays, indicating that we estimate a lower bound of the holiday effect.

Figure 3.6: RDD estimates in absolute and relative terms



Notes: Pane (a) of this figure shows the RDD estimates in terms of DDDs. The dots correspond to the point estimates, and the horizontal lines indicate the 95%-confidence intervals. We employ robust standard errors. Pane (b) shows the main estimates in relation to the annual baseline level of DDDs purchased.

Table 3.3: RDD Estimates in DDDs

	average below cutoff		baseline	estimate		diff. in % of baseline
	Christmas	summer		Christmas	summer	
antidepressants	2.008	1.604	1.34	-0.625***	-0.411***	15.98%
	(0.057)	(0.037)		(0.076)	(0.055)	
antidiabetics	2.831	2.013	1.77	-1.087***	-0.464***	35.15%
	(0.124)	(0.036)		(0.159)	(0.062)	
antihyperlipidemics	2.237	1.677	1.44	-0.865***	-0.402***	32.05%
	(0.083)	(0.021)		(0.105)	(0.04)	
antihypertensives	2.79	2.087	1.84	-1.07***	-0.458***	33.34%
	(0.118)	(0.032)		(0.144)	(0.053)	
insulins	2.085	1.751	1.46	-0.906***	-0.344***	38.49%
	(0.069)	(0.04)		(0.115)	(0.075)	
chronic combined	3.309	2.581	2.23	-1.111***	-0.577***	23.88%
	(0.105)	(0.024)		(0.133)	(0.047)	

Notes: Average below the cutoff corresponds to the point estimate to the left of the cutoff, the estimate is the result of estimating Equation 3.5.2. We include weekday fixed effect. The baseline corresponds to the average daily amount of DDDs purchased in 2016. For the Christmas estimates the days between the last Friday before Christmas 2016 and the days before the first Monday after new year are omitted. The cutoff in summer is set to July 15^{th}. Sundays and holidays are excluded from the estimation. If pharmaceuticals of several of the groups are purchased on a given day, the amount of DDDs for chronic combined corresponds to the average amount of DDDs. Robust standard errors are in parentheses. $^{***}p < 0.001,^{**}p < 0.01,^{*}p < 0.05$.

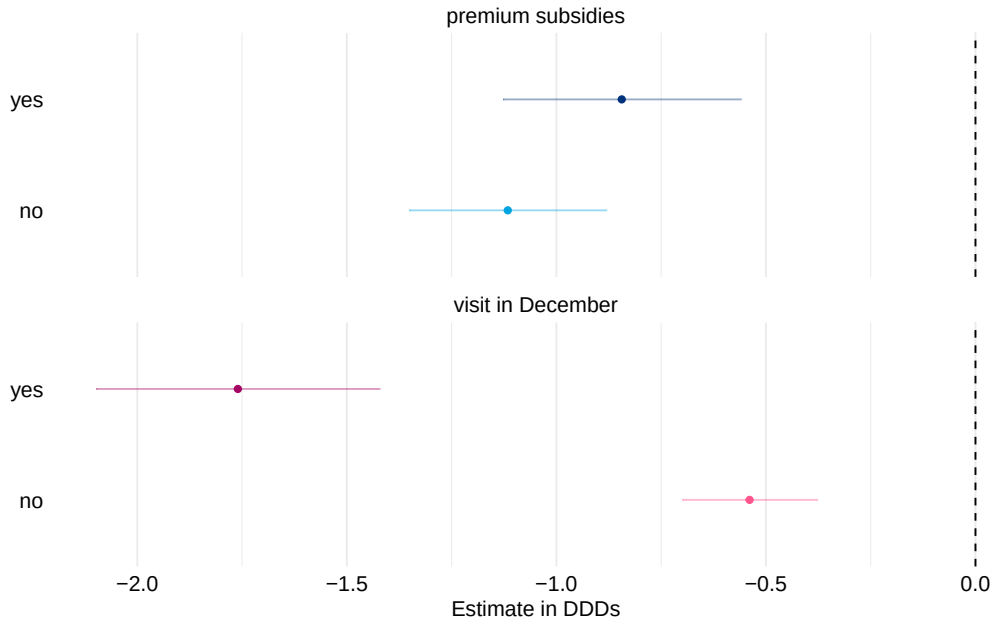
3.6.3 Extensions

Our main results show that the amount of prescription drugs purchased is substantially higher towards the end of the year, compared to the beginning of the subsequent year. There are mainly two plausible explanations. First, patients may be spot price biased and therefore do not consider the expected end-of-year price when making purchasing decisions, but overreact to the salient increase in the spot price induced by the deductible reset. Second, patients may indeed incorporate the expected end-of-year price in their purchasing decision but anticipate that they won't be able to pay the pharmaceuticals out of pocket due to liquidity constraints.

To test the latter explanation, we approximate liquidity constraints by premium subsidy receipt, and conduct the main analysis separated by premium subsidy status. More specifically, patients that receive more than the average premium subsidy amount in the respective canton, are categorized as subsidy recipients and those that do not receive any subsidy are

the comparison group.[15] The upper pane of Figure 3.7 shows that the results are somewhat unexpected. The effect is smaller in absolute terms for patients with potential liquidity constraints. However, the difference is not statistically significant. Thus, there is no evidence that liquidity constraints explain our main results. In contrast, it suggests that rather high income people with potentially better understanding of the system, tend to react more strongly to the deductible reset.

Figure 3.7: RDD estimates by subgroups



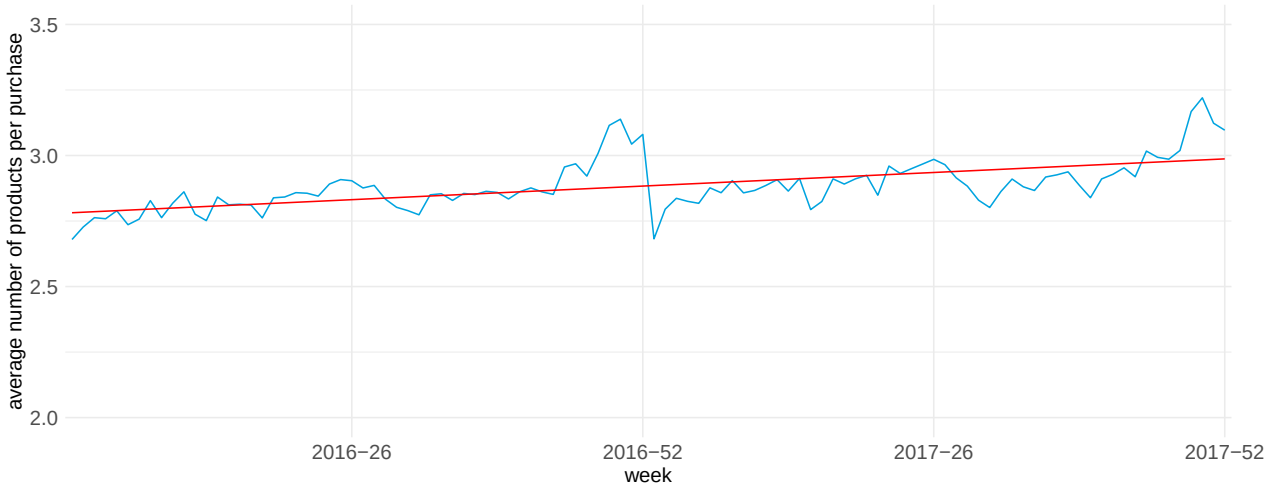
Notes: This figure shows RDD estimates for all chronic drugs combined differentiated by subgroups. The upper pane plots the RDD estimates by premium subsidy status, where patients are categorized as premium subsidy recipients if they receive more than the cantonal average amount of premium subsidies. The category no premium subsidies consists of patients that do not receive any premium subsidies. The lower pane distinguishes by patients' having a physician visit in December of 2016.

To further elaborate underlying reasons for the main results, we analyse whether the effects are potentially driven by individuals who visit a physician in December. The lower pane of Figure 3.7 shows that this is actually the case. In comparison to the effect size of -0.5 DDDs for the group without physician visits in December, the effect is more than three times as large for patients with a visit in December. This finding suggests, that a large part of the overall effect can be explained by patients who visit a physician in December. However, it remains unclear whether patients visit a physician to fill their prescription or if they visit the physician due to other reasons and use this opportunity to restock their chronic medication as well. Figure 3.8 provides suggestive evidence for this supposition as the average number of distinct

[15] We omit individuals from the analysis that receive only a small amount of subsidies as these are often comparably high income individuals which are unlikely to suffer from liquidity constraints.

pharmaceuticals per purchase peaks in December. The red line represents the general trend over the years 2016 - 2017.[16]

Figure 3.8: Average weekly number of distinct products per purchase



Notes: This figure shows the average number of distinct pharmaceutical products per purchase and week for the years 2016 - 2017. The red line represents the linear trend of the number of distinct products per purchase. Note that the average is calculated conditional on a purchase.

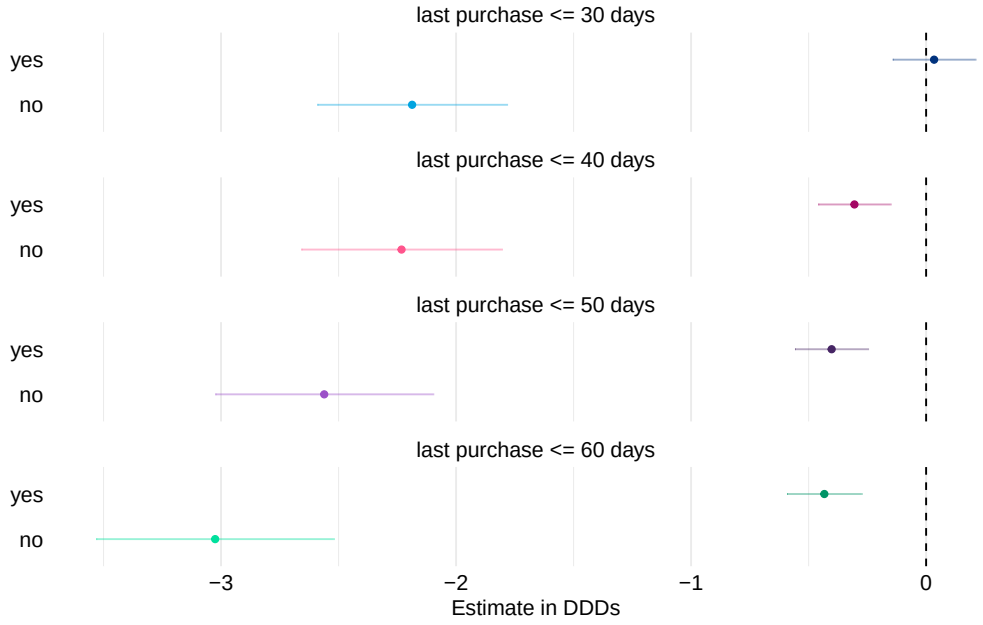
Moreover, the finding for patients without physician visits in December shows approximately the part of the main effect purely driven by the price incentive. Dividing groups of patients based on the time passed between their last purchase before December 1st yields very similar results as presented in Figure 3.9. We observe that the effect size increases with the number of days between the last purchase before December and December 1st. This is not surprising as with each additional day that passes, the probability of needing to refill the pharmaceutical stock increases.

Assuming that individuals generally purchase a package containing 90 DDDs,[17] we should not observe any significant effect for patients that already had a purchase in November, which is consistent with our findings. However, if we augment the days from 30 to 40, we observe a significant negative effect of around -0.5 DDDs, which stays constant for the subgroups that had a purchase within the last 50 and 60 days before December 1st. In contrast, the effect size grows from around -2.2 DDDs up to -3 DDDs for the subgroup that had no purchase within the last 30 or 60 days before December 1st, respectively. These findings provide further evidence that there is some stockpiling, i.e., some individuals purchase additional medications in December even though based on previous purchases we would expect them to buy at a later point in time.

[16] The upwards trend can be explained by the ageing of patients, which generally increases the probability of additional illnesses.

[17] The most common package sizes of chronic drugs contain 90 DDDs corresponding to a total dosage lasting for three months.

Figure 3.9: Subgroup analysis by days since last purchase before December 1st



Notes: This figure shows RDD estimates for all chronic drugs combined differentiated by subgroups depending on the number of days that passed since the last purchase before December 2016 and December 1st in 2016. Individuals in the "yes" group had a purchase that occurred within 30, 40, 50 or 60 days, respectively, before December 1st in 2016. The "no" group, had purchases that occurred further back in the past.

3.7 Conclusion

This study analyses whether individuals with chronic conditions who appear rational and forward-looking with respect to their deductible choice are forward-looking in the timing of their prescription drug purchases. Due to the deductible reset at the beginning of the new year, the spot price strongly increases in January while the expected end-of-year price remains largely unchanged. We use this setting to test whether patients react to the spot price or the expected end-of-year price.

We find compelling evidence that there is a strong increase in the volume of drugs in the last weeks of the year, a behavior we term Christmas shopping. This excess volume is compensated by a below-average volume in the first weeks of the following year. Given that the expected end-of-year price hardly changes as opposed to the spot price which drastically increases due to the deductible reset, we conclude these individuals strongly react to spot prices, indicating a spot price bias to some extent, which is consistent with previous findings (Brot-Goldberg et al., 2017; Abaluck et al., 2018; Simonsen et al., 2021a)

The additional amount of DDDs purchased in December compared to January corresponds to approximately 50% of the yearly average amount of daily DDDs purchased. Around two thirds of this observed effect can be explained by a holiday effect, meaning that patients in-

creasingly buy prescription drugs just before Christmas holidays in order to be sure to have enough medications during the holidays. In contrast to Simonsen et al. (2021a), we do not find evidence for liquidity constraints as a driving mechanism (based on a rather crude indicator for low income). This might be due to the specific billing procedure in Switzerland where patients in general do not pay for the medication at the pharmacy, but are billed with some delay by the insurance company (if there is cost-sharing).

From a welfare point of view, Christmas shopping behavior in the prescription drug market has no direct financial impact on the health care system. First of all, there is no evidence for excess demand for prescription drugs. Individuals simply shift purchases, which they would have made early in the following year, to the end of the current year. This implies that out-of-pocket payments for prescription drugs are shifted to another health care good consumed early in the following year, so there is no cost saving at all for those engaging in this behavior. Nevertheless, there may be possible negative consequences such as drug shortages, if patients' prescription drug demand in December leads to shortages in the following months.

This paper contributes to the literature showing that deductibles in health insurance can induce irrational and even dangerous behavior (Brot-Goldberg et al., 2017; Chandra et al., 2021). Individuals may delay adhering to prescriptions, even if they know they will exceed the deductible eventually during the year. These findings suggest that in health insurance alternatives to deductibles should be considered for treatments such as medication for chronic conditions. One possibility would be to exempt them from the deductible, with only a low co-payment. Such alternatives should be complemented with precise information for the patient, such that they understand the rules and can make better decisions.

3.A Appendix I

3.A.1 Additional Descriptives

Table 3.A.1: Combination of Conditions

Condition	Number of patients	Share
hyperlipidemia & hypertension	25,050	34.1%
depression	13,083	17.8%
diabetes type 2 & hyperlipidemia & hypertension	6,790	9.2%
depression & hypertension	4,447	6.0%
diabetes type 2 & hypertension	4,289	5.8%
depression & hyperlipidemia & hypertension	3,786	5.1%
diabetes type 2	2,049	2.8%
depression & hyperlipidemia	1,834	2.5%
diabetes type 1 & diabetes type 2 & hyperlipidemia & hypertension	1,752	2.4%
hypertension	1,586	2.2%
hyperlipidemia	1,416	1.9%
diabetes type 2 & hyperlipidemia	1,241	1.7%
diabetes type 1	1,073	1.5%
depression & diabetes type 2 & hyperlipidemia & hypertension	916	1.2%
diabetes type 1 & diabetes type 2 & hypertension	659	0.9%
diabetes type 1 & hyperlipidemia & hypertension	627	0.9%
depression & diabetes type 2 & hypertension	598	0.8%
diabetes type 1 & hypertension	404	0.5%
depression & diabetes type 1 & diabetes type 2 & hyperlipidemia & hypertension	340	0.5%
depression & diabetes type 2	320	0.4%
depression & diabetes type 2 & hyperlipidemia	244	0.3%
diabetes type 1 & diabetes type 2	215	0.3%
diabetes type 1 & hyperlipidemia	207	0.3%
diabetes type 1 & diabetes type 2 & hyperlipidemia	196	0.3%
depression & diabetes type 1 & diabetes type 2 & hypertension	100	0.1%
depression & diabetes type 1 & hyperlipidemia & hypertension	81	0.1%
depression & diabetes type 1	60	0.1%
depression & diabetes type 1 & diabetes type 2 & hyperlipidemia	54	0.1%
depression & diabetes type 1 & hypertension	40	0.1%
depression & diabetes type 1 & diabetes type 2	40	0.1%
depression & diabetes type 1 & hyperlipidemia	25	0.0%
Total	73,522	100.0%

Notes: This table shows the number of patients by combination of conditions in absolute terms and relative to total sample. For example, 25,050 patients suffer from hyperlipidemia and hypertension, which corresponds to 34.1% of the entire sample. Patients are only included in one group, i.e., patients in depression are those that exclusively suffer from depression.

Table 3.A.2: Substances Overview

ATC	Condition	Substance
A10AB01	diabetes type 1	insulinum humanum adnr
A10AB01	diabetes type 1	insulinum humanum adnr solutum
A10AB04	diabetes type 1	insulinum lisprum
A10AB05	diabetes type 1	insulinum aspartum

Continuation of Table 3.A.2

ATC	Condition	Substance
A10AB06	diabetes type 1	insulinum glulisinum
A10AC01	diabetes type 1	insulinum humanum adnr
A10AC01	diabetes type 1	insulinum humanum adnr isophanum
A10AD01	diabetes type 1	insulinum humanum adnr
A10AD04	diabetes type 1	insulinum lisprum
A10AD05	diabetes type 1	insulinum aspartum
A10AD06	diabetes type 1	insulinum degludecum, insulinum aspartum
A10AD06	diabetes type 1	insulinum degludecum, insulinum aspartum, insulinum humanum adnr
A10AD06	diabetes type 1	insulinum humanum adnr degludecum, insulinum aspartum
A10AE04	diabetes type 1	insulinum glarginum
A10AE05	diabetes type 1	insulinum detemirum
A10AE06	diabetes type 1	insulinum humanum adnr degludecum
A10AE06	diabetes type 1	insulinum degludecum
A10AE54	diabetes type 2	insulinum glarginum, lixisenatidum
A10AE56	diabetes type 2	insulinum humanum adnr degludecum, liraglutidum
A10AE56	diabetes type 2	insulinum degludecum, liraglutidum
A10BA02	diabetes type 2	metformini hydrochloridum
A10BB01	diabetes type 2	glibenclamidum
A10BB04	diabetes type 2	glibornuridum
A10BB09	diabetes type 2	gliclazidum
A10BB12	diabetes type 2	glimepiridum
A10BD05	diabetes type 2	pioglitazonum, metformini hydrochloridum
A10BD07	diabetes type 2	sitagliptinum, metformini hydrochloridum
A10BD07	diabetes type 2	metformini hydrochloridum, sitagliptinum
A10BD08	diabetes type 2	vildagliptinum, metformini hydrochloridum
A10BD10	diabetes type 2	metformini hydrochloridum, saxagliptinum
A10BD11	diabetes type 2	linagliptinum, metformini hydrochloridum
A10BD13	diabetes type 2	alogliptinum, metformini hydrochloridum
A10BD15	diabetes type 2	metformini hydrochloridum, dapagliflozinum
A10BD16	diabetes type 2	canagliflozinum, metformini hydrochloridum
A10BD19	diabetes type 2	empagliflozinum, linagliptinum
A10BD20	diabetes type 2	empagliflozinum, metformini hydrochloridum
A10BD20	diabetes type 2	empagliflozinum, metformini hydrochloridum, metforminum
A10BF01	diabetes type 2	acarbosum
A10BG03	diabetes type 2	pioglitazonum
A10BH01	diabetes type 2	sitagliptinum
A10BH02	diabetes type 2	vildagliptinum
A10BH03	diabetes type 2	saxagliptinum
A10BH04	diabetes type 2	alogliptinum
A10BH05	diabetes type 2	linagliptinum
A10BJ01	diabetes type 2	exenatidum
A10BJ02	diabetes type 2	liraglutidum
A10BJ03	diabetes type 2	lixisenatidum
A10BJ03	diabetes type 2	lixisenatidum, lixisenatidum
A10BJ05	diabetes type 2	dulaglutidum
A10BJ06	diabetes type 2	semaglutidum
A10BK01	diabetes type 2	dapagliflozinum
A10BK02	diabetes type 2	canagliflozinum
A10BK03	diabetes type 2	empagliflozinum
A10BX02	diabetes type 2	repaglinidum
A10BX03	diabetes type 2	nateglinidum
A10BX04	diabetes type 2	exenatidum
A10BX07	diabetes type 2	liraglutidum
A10BX09	diabetes type 2	dapagliflozinum
A10BX11	diabetes type 2	canagliflozinum
A10BX12	diabetes type 2	empagliflozinum
A10BX14	diabetes type 2	dulaglutidum
C02AC05	hypertension	moxonidinum
C02CA04	hypertension	doxazosinum

Continuation of Table 3.A.2

ATC	Condition	Substance
C02DC01	hypertension	minoxidilum
C03AA03	hypertension	hydrochlorothiazidum
C03BA11	hypertension	indapamidum hemihydricum
C03BA11	hypertension	indapamidum
C03DA04	hypertension	eplerenonum
C03EA01	hypertension	amiloridi hydrochloridum anhydricum, hydrochlorothiazidum
C07AA05	hypertension	propranololi hydrochloridum
C07AB02	hypertension	metoprololi tartras (2:1)
C07AB03	hypertension	atenololum
C07AB07	hypertension	bisoprololi fumaras (2:1)
C07AB08	hypertension	celiprololi hydrochloridum
C07AB12	hypertension	nebivololum
C07AG01	hypertension	labetaloli hydrochloridum
C07AG02	hypertension	carvedilolum
C07BB07	hypertension	bisoprololi fumaras (2:1), hydrochlorothiazidum
C07CB03	hypertension	atenololum, chlortalidonum
C08CA01	hypertension	amlodipinum
C08CA02	hypertension	felodipinum
C08CA03	hypertension	isradipinum
C08CA05	hypertension	nifedipinum
C08CA08	hypertension	nitrendipinum
C08CA13	hypertension	lercanidipinum hydrochloridum
C08DA01	hypertension	verapamili hydrochloridum
C08DB01	hypertension	diltiazemi hydrochloridum
C09AA01	hypertension	captoprilum
C09AA02	hypertension	enalaprili maleas
C09AA03	hypertension	lisinoprilum
C09AA04	hypertension	perindoprilum argininum
C09AA04	hypertension	perindoprilum tosylatum
C09AA04	hypertension	perindoprilum-tert-butylaminum
C09AA05	hypertension	ramiprilum
C09AA06	hypertension	quinaprilum
C09AA07	hypertension	benazeprili hydrochloridum
C09BA01	hypertension	captoprilum, hydrochlorothiazidum
C09BA02	hypertension	enalaprili maleas, hydrochlorothiazidum
C09BA03	hypertension	lisinoprilum, hydrochlorothiazidum
C09BA04	hypertension	perindoprilum argininum, indapamidum
C09BA04	hypertension	perindoprilum tosylatum, indapamidum
C09BA04	hypertension	perindoprilum, indapamidum
C09BA04	hypertension	perindoprilum-tert-butylaminum, indapamidum
C09BA05	hypertension	ramiprilum, hydrochlorothiazidum
C09BA05	hypertension	ramiprilum, piretanidum
C09BA06	hypertension	quinaprilum, hydrochlorothiazidum
C09BA09	hypertension	fosinoprilum natricum, hydrochlorothiazidum
C09BB02	hypertension	lercanidipinum, enalaprili maleas
C09BB04	hypertension	perindoprilum tosylatum, amlodipinum
C09BB04	hypertension	perindoprilum argininum, amlodipinum
C09BB10	hypertension	verapamili hydrochloridum, trandolaprilum
C09BX01	hypertension	perindoprilum argininum, amlodipinum, indapamidum
C09BX02	hypertension	bisoprololi fumaras (2:1), perindoprilum argininum
C09CA01	hypertension	losartanum kalicum
C09CA02	hypertension	eprosartanum
C09CA03	hypertension	valsartanum
C09CA04	hypertension	irbesartanum
C09CA06	hypertension	candesartanum cilexetilum
C09CA07	hypertension	telmisartanum
C09CA08	hypertension	olmesartani medoxomilum
C09CA09	hypertension	azilsartanum medoxomilum
C09DA01	hypertension	losartanum kalicum, hydrochlorothiazidum
C09DA02	hypertension	eprosartanum, hydrochlorothiazidum

Continuation of Table 3.A.2

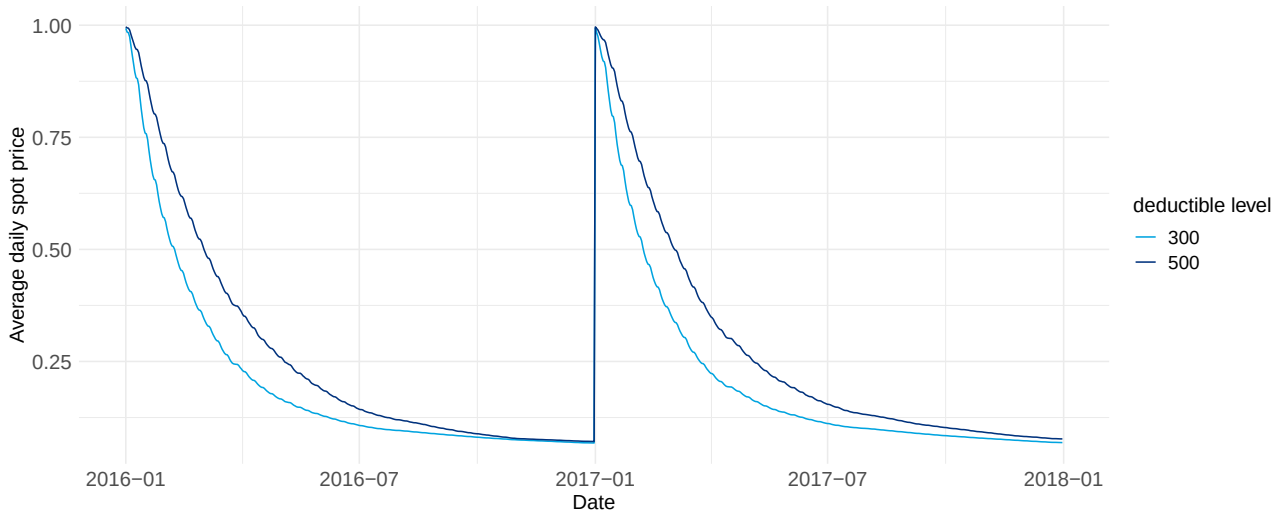
ATC	Condition	Substance
C09DA03	hypertension	valsartanum, hydrochlorothiazidum
C09DA04	hypertension	irbesartanum, hydrochlorothiazidum
C09DA06	hypertension	candesartanum cilexetilum, hydrochlorothiazidum
C09DA07	hypertension	telmisartanum, hydrochlorothiazidum
C09DA08	hypertension	olmesartani medoxomilum, hydrochlorothiazidum
C09DB01	hypertension	amlodipinum, valsartanum
C09DB02	hypertension	olmesartani medoxomilum, amlodipinum
C09DX01	hypertension	amlodipinum, valsartanum, hydrochlorothiazidum
C09DX03	hypertension	olmesartani medoxomilum, amlodipinum, hydrochlorothiazidum
C09XA02	hypertension	aliskirenum
C09XA52	hypertension	aliskirenum, hydrochlorothiazidum
C10AA01	hyperlipidemia	simvastatinum
C10AA03	hyperlipidemia	pravastatinum natricum
C10AA04	hyperlipidemia	fluvastatinum
C10AA05	hyperlipidemia	atorvastatinum
C10AA07	hyperlipidemia	rosuvastatinum
C10AA08	hyperlipidemia	pitavastatinum
C10AB02	hyperlipidemia	bezafibratum
C10AB04	hyperlipidemia	gemfibrozilum
C10AB05	hyperlipidemia	fenofibratum
C10AC01	hyperlipidemia	colestyraminum-20
C10AC01	hyperlipidemia	resina polystyrenolica anionica fortis
C10AC02	hyperlipidemia	colestipoli hydrochloridum
C10AD06	hyperlipidemia	acipimoxum
C10AX09	hyperlipidemia	ezetimibum
C10AX13	hyperlipidemia	evolocumabum
C10AX14	hyperlipidemia	alirocumabum
C10BA02	hyperlipidemia	simvastatinum, ezetimibum
C10BA05	hyperlipidemia	ezetimibum, atorvastatinum
C10BA06	hyperlipidemia	ezetimibum, rosuvastatinum
J01AA02	antibiotics	doxycyclinum
J01AA04	antibiotics	lymecyclinum
J01AA08	antibiotics	minocyclinum
J01CA04	antibiotics	amoxicillinum anhydricum
J01CE02	antibiotics	phenoxymethylpenicillinum kalicum
J01CE10	antibiotics	phenoxymethylpenicillinum benzathinum
J01CF05	antibiotics	flucloxacillinum
J01CR02	antibiotics	amoxicillinum anhydricum, acidum clavulanicum
J01CR02	antibiotics	acidum clavulanicum, amoxicillinum anhydricum
J01CR05	antibiotics	piperacillinum, tazobactamum
J01DB04	antibiotics	cefazolinum
J01DC02	antibiotics	cefuroximum
J01DC04	antibiotics	cefaclorum
J01DD02	antibiotics	ceftazidimum
J01DD04	antibiotics	ceftriaxonum
J01DD08	antibiotics	cefiximum anhydricum
J01DD13	antibiotics	cefpodoximum
J01DD14	antibiotics	ceftibutenum anhydricum
J01DE01	antibiotics	cefepimum
J01DF01	antibiotics	aztreonamum
J01DH02	antibiotics	meropenemum
J01DH03	antibiotics	ertapenemum
J01EE01	antibiotics	sulfamethoxazolum, trimethoprimum
J01FA01	antibiotics	erythromycinum
J01FA09	antibiotics	clarithromycinum
J01FA10	antibiotics	azithromycinum
J01FF01	antibiotics	clindamycinum
J01GB01	antibiotics	tobramycinum
J01GB06	antibiotics	amikacinum

Continuation of Table 3.A.2

ATC	Condition	Substance
J01MA01	antibiotics	ofloxacinum
J01MA02	antibiotics	ciprofloxacinum
J01MA06	antibiotics	norfloxacinum
J01MA12	antibiotics	levofloxacinum
J01MA14	antibiotics	moxifloxacinum
J01MA14	antibiotics	moxifloxacinum hydrochloridum
J01XA01	antibiotics	vancomycinum
J01XA02	antibiotics	teicoplaninum
J01XB01	antibiotics	colistimethatum natricum
J01XC01	antibiotics	natrii fusidas
J01XE01	antibiotics	nitrofurantoinum
J01XX01	antibiotics	fosfomycinum
J01XX08	antibiotics	linezolidum
J01XX09	antibiotics	daptomycinum
N06AA04	depression	clomipramini hydrochloridum
N06AA09	depression	amitriptylinum
N06AA12	depression	doxepinum
N06AB03	depression	fluoxetinum
N06AB04	depression	citalopramum
N06AB05	depression	paroxetinum
N06AB06	depression	sertralinum
N06AB08	depression	fluvoxamini maleas
N06AB10	depression	escitalopramum
N06AG02	depression	moclobemidum
N06AX03	depression	mianserini hydrochloridum
N06AX05	depression	trazodoni hydrochloridum
N06AX11	depression	mirtazapinum
N06AX12	depression	bupropioni hydrochloridum
N06AX16	depression	venlafaxinum
N06AX18	depression	reboxetinum
N06AX21	depression	duloxetinum
N06AX22	depression	agomelatinum
N06AX26	depression	vortioxetinum

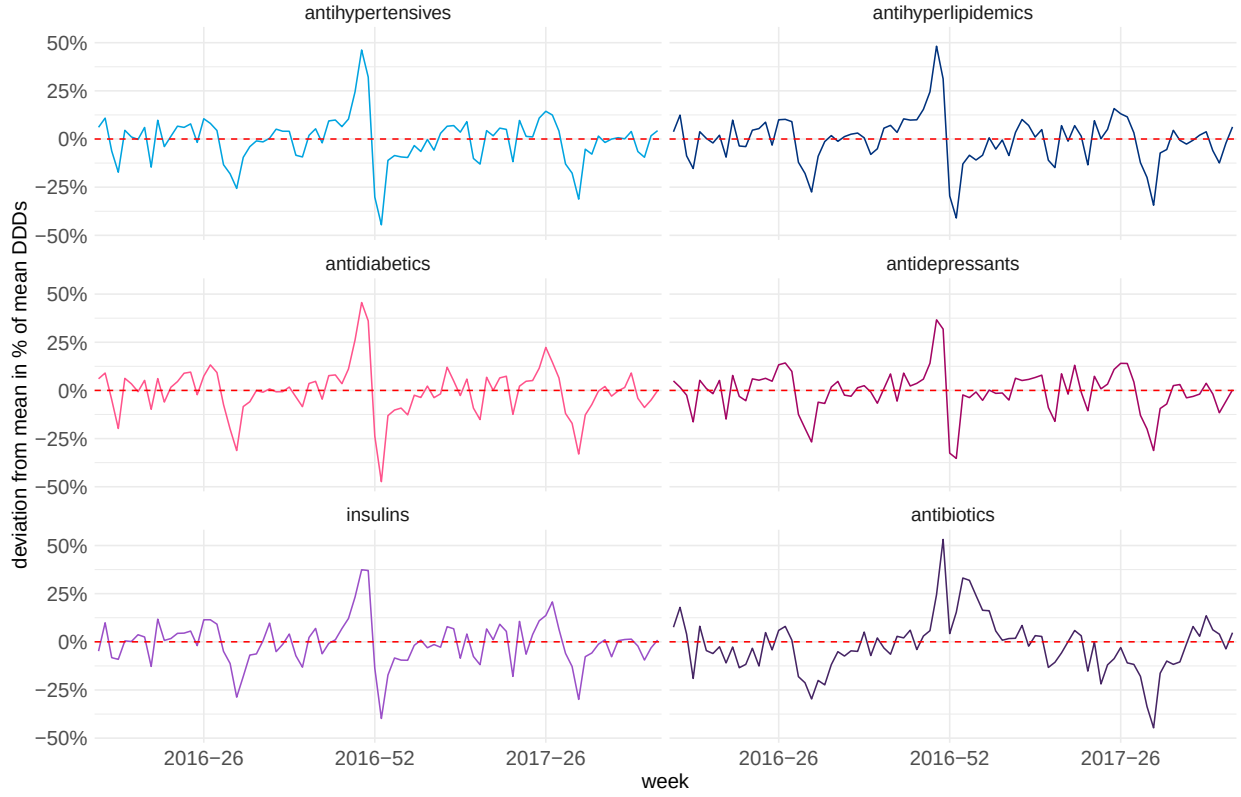
Notes: This table lists all ATC codes that we consider for the treatment of the respective condition. The rightmost column additionally contains information about the specific substance.

Figure 3.A.1: Empirical spot price 2016 - 2017 by deductible level



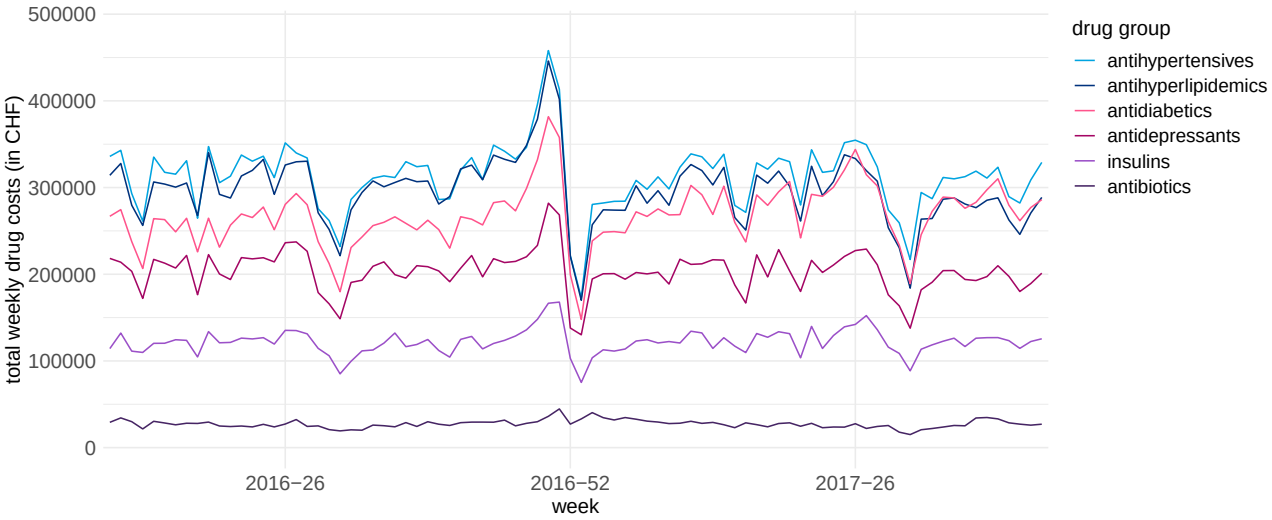
Notes: This figure shows the empirical evolution of the spot price by deductible level over the years 2016 - 2017. The average daily spot price corresponds to the daily sample averages of individual spot prices. Individual daily spot prices are calculated as illustrated in Section 3.A.2.

Figure 3.A.2: Average deviation from mean weekly DDDs by drug group



Notes: This figure plots the evolution of the weekly %-deviation from the average weekly amount of DDDs purchased for each of the considered drug groups separately. The time period is between March 2016 until October 2017.

Figure 3.A.3: Total weekly drug costs by drug group



Notes: This figure directly compares the evolution of the total weekly costs by drug group from March 2016 to October 2017. Costs are measured in CHF.

3.A.2 Definition of Spot Price

The spot price corresponds to the share of the total price that the patient has to pay out-of-pocket and is easily visible on the bill received from the health insurer. The empirical spot price is calculated in the following way,

$$p_{it}^s = \begin{cases} 1 & \text{if } Y_{it}^c \leq d_i \\ \dfrac{d_i - Y_{it-1}^c}{Y_i t} + 0.1 \cdot \dfrac{Y_{it}^c - d_i}{Y_{it}} & \text{if} Y_{it-1}^c < d_i \quad \text{and} \quad Y_{it}^c > d_i. \\ 0.1 & \text{if} Y_{it-1}^c \geq d_i \quad \text{and} \quad Y_{it}^c \leq l_i \\ 0.1 \cdot \dfrac{l_i - Y_{it-1}^c}{Y_{it}} & \text{if} Y_{it-1}^c < l_i \quad \text{and} \quad Y_{it}^c > l_i \\ 0 & \text{if} Y_{it-1}^c \geq l_i \end{cases}$$

where p_{it}^s is the spot price at time t for individual i, Y_{it}^c are accumulated total health care expenditures of individual i at time t and Y_{it} are total health care expenditures of individual i at time t. The deductible level of individual i is denoted by d_i, and $l_i = d_i + 7000$ is the stop-loss amount of individual i.

3.A.3 Robustness

Main Results in CHF

Table 3.A.3: RDD Estimates in CHF

	average below cutoff		baseline	estimate		diff. in % of baseline
	Christmas	summer		Christmas	summer	
antidepressants	1.962	1.611	1.33	-0.602***	-0.426***	13.19%
	(0.051)	(0.042)		(0.068)	(0.058)	
antidiabetics	3.571	2.547	2.18	-1.346***	-0.588***	34.78%
	(0.146)	(0.038)		(0.188)	(0.083)	
antihyperlipidemics	1.783	1.315	1.14	-0.72***	-0.287***	37.85%
	(0.059)	(0.024)		(0.076)	(0.041)	
antihypertensives	1.576	1.185	1.03	-0.603***	-0.256***	33.54%
	(0.067)	(0.023)		(0.084)	(0.035)	
insulins	4.993	4.146	3.44	-2.205***	-0.82***	40.20%
	(0.173)	(0.103)		(0.28)	(0.183)	
chronic combined	4.287	3.241	2.78	-1.603***	-0.73***	31.43%
	(0.131)	(0.031)		(0.173)	(0.068)	

Notes: Average below the cutoff corresponds to the point estimate to the left of the cutoff, the estimate is the result of estimating Equation 3.5.2. The baseline corresponds to the average daily drug costs (in CHF) in 2016. For the Christmas estimates the days between the last Friday before Christmas 2016 and the days before the first Monday after new year are omitted. The cutoff in summer is set to July 15^{th}. Robust standard errors are in parentheses. $^{***}p < 0.001,^{**}p < 0.01,^{*}p < 0.05$.

Table 3.A.4: RDD Estimates in Terms of DDDs Including Sundays and Holidays

	average below cutoff		baseline	estimate		diff. in % of baseline
	Christmas	summer		Christmas	summer	
antidepressants	1.967	1.609	1.34	-0.559***	-0.385***	13.03%
	(0.062)	(0.041)		(0.084)	(0.075)	
antidiabetics	2.767	2.027	1.77	-0.978***	-0.44***	30.31%
	(0.133)	(0.054)		(0.173)	(0.116)	
antihyperlipidemics	2.188	1.69	1.44	-0.775***	-0.381***	27.27%
	(0.094)	(0.036)		(0.122)	(0.076)	
antihypertensives	2.727	2.106	1.84	-0.962***	-0.436***	28.64%
	(0.13)	(0.047)		(0.163)	(0.092)	
insulins	2.032	1.754	1.46	-0.81***	-0.326**	33.11%
	(0.079)	(0.052)		(0.128)	(0.107)	
chronic combined	3.243	2.6	2.23	-0.996***	-0.547***	20.11%
	(0.12)	(0.044)		(0.156)	(0.113)	

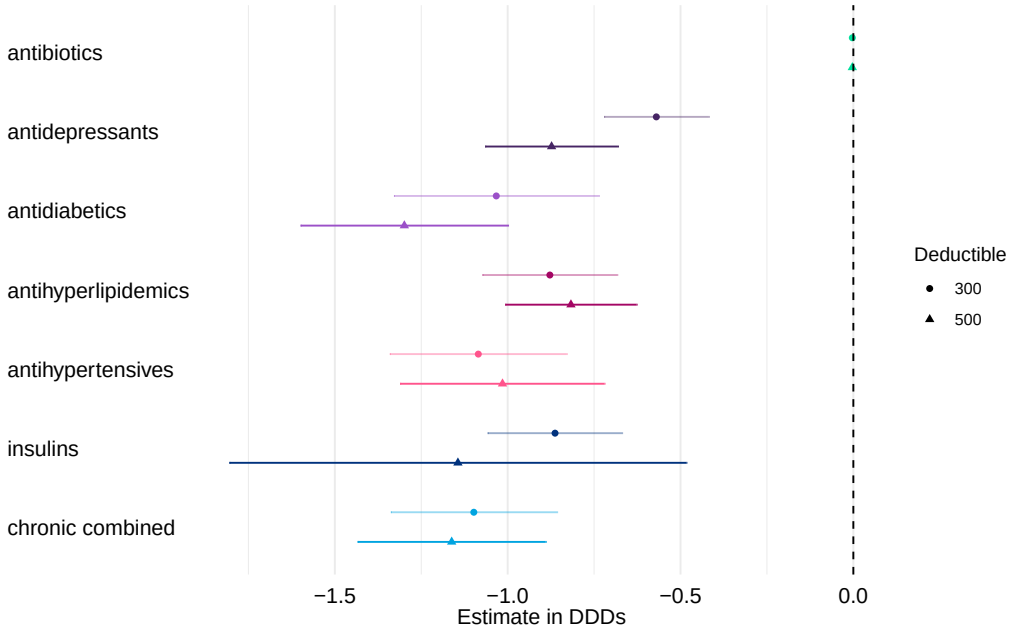
Notes: Average below the cutoff corresponds to the point estimate to the left of the cutoff, the estimate is the result of estimating Equation 3.5.2. The baseline corresponds to the average daily amount of DDDs purchased in 2016. For the Christmas estimates the days between the last Friday before Christmas 2016 and the days before the first Monday after new year are omitted. The cutoff in summer is set to July 15^{th}. If pharmaceuticals of several of the groups are purchased on a given day, the amount of DDDs for chronic combined corresponds to the average amount of DDDs. Robust standard errors are in parentheses. $^{***}p < 0.001$,$^{**}p < 0.01$,$^{*}p < 0.05$.

Table 3.A.5: RDD Estimates in Terms of DDDs Without Using day of the week fixed-effects

	average below cutoff		baseline	estimate		diff. in % of baseline
	Christmas	summer		Christmas	summer	
antidepressants	1.903	1.524	1.34	-0.604**	-0.391**	15.91%
	(0.152)	(0.106)		(0.198)	(0.147)	
antidiabetics	2.659	1.99	1.77	-1.029**	-0.403	35.26%
	(0.257)	(0.169)		(0.329)	(0.263)	
antihyperlipidemics	2.101	1.6	1.44	-0.808**	-0.349	31.75%
	(0.224)	(0.144)		(0.288)	(0.216)	
antihypertensives	2.688	1.975	1.84	-0.998**	-0.395	32.84%
	(0.276)	(0.166)		(0.353)	(0.25)	
insulins	2.118	1.682	1.46	-0.87***	-0.314	38.12%
	(0.166)	(0.11)		(0.217)	(0.182)	
chronic combined	3.156	2.462	2.23	-1.041**	-0.514	23.57%
	(0.295)	(0.19)		(0.385)	(0.288)	

Notes: Average below the cutoff corresponds to the point estimate to the left of the cutoff, the estimate is the result of estimating Equation 3.5.2 without including day of the week fixed-effects. The baseline corresponds to the average daily amount of DDDs purchased in 2016. For the Christmas estimates the days between the last Friday before Christmas 2016 and the days before the first Monday after new year are omitted. The cutoff in summer is set to July 15^{th}. Sundays and holidays are excluded from the estimation. If pharmaceuticals of several of the groups are purchased on a given day, the amount of DDDs for chronic combined corresponds to the average amount of DDDs. Robust standard errors are in parentheses. $^{***}p < 0.001$,$^{**}p < 0.01$,$^{*}p < 0.05$.

Figure 3.A.4: RDD estimates in DDDs by deductible level



Notes: This figure directly compares the RDD estimates in terms of DDDs by deductible level. The dots and triangles correspond to the point estimates, and the horizontal lines indicate the 95%-confidence intervals. We employ robust standard errors.

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Statement of Authorship

I declare herewith that I wrote this thesis on my own, without the help of others. Wherever I have used permitted sources of information, I have made this explicitly clear within my text and I have listed the referenced sources. I understand that if I do not follow these rules that the Senate of the University of Bern is authorized to revoke the title awarded on the basis of this thesis according to Article 36, paragraph 1, litera r of the University Act of September 5th, 1996.

Selbständigkeitserklärung

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Bern, 27. März 2024

Linn Hjalmarsson